

# The Impact of the Epidemic on Risk-Taking in Commercial Banks

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## Abstract

*The outbreak of the COVID-19 epidemic in 2020 significantly impacted various industries and the overall economy, with China's GDP showing negative growth in the first quarter of that year, threatening the banking sector. Despite the limited direct effect on the scale of lending by Chinese commercial banks, non-performing loans experienced a significant increase. This study examines the influence of the epidemic on commercial banks' risk-taking behavior. It finds that the epidemic enhances risk-taking by increasing economic losses, directly through financial losses and indirectly through rising business risks, reduced profitability, and changes in enterprise cash reserves. Moreover, the study highlights that insurance protection and bank risk management are moderating, with stronger protections weakening the impact on risk-taking. Additionally, the heterogeneity of local banks reveals that those serving rural areas experience greater risk-taking impacts than banks focused on urban industrial and commercial groups.*

**Keywords:** *Epidemic, Bank Risk, Risk-Taking.*

## Introduction

In late 2019, an outbreak emerged in Wuhan, leading to the city's lockdown on January 23, 2020. The Chinese Central People's Government declared a "national state of emergency" and implemented strict restrictions on the movement of people to contain the spread of the epidemic. The epidemic also affected the banking sector, with all industries shutting down or even closing down. Restrictions on the movement of people directly affect the operation of banks and their business, and customers' liquidity affects the profitability and risk of banks. As China's financial system is primarily driven by indirect finance, with commercial banks being the most prevalent financial institutions, the epidemic will likely pose risks to the micro-banking sector due to real economic losses.

The relationship between epidemics and bank risk has become a significant topic in academic research. While some international studies have demonstrated that epidemics negatively impact bank risk (Noth and Schüwer, 2023; Chavaz, 2022; Klomp, 2014), there remains a lack of empirical research examining how epidemics influence bank risk. Therefore, based on the existing theories and the economic losses caused by the epidemic in China, this paper poses the question: did the epidemic in China lead to more risk-taking by local commercial banks by affecting firms and households, which in turn was transmitted to the banking sector? Additionally, epidemic prevention and control measures and banks' risk management strategies may have played a role in moderating this process. For instance, did banks' well-established insurance mechanisms and strong capital management before the epidemic help mitigate its impact on bank risk? The type of bank also likely influences risk-taking behavior, with potential differences in how various local commercial banks responded to the epidemic. For example, banks serving prefecture-level and provincial capitals may have differed from those focused on county economies in their risk management approaches. Research into these factors would offer valuable empirical insights into the economic consequences of the epidemic and provide practical implications for managing financial risks, ensuring economic security, and fostering development.

The contributions of this paper are to investigate the effect of epidemics on commercial banks' risk-taking in the context of China's epidemics and to verify its theoretical mechanism, enriching the research on the relationship between epidemics and banks' risk-taking; to analyze how the relevant systems regulate the

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impact of outbreaks on banks' risks from the perspectives of catastrophe insurance coverage and banks' risk management, and to provide theoretical support to the policy formulation. Additionally, the impact of epidemics on banks' risk-taking will be assessed by comparing the differences among various types of local commercial banks. It further provides policy suggestions to mitigate epidemic-related banking risks.

## Literature Review

There are limited direct studies on the impact of the Covid-19 epidemic on commercial banks' risk-taking. Therefore, this study starts with a literature review of how the Covid-19 epidemic has affected commercial banks.

Studies on the current state of commercial bank operations during the epidemic have highlighted several impact areas. Zhao et al. (2021) suggest that factors such as the economic environment, policy direction, and customer demand influence bank loan businesses, and in the long run, the epidemic may drive bank development. Similarly, Yang (2022) contends that while the epidemic may lead to a short-term increase in banks' non-performing loan ratios, it could be beneficial in the long term. Zhu (2021) discovered that although the capital market volatility impacts banks in the short term, it helps to improve their profits in the long term.

Regarding the problems in the development of commercial banks during the pandemic, scholars believe that various factors constrain the development of banks. Ju (2022) notes that the credit capacity of financial institutions, which is closely tied to the financing ability of businesses, has been significantly impacted by the epidemic. Luo and Tian (2021) argue that a series of chain effects triggered by the epidemic adversely affected bank profits, which they categorize into three channels: net interest margin, asset risk, and Internet financial competition. Zhu (2021) says that the New Crown Epidemic, the worst public health crisis since World War II, affects the banking business in the short term, narrowing deposit and loan spreads and deposit losses. Still, in the long term, it will accelerate the transformation of banking operations towards retail services.

Regarding the impact of the COVID-19 epidemic on commercial banks, scholars agree that while the epidemic poses significant threats to these institutions, it also presents opportunities for them. Minsheng Bank Research Institute group (2020) pointed out that the epidemic led to a short-term decline in supply and demand, and the industry was widely affected. However, the impact on the banking industry is primarily indirect, and the overall risk remains manageable. Wu (2020) claimed that the epidemic has exacerbated the risk of corporate defaults and increased the difficulty of handling non-performing assets, which requires a high degree of attention. Li (2020) analyzes credit risk, pointing out that economic downward pressure exacerbates banks' credit risk, and control should be strengthened. By constructing a bank risk stress index, Liangs (2020) argues that the epidemic has hit economic activities hard, and banks' overall risk has risen. Xu and He (2020) emphasized that small and medium-sized banks already faced high risks before the epidemic, further aggravating the pressure of non-performing assets growth. Lu (2020) points out that the increase in NPLs is mainly due to the delay in corporate repayment, but in the long run, it will help to improve banks' risk resistance. Li (2020) suggests that commercial banks shift to a smart business model in the post-epidemic period and strengthen online and offline integration. Wang (2021) suggests that the epidemic's impact on banks' performance is most evident in operating income and net profit, with significant effects in the short term. In contrast, through empirical research, Zheng and Sun (2022) found that economic growth and bank profitability are positively correlated in the short term but exhibit a negative correlation in the medium and long term.

Regarding research on the countermeasures commercial banks use to cope with the epidemic, academics generally agree that the situation should be analyzed from multiple perspectives, with corresponding solution strategies proposed based on theoretical foundations, to maximize the benefits for commercial banks. Wang (2021) suggests that commercial banks should strive to turn the crisis into an opportunity and reduce risks while injecting vitality into development by taking responsibility, accelerating digitalization and platform transformation, supporting the development of emerging industries, and enhancing user

experience. Nan (2020) suggests pursuing flexible policies at the macro level, improving pricing power from the market perspective, utilizing blockchain technology in risk prediction, and promoting the digital economy from the development perspective. Zhong & Guo (2020) suggest that small and medium-sized banks should leverage their advantage in “soft information,” accelerate their digital transformation, enhance their asset-liability structure, optimize their financial ecosystems, and address the systemic and institutional issues hindering their development.

### *Theoretical Analysis and Research Hypotheses*

#### *The Impact of the Epidemic on Banks' Risk-Taking*

The effect of the epidemic on commercial banks' risk-taking is primarily seen in the fact that the epidemic will cause the destruction of physical assets and the decline in profitability of the credit subjects of commercial banks-households and enterprises, which will bring direct and indirect economic losses to households and enterprises, reduce the value of the collaterals of the banks' credit assets and the solvency of the credit subjects and their willingness to repay debts, and then affect the quality of the banks' credit assets and raise the bank's risk-taking level. Firstly, from the perspective of direct economic losses, the epidemic can result in the destruction or loss of physical assets owned by households and businesses, reducing the quality of bank credit assets secured by these assets and increasing risk (Klomp, 2014). Additionally, if the physical assets or collateral damaged by the epidemic were not insured in advance, or if the risk was underestimated, the financial losses would be directly transferred to households and enterprises. This would weaken their balance sheets, lower their repayment capacity, heighten the likelihood of loan defaults, and potentially lead to bank losses or bankruptcies (Lambert et al., 2022). Second, as far as indirect losses are concerned, epidemics can cause damage to crops and destruction of infrastructure, leading to higher prices of agricultural products, disruption of supply chains, higher transportation costs, higher costs of production and living for firms and households, and reduced incomes. At the same time, epidemics can also lead to interruptions in production, disruptions in product sales, increased business risk, and declines in profitability and expected future cash flows. Existing research has shown that epidemics negatively affect the cash flows of U.S. firms, leading them to rely more on bank lines of credit to mitigate the risks associated with declining cash flows (Brown et al., 2021). Regarding profitability, epidemics reduce firms' profitability (Hong et al., 2018), and the greater the risk of epidemic fluctuations in a firm's location, the higher the volatility in its profitability (Huang et al., 2017).

Meanwhile, in terms of operational risk to firms, banking institutions have incorporated the factor of public health emergencies in their lending assessment of firms. Epidemics cause banks to raise lending rates to firms, making firms' financing costs vulnerable to epidemics, which raises firms' operational risk (Javadi & Masum, 2021). With impaired business capacity, firms' ability and willingness to repay decline, and bank credit defaults rise. A simulation analysis by Dafermos et al. (2022) using global data shows that epidemics damage commercial banks' soundness by damaging firms' assets, decreasing their profitability, deteriorating firms' liquidity, and increasing defaults on firms' loans.

Epidemics not only cause property losses for economic agents but also transmit through various channels to the banking system, thereby increasing the risk-taking of commercial banks. Wang and Wang (2021) demonstrate that public health emergencies impact the banking system through pathways such as the reduction of corporate assets and a decline in total factor productivity, resulting in a substantial rise in bank default rates. Epidemics can directly or indirectly raise the default rate of bank credit assets through the channels of depreciation of collateralized assets, decline in corporate profitability, and deterioration of households' financial conditions, thus increasing the level of risk-taking by banks. Based on this, the paper presents empirical hypothesis 1:

Hypothesis 1: Epidemics elevate the risk-taking levels of local commercial banks in China, with the primary mechanism being the transmission of direct and indirect economic losses from the epidemic affecting the enterprise and household sectors to the banking sector.

*The Moderating Effect of Insurance Coverage and Bank Risk Management on the Risk Faced by Banks During Epidemic Situations.*

Insurance plays a role as a “shock absorber” in society, and expanding the coverage and depth of insurance can help improve the ability of society and the economy to cope with changes in epidemics (Wang, Xiangnan, 2020). Epidemics can cause property losses for businesses and households, particularly damage to physical collateral and disruption of business activities, directly impacting insurance companies that cover these risks (Scott et al., 2021). If post-disaster compensation is inadequate, the epidemic may worsen the financial position of businesses and households, negatively impacting their balance sheets and increasing the likelihood of loan defaults, thereby transmitting risks to the banking system (Olovsson, 2023). As a result, pre-disaster insurance and post-disaster relief are crucial. However, since epidemics are low-probability events, insurance companies often hesitate to offer coverage for such risks.

Additionally, insurance coverage is often insufficient due to the unpredictable nature of epidemics and the potential for small outbreaks at any time. In the event of an epidemic, losses would be directly transferred to businesses and households, weakening their solvency and thus increasing banks’ risk. In contrast, countries with more excellent insurance coverage are more capable of recovering quickly from the financial impacts of an epidemic (Feyen et al., 2020). In developed countries with higher insurance coverage, epidemics have a smaller impact on bank loan default rates (Klomp, 2014).

In China, the state encourages insurance companies to launch epidemic prevention and control insurance but lacks an effective implementation mechanism. In recent years, China has mainly relied on government finances for epidemic relief but only provides minimal post-disaster assistance, and commercial insurance is still needed to supplement and improve the disaster relief mechanism. China’s disaster insurance coverage is low, with a payout rate of only 5%, whereas in Europe and the United States, this rate can reach 70% (Wang et al., 2021). Therefore, the economic losses from the epidemic may be transmitted to the banking system, and increased insurance coverage could help mitigate banks’ risk-taking.

A bank’s capital adequacy level is a key factor influencing its risk-taking behavior (Basher et al., 2017). From a bank’s risk management perspective, capital adequacy reflects its ability to cope with risk and determines its ability to withstand adverse shocks. After an epidemic, banks may encounter a high volume of non-performing loans, resulting in capital depletion, worsened business conditions, and potentially even a bank run (Klomp, 2014). Schüwer et al. (2022) observed that banks in regions severely affected by epidemics tend to raise their capital ratios to better protect against future risks and reduce potential losses. Consequently, banks should maintain higher capital reserves to handle disaster-related shocks effectively. Schydrowsky (2020) argues that capital adequacy requirements are a vital tool for regulators in managing the impact of epidemic shocks. Likewise, Ozili (2021) recommends that central banks require financial institutions to use their risk reserves to recover quickly from the effects of epidemics or charge a fixed interest rate on risk capital to compensate for asset losses. Therefore, commercial banks should strengthen their capital management to mitigate the adverse impacts of epidemics and lower their risk-taking. Based on this, empirical hypothesis 2 is proposed.

Hypothesis 2: Increasing insurance coverage and maintaining adequate bank capital levels will help mitigate the epidemic’s impact on their risk-taking.

*Heterogeneity Analysis of the Epidemic’s Impact on Banks’ Risk-Taking*

In China, the epidemic’s effect on the risk-taking of local commercial banks may differ based on the banks’ target customers and business scope. Local commercial banks serving commerce and industry in prefectural and provincial capital cities tend to be more resilient to risk. In contrast, those primarily focused on serving the county economy are generally less resilient. First, local commercial banks that serve mainly the three rural areas (agriculture, rural areas, and farmers) are likely to be more affected by epidemic risk. County banks are smaller and less risk-resistant than banks serving urban commerce and industry (Bougatef & Mgadmi, 2016). In terms of sectoral sensitivity, agriculture is more vulnerable to the impact of the epidemic, which has affected agricultural production, marketing, and trade, among others. It has caused hardship for

some agricultural practitioners, leading to a decline in farmers' repayment capacity and increasing banks' credit risk (Pelka et al., 2015). Epidemics have also been shown to affect agricultural output directly (Teng et al., 2022). The business of county banks is mainly dependent on the county economy, and most county economies are dominated by agriculture, thus making it difficult to diversify the risks associated with epidemics. In addition, the slow development of insurance business in counties and the low coverage level further exacerbate the epidemic's impact on production and investment activities. As a result, local banks serving the county economy are exposed to higher risks than local banks serving commerce and industry in prefectural and provincial capital cities. Building on this, the paper presents hypothesis 3: Hypothesis 3: The epidemic's effect on the risk-taking of local commercial banks in counties, which mainly cater to rural areas, will be more pronounced than that on banks serving industrial and commercial sectors, as well as households in prefecture and provincial cities.

### *Construction of Benchmark Regression Model*

$$\text{Risk}_{i,t} = \alpha_0 + \alpha_1 \text{Risk}_{i,t-1} + \alpha_2 \text{Risk}_{i,t-2} + \alpha_3 \text{Covid}_{r,t} + \sum_{n=4}^7 \alpha_n X_{i,t-1} + \alpha_8 \text{Gap}_{r,t} + \alpha_9 \text{Area}_r + u_i + \lambda_t + \varepsilon_{i,t}$$

In equation 3-1,  $i$  denotes a specific bank,  $t$  represents a particular year, and  $r$  indicates the prefecture-level city or provincial capital city where the head office of a local commercial bank is located. The dependent variable,  $\text{Risk}_{i,t}$  reflects the individual risk-taking of bank  $i$  during period  $t$ . The measures of bank risk-taking include NPL (non-performing loans) and Z-score. Given the persistence of bank risk, meaning the previous level of risk may influence the current level, the explanatory variables in the model include the first-order lagged term  $\text{Risk}_{i,t-1}$ , and the second-order lagged term  $\text{Risk}_{i,t-2}$  of the dependent variable.  $\text{Covid}_{r,t}$  represents the epidemic indicator,  $X_{i,t-1}$  refers to the micro-level control variables of the banks, and  $\text{Gap}_{r,t}$  is the local economic output gap, acting as the regional-level control variable. The binary variable  $\text{Area}_r$  reflects the economic characteristics and bank behavior in the region of the bank's headquarters.  $u_i$  accounts for individual bank effects,  $\lambda_t$  represents annual time fixed effects, and  $\varepsilon_{i,t}$  represents the residual terms.

This study employs the System Generalized Method of Moments (SYS-GMM) for equation 3-1 estimation to address potential bias in estimating the dynamic panel model using Ordinary Least Squares (OLS).

### *Variable Definition*

#### *Dependent Variable*

$\text{Risk}_{i,t}$  represents the degree of risk-taking by commercial banks. This study uses the non-performing loan ratio (NPL) and Z-score as the main indicators of bank risk. Additionally, the loan provisioning ratio (LLR) and the volatility of return on assets (SdROA) are employed for robustness checks. There is a negative correlation between bank risk and the Z-score, meaning that a higher Z-score indicates a lower likelihood of bankruptcy, which is typically a positive outcome. Since the distribution of Z-values is skewed, this study follows the convention of taking the natural logarithm and inverting them ( $\ln Z$ ) in order to interpret the regression results consistently. The loan provisioning ratio (LLR) is the proportion of loan loss provisions compared to the total loans, reflecting bank's judgment and level of risk-taking. According to the definition,  $\text{LLR} = \text{Loan Loss Provision} / \text{Total Loans} = (\text{Loan Loss Provision} / \text{Non-Performing Loans}) * (\text{Non-Performing Loans} / \text{Total Loans}) = \text{Provision Coverage Ratio} * \text{Non-Performing Loan Ratio}$ .

#### *Core Explanatory Variables*

Starting in January 2020, COVID-19 began to spread across the country, coinciding with the New Year's Spring Festival travel period. The initial lack of understanding about the virus and the festive atmosphere allowed the epidemic to spread quickly among people. As a result, this study designates the years before 2019, when the epidemic was not present, as 0, and the years after 2019 as 1.

### Control Variables

Micro-level control variables include bank asset size (Size, measured in natural logarithms), net interest margin level (Nim, reflecting the profitability of interest-earning assets), equity asset ratio (EA, measuring the bank's financial leverage capacity), and deposit share (Dep, reflecting the bank's liability structure). The regional-level control variables include the output gap (Gap) and regional characteristics (Area) of the head office location based on the Hu Huanyong line that divides the Southeast and Northwest regions. In addition, to control for the impact of regional economic levels and time effects, this study introduces year-fixed effects (Year effects) to ensure the robustness of the results.

This study focuses on national and local commercial banks, including urban and rural ones. Based on the availability of relevant data, the analysis sample consists of unbalanced panel data from 281 local commercial banks in China from 2012 to 2023. Data for the control variables and other factors are sourced from the National Bureau of Statistics website, the Wind database, and the China Urban Statistical Yearbook. To minimize the impact of extreme values on the analysis, continuous variables are Winsorized at the 1%-99% level.

## Findings

### Descriptive Statistic

The descriptive statistics for the main variables are presented in Table 1. Table 1 shows that among the risk characteristics of commercial banks' credit asset structure allocation, the minimum value of NPL is 0.03, the maximum value is 12.25, the minimum value of lnZ is 2.1497. The maximum value is 6.5942, which suggests a large difference in the risk characteristics of local commercial banks in China. In addition, considering the multicollinearity problem, this study carried out the Variance Inflation Factor (VIF) test on the relevant variables. The test results show that the VIF of the independent variables are all less than 5, indicating that the covariance problem is not obvious.

**Table 1. Descriptive Statistics of the Main Variables**

Variable	Variable Meaning	Mean	Standard deviation	Minimum value	Maximum value
NPL	Non-performing loan ratio	2.1925	1.8526	0.0300	12.2500
lnZ	Z-score	4.1616	0.9063	2.1497	6.5942
LLR	Loan provisioning ratio	4.1721	1.7846	1.1914	9.7627
SdROA	Volatility of asset return	0.1895	0.2094	0.0002	2.9218
Size	Logarithmic bank asset size	10.1247	1.3579	7.4202	13.6000
Nim	Net interest margin	2.5514	1.1039	0.3603	5.6012
Dep	Deposit ratio	75.8112	13.3329	35.3943	93.8645
EA	Equity asset ratio	7.4877	2.6176	2.1015	17.0510
Gap	Output gap	0.0291	1.2516	-3.1329	3.2243
Area	Hu Huanyong Line	0.9331	0.2499	0.0000	1.0000
Car	Capital adequacy level	13.5290	3.6289	2.6000	29.5800
Ins	Insurance depth	1.0626	0.4308	0.0600	6.0500

### Benchmark Regression Results

The regression results examining the impact of the epidemic on the risk-taking behavior of local commercial banks are presented in Table 2. The findings indicate that the coefficients for both the first-order and second-order lagged terms of bank risk are significant, suggesting a certain level of persistence in the risk-taking behavior of local commercial banks. Additionally, the coefficients for the epidemic (Covid) variable are significantly positive in the models with NPL and lnZ as dependent variables, indicating that the epidemic has a substantial positive effect on the risk-taking behavior of local commercial banks. In the

estimation results presented in Table 4, the AR (2) values are all greater than 0.1, suggesting that the null hypothesis of no second-order or higher-order serial correlation in the disturbance term cannot be rejected. Furthermore, the p-values for Hansen's statistic pass the test, confirming no over-identification, thus validating the dynamic panel estimation and supporting Hypothesis 1. In China, epidemics increase the default rate of bank credit assets and elevate risk-taking within the banking sector.

**Table 2. Baseline Regression Results on the Epidemic's Effect on Commercial Bank Risk-Taking**

Variable	NPL			lnZ		
	(1)	(2)	(3)	(4)	(5)	(6)
L. NPL	0.495*** (0.072)	0.496*** (0.073)	0.582*** (0.076)			
L2. NPL	-0.098* (0.057)	-0.098* (0.056)	-0.055 (0.047)			
L. lnZ				0.417*** (0.042)	0.418*** (0.041)	0.395*** (0.131)
L2. lnZ				-0.226*** (0.035)	-0.226*** (0.035)	-0.157 (0.138)
Covid			0.060** (0.027)			0.092** (0.041)
L. Size	-0.327*** (0.098)	-0.331*** (0.106)	-0.298*** (0.089)	-0.215*** (0.056)	-0.223*** (0.064)	-0.194* (0.105)
L. Nim	0.134 (0.112)	0.135 (0.113)	0.014 (0.093)	-0.062 (0.060)	-0.061 (0.060)	-0.201 (0.193)
L. Dep	-0.007 (0.007)	-0.008 (0.007)	-0.000 (0.006)	-0.006 (0.005)	-0.007 (0.006)	0.004 (0.009)
L. EA	-0.081 (0.063)	-0.085 (0.067)	-0.020 (0.042)	-0.057** (0.024)	-0.056** (0.024)	-0.037 (0.059)
Gap	-0.050 (0.034)	-0.045 (0.030)	-0.002 (0.108)	-0.023 (0.028)	-0.022 (0.027)	-0.004 (0.032)
Area	-0.142 (0.155)	-0.135 (0.162)	-0.207 (0.148)	-0.110 (0.154)	-0.101 (0.158)	-0.459 (0.663)
Constant	6.359*** (1.861)	6.101*** (1.716)	4.551*** (1.429)	-0.219 (0.877)	-0.109 (1.039)	-1.177 (1.819)
Baneffects	YES	YES	YES	YES	YES	YES
Yeareffects	YES	YES	YES	YES	YES	YES
N	1216	1216	1216	1040	1040	1040
AR(2)	0.276	0.286	0.239	0.286	0.285	0.552
Hansenp	0.222	0.225	0.277	0.235	0.256	0.312

Note: (1)The models are estimated using a one-step systematic GMM approach. L. NPL and L2. NPL represents the first- and second-order lags of NPL, respectively, while L. lnZ and L2. lnZ denotes the first- and second-order lags of lnZ. (2) Bank and year effects refer to the bank-specific and year-fixed effects, respectively. (3) AR(2) represents the second-order autocorrelation test, with the p-value used for statistical inference; the p-values of Hansen's statistic all pass the test, indicating no over-identification. (4) Standard errors are shown in parentheses beneath the coefficients of each variable, and \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

*Robustness Testing**Replacing the Sample Period*

The sample period for the benchmark regression in this study is 2012-2023. However, this period's length may impact the robustness of the empirical results from the benchmark model. Due to this reason, in this part of the robustness test, this study firstly excludes the sample of 2012-2015 and does a further regression test on the data sample of 2016-2023. The robustness results are shown in Table 3, and the sample period does not affect the robustness of the benchmark results.

**Table 3. Regression Results with Replacement of Sample Intervals**

Variable	NPL			lnZ		
	(1)	(2)	(3)	(4)	(5)	(6)
L. NPL	0.532***	0.598***	0.608***			
	(0.142)	(0.088)	(0.084)			
L2. NPL	-0.075	-0.024	-0.070			
	(0.068)	(0.045)	(0.050)			
L. lnZ				0.412***	0.361***	0.362**
				(0.044)	(0.097)	(0.156)
L2. lnZ				-0.227***	-0.163**	-0.164
				(0.037)	(0.067)	(0.143)
Covid			0.055**			0.108**
			(0.027)			(0.048)
ControlVal	YES	YES	YES	YES	YES	YES
Bankeffects	YES	YES	YES	YES	YES	YES
Yeareffects	YES	YES	YES	YES	YES	YES
N	1095	1095	1095	978	978	978
AR(2)	0.292	0.267	0.245	0.438	0.233	0.708
Hansenp	0.155	0.222	0.310	0.243	0.272	0.123

Note: (1) The models are estimated using a one-step systematic GMM approach. L. NPL and L2. NPL represents the first-order and second-order lags of NPL, respectively, while L. lnZ and L2. lnZ represents the first-order and second-order lags of lnZ. (2) Bankeffects and Yeareffects denote bank-individual and year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values of Hansen's statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are in parentheses under the coefficients of each variable, and \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively, as follows.

*Excluding Local Commercial Banks Operating Across Provinces*

The foregoing shows that in matching control variables at the epidemic and regional levels for local commercial banks operating across regions, this study matches the data in the region where the head office of the bank, which has a higher share of its credit asset business, is located. In order to avoid the possible impact of data matching on the regression results of the benchmark model and to ensure the robustness of the results, this study excludes commercial banks operating across provinces from the sample and conducts robustness tests on the sample. The regression results are presented in Table 4. The findings in Table 4



suggest that excluding commercial banks operating across provinces does not affect the benchmark regression results, confirming that the results remain robust.

**Table 4. Regression Results Excluding Local Commercial Banks Operating Across Provinces**

Variable	NPL			lnZ		
	(1)	(2)	(3)	(4)	(5)	(6)
L. NPL	0. 563*** (0. 124)	0. 535*** (0. 118)	0. 578*** (0. 078)			
L2. NPL	-0. 086 (0. 058)	-0. 056 (0. 049)	-0. 057 (0. 048)			
L. lnZ				0. 497*** (0. 106)	0. 170*** (0. 043)	0. 399*** (0. 124)
L2. lnZ				-0. 348** (0. 140)	-0. 440*** (0. 036)	-0. 143 (0. 130)
Covid			0. 056** (0. 027)			0. 085** (0. 039)
ControlVal	YES	YES	YES	YES	YES	YES
Bankeffects	YES	YES	YES	YES	YES	YES
Yeareffects	YES	YES	YES	YES	YES	YES
N	1100	1100	1100	933	933	933
AR(2)	0. 379	0. 330	0. 260	0. 076	0. 262	0. 266
Hansenp	0. 150	0. 227	0. 482	0. 216	0. 276	0. 261

Note: (1)The models are estimated using a one-step systematic GMM approach. L. NPL and L2. NPL represent the first-order and second-order lags of NPL, respectively, while L. lnZ and L2. lnZ represent the first-order and second-order lags of lnZ.; (2) Bankeffects and Yeareffects denote bank-individual and year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values of Hansen's statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are provided in parentheses beneath the coefficients of each variable, with \*, \*\*, and \*\*\* indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

#### *Replacement of Dependent Variables*

To verify the robustness of the results, this study performs a robustness test on the benchmark model by using the loan provisioning ratio (LLR) and the volatility of return on assets (SdROA) as alternative proxy variables for measuring the risk-taking behavior of local commercial banks. The loan provisioning ratio reflects the proportion of allowances for bad and doubtful debts set aside by bank managers based on their risk assessments, which, to some extent, also indicates the bank's level of risk-taking. The regression results are presented in Table 5. The findings in Table 5 suggest that substituting the dependent variables did not alter the empirical results, further confirming the robustness of the findings.

**Table 5. Results of Regression with Replacement of Dependent Variable**

Variable	NPL			lnZ		
	(1)	(2)	(3)	(4)	(5)	(6)
L. NPL	0. 742*** (0. 071)	0. 727*** (0. 064)	0. 765*** (0. 086)			
L2. NPL	-0. 019 (0. 074)	-0. 017 (0. 076)	0. 028 (0. 046)			
L. SdROA				0. 614*** (0. 116)	0. 619*** (0. 114)	0. 498*** (0. 026)
L2. SdROA				-0. 136*** (0. 035)	-0. 122*** (0. 029)	-0. 173*** (0. 022)
Covid			0. 057** (0. 024)			0. 007** (0. 004)

ControlVal	YES	YES	YES	YES	YES	YES
Bank effects	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES
N	1013	1043	1013	1043	1013	1043
AR(2)	0. 530	0. 541	0. 456	0. 955	0. 985	0. 916
Hansenp	0. 298	0. 356	0. 263	0. 169	0. 178	0. 137

Note: (1) Models are estimated using a single-step systematic GMM; L. NPL and L2. NPL denote first- and second-order lags of NPL; L. lnZ and L2. lnZ denote first- and second-order lags of lnZ; (2) Bankeffects and Yeareffects denote bank-individual and year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values of Hansen’s statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are presented in parentheses below the coefficients of each variable, with \*, \*\*, and \*\*\* indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

*A Mechanistic Test of the Impact of Epidemics on Bank Risk-Taking*

*Mechanism of Direct Loss Impact on Economic Agents*

The theoretical analysis outlined above suggests that the epidemic leads to the destruction of physical assets and a decline in the profitability of households and businesses. This results in both direct and indirect economic losses for these entities, diminishing the value of collateral for bank credit assets and borrowers’ debt-servicing capacity and willingness. Consequently, this impacts the quality of bank credit assets and increases the level of bank risk-taking. Building on this, this section explores how the epidemic affects bank risk-taking, focusing on both the direct economic losses and the indirect effects on the operational capacity of economic agents.

To begin, a mediation effect test model is constructed based on equation 3-1, utilizing the stepwise test approach by Baron and Kenny (1986) to examine how the epidemic influences bank risk-taking by affecting economic losses.

$$Dis_{loss}_{i,t} = \vartheta_0 + \vartheta_1 Dis_{loss}_{i,t-1} + \vartheta_2 Dis_{loss}_{i,t-2} + \vartheta_3 Covid_{r,t} + \sum_{n=4}^7 \vartheta_n X_{i,t-1} + \vartheta_8 Gap_{r,t} + \vartheta_9 Area_r + u_i + \lambda_t + \varepsilon_{i,t}$$

$$Risk_{i,t} = \gamma_0 + \gamma_1 Risk_{i,t-1} + \gamma_2 Risk_{i,t-2} + \gamma_3 Dis_{loss}_{i,t} + \gamma_4 Covid_{r,t} + \sum_{n=5}^8 \gamma_n X_{i,t-1} + \gamma_9 Gap_{r,t} + \gamma_{10} Area_r + u_i + \lambda_t + \varepsilon_{i,t}$$

equations 4-1

Dis\_loss represents the direct economic loss caused by the epidemic. According to the stepwise test method, a mediating effect exists when all the coefficients are significant. If at least one of the coefficients is not significant, the Sobel test is needed to assess the presence of a mediating effect. The regression results are presented in columns (2) and (3), as well as columns (5) and (6) of Table 6. In particular, the regression results in columns (2) and (5) show that the coefficient of epidemic is significantly positive when the dependent variable is the economic loss of epidemic; meanwhile, the results in columns (3) and (6) show that the economic loss caused by epidemic enhances banks’ risk-taking. The above results indicate that epidemics can act on the mechanism of influencing bank risk-taking by causing economic losses to economic agents.

**Table 6. Regression Results of the Direct Economic Loss Impact Mechanism Test**

Variable	NPL	Dis_loss	NPL	lnZ	Dis_loss	lnZ
	(1)	(2)	(3)	(4)	(5)	(6)

L. NPL	0. 582***		0. 358***			
	(0. 076)		(0. 033)			
L2. NPL	-0. 055		-0. 057*			
	(0. 047)		(0. 031)			
L. lnZ				0. 395***		0. 439***
				(0. 131)		(0. 119)
L2. lnZ				-0. 157		-0. 157
				(0. 138)		(0. 151)
L. Dis_loss		0. 045*			0. 050**	
		(0. 023)			(0. 024)	
L2. Dis_loss		-0. 006			0. 002	
		(0. 022)			(0. 025)	
Covid	0. 060**	0. 067***	0. 025	0. 092**	0. 091***	0. 015
	(0. 027)	(0. 012)	(0. 022)	(0. 041)	(0. 016)	(0. 032)
Dis_loss			0. 275**			0. 396*
			(0. 116)			(0. 224)
ControlVal	YES	YES	YES	YES	YES	YES
Bank effects	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES
N	1216	1510	1216	1040	1510	1040
AR(2)	0. 239	0. 297	0. 148	0. 552	0. 176	0. 504
Hansenp	0. 277	0. 166	0. 208	0. 312	0. 204	0. 123

Note: (1) Models are estimated using a single-step systematic GMM; L. NPL and L2. NPL denote first- and second-order lags of NPL; L. lnZ and L2. lnZ denote first- and second-order lags of lnZ; (2) Bankeffects and Yeareffects denote bank-individual and year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values of Hansen's statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are in parentheses under the coefficients of each variable, and \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively, as follows.

#### *Indirect Impact of the Damage to the Business Capacity of Enterprises*

The aforementioned theoretical analysis shows that the epidemic will not only bring direct economic losses to the main subjects of bank credit - households and enterprises but also adversely affect the future operating conditions, profitability, and cash flow of households and enterprises. Considering the difficulty of obtaining microdata for households, this study tests the existence of an indirect mechanism of an epidemic affecting bank risk-taking because the epidemic affects the business capacity of enterprises (including business risk, profitability, and cash reserves), affecting bank risk-taking. Since the microdata of banks and enterprises cannot be matched with simple bank-enterprise matching, in order to test this mechanism, this study sets up the following two-stage model with reference to the research methods of Bertrand and Mullainathan (2001). First, in order to test the impact of the epidemic on the business capacity of enterprises, this study sets up a model similar to the benchmark model at the enterprise level, i.e., a 1-stage regression model:

$$F_{f,t} = \delta_0 + \delta_1 F_{f,t-1} + \delta_2 F_{f,t-2} + \delta_3 \text{Covid}_{r,t} + \sum_{n=4}^7 \delta_n X_{f,t-1} + \delta_8 \text{Gap}_{r,t} + \delta_9 \text{Area}_r + u_f + \lambda_t + \varepsilon_{f,t}$$

equations 4-2

In Eq. 4-2, f, t, and r denote the enterprise (f), time (t), and the prefecture-level and provincial capital city where the sample enterprises are located (r), respectively. In this study, the business-type indicators of the enterprise sector (F) are used as the dependent variables. According to Ge et al. (2021) and others, this study specifies the indicators of business capacity of enterprises as business risk (Fzs), profitability Fpro (operating profit/total assets), and change in cash reserves Fcash (net increase in cash and cash equivalents/total assets). The firm-level control variables X selected for the model mainly include firm size

Fsize (logarithm of total assets), Tobin's Q value Ftobin (market capitalization/total assets), firm's growth capacity Fgrowth (operating revenue growth rate), and market concentration Fhhi (HuffPost index) at the industry level where the firm is located. Meanwhile, the regional level includes the local economic output gap Gap and Area, a dummy variable that characterizes the regional economy with the Hu Huanyong line. In the selection of enterprise samples, according to the related research of Brown et al. (2021) and Huang et al. (2017), enterprises in industries susceptible to the risk of epidemics are mainly selected. Based on the 2012 edition of the industry classification by the Securities and Futures Commission, the industries of the enterprises included in the model sample, after screening, encompass agriculture, forestry, animal husbandry, fisheries, mining, construction, wholesale and retail trade, transportation, real estate, accommodation and catering, and business services. Finally, 479 A-share non-financial listed companies were selected. The data for the listed enterprises are from Cathay Pacific's database.

Based on the estimated values of the regression coefficients in Eq. 4-2, this study defines a new estimator in the region and time dimensions, which is used to connect the 1-stage model and the 2-stage model:

$$F_{r,t} = d_3 * Covid_{r,t}$$

Equations 4-3

Since individual firms and time-fixed effects have been controlled for in Eq. 4-2, the estimate of the coefficient d3 in Eq. 4-2 reflects the average impact of the epidemic on the business capacity of firms in each region after excluding individual firms and macro-environmental factors. Therefore, the  $F_{r,t}$  obtained by cross-multiplying d3 in Eq. 4-3 and the epidemic  $Covid_{r,t}$  measures the estimated value of the change in the enterprise business indicator F in the region caused by the epidemic at the city level. Further, this study replaces the estimate  $F_{r,t}$  with  $Covid_{r,t}$  in Equation 3-1, resulting in the following 2-stage regression model. Based on the sign and significance of the coefficient  $\varphi_3$  in this model, the indirect mechanism by which the epidemic affects banks' risk-taking by influencing firms' operational capacity can finally be identified.

$$Risk_{i,t} = \varphi_0 + \varphi_1 Risk_{i,t-1} + \varphi_2 Risk_{i,t-2} + \varphi_3 \hat{F}_{r,t} + \sum_{n=4}^7 \varphi_n X_{i,t-1} + \varphi_8 Gap_{r,t} + \varphi_9 Area_r + u_i + \lambda_t + \varepsilon_{i,t}$$

equations 4-4

In particular, the sign and significance of the regression coefficient  $\varphi_3$  in Eqs. 4-4 then allows for the final identification of the indirect mechanism by which the epidemic affects bank risk-taking by influencing firms' ability to do business and, in turn, banks' risk-taking.

Table 7 presents the results of the first-stage regression in the test of the indirect influence mechanism. The mechanism analysis in this study tests that epidemics act on bank risk-taking through firms' business risk Fzs, firms' profitability Fpro, and changes in firms' cash reserves Fcash. The regression results from Table 7 show that epidemics lead to an increase in firm business risk Fzs, firm profitability Fpro, and a decrease in cash stock changes Fcash. This is largely in line with the findings of the empirical study by Brown et al. (2021).

**Table 7. Regression Results of the Direct Economic Loss Impact Mechanism Test**

Variable	Fzs	Fpro	Fcash
	(1)	(2)	(3)
L. Fzs	0.724*** (0.066)		
L2. Fzs	-0.022 (0.038)		
L. Fpro		0.066*** (0.007)	

L2. Fpro		-0.165***	
		(0.007)	
L. Fcash			0.244***
			(0.069)
L2. Fcash			-0.082***
			(0.021)
Covid	-3.785**	-0.232**	-0.341**
	(1.745)	(0.101)	(0.157)
ControlVal	YES	YES	YES
Firmeffects	YES	YES	YES
Year effects	YES	YES	YES
N	2971	3695	3695
AR(2)	0.110	0.662	0.200
Hansenp	0.095	0.077	0.190

Note: (1) L. Fzs and L2. Fzs denote first and second-order lags of Fzs, L. Fpro, and L2. Fpro denotes first and second-order lags of Fpro, L. Fcash, and L2. Fcash denotes first and second-order lags of Fpro; (2) Firm effects and Year effects denote firm, individual effects, and year-fixed effects; (3) To reduce endogeneity, firms' micro-control variables are lagged by one period; (4) Others are as in the notes to Table 4.

Table 8 presents the estimation results of the second-stage regression. The findings indicate that the regressions of bank lnZ values and NPL ratios on the estimated indicators of changes in the following three business capacity variables—FzS, Fpro, and Fcash—are all significantly negative. Combined with the 1-stage regression estimation results, this suggests that the epidemic would further validate Hypothesis 1 by elevating the business risk of regional firms, reducing their profitability and cash stock, and thus elevating local bank risk-taking.

**Table 8. Test of the Indirect Effect Mechanism of Impaired Business Capacity: 2-Stage Regression**

Variable	NPL			lnZ		
	(1)	(2)	(3)	(4)	(5)	(6)
L. NPL	0.551***	0.596***	0.594***			
	(0.111)	(0.078)	(0.078)			
L2. NPL	-0.073	-0.070	-0.069			
	(0.050)	(0.047)	(0.047)			
LlnZ				0.350***	0.227*	0.395***
				(0.111)	(0.131)	(0.131)
L2. lnZ				-0.105	-0.037	-0.157
				(0.132)	(0.110)	(0.138)
Fzs	-0.013**			-0.016**		
	(0.006)			(0.008)		
Fprc		-0.224**			-0.238**	
		(0.110)			(0.113)	
Fcash			-0.143**			-0.269**
			(0.071)			(0.120)
ControlVal	YES	YES	YES	YES	YES	YES
Bank effects	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES
N	1216	1216	1216	1040	1040	1040
AR(2)	0.316	0.274	0.275	0.295	0.057	0.552
Hansenp	0.219	0.301	0.219	0.485	0.403	0.312

Note: (1) Models are estimated using a single-step systematic GMM; L. NPL and L2. NPL denote first- and second-order lags of NPL; L. lnZ and L2. lnZ denote first- and second-order lags of lnZ; (2) Bankeffects and Yeareffects denote bank-individual and

year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values of Hansen's statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are in parentheses under the coefficients of each variable, and \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively, as follows.

### *Moderating Effects of Insurance Coverage Levels, Bank Risk Management*

The aforementioned theoretical analysis suggests that both the ex-ante level of catastrophe insurance coverage and the level of bank risk management are likely to moderate the epidemic's impact on bank risk-taking. This study draws on the study of Zhu et al. (2020) and uses the ratio of the premium income<sup>23</sup> of the head office of each sample bank in the city of its head office in the lagged period to the GDP of the city in which it is located (Ins), i. e. , the index of the depth of insurance in the lagged period, as a proxy variable for the level of ex-ante catastrophic insurance coverage; and concerning the related studies of Yan et al. (2020), Shen et al. (2012) and so on, we use the capital adequacy ratio (Car) in the lag period as a proxy variable for the bank's capital management level. The moderating effects of the level of insurance protection and bank risk management are examined by constructing the cross-multiplier term between the above variables and the epidemic proxy variable. In the model, this study uses the variable Mod to represent the two moderating variables of disaster insurance depth (Ins) and bank capital adequacy (Car). To this end, the following econometric model is constructed on the basis of equation 3-1:

$$\text{Risk}_{i,t} = \theta_0 + \theta_1 \text{Risk}_{i,t-1} + \theta_2 \text{Risk}_{i,t-2} + \theta_3 \text{Covid}_{r,t} + \theta_4 \text{Covid}_{r,t} \times \text{Mod}_{i,t-1} \\ + \theta_5 \text{Mod}_{i,t-1} + \sum_{n=6}^9 \theta_n X_{i,t-1} + \theta_{10} \text{Gap}_{r,t} + \theta_{11} \text{Area}_r + u_i + \lambda_t + \varepsilon_{i,t}$$

Equations 4-5

The results of the full-sample estimation of Equations 4-5 are presented in Table 9. The direction of the coefficients on the other variables in Eq. 3-1 does not change significantly after adding the cross terms for depth of insurance and capital adequacy, in turn reflecting the robustness of the findings. Table 9 The results of the regressions in which the moderating variable of Eqs. 4-5 is the depth of insurance (Ins), shown in columns (1) and (3). The results show that the epidemic and the cross-term coefficients representing the insurance depth variable are significantly negative. This suggests that a stronger insurance protection mechanism in advance, along with sufficient compensation for the losses of real economic agents following a disaster, will be more effective in mitigating the epidemic's impact on banks' risk-taking. This result suggests that the more perfect the insurance protection mechanism, the faster it can recover from the shock of the epidemic impact (Feyen et al., 2020), further weakening the impact of the epidemic on bank risk-taking.

The moderating variables of Eqs. 4-5, shown in columns (2) and (4) are the regression results of capital adequacy (Car). The results show that the coefficients of the cross-multiplier terms of epidemic and bank capital adequacy are similarly significantly negative in the model test for both dependent variables. Since capital adequacy determines the robustness of banks against adverse shocks, ensuring banks' capital adequacy is conducive to counteracting bank risks caused by epidemics. This is generally consistent with the finding that capital adequacy can be used to mitigate the impact of epidemics on financial sector risk, as Schydrowsky (2020) indicated in the previous theory. Hypothesis 2 is tested.

**Table 9. Regression Results on the Moderating Effects of Insurance Coverage Levels, Bank Capital Management**

Variable	NPL		lnZ	
	(1)	(2)	(3)	(4)
L. NPL	0.606***	0.407***		
	(0.079)	(0.090)		
L2. NPL	-0.100**	-0.111		
	(0.042)	(0.079)		

LlnZ			0.356***	-0.031
			(0.063)	(0.044)
L2. lnZ			-0.274**	-0.497**
			(0.063)	(0.035)
Covid	0.284***	0.326*	0.211***	0.219***
	(0.102)	(0.138)	(0.076)	(0.084)
Covid*L. Ins	-0.222**		-0.166*	
	(0.104)		(0.069)	
L. Ins	1.648		0.062	
	(0.955)		(0.359)	
Covid*L. Car		-0.024*		-0.017***
		(0.010)		(0.006)
L. Car		0.029		0.011
		(0.073)		(0.021)
ControlVal	YES	YES	YES	YES
Bank effects	YES	YES	YES	YES
Year effects	YES	YES	YES	YES
N	1137	1206	965	1005
AR(2)	0.261	0.176	0.911	0.172
Hansenp	0.334	0.212	0.239	0.284

Note: (1) Models are estimated using a single-step systematic GMM; L. NPL and L2. NPL denotes first- and second-order lags of NPL; L. lnZ and L2. lnZ denote first- and second-order lags of lnZ; (2) Bank effects and Yeareffects denote bank-individual and year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values for the Hansen statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are in parentheses under the coefficients of each variable, and \*, \*\*, and \*\*\* denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

#### *Heterogeneity Analysis of the Impact of Epidemics on Bank Risk-Taking*

To further explore the impact of the epidemic on the risk-taking behavior of local commercial banks with varying scopes of operation and service targets, this study introduces the cross-multiplier term ( $Covid_{i,t} \times County_{i,t}$ ) in the context of the dummy variable for local commercial banks. The location of the head office of the local commercial bank is used as the criterion for classification. Based on Eq. 3-1, this approach tests whether there are differences in the epidemic's impact on risk-taking between local commercial banks primarily serving county economies and those primarily serving industrial and commercial economies in prefecture-level or provincial capital cities. Here, the "county" variable is a dummy that takes the value of 1 if the head office of the local commercial bank is at a prefecture-level or provincial capital city and zero if the head office is located in a county city. This leads to the following econometric model:

$$\begin{aligned}
 Risk_{i,t} = & \beta_0 + \beta_1 Risk_{i,t-1} + \beta_2 Risk_{i,t-2} + \beta_3 Covid_{r,t} + \\
 & \beta_4 Covid_{r,t} \times County_{i,t} + \beta_5 County_{i,t} + \sum_{n=6}^9 \beta_n X_{i,t-1} + \\
 & \beta_{10} Gap_{r,t} + \beta_{11} Area_{r,t} + u_i + \lambda_t + \varepsilon_{i,t}
 \end{aligned}$$

Equations 4-6

Therefore, epidemic (Covid) is used as a variable in equations 4-6. Table 10 shows the regression results of equation 4-6. The regression results show that the coefficient of the epidemic (COVID) on bank risk-taking is significantly positive, reflecting the robustness of the estimation of equation 3-1. The coefficients of the

cross-multiplier terms of the dummy variables of epidemic and local commercial banks serving county economies and local commercial and industrial economies serving local and provincial capital cities are significantly negative in the model with NPL, lnZ, and LLR as dependent variables, indicating that the impact of the epidemic on risk-taking of local commercial banks mainly serving county economies will be greater relative to local commercial banks serving local and provincial capital cities' commercial and industrial economies. Thus, Hypothesis 3 is verified. The reasons may be twofold: on the one hand, relative to local commercial banks serving the economy of prefecture-level and provincial capital cities, local commercial banks serving the county economy are more susceptible to the impact of the epidemic event on their scope of operation and service targets. The customers of local commercial banks in counties are mainly concentrated in the three rural customers, and they are relatively more affected by the epidemic risk. In industries particularly sensitive to the epidemic disaster, if the epidemic persists for a longer duration and has a broader impact, a significant number of agricultural loans may become non-performing. This, in turn, would increase the credit risk for local commercial banks in county areas.

On the other hand, the development of the insurance business related to the economy of the counties has been slow, and the insurance protection level is low, and the ability to resist risks is not as good as that of local commercial banks serving the economy of prefecture-level and provincial capital cities, so the risk of transferring the real economic losses to the local commercial banks serving the county economy will also increase.

**Table 10. Heterogeneity Regression Results for County and Non-County Local Commercial Banks**

Variable	NPL	lnZ	LLR	SdROA
L. NPL	0.312*** (0.033)			
L2. NPL	-0.091*** (0.031)			
L. lnZ		0.050 (0.034)		
L2. lnZ		-0.577*** (0.033)		
L. LLR			0.254*** (0.035)	
L2. LLR			-0.228*** (0.031)	
L. SdROA				0.621*** (0.029)
L2. SdROA				-0.120*** (0.024)
Covid	0.197*** (0.070)	0.111** (0.055)	0.162*** (0.051)	-0.016 (0.012)
Covid*County	-0.181*** (0.070)	-0.104* (0.060)	-0.144*** (0.052)	0.014 (0.013)
County	-0.012 (0.253)	-1.009*** (0.238)	-2.781*** (0.285)	-0.034 (0.025)
ControlVal	YES	YES	YES	YES
Bank effects	YES	YES	YES	YES
Year effects	YES	YES	YES	YES
N	1216	1040	1013	1043
AR(2)	0.249	0.142	0.587	0.947
Hansenp	0.230	0.197	0.225	0.110



Note: (1) Models are estimated using a single-step systematic GMM; L, NPL and L2. NPL denotes first- and second-order lags of NPL; L, LnZ and L2. LnZ denote first- and second-order lags of LnZ; (2) Bank effects and Yeaffects denote bank-individual and year-fixed effects, respectively; (3) AR(2) stands for second-order autocorrelation test, which is the p-value for statistical inference, and the p-values for the Hansen statistic all pass the test, indicating that there is no over-identification; (4) Standard errors are in parentheses under the coefficients of each variable, and \*, \*\*, and \*\*\* denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

## Summary, Conclusions and Recommendations

Building on theoretical analysis, this study empirically examines the impact of epidemics on the risk-taking behavior of local commercial banks and explores the underlying mechanisms. It also assesses the moderating role of ex-ante disaster insurance coverage levels and bank capital adequacy management in shaping the epidemic's effect on bank risk-taking. Additionally, the study investigates the heterogeneity of the epidemic's impact on risk-taking across different banks. The empirical results indicate that:

First, epidemics significantly enhance bank risk-taking. The probable reason for this is the high degree of impact and loss that epidemics bring to the real economy. At the beginning of 2020, the COVID-19 epidemic swept across the country, with severe impacts on the manufacturing and service sectors. In the manufacturing sector, such as the automobile manufacturing industry, the entire industry chain came to a standstill as the resumption of work in the upstream and downstream chains was blocked, and a large number of companies were at risk of being replaced, especially in the international supply chain where the inability to make deliveries on time could lead to long-term substitution. The service sector has also been hit hard, with hotels, tourism, transportation, and catering almost coming to a standstill, incurring heavy losses and being forced to maintain passive operations. Together, these factors had a significant impact on banks' risk-taking.

Second, the epidemic elevated the level of bank risk-taking by bringing direct and indirect channels of economic loss to the main body of bank credit. First, in terms of the direct economic loss impact mechanism, this study introduces the economic loss mediator variable through the principle of stepwise test of the mediation effect model and finds that the epidemic enhances bank risk-taking through economic loss, which illustrates that the epidemic will act on bank risk-taking by bringing economic loss to bank credit subjects. In addition to the direct economic loss channel, in terms of the indirect impact channel, the addition of variables related to business capacity using a two-stage model empirical test found that the epidemic will also enhance the level of bank risk-taking through the mechanism of enhancing the region's business risk, reducing corporate profitability and changes in corporate cash reserves.

Third, both the ex-ante level of insurance coverage and the level of bank risk management moderated the impact of the epidemic on bank risk-taking. First, the study's results, using the depth of insurance as a moderating variable, show that the coefficient of the cross-term between the epidemic and the depth of insurance is significantly negative. This suggests that a stronger ex-ante insurance protection mechanism helps mitigate the impact of the epidemic on bank risk-taking. Furthermore, the coefficient of the cross-multiplier term between the bank capital adequacy variable, which represents bank risk management, and the epidemic is significantly negative, indicating that maintaining adequate bank capital strengthens banks' ability to withstand epidemic-related risks.

Fourth, heterogeneity in the impact of the epidemic on bank risk-taking can arise from differences between various local commercial banks. The specific findings suggest that the epidemic has a greater effect on the risk-taking behavior of local commercial banks in county areas compared to those that primarily serve industrial and commercial groups and households in prefecture-level and provincial capital cities.

Based on the above findings, this study puts forward the following recommendations: in the post-pandemic era, in order to cope with the impact of public health emergencies on the real economy and the financial system, the government, financial institutions, and relevant enterprises need to strengthen their risk management capabilities and mitigate systemic risks. At the macro level, financial supervision should be strengthened to enhance the early warning and monitoring capacity of market risks by dynamically adjusting indicators such as capital adequacy, leverage, and liquidity ratios, as well as deepening the reform of the

financial system to promote the flow of capital to the real economy. Promoting consumption recovery, expanding domestic demand, and stabilizing income distribution are also crucial, and economic vitality should be restored by steadily promoting the resumption of work and production and optimizing resource allocation. The banking industry needs to improve its internal governance and risk monitoring system, strengthen its digital transformation and coordination mechanism, support the resumption of production through intelligent services and efficient financial tools, diversify risks, and ensure the flow of credit resources to key areas. In addition, we should accelerate the development of emerging economic sectors such as biomedicine, artificial intelligence, and industrial internet and promote the deep integration of traditional industries with digital technology to inject new impetus for economic growth. Meanwhile, upgrading the level of insurance protection and strengthening bank capital management are also important means to prevent risks. The insurance system needs to innovate product design, expand insurance coverage for public health events, increase social participation through tax incentives and policy incentives, and establish public health emergency funds and insurance pools to spread risk pressure. In terms of bank capital management, banks should ensure adequate capital reserves, improve risk management mechanisms, promote digitalized operational transformation, and enhance crisis response capabilities. By strengthening regulation and compliance, optimizing asset structure, and promoting business diversification, financial institutions can enhance their risk resistance and help economic recovery. Governments, financial institutions, and all sectors of society need to work together to address future challenges through policy support and resource integration and to realize the sustainable and stable development of the financial and economic systems.

## References

- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- Basher, S. A., Kessler, L. M., & Munkin, M. K. (2017). Bank capital and portfolio risk among Islamic banks. *Review of Financial Economics*, 34(1), 1–9. <https://doi.org/10.1016/j.rfe.2017.03.004>
- Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability. *Journal of Financial Stability*, 54, 100867. <https://doi.org/10.1016/j.jfs.2021.100867>
- Bertrand, M., & Mullainathan, S. (2001). Are CEOs rewarded for luck? The ones without principals are. *The Quarterly Journal of Economics*, 116(3), 901–932. <https://doi.org/10.1162/00335530152466269>
- Bougatef, K., & Mgdmi, N. (2016). The impact of prudential regulation on bank capital and risk-taking: The case of MENA countries. *The Spanish Review of Financial Economics*, 14, 51–56.
- Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering cash flow shocks. *The Journal of Finance*, 76(4), 1731–1772. <https://doi.org/10.1111/jofi.13024>
- Chavaz M. (2014). Riders of the Storm: Economic Shock & Bank Lending in a Natural Experiment [R]. Working study [8] Feyen, E., Utz, R., Huertas, I. Z., Bogdan, O., & Moon, J. (2020). Macro-Financial aspects of climate change. In World Bank, Washington, DC eBooks. <https://doi.org/10.1596/1813-9450-9109>
- Hong, H., Li, F. W., & Xu, J. (2018). Climate risks and market efficiency. *Journal of Econometrics*, 208(1), 265–281. <https://doi.org/10.1016/j.jeconom.2018.09.015>
- Huang, H.H., Kerstein, J. & Wang, C. (2017). The impact of climate risk on firm performance and financing choices: An international comparison. *J Int Bus Stud* 49, 633–656 (2018). <https://doi.org/10.1057/s41267-017-0125-5>
- Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability*, 13, 180–192.
- Lambert, C., Noth, F., & Schüwer, U. (2012). How Do Banks React to Increased Asset Risks? Evidence from Hurricane Katrina. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2022096>
- Noth, F., & Schüwer, U. (2017). Natural Disaster and Bank Stability: Evidence from the U.S. Financial System. *European Economics: Macroeconomics & Monetary Economics eJournal*.
- Noth, F., & Schüwer, U. (2014). The effect of natural disasters on bank failures. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2506710>
- Olovsson C. (2023). Is Climate Change Relevant for Central Banks?. *Sveriges Riksbank Economic Commentaries*
- Ozili, P.K. (2021). Managing Climate Change Risk: The Policy Options for Central Banks. *Environmental Economics eJournal*.
- Pelka, N., Musshoff, O., & Weber, R. (2015). Does weather matter? How rainfall affects credit risk in agricultural microfinance. *Agricultural Finance Review*, 75(2), 194–212. <https://doi.org/10.1108/af-10-2014-0030>
- Schydrowsky D M. (2015). Prudential Regulations for Greening the Financial System: Coping with Climate Disasters [J]. *Latin American Journal of Central Banking*, 1(1-4):100010.
- Scott, M., Huizen J. V., Jung, C. (2021). The Bank of England's Response to Climate Change [J]. *Bank of England Quarterly Bulletin*, Q2:98-109.
- HU Qi, ZHU Minglai. (2021). The impact of the basic health insurance integration policy for urban and rural residents on the development of commercial health insurance in China—an empirical analysis based on the PSM-DID method [J]. *Finance and Economics*, (12):50-60

- Ju Yali. (2022). A study on the impact of the new coronary pneumonia epidemic on banking financial institutions based on event analysis—The case of legalized banking institutions in province A. *Financial Theory and Practice* Panel. (2020). Analysis of the Impact of the Covid-19 epidemic Epidemic on China's Economy and Finance and Policy Recommendations. *North China Finance*,2, 1-9
- Li Jianhong. (2020). Impact and Prospect of the Covid-19 epidemic Epidemic on the Operation and Management of Commercial Banks. *Financial Development Research*.
- Li Mingxiao. (2020). Prospective Control of Credit Risk. *China Finance* ,18, 40-42.
- Liang Si. (2020)Research on the risk of Chinese commercial banks based on CBSI index. *Financial Theory and Practice*,10, 38-44.
- Liu N. (2020)Analysis of business development situation and countermeasures of commercial banks under the new coronary pneumonia epidemic. *Times Economy and Trade*, 11.
- Lu Minfeng. (2020). Small and Medium Commercial Banks: Epidemic Crisis, Credit Risk Superposition and Preventive Countermeasures. *North China Finance*, 06.
- Luo Qi,Tian Wen. (2021). Study on the Profitability of Chinese Commercial Banks under the Impact of the Covid-19 epidemic Epidemic. *Financial Economy*, 03.
- TENG Jian,WANG Jiahui. (2022). Impact and inspiration of the Covid-19 epidemic epidemic on agricultural and rural economy. *Agricultural Technology and Equipment*, 06, 51-53.
- Wang Shixian. (2021). Transformation Practices and Insights of Small and Medium-sized Banks under the impact of the Covid-19 epidemic Epidemic[J]. *SAR Economy*, 05.
- Wang Weiguang. (2020). The Impact and Opportunities of the Covid-19 epidemic Epidemic for Commercial Banks' Online Financial Business. *Statistics and Management*, 04.
- Wang Xiangnan. (2020). Climate change and the insurance industry: impacts, adaptation and mitigation. *Financial Regulation Research*, 11, 46-61.
- WANG Xin, JIANG Jingjing. (2021). Climate-related financial risks: differences between Chinese and foreign insurance industries and their responses. *International Economic Review*, 05, 22-33+4-5.
- Wang Yao,Wang Wenwei. (2021). A study on the effect of environmental disaster shocks on bank default rate: a theoretical and empirical analysis. *Financial Research*, 12, 38-56.
- WU Yuan Yuan. (2020). Risk Aggregation and Countermeasures in China's Banking Sector in the Post-Epidemic Era. *Banker*, 9, 69-71.
- Xu Zhenhui,He Dexu. (2020). Focusing on prevention and control of small and medium-sized commercial bank risks under the impact of the epidemic. 5, 62-65.
- Yang Kaisheng. (2022). Current Situation and Prospect of Wealth Management Business of Commercial Banks. *Economic Digest*, 09.
- Zhao Xiaoxin, Sun Yuna, Kou Bin. (2021). Research on the operating condition of banking industry under the influence of epidemic—an analysis based on Pearson's correlation model. *Heilongjiang Finance*, 11.
- Zheng Lujun,Sun Yi. (2022). Credit Risk Shock and Heterogeneity Test of Covid-19 epidemic Epidemic on Rural Commercial Banks—Taking 110 Rural Commercial Banks in Shandong Province as an Example. *Financial Development Research*, 08.
- Zhong Zhen,Guo Li. (2020). Development Status and Challenges of Small and Medium-sized Banks in China and the United States under the Impact of the Epidemic. *Southwest Finance*, 11.
- Zhu Hongju. Impact of the Covid-19 epidemic Epidemic on Commercial Banks and Countermeasures. *Modernization of Shopping Malls*, 14.
- ZHU Jiasheng. (2021). The Impact and Inspiration of the Covid-19 Epidemic on the Operation and Management of Commercial Banks—Taking Industrial and Commercial Bank as an Example. *Modern Business*, 07.