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COVID-19 and credit risk variation across banks: International insights

Albert Acheampong¹  | Ngozi Ibeji² | Albert Danso³ 

¹Nottingham Business School, Nottingham Trent University, Nottingham, United Kingdom

²University of Northampton, Northampton, Waterside, United Kingdom

³De Montfort University, Leicester Castle Business School, Leicester, United Kingdom

Correspondence

Albert Acheampong, Nottingham Trent University, NG1 4BU, Nottingham, United Kingdom.

Email: albert.acheampong@ntu.ac.uk

Abstract

This paper focuses on utilizing non-performing loans (NPLs) as the primary indicator of credit risk to analyze how various bank and country-level characteristics influence changes in credit risk within and between banks across China, Europe, and the U.S. during the COVID-19 period. Over 4,959 bank-quarter observations (from Q4 2019 to Q4 2021), it becomes evident that COVID-19 significantly contributes to the variation in NPLs, underscoring its adverse impact on credit risk. This pattern is consistent across all countries; however, Chinese banks exhibit more robust capabilities in managing credit risk exposure compared to their European and U.S. counterparts. These findings offer significant implications for policymakers, investors, and regulators who are concerned about the repercussions of global pandemics on financial institutions.

JEL CLASSIFICATION

G21, Q01

1 | INTRODUCTION

Similar to the European debt and subprime mortgage crises, the COVID-19 pandemic caused global market instability and devastated many economies and lives. The pandemic affected over 80 million individuals globally, resulting in a severe economic downturn, according to the World Health Organization (2020). The first shockwave caused global stock markets to drop, affecting oil prices. Since the pandemic was unprecedented, many banks and firms had to modify their growth estimates. Also, most countries had to balance economic growth with concerns for their citizens' health (Daly et al., 2019).

The COVID-19 pandemic affected banks, consumers, suppliers, and governments in unprecedented ways. For instance, the sudden exogenous shock alerted banks to the necessity of anticipating exceedingly difficult future issues. This pandemic affected banking operations worldwide and highlighted the need for preventive

measures for depositors and counterparties (e.g., Delis et al., 2021; Kargar et al., 2021). Banks struggled to meet capital requirements and operate cost-effectively during the crisis, which weakened them.

Indeed, the COVID-19 pandemic threatened corporations, individuals, and economies' creditworthiness. Lower consumption demand was caused by enterprises closing and laying off workers owing to financial difficulty. Many firms' solvency and going concern were questioned due to significant leverage and debt burdens. Bank balance sheets suffered when debtors' finances worsened. Agca et al. (2023) compared banks' performance during the COVID-19 period to that during the 2007/08 global financial crisis and concluded that the two were similar. Indeed, COVID-19's effects on the stock market (e.g., Haddad et al., 2021; Kargar et al., 2021; O'Hara & Zhou, 2021; Shabir et al., 2023), firm responses (e.g., Ding et al., 2021; Fahlenbrach et al., 2021; Ramelli & Wagner, 2020; Xue et al., 2021), and sovereign credit risk (e.g., Daehler et al., 2021; Pan et al., 2021) have been

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extensively studied. These studies have mostly used Credit Default Swap (CDS) spreads to estimate credit risk.

However, few studies have examined how COVID-19 affects bank credit risk, particularly non-performing loans. This article addresses this gap and examines bank and country credit risk variances. This study is important since COVID-19 produced a dramatic economic slowdown, causing loan defaults and rising non-performing loans (NPLs) for financial institutions globally. According to Ding et al. (2021), researchers feel the COVID-19 pandemic's effects are unclear and require empirical research. Thus, knowing the financial effects of the COVID-19 pandemic is crucial.

We employ NPLs as the primary credit risk measure because NPLs are considered a more effective indicator of financial firms' credit risk (Ghosh, 2015). The European Banking Authority (EBA) reports that NPLs persist as the primary credit risk for banks within the European Union (E.U.). Existing evidence suggests that NPLs serve as one of the leading indicators of credit risk and are strongly linked to the likelihood of corporate default and financial turmoil (Ghosh, 2015). We focus on the banking sector due to its heightened exposure to the adverse effects of the COVID-19 pandemic. Banks constitute the primary funding source for both households and businesses; as such, it is irrefutable that the pandemic impacted the capacity of borrowers to fulfill their repayment obligations. Our paper focuses on China, Europe, and the U.S. because these areas were among the countries that were highly infected by COVID-19 (Elnahass et al., 2021). We employ quarterly data from Q4 2019 to Q4 2021, leading to 4,959 observations from a sample of 551 banks.

Findings reveal that the COVID-19 pandemic was significantly and positively associated with credit risk, as measured by NPLs. This indicates that a considerable variation in NPLs across countries within and between banks over the period under study can be explained by COVID-19. At the country level, findings reveal that all variables exhibit higher explanatory power over credit risk over time. This suggests that COVID-19 accounts for a substantial disparity in NPLs within banks and among countries over the observed time frame. At the country level, it is observed that, over time, all variables demonstrate a greater degree of explanatory power to credit risk, suggesting that COVID-19 contains an economically significant estimate relevant to explaining banks' credit risk across China, Europe, and the U.S. These findings are consistently observed for all countries in the sample used for this study. Further analysis reveals that, while the impact of COVID-19 on bank credit risk exists in all countries, the economic consequences in China appear to be comparatively lesser compared to those of the U.S. and Europe. China tends to possess high-risk management in addition to corporate governance structures coupled with high-quality assets in its banking industry. In addition, large firms were better positioned to manage credit risk exposure than small firms. This finding is consistent across all three economies. Our results are robust to various econometric checks and alternative credit risk measures.

The findings from this study make the following contributions to the literature: First, we concentrate on bank-level credit risk, utilizing Non-Performing Loans (NPLs) as our primary measure. While previous

studies have often employed the Credit Default Swap (CDS) spread (e.g., Agca et al., 2023; Hasan et al., 2023) as the benchmark for assessing credit risk, our research offers a distinct focus on NPLs. Second, findings from prior studies suggest that an increase in NPLs produces a high cost of funding and corporate debt overhang (Aiyar et al., 2015). Other studies report that an increase in NPLs results in a fall in a country's overall output in the post-crisis period and brings about resilience to the exogenous COVID-19 pandemic (Lee et al., 2021). This paper adds to this literature by examining the banks within countries more resilient to the exogenous COVID-19 pandemic. Distinct from prior studies, the outbreak of COVID-19 is a health-stimulated crisis not influenced by macroeconomic factors such as a financial imbalance in the finance sector. Therefore, previous studies' findings may not apply to this health-stimulated crisis. Third, unique from prior studies, our paper also examines the variations in credit risk over time while associating these variations with the changes in COVID-19. Our study uses NPLs over nine quarters to investigate the pandemic's effects on bank credit risk. We employ RMMA to address nested effects and variances at different levels over time, which is often disregarded in OLS applications (Robinson, 2003), making our findings more robust than those of previous studies.

The rest of the paper is organized as follows: Section 2 discusses the literature review and research hypothesis. Section 3 describes the data and empirical models. Section 4 presents the empirical findings. Section 5 offers further analysis and robustness checks, and, finally, Section 6 provides conclusions and some suggestions for further studies.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 | Credit risk of banks

Within China's banking industry, it is widely believed that banks exhibit extremely high corporate governance structures and risk management potentials and, most importantly, have solid asset quality (Chen et al., 2013). Regardless, the COVID-19 pandemic adversely impacted the banks' credit assets. In 2015, the China Banking Regulatory Commission (CBRC) reported the NPLs ratio of banks to be 1.67%. Regarding asset size, the top six banks in China report approximately 62% of the accumulated NPLs balance of banks, representing RMB 800 billion (Zhang et al., 2019). These top six banks' total credit assets amounted to 72 trillion yuan by the close of 2019, with NPL balance of 2 trillion yuan. This mainly implies that the deterioration of banks' credit assets is higher than the CBRC forecast (Chen et al., 2020). Many professional publications and academics suggest that the NPLs ratio of Chinese banks is on a nosedive. The reliability of Chinese banks' NPLs requires much improvement. For example, Agricultural Bank and China Merchants Bank, among the big six banks in China, reveal a migration rate of problematic loans as high as 18% and 50%, respectively (Twum et al., 2022).

In the U.S., the lockdown resulted in very high unemployment rates. The reported GDP contraction in the first quarter of 2020 was 5% (Delis et al., 2021). This was above analysts' expectations. The crisis's quantum impact made the Federal Reserve Board estimate that COVID-19 pandemic-related loan losses would reach about \$700 billion for the big banks in the worst-case scenario, causing banks to shut down their capital minimums. In Europe, the problem of NPLs remains a legacy of the economic difficulties following the global budgetary crisis.¹ A report by the IMF Financial Soundness Indicators shows that, on average, the E.U.'s NPLs got close to 10% between 2014 and 2018, while, for other advanced economies, this was approximately 0.8% (IMF, 2020).² The ECB president at this time, Mario Draghi, expressed severe concern, indicating many adverse loans and structural deficiencies in the E.U.'s banking system. He mentioned the weakness of inefficient and costly debt recovery processes, insufficient internal governance systems in the banks, and misaligned incentives that prevent a smooth and quick resolution of NPLs.

Regardless of the recovery rate in the E.U., which is classified to be slow (heterogeneous across member states), as indicated in their balance sheets, the problem of NPLs remains (Enria, 2020).³ The policy debate includes assertions that NPLs are behind the economic inefficiencies in most E.U. economies (e.g., ESRB, 2017). Adverse loans are not only credited because of the weak profitability of the E.U. banking industry but also because of the E.U.'s weak growth in tepid recoveries in productivity and output, as well as bank lending. The provision of unfavorable loans could serve as a crucial source of sustenance for companies that are effectively non-viable, commonly referred to as "zombie" firms (Andrews & Patroulakis, 2019).

2.2 | COVID-19 pandemic implications

The COVID-19 pandemic's impact on economies and financial markets has been the subject of numerous extant studies, with particular attention given to the response of stock markets at both sectoral and market-wide levels. The COVID-19 pandemic engendered a discernible diminution in the valuation and fluidity of corporate bond offerings, alongside an observable escalation in transactional expenditures (Kargar et al., 2021; O'Hara & Zhou, 2021). Delis et al. (2021) use the S&P 500 index, and they posit that COVID-19 negatively impacted the volatility of market returns, which they explain as being more severe than the global financial crisis in 2007/08. Baker et al. (2020) implemented new measures for assessing risk from COVID-19 and found that the COVID-19 pandemic resulted in unprecedented uncertainty in the stock market. In addition, Ftiti et al. (2021) also found that a news report on COVID-19-related deaths resulted in increased stock market volatility and decreased liquidity.

Other studies examine the impact of the COVID-19 pandemic on stock market reaction focusing on the firm level. Focusing on the Chinese market, Xue et al. (2021) found a significant fall in stock prices of

firms in China after the COVID-19 pandemic. Considering sector impact, they report that the healthcare and technology sectors experienced a minor hit. Fahlenbrach et al. (2021), focusing on the U.S. market, find that firms exhibiting lower short-term debt experienced lower stock price volatility. The critical concern of the U.S. stock market was the supply chain exposure of firms in the early stage of COVID-19, and during the later stage, where there was widespread disease, it translated into poor financial condition (Ramelli & Wagner, 2020). Ding et al. (2021) used 61 countries, and their findings revealed that the key drivers of stock price reactions were supply chain exposure and financial conditions.

Along the same lines, some studies examine the impact of the COVID-19 pandemic on firm and sovereign credit risks. Prior studies use sovereign CDS spread and find that sovereign credit risk positively correlates with the number of COVID-19-related deaths (Agca et al., 2023; Tevfik Kartal, 2020). The consequences of this are more profound in countries that exhibit small fiscal capacity and strong relief policies (Keliuotytė-Staniulienė & Daunaravičiūtė, 2021). In terms of sector, although the consequences of the COVID-19 pandemic affected all sectors, they were profound for non-financial firms, especially firms that exhibited higher stock volatility, financial constraints, lower profitability, and poor credit ratings (Hasan et al., 2023). Daehler et al. (2021) employ a two-stage econometric design to illuminate the evolution of emerging market sovereign CDS spreads using the first half of 2020. Their findings reveal that COVID-19-specific risk factors did not drive emerging markets' CDS spreads; rather they were driven by traditional determinants such as oil shocks. All in all, the impact of the COVID-19 pandemic on diverse aspects has been examined by prior studies and supported by rich evidence. However, although a few studies examine the effect on credit risk at the firm level focusing on CDS spread, no study explores how the COVID-19 pandemic influenced the credit risk of banks captured using non-performing loans across China, Europe, and the U.S. We address this gap by concentrating on the use of NPLs as the measure of credit risk, specifically within the banking sector.

Globally, the COVID-19 pandemic's impact on financial firms was undoubtedly severe. According to the New York Times (2020), financial markets worldwide (e.g., S&P 500, Russell 2000, FTSE 250, and Dow Jones) experienced their share of severe impacts from the COVID-19 pandemic. Prior studies report that financial institutions were greatly exposed to this impact (e.g., Elnahass et al., 2021; Giofré, 2022; Kwabi et al., 2020). Rizwan et al. (2022) indicate that banks' business models were highly exposed to economic shocks. On this note, considering the unexpected outbreak of the global COVID-19 pandemic, banks were at a severe risk, which could be viewed along the lines of liquidity insurance. For example, banks faced significant credit risk due to cash management challenges and difficulties in debt servicing stemming from business closures, as well as diminished demand for goods and services resulting from lockdowns. In addition, the volume of bank lending fell heavily because private sector investment and consumption declined significantly.

Resource dependence theory advocates state that firms require resources from the external environment in order to survive because firms cannot entirely rely on themselves for survival (Pfeffer, 2019). However, the pandemic made access to resources much more difficult. Central banks and regulatory bodies tried to address the crisis to maintain bank stability. However, the implementation of lockdown policies and the associated repercussions heightened apprehension regarding the resilience of financial institutions. Amidst the proliferation of business closures and bankruptcies, accompanied by a deceleration in capital financing and insufficient liquidity within financial institutions, the lending capabilities of banks experienced a notable diminution. This, in turn, augmented the liquidity risk posed by banks' assets and liabilities. The COVID-19 pandemic's harmful influence on firms' operations and, consequently, on their credit quality exacerbated the default risk faced by banks, owing to the close association between businesses and financial institutions, as indicated by Duan et al. (2021). Based on the argument above, we argue that the COVID-19 pandemic escalated credit risk for banks. This forms the basis of our hypothesis, which states that:

H1. The COVID-19 pandemic increased the credit risk of banks.

3 | METHODOLOGY

3.1 | Sample and econometric approach

The sample consists of 551 banks across the U.S., Europe, and China which cover data for nine quarters (i.e., Q4 2019 to Q4 2021). This results in 4959 bank quarter observations. Quarterly data is employed because daily and monthly data is not available for most accounting and financial variables. The financial and accounting data source is DataStream Eikon, whereas country-level data is obtained from the World Bank.

3.2 | Variable measurement

3.2.1 | COVID-19 pandemic

The present study employed the quarterly cumulative number of deaths in a given country to capture the degree of exposure to the COVID-19 pandemic. In December 2019, the initial instance of COVID-19 was documented in Wuhan, China, whereas the earliest COVID-19 death was recorded on January 11, 2020. The COVID-19 data for the relevant countries was obtained for the period spanning from Q4 2019 to Q4 2021. Precisely, we captured COVID-19 for each country, k , in the quarter, t , as follows:

$$Covid19_{kt} = \ln(1 + Confirmed\ Deaths_{kt}) + \ln(1 + Confirmed\ Deaths_{kt-1}) \quad (1)$$

3.2.2 | Credit risk

We measure credit risk using NPLs which are obtained from Thomson Reuters Eikon. Following Demir and Danisman (2021) and Ghosh (2015), we measure NPLs as the total loan default scaled by total assets. A report by the EBA in 2019 reveals that NPL is the critical credit risk European banks face. Practically and theoretically, NPLs remain one of the leading credit risk indicators and are highly associated with default and financial distress (Ghosh, 2015). This suggests that NPLs are highly ranked in assessing financial industry credit risk. As part of our robustness checks, we employ loan-loss provision and Ohlson's o-score as alternative credit risk measures.

3.2.3 | Bank-level variables

Following prior literature, we employ the following bank-level variables: bank size (SIZE), financial leverage (LEVERAGE), market-to-book value (MTBOOK), return on equity (ROEQUITY), the market value of equity (MVEQUITY), the natural logarithm of Tobin Q (TOBIN-Q), and diversified income (DIVINCOME). SIZE is captured as the natural logarithm of total assets (e.g., Acheampong & Elshandidy, 2021; Elnahass et al., 2021); LEVERAGE is captured as the total debt scaled by total assets (e.g., Acheampong & Elshandidy, 2021; Elnahass et al., 2021); MTBOOK is captured as the market value of equity scaled by book value of equity, where higher value implies higher current market valuation (e.g., Elnahass et al., 2021); ROEQUITY, which represents profitability, is captured using return on equity (e.g., Acheampong & Elshandidy, 2021; Elnahass et al., 2021); MVEQUITY is captured using the natural logarithm of market value of equity (e.g., Elnahass et al., 2021); TOBIN-Q is the sum of total debt and market value of equity scaled by book value of equity, where higher value indicates higher forward-looking market valuation (e.g., Elnahass et al., 2021); DIVINCOME is captured as the share of non-interest income in total revenues and shows the revenues from sources other than interest, such as trading activities, fees, and commissions (e.g., Acheampong & Elshandidy, 2021; Demir & Danisman, 2021).

3.2.4 | Country-level variables

At the country level, we employ the following variables following prior literature: economic support index (ECON_INDEX), stringency index (STR_INDEX), governance perception (GOV_INDEX), GDP per capita (GDP), and inflation (INFLATION). ECON_INDEX is computed as the mean value of the individual two-component policy response indicators that pertain to the economic response. The range of the variable under consideration extends from 0 to 100 (e.g., Demir & Danisman, 2021); STR_INDEX captures the degree of rigor exhibited by government measures in response to the COVID-19 outbreak. It is computed as the mean of the nine constituent policy response indicators of containment and closure. The numerical values are delineated within the range of 0 to 100 (e.g., Demir &

Danisman, 2021; Hale et al., 2020); GOV_INDEX is the collective mean of six imperative measures of country governance: government effectiveness; corruption; political stability; the rule of law; regulatory quality; and voice and accountability (e.g., Demir & Danisman, 2021); GDP is captured as the natural logarithm of gross domestic products per capita (e.g., Acheampong & Elshandidy, 2021; Demir & Danisman, 2021; Elnahass et al., 2021); INFLATION is the annual inflation rate, which is measured as the percentage variation in the consumer price index (e.g., Acheampong & Elshandidy, 2021). All variables are winsorized in the models; Appendix A describes all variables employed.

3.2.5 | Econometric model

Considering the nested nature of our data, we employ multilevel analysis to examine two credit risk levels simultaneously. Using OLS regression on nested data fails because the assumption of independence is violated and misses significant group-level effects (Luke, 2004). Nested data causes dependencies at a different level, referred to as intra-class correlation (ICC). In light of our data, having banks nested in the same country could lead to correlated errors. To mitigate this, we employ RMMA with a restricted maximum likelihood estimation approach, accounting for all levels within our analysis. RMMA has the advantage of providing flexible tools to deal with hierarchical data in line with hypothesis testing and formulation of models (Elshandidy & Acheampong, 2021; Robinson, 2003). We therefore conduct our analysis at two levels (bank and country) to capture the variations in credit risk. By employing RMMA, we assume that variables are repeated over time, and this portrays additional analytical issues, which are observations across time that are correlated with the group to which they belong (Acheampong & Elshandidy, 2021). Therefore, they form a robust within-cluster correlation. Thus, we first develop an empty (null) model that entails no predictors purposely to obviate any dependent variables' influence. Put differently, the empty model estimates each level's relative significance in the dependent variable's variance. To identify the proportion accounted in the total credit risk variation by the independent variables, we calculate approximately adjusted R^2 at both levels. In addition, examining each model's accuracy compared to the empty model, we included changes in the -2 Log Likelihood and chi-square test. Ideally, a decline in the difference indicates model improvement. The model we estimate at two different levels is shown below:

$$NPL_{tik} = \beta_{0ik} + \beta_1 T_{tik} + \sum_{n=1}^{Nr} \beta_{rn} Xb_{lnik} + \sum_{n=1}^{Nc} \beta_{cn} Xcl_{nik} + \varepsilon_{tik} + r_{ik} \quad (2)$$

NPL_{tik} represents the non-performing loan (credit risk) of bank i within country k during a time, t . β_{0ik} is the intercept of bank i situated in country k . The coefficient β_1 denotes the rate of change of the dependent variable for bank i in country k . T_{tik} denotes the

linear component of bank i within country k during time t . It assumes the primary role at level 1. B_{rn} represents the influence exerted by Xb_{lnik} , which consists of a set of bank-level variables on the linear element of the credit risk factor, and B_{cn} represents the influence exerted by Xcl_{nik} , which consists of a set of country-level variables, on the linear element of the credit risk factor. ε_{tik} and r_{ik} are the two different levels, respectively. Appendix A describes all the variables employed.

4 | DISCUSSION

4.1 | Descriptive statistics

The descriptive statistics for the variables employed are reported in Table 1 (Panel A). We report the statistics for both pre-COVID and COVID periods.⁴ The two-sample t-tests reveal an increase in credit risk as measured by NPLs in the COVID-19 period compared to the pre-COVID period. Specifically, the mean of NPLs increased from 6% to approximately 10%. This reflects a weakening capacity of the banking industry to mitigate risk and sustain financial operations in light of the COVID-19 pandemic. This confirms Rizwan et al.'s (2022) finding of bank business models being highly exposed to economic shocks. The significant t-test coefficient confirms this. We also observe a deterioration in the financial performance of banks during the COVID period. The mean ROA slumped from 9% to 7.9%. In addition, the market valuation of banks shrinks, which is evident by the deterioration of forward-looking proxies, the market value of equity, and market-to-book value. These findings are evident in the results of the significant two-sample t-test.

Firm size also drops during COVID-19, with the mean decreasing from 7.1% to 6.5%. This is also evident from the significant two-sample t-test. Banks' fall in total assets might explain why the return on equity increased after the COVID-19 pandemic. Regarding the country level, the average economic and governance index across our sample indicates that, in all countries, regulators put policies in place to strengthen credit risk management systems within the banking sector. Banks' credit risk during the COVID-19 pandemic increased, impacting their financial performance and stability. The descriptive statistics initially depict a significantly weaker financial performance and lower efficiency cost for the banking sector after the emergence of the COVID-19 pandemic. This confirms the findings of Elnahass et al. (2021) and Kwabi et al. (2020). From the correlation matrix in Table 1 (Panel B), we observe accepted correlation coefficients (< 0.7), which deal with the issue of multicollinearity. In addition, we also report the variance inflation factor (VIF) for all regression analyses. It is essential to note that a significant and positive association exists between COVID-19 and credit risk. This provides preliminary evidence of the extant adverse impact of the COVID-19 pandemic on the banks' credit risk, which supports our hypothesis.

TABLE 1 (Panel A). Descriptive statistics.

	N	1st Q.	3rd Q.	Std. dev.	Median	Mean (COVID sample)	Mean (pre-COVID sample)	Two-sample T-test (two-tailed)
COVID19	4,959	-1.119	1.027	1.568	1.568	0.980	0.9801	2.345***
NPLs	4,959	0.002	0.090	0.843	0.843	0.098	0.060	18.059***
SIZE	4,959	6.382	7.731	0.987	0.987	6.510	7.126	-6.171
LEVERAGE	4,959	0.028	0.224	0.173	0.173	0.342	0.156	21.628***
MTBOOK	4,959	0.650	0.9359	0.424	0.424	0.546	0.936	19.436***
ROEQUITY	4,959	6.050	9.006	5.039	5.039	7.990	9.006	111.58***
MVEQUITY	4,959	0.538	0.681	0.122	0.122	0.509	0.615	353.95***
TOBIN-Q	4,959	0.494	0.714	0.166	0.166	5.869	0.598	213.75***
DIVINCOME	4,959	0.128	0.339	0.152	0.152	0.823	0.246	4.234*
ECON_INDEX	4,959	8.00	13.00	5.384	5.384	11.153	-	-
STR_INDEX	4,959	4.000	4.000	0.386	0.386	3.818	-	-
GOV_INDEX	4,959	0.715	1.026	0.240	0.240	0.808	-	-
GDP	4,959	0.078	1.707	1.824	1.824	0.822	-	-
INFLATION	4,959	1.222	4.849	1.945	1.945	2.382	-	-

Note: this table presents the descriptive statistics of the variables employed in this study. The mean for all variables is presented separately for covid (COVID sample) period and pre-COVID (pre-COVID sample) period. Pre-COVID period spans from Q1 2016 to Q4 2018 whereas the COVID period reflects Q4 2019 to Q4 2021. All continuous variables are winsorized at 1st and 99th percentiles. Appendix A reports the definition of all variables.

4.2 | The impact of the COVID-19 pandemic on credit risk – within and between variation analysis

To test our hypothesis, RMMA is employed to understand the variation of credit risk explained at the bank and country levels. Table 2 reports four different models; the null model is run without any predictor to assess the need for unexplained variations at both levels. Model I has no controls (both at the bank and country levels), Model II augments bank-level controls, and Model III augments country-level controls.

From the null model, 37% of credit risk variations are observed at level 1 (within banks) over time, whereas 62% are observed at level 2 (between banks). These variations are significant at the p-values of 0.048 and 0.033, respectively, and thus suggest the potential for capturing further variations by augmenting bank and country-level variables. Model I reveals credit risk to have a positive and significant association with COVID-19 at the p-value of 0.000. This indicates that the outbreak of the COVID-19 pandemic significantly influenced banks' credit risk. The economic effect reveals that a 1 % standard deviation increase in COVID-19 results in a 0.014 increase in credit risk as measured by NPLs. The model captures 10% (Adjusted R^2) of the total variations between banks across the countries under consideration. Also, the variations decreased by 13% $[(0.62-0.55)/0.55]$ to 55% compared with the null model at the p-value of 0.000.

Model II reports a positive and significant association between COVID-19 and credit risk. All bank-level variables are significantly associated with credit risk except Tobin-Q and ROEQUITY. The model captures 12% (Adjusted R^2) of the total variations between banks across the countries under consideration. The negative association between bank size and credit risk suggests that, as banks increase in

size measured using total assets, they exhibit a decrease in credit risk. This is also true for an increase in the market-to-book ratio, where banks tend to record lower levels of credit risk. Large banks possess the ability to manage credit risk. The significant and positive association of financial leverage indicates that highly leveraged banks are subject to more heightened credit risk. Considering these results, bank variables capture substantial variations in credit risk between banks and, most importantly, reduce some unexplained variations between banks across the countries considered rather than the unexplained variances within banks over the years considered.

From Model III, in addition to the significant association between credit risk and COVID-19, all country-level variables exhibit statistical significance with credit risk. Country governance shows a significant and negative association with credit risk because banks operating in better-governed economies have more confidence and capabilities in dealing with credit risk. In light of the significance of the stringency index, banks operating in countries that exert effective efforts in response to COVID-19 reported lower levels of credit risk because policies were put in place as shock absorbers for any risk exposure. Banks in countries with high GDP per capita report lower levels of credit risk.

A significant improvement in the model's ability to capture variations in credit risk is seen by augmenting the country-level variables. Therefore, bank and country variables can explain 51% of the total variations in credit risk between China, Europe, and U.S. banks. The augmentation of country variables increases the model's ability by more than 100% compared to Model II (i.e., only bank-level variables). This is well anticipated because the employed variables might exert a direct impact on each country's regulations, which then can be seen as a key driver in their credit risk management framework and thus an essential driver of credit risk variations. These results imply that it is

TABLE 1 (Panel B). Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
COVID19	1.000	0.255	−0.308	−0.162	−0.522	−0.529	−0.411	−0.279	0.048	0.452	0.293	0.096	−0.094	−0.337
NPLs		1.000	−0.318	−0.148	0.021	−0.009	−0.271	−0.266	−0.017	0.040	−0.013	0.128	−0.019	0.014
SIZE			1.000	0.522	−0.225	−0.046	0.516	0.585	0.343	0.228	0.090	−0.498	0.018	−0.106
LEVERAGE				1.000	−0.347	−0.108	0.575	0.547	0.113	0.260	0.076	−0.522	0.009	−0.203
MTB					1.000	0.486	−0.181	−0.299	−0.082	−0.282	−0.186	0.385	0.007	0.312
ROEQUITY						1.000	0.043	−0.068	0.041	−0.266	0.007	0.106	0.108	0.254
MVEQUITY							1.000	0.547	0.272	0.129	0.069	−0.541	0.025	−0.113
TOBIN-Q								1.000	0.285	0.264	0.075	−0.639	0.007	−0.113
DIVINCOME									1.000	0.494	0.082	−0.014	−0.049	−0.064
ECON_INDEX										1.000	0.361	−0.283	0.001	−0.158
STR_INDEX											1.000	−0.283	0.263	0.098
GOV_INDEX												1.000	−0.032	0.239
GDP													1.000	0.178
INFLATION														1.000

Note: this table reports the correlation matrix of all variables. Significant coefficients are highlighted in bold. Appendix A reports the definition of all variables.

TABLE 2 Impact of COVID-19 pandemic on credit risk (NPLs) of banks.

DV: NPLs	Ex. sign	Null	Model I	Model II	Model III
Intercept	(?)	0.0768* −0.0713	10.0459*** 0	7.1208*** 0	11.6959*** 0
COVID19	(+)		0.0166*** 0	0.0196*** 0	0.0822*** 0
Bank-level variables					
SIZE	(−)			−0.0525*** 0	−0.0110*** −0.0009
LEVERAGE	(+)			0.0290* −0.0791	0.1026*** 0
MTB	(−)			−0.0241*** 0	−0.0143*** 0
ROEQUITY	(−)			−0.002 −0.3334	0.0025*** 0
MVEQUITY	(−)			−0.2542*** 0	−0.1887*** 0
TOBIN-Q	(?)			0.0068 −0.7507	−0.0029 −0.845
DIVINCOME	(−)			0.0369** −0.029	−0.0402*** 0
Country-level variables					
ECON_INDEX	(−)				−0.0018*** 0
STR_INDEX	(−)				−0.0663*** 0
GOV_INDEX	(−)				0.1425*** 0
GDP	(−)				−0.0181*** 0
INFLATION	(+)				−0.0213*** 0
Time	(?)	−0.0001 −0.1912	−0.0049*** 0	−0.0034*** 0	−0.0059*** 0
Year fixed effects		No	Yes	Yes	Yes
Intra-class correlation (ICC)					
Repeated measures - σ^2		37%** −0.0478	44%*** 0	46%*** 0	47%*** 0
Intercept - τ_{00}		62%** −0.033	55%*** 0	53%*** 0	52%*** 0
Time - τ_{11}		1% −0.8345	1%*** 0	1%*** 0	1%*** 0
Model fit statistics					
Adjusted R ²			10%	12%	51%
AIC		−11,691	−17,763	−17,902	−21,077
−2 Loglikelihood		5,852	8,888	8,965	10,557
Chi-square			<.0001	<.0001	<.0001
VIF (mean)		2.619	3.474	3.314	3.756

TABLE 2 (Continued)

DV: NPLs	Ex. sign	Null	Model I	Model II	Model III
VIF (max)		6.404	6.607	8.367	8.709
Observation		4,959	4,959	4,959	4,959

Note: This table shows the RMMA with fixed effects. No intercept in the null model. Model 1 has dependent variables only, Model 2 has bank-level variables, and Model 3 adds country-level variables. Dependent variable = NPLs (Non-performing loans), calculated as the sum of non-accrual, reduced, renegotiated past-due loans minus assets acquired in foreclosures divided by total assets. ICC is reported, reflecting the variance at each level. Level 1 measures variance within banks over time. Δ -2LL compares model improvement with the null model, and chi-square compares improvement statistically. ***, **, and * indicate the coefficient's importance at 1%, 5%, and 10% levels. Appendix A defines all variables.

TABLE 3 Country analysis.

DV: NPLs	Ex. sign	U.S. Model I	Europe Model II	China Model III
Intercept	(?)	8.721*** 0	−0.241* −0.071	−7.485*** 0
COVID19	(+)	0.278*** 0	0.142*** 0	0.060*** 0
Bank-level variables				
SIZE	(−)	−0.019*** 0	−0.093*** 0	−0.062** −0.03
LEVERAGE	(+)	0.184*** 0	0.054*** 0	0.108 −0.256
MTB	(−)	0.018*** 0	0.022*** 0	0.01 −0.037
ROEQUITY	(−)	0.003*** 0	0.138*** 0	0.001 −0.198
MVEQUITY	(−)	0.154*** 0	0.107*** 0	−0.764*** −0.007
TOBIN-Q	(?)	0.015*** 0	0.061*** 0	0.101 −0.528
DIVINCOME	(−)	−0.064*** 0	−0.091*** 0	−0.114** −0.014
Country-level variables				
ECON_INDEX	(−)	−0.038*** 0	0.062*** 0	−0.086*** 0
STR_INDEX	(−)	0.250*** 0	−0.369*** 0	−0.149** 0
GOV_INDEX	(−)	−0.185*** 0	0.469*** 0	−0.328* −0.063
GDP	(−)	−0.031*** 0	−0.043*** 0	−0.091** −0.047
INFLATION	(+)	−0.031*** 0	−0.051*** 0	0.133*** 0
Time	(?)	−0.032*** 0	−0.369*** 0	−0.004** −0.027
Year fixed effects		Yes	Yes	Yes
Intra-class correlation (ICC)				
Repeated measures - σ^2		48%*** 0	46%*** 0	44%*** 0

(Continues)

TABLE 3 (Continued)

DV: NPLs	Ex. sign	U.S. Model I	Europe Model II	China Model III
Intercept - τ_{00}		51%*** 0	53%*** 0	55%*** 0
Time - τ_{11}		1%*** 0	1%*** 0	1%*** 0
Model fit statistics				
Adjusted R ²		82%	84%	15%
AIC		-18,047	-7,072	-4,408
-2 Loglikelihood		9,042	3,552	2,218
Chi-square		<.0001	<.0001	<.0001
VIF (mean)		2.619	2.619	2.619
VIF (max)		6.404	6.404	6.404
Observation		3,204	1,269	486

Note: This table shows the RMMA with fixed effects. No intercept in the null model. Model 1 has dependent variables only, Model 2 has bank-level variables, and Model 3 adds country-level variables. Dependent variable = NPLs (Non-performing loans), calculated as the sum of non-accrual, reduced, renegotiated past-due loans minus assets acquired in foreclosures divided by total assets. ICC is reported, reflecting the variance at each level. Level 1 measures variance within banks over time. Δ -2LL compares model improvement with the null model, and chi-square compares improvement statistically. ***, **, and * indicate the coefficient's importance at 1%, 5%, and 10% levels. Appendix A defines all variables.

necessary to consider a country's economic, stringency, and governance indexes in explaining credit risk due to their significant and direct impact on the model. These results support H1 and are consistent with prior studies (Elnahass et al., 2021; Rizwan et al., 2022).

5 | FURTHER ANALYSIS AND ROBUSTNESS CHECKS

5.1 | Tests for China, E.U., and U.S.

Table 3 reports the extant impact of the COVID-19 pandemic on the credit risk of banks in the three countries: Panel A (U.S.), Panel B (Europe), and Panel C (China). Firstly, we observe that credit risk during the COVID-19 period tends to be higher in the U.S. than in Europe and China (see Appendix B). The credit risk in China for our sample banks is lower, providing primary evidence that Chinese banks possess strong capabilities to mitigate credit risk. From Table 3, COVID-19 is negative and significantly associated with credit risk in all three countries. To assess the extent of impact per country, we estimate the economic significance of this effect. A 1 % age standard deviation increase in COVID-19 results in approximately a 2.4%, 1.2%, and 0.3% increase in credit risk for banks in the U.S., Europe, and China, respectively. Again, we observe that Chinese banks in our sample are less affected by the outbreak of the COVID-19 pandemic. This reflects the high corporate governance structures and risk management potential in addition to the extreme asset quality in China's banking industry (Chen et al., 2013, 2020).

All bank-level variables exhibit statistical significance with credit risk. We observe that the market value of equity within these

countries differs significantly. The MVEQUITY represents a forward-looking indicator for banks in our sample, which is high for China (10.050) compared to the U.S. and Europe. This suggests that, during the COVID-19 outbreak, Chinese banks, compared to those in the U.S. and Europe, experienced improvement in their market valuation (Chen et al., 2020). On the other hand, European banks experienced deterioration in their market valuation. We observe from Table 3 that MVEQUITY is negatively associated with credit risk for Chinese and U.S. banks, but the reverse is observed for European banks. As European banks experienced deterioration in their market valuation compared with China and the U.S., a negative association is expected.

Regarding country-level variables, the economic index is negatively associated with credit risk in the U.S. and China but not Europe. The economic index, governance index, and GDP growth per capita exhibit consistent statistical coefficient signs with credit risk. It is essential to mention that the results shed light on the far-reaching destructive impact of the outbreak of the COVID-19 pandemic in the banking sector, irrespective of the individual country analysis.

5.2 | The effect of bank size

As part of our additional analysis, we examine the differential impact of the COVID-19 pandemic on banks' credit risk, specifically at large and small banks. We employ the mean of bank size (i.e., 7.126) as the cut-off for classifying these banks. We report the results in Table 4 Panel A for large banks and Panel B for small banks, respectively. We find a significant and positive association between COVID-19 and credit risk as measured by NPLs for both large and small banks. That

TABLE 4 Sample analysis – large and small sample.

DV: NPLs	Ex. sign	Model I Large sample	Model II Small sample
Intercept	(?)	–0.016 –0.88	–7.262*** 0
COVID19	(+)	0.064*** 0	0.113*** 0
Bank-level variables			
SIZE	(–)	–0.011 –0.185	0.011** –0.015
LEVERAGE	(+)	0.081*** 0	0.155*** 0
MTBOOK	(–)	–0.016*** 0	–0.004*** 0
ROEQUITY	(–)	0.002*** 0	0.002*** 0
MVEEQUITY	(–)	0.09 –0.264	0.146*** 0
TOBIN-Q	(?)	–0.003 –0.93	0.012 –0.34
DIVINCOME	(–)	–0.042*** –0.003	–0.039*** 0
Country-level variables			
ECON_INDEX	(–)	–0.001** –0.024	–0.001 –0.868
STR_INDEX	(–)	0.036*** 0	0.108*** 0
GOV_INDEX	(–)	0.097*** 0	0.383*** 0
GDP	(–)	–0.013*** 0	–0.027*** 0
INFLATION	(+)	–0.016*** 0	–0.030*** 0
Time	(?)	0.001 –0.945	0.003*** 0
Year fixed effects		Yes	Yes
Repeated measures - σ^2		48%*** 0	44%*** 0
Intercept - τ_{00}		51%*** 0	55%*** 0
Time - τ_{11}		1%*** 0	1%*** 0
Adjusted R ²		63%	56%
AIC		–8,615	–12,149
–2 Loglikelihood		4,321	6,093
VIF (mean)		2.619	2.619
VIF (max)		6.404	6.404
Observation		2,304	2,655

Note: This table shows RMMA for two samples; countries with over 100 obs are large, and those with under 100 obs are small. Dependent variables: NPLs, OSCORE, ZSCORE. Year-fixed effects included in models. ***, **, and * indicate the coefficient's importance at 1%, 5%, and 10% levels. Appendix A defines all variables.

is, both small and large banks have been severely affected by the outbreak of the COVID-19 pandemic regarding credit risk. Our results indicate that small banks, compared to large banks, exhibited less capability in dealing with credit risk during the early stages of the COVID-19 pandemic.

5.3 | Alternative measures of credit risk – loan-loss provision and Ohlson's O-score

Since NPLs remain one of the leading credit risks faced by financial institutions worldwide, scholars tend to overlook the credit risk represented in cases of deteriorated exposure. In addition, prior studies consider differences in accounting policies and the measurement of default across countries to influence NPLs reported in the books of accounts (Acheampong & Elshandidy, 2021). However, the risk associated with non-deteriorated exposures affects capital ratios and risk-weighted averages and thus may indicate an incentive for banks to request the validation of internal models. As overlooking this aspect of credit risk may lead to bias in the analysis, as part of the robustness checks to analyze H1 using alternative credit risk measures, loan-loss provision (LLP) and Ohlson's o-score (OSCORE) are employed. A key advantage of LLP is that it captures credit risk in performing loans (Cucinelli et al., 2018). This shows that LLP exhibits a positive link with NPLs and thus serves as a means of reviewing capital structure. OSCORE is also a widely used credit risk measure (Acheampong & Elshandidy, 2021).

Results are reported in Table 5 Panel A (LLP) and Panel B (OSCORE). Results confirm a positive and significant association between LLP and COVID-19 and OSCORE and COVID-19 at the p-value of 0.000. This complements our main findings of the adverse impact of COVID-19 on credit risk. From the results above, it is reasonable to conclude that COVID-19 adversely affected banks' financial stability.

5.4 | Robustness checks

5.4.1 | Estimation – generalized method of moments (GMM)

The likelihood of endogeneity problems might arise from the causal link between credit risk and the independent variables. It may also occur from omitted variables and measurement errors.⁵ Therefore, we employ a lag approach and GMM estimator to address selection bias.

GMM presents a viable mechanism for regulating latent effects by converting variables into first differences, thereby leading to the decline in heterogeneity and the inadvertent bias stemming from left-out variables (Nguyen et al., 2012). Considering the nature of our data (i.e., nested), we employ within and between variations of exogenous variables; however, only the within variation is considered endogenous (Finch et al., 2016). We re-estimate Model III of our primary analysis and report the results in Table 6 (Panel A). We find similar

TABLE 5 Alternative measures of credit risk – loan-loss provision and O-score.

DV	Ex. sign	Panel A: loan-loss provision (LLP)		Panel B: Ohlson's O-score (OSCORE)	
		Model I	Model II	Model I	Model II
Intercept	(?)	1.439*** 0	1.711*** 0	−88.366*** 0	−56.205*** 0
COVID19	(+)	−0.0001** −0.011	0.004** −0.017	0.009*** −0.002	0.028*** 0
Bank-level variables					
SIZE	(−)	−0.003*** 0	−0.003*** 0	0.052*** 0	0.069*** 0
LEVERAGE	(+)	−0.010*** 0	−0.008*** 0	0.307*** 0	0.260*** 0
MTBOOK	(−)	−0.004 −0.18	0 −0.819	−0.063*** 0	0.014 −0.202
ROEQUITY	(−)	−0.001*** 0	−0.002*** 0	0.001* −0.071	0.002** −0.032
MVEEQUITY	(−)	0.034*** 0	0.034*** 0	−0.126 −0.167	−0.230** −0.011
TOBIN-Q	(?)	0.013*** 0	0.013*** 0	−0.260*** −0.001	−0.266*** 0
DIVINCOME	(−)	0.009*** 0	0.010*** 0	−0.012 −0.738	0.021 −0.594
Country-level variables					
ECON_INDEX	(−)		0.010* −0.055		−0.004*** −0.001
STR_INDEX	(−)		0.006** −0.024		0.091*** 0
GOV_INDEX	(−)		0.006*** −0.004		−0.041 −0.285
GDP	(−)		−0.001** −0.004		−0.012*** 0
INFLATION	(+)		−0.002*** 0		−0.020*** 0
Time	(?)	−0.001*** 0	−0.008*** 0	0.043*** 0	0.027*** 0
Year fixed effects		Yes	Yes	Yes	Yes
Intra-class correlation (ICC)					
Repeated measures - σ^2		40%*** 0	68%*** 0	57%*** 0	57%*** 0
Intercept - τ_{00}		59%*** 0	31%*** 0	42%*** 0	42%*** 0
Time - τ_{11}		1%*** 0	1%*** 0	1%*** 0	1%*** 0
Model fit statistics					
Adjusted R ²		12%	63%	18%	89%
AIC		−38,964	−38,909	−3,098	−3,429
−2 Loglikelihood		19,496	19,474	1,563	1733
Chi-square			<.0001	<.0001	<.0001

TABLE 5 (Continued)

DV	Ex. sign	Panel A: loan-loss provision (LLP)		Panel B: Ohlson's O-score (OSCORE)	
		Model I	Model II	Model I	Model II
VIF (mean)		2.619	3.474	3.314	3.756
VIF (max)		6.404	6.607	8.367	8.709
Observation		4,959	4,959	4,959	4,959

Note: This table shows the robustness checks taking loan-loss provision (LLP) and Ohlson's Oscore (OSCORE) as credit risk alternative measures. LLP is defined as the loan default at the end of the fiscal year multiplied by total outstanding loans, and OSCORE is determined following Ohlson's (1980) formulae. The sample comprises 4,959 banks across the U.S., Europe, and China from 2005 to 2021. P-values are reported in parentheses. Model fit statistics and the number of bank-year observations are reported at the bottom of the table. The description of all other variables is presented in Appendix A.

TABLE 6 Endogeneity – GMM and lag analysis.

		Panel A: GMM		Panel B: lagged IV	
DV: NPLs	Ex. sign	Model I		Model II	
Intercept	(?)	3.709***		−2.231	
		0		−0.393	
COVID19	(+)	0.118***			
		0			
COVID19 _{t-1}	(+)			0.016***	
				0	
Bank-level variables					
SIZE	(−)	0.010***		−0.055***	
		−0.004		0	
LEVERAGE	(+)	−0.162***		−0.072***	
		0		−0.002	
MTBOOK	(−)	0.004***		0.011***	
		−0.003		−0.002	
ROEQUITY	(−)	0.003***		−0.001***	
		0		−0.001	
MVEEQUITY	(−)	0.175***		0.239***	
		0		0	
TOBIN-Q	(?)	0.014*		0.008	
		−0.084		−0.701	
DIVINCOME	(−)	−0.046***		0.048***	
		0		−0.003	
Country-level variables					
ECON_INDEX	(−)	0.003***		0.007*	
		0		−0.09	
STR_INDEX	(−)	0.088***		−0.016***	
		0		0	
GOV_INDEX	(−)	0.347***		−0.085***	
		0		0	
GDP	(−)	−0.027***		−0.003	
		0		−0.196	
INFLATION	(+)	−0.032***		−0.001***	
		0		0	
Time		−0.012***		0.003	
		0		−0.311	

(Continues)

TABLE 6 (Continued)

	Panel A: GMM	Panel B: lagged IV
Year fixed effects		Yes
Intra-class correlation (ICC)		
Repeated measures - σ^2	48%*** 0	45%*** 0
Intercept - τ_{00}	51%*** 0	54%*** 0
Time - τ_{11}	1%*** 0	1% -0.293
Model fit statistics		
Adjusted R ²	61%	34%
AIC	-18,923	-17,526
-2 Loglikelihood	9,276	8,782
Chi-square	<.000	<.000
Observation	4,959	4,959

Note: This table reports the estimated coefficients for endogeneity tests. Panel A tests for endogeneity using GMM, and Panel B estimates using Lag 1 of credit risk (NPL_{t-1}). NPLs are the dependent variable in both Panels. ***, **, and * indicate the coefficient's importance at 1%, 5%, and 10% levels. Appendix A defines all variables.

results to our main results; thus the COVID-19 pandemic is significant and positively associated with credit risk. This confirms the extant adverse impact of the COVID-19 pandemic on credit risk in the banking industry. Our findings are thus not subject to endogeneity concerns.

5.4.2 | Lag analysis

In addition, using the lag approach, we regress the dependent variable on the lag principal independent variables (Acheampong & Elshandidy, 2021). We replicate Model III (Table 2), including bank and country-level variables. We report the results in Table 6 (Panel B). Findings reveal that the lag coefficient of COVID-19 is positive and significantly associated with NPLs at the p-value of 0.000. This indicates that the worsening COVID crisis in the immediate previous quarters led to increased credit risk the quarter after. We interpret this to mean that reported deaths coupled with government regulations ensuring the safety of the people during the lockdown and business shutdowns placed a great deal of pressure on people who could not commit to their credit agreement, and hence defaulted on their loans. A one percent increase in the standard deviation of COVID-19 on average leads to a rise in NPLs by 0.9%, confirming our main findings and thus indicating no endogeneity concerns.

6 | CONCLUSION

Empirical evidence shows that COVID-19 could cause a prolonged global recession and lead to a significant economic downturn. This paper examines how the COVID-19 pandemic impacts credit risk.

This paper's context is particularly interesting in the ongoing discussion about COVID-19's impact on economies and classes of banks. By employing non-performing loans as the measure of credit risk for 551 banks across China, Europe, and the U.S., leading to 4,959 bank-year observations, we find, consistent with our expectations, that the COVID-19 pandemic has severely affected bank credit risk positions geared toward financial stability. These results are consistently observed across various countries, with bank sizes (small and large) under consideration. Although the effect of COVID-19 is severe for banks, banks in China tend to record lower levels of impact compared to the U.S. and Europe due to the substantial credit risk and corporate governance structures in place coupled with a very high-quality asset level. The principal findings remain consistent and robust when analyzed under diverse model specifications, including the generalized method of moments (GMM) and lag analysis, which effectively account for potential endogeneity challenges and selection bias inherent in the sample.

Our paper has implications for market participants and regulators. COVID-19 harms bank credit risk regardless of bank size or location. As policymakers worry about a recession and potential depression, the pandemic's effects on bank stability could be significant due to disruptions in the global supply chain, lower demand for imports, and reduced tourism and business travel. G7 economies have implemented measures like quantitative easing, interventions, and stimulus packages; however, the survival of banks in less developed economies remains questionable. Our study offers key insight into the IMF's post-COVID-19 banking industry debates. Our findings inform investors and regulators about the impact of COVID-19 on global banks.

The current study provides essential insights to enrich the ongoing dialog initiated by the International Monetary Fund regarding the future trajectory of the banking sector in the aftermath of

the COVID-19 pandemic. The findings of this study hold significant implications for investors and regulators as they navigate the unprecedented effects of the COVID-19 pandemic on global banking systems. This study underscores the need for concerted efforts to bolster the banking sector. A lack of a coordinated approach may impede effective interaction between diverse market actors and erode public confidence in the intermediation framework over the long haul. Consequently, multi-stakeholder collaboration is imperative for sustainable banking practices and stability in the financial industry.

CONFLICT OF INTEREST STATEMENT

The authors declare that they do not have any conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Albert Acheampong  <https://orcid.org/0000-0002-9489-5751>

Albert Danso  <https://orcid.org/0000-0002-1971-413X>

ENDNOTES

- ¹ See EBA (2019) for more details on the E.U. NPLs problem.
- ² Generally, Southern and Central America, in addition to Asia, records average NPLs below 5%. It is 10% across the Middle East, Commonwealth states, and Africa. See: <https://data.imf.org/>.
- ³ A report by the EBA in 2020 during the fourth quarter highlights increasing NPLs volume due to COVID-19.
- ⁴ The pre-COVID period spans from Q1 2016 to Q4 2018 whereas the COVID period reflects the Q4 2019 to Q4 2021 period.
- ⁵ The endogeneity problem can be mitigated by applying RMMA, which takes into consideration firm-specific and time-invariant effects that could potentially influence credit risk (Acheampong & Elshandidy, 2021; Elshandidy & Acheampong, 2021). In addition, we also apply fixed-effect estimation, which is introduced in our main model (Table 2).

REFERENCES

- Acheampong, A., & Elshandidy, T. (2021). Does soft information determine credit risk? Text-based evidence from European banks. *Journal of International Financial Markets Institutions Money*, 75, 101303. <https://doi.org/10.1016/j.intfin.2021.101303>
- Agca, S., Birge, J. R., Wang, Z., & Wu, J. (2023). The impact of COVID-19 on supply chain credit risk. *Production and Operations Management*, 32(12), 4088–4113. <https://doi.org/10.2139/ssrn.3639735>
- Aiyar, S., Calomiris, C. W., & Wieladek, T. (2015). Bank capital regulation: Theory, empirics, and policy. *IMF Economic Review*, 63(4), 955–983. <https://doi.org/10.1057/imfer.2015.18>
- Andrews, D., & Petroulakis, F. (2019). Breaking the shackles: weak banks and depressed restructuring in Europe. OECD Economics Department Working Papers, 1433. Available at: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2240~61e2d9dfec.en.pdf>
- Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyotin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, 10(4), 742–758. <https://doi.org/10.1093/rapstu/raaa008>
- Chen, J. Z., Lobo, G. J., Wang, Y., & Yu, L. (2013). Loan collateral and financial reporting conservatism: Chinese evidence. *Journal of Banking & Finance*, 37, 4989–5006. <https://doi.org/10.1016/j.jbankfin.2013.09.003>
- Chen, Z., Poncet, S., & Xiong, R. (2020). Local financial development and constraints on domestic private-firm exports: Evidence from city commercial banks in China. *Journal of Comparative Economics*, 48, 56–75. <https://doi.org/10.1016/j.jce.2019.09.005>
- Cucinelli, D., Di Battista, M. L., Marchese, M., & Nieri, L. (2018). Credit risk in European banks: The bright side of the internal ratings based approach. *Journal of Banking & Finance*, 93, 213–229. <https://doi.org/10.1016/j.jbankfin.2018.06.014>
- Daehler, T. B., Aizenman, J., & Jinjarak, Y. (2021). Emerging markets sovereign CDS spreads during COVID-19: Economics versus epidemiology news. *Economic Modelling*, 100, 105504. <https://doi.org/10.1016/j.econmod.2021.105504>
- Daly, K., Batten, J. A., Mishra, A. V., & Choudhury, T. (2019). Contagion risk in global banking sector. *Journal of International Financial Markets Institutions Money*, 63, 101136. <https://doi.org/10.1016/j.intfin.2019.101136>
- Delis, M. D., Savva, C. S., & Theodossiou, P. (2021). The impact of the coronavirus crisis on the market price of risk. *Journal of Financial Stability*, 53, 100840. <https://doi.org/10.1016/j.jfs.2020.100840>
- Demir, E., & Danisman, G. O. (2021). Banking sector reactions to COVID-19: The role of bank-specific factors and government policy responses. *Research in International Business and Finance*, 58, 101508. <https://doi.org/10.1016/j.ribaf.2021.101508>
- Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics*, 141, 802–830. <https://doi.org/10.1016/j.jfineco.2021.03.005>
- Duan, Y., El Ghoul, S., Guedhami, O., Li, H., & Li, X. (2021). Bank systemic risk around COVID-19: A cross-country analysis. *Journal of Banking & Finance*, 133, 106299. <https://doi.org/10.1016/j.jbankfin.2021.106299>
- EBA. (2019) EBA report on non-performing loans. Progress made and challenges ahead. Available at: <https://service.betterregulation.com/document/411520>
- Elnahass, M., Trinh, V. Q., & Li, T. (2021). Global banking stability in the shadow of Covid-19 outbreak. *Journal of International Financial Markets Institutions Money*, 72, 101322. <https://doi.org/10.1016/j.intfin.2021.101322>
- Elshandidy, T., & Acheampong, A. (2021). Does hedge disclosure influence cost of capital for European banks? *International Review of Financial Analysis*, 78, 101942. <https://doi.org/10.1016/j.irfa.2021.101942>
- Enria, A., 2020. Non-Performing Loans in the Euro Area – Where do we Stand?, in: EDIS, NPLs, Sovereign Debt and Safe Assets. pp. 149–152. <https://doi.org/10.1515/9783110683073-011>
- ESRB. (2017) Resolving non-performing loans in Europe. Reporting by the European Systemic Risk Board. Available at: https://www.esrb.europa.eu/pub/pdf/reports/20170711_resolving_npl_report.en.pdf
- Fahlenbrach, R., Rageth, K., & Stulz, R. M. (2021). How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis. *Review of Financial Studies*, 34, 5474–5521. <https://doi.org/10.1093/rfs/hhaa134>
- Finch, W.H., Bolin, J.E., Kelley, K., 2016. Multilevel Modeling Using R, Multilevel Modeling Using R. <https://doi.org/10.1080/00949655.2020.1805564>
- Ftiti, Z., Ben Ameur, H., & Louhichi, W. (2021). Does non-fundamental news related to COVID-19 matter for stock returns? Evidence from Shanghai stock market. *Economic Modelling*, 99, 105484. <https://doi.org/10.1016/j.econmod.2021.03.003>
- Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20, 93–104. <https://doi.org/10.1016/j.jfs.2015.08.004>
- Giofré, M. (2022). Foreign investment in times of COVID-19: How strong is the flight to advanced economies? *Journal of Multinational Financial*

- Management, 64, 100735. <https://doi.org/10.1016/j.mulfin.2022.100735>
- Haddad, V., Moreira, A., & Muir, T. (2021). When selling becomes viral: Disruptions in debt markets in the COVID-19 crisis and the Fed's response. *Review of Financial Studies*, 34, 5309–5351. <https://doi.org/10.1093/rfs/hhaa145>
- Hale, T., Angrist, N., Cameron-Blake, E., Hallas, L., Kira, B., Majumdar, S., Petherick, A., Phillips, T., Tatlow, H., Webster, S. (2020) Variation in government responses to COVID-19|Blavatnik School of Government. Work. Pap. Version 7.
- Hasan, I., Marra, M., To, T. Y., Wu, E., & Zhang, G. (2023). COVID-19 pandemic and global corporate CDS spreads. *Journal of Banking & Finance*, 147, 106618. <https://doi.org/10.2139/ssrn.3858059>
- IMF. (2020) IMF Annual report|covid 19. Available at: <https://www.imf.org/external/pubs/ft/ar/2020/eng/spotlight/covid-19/>
- Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P. O., & Zúñiga, D. (2021). Corporate bond liquidity during the COVID-19 crisis. *Review of Financial Studies*, 34, 5352–5401. <https://doi.org/10.1093/rfs/hhab063>
- Keliuotytė-Staniulienė, G., & Daunaravičiūtė, K. (2021). The global green bond market in the face of the COVID-19 pandemic. *Financial Markets, Institutions and Risks*, 5, 50–60. [https://doi.org/10.21272/fmir.5\(1\).50-60.2021](https://doi.org/10.21272/fmir.5(1).50-60.2021)
- Kwabi, F. O., Boateng, A., & Du, M. (2020). Impact of central bank independence and transparency on international equity portfolio allocation: A cross-country analysis. *International Review of Financial Analysis*, 69, 101464. <https://doi.org/10.1016/j.irfa.2020.101464>
- Lee, S. Y. T., Park, M., & Shin, Y. (2021). Hit harder, recover slower? Unequal employment effects of the COVID-19 shock. *Fed. Reserv. Bank St. Louis Rev.*, 103, 367–384. <https://doi.org/10.20955/r.103.367-83>
- Luke, D. A. (2004). *Multilevel modeling (university paper series on quantitative applications in the social sciences)* (pp. 7–143). Sage.
- Nguyen, M., Skully, M., & Perera, S. (2012). Market power, revenue diversification and bank stability: Evidence from selected south Asian countries. *Journal of International Financial Markets, Institutions & Money*, 22, 897–912. <https://doi.org/10.1016/j.intfin.2012.05.008>
- O'Hara, M., & Zhou, X. A. (2021). Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. *Journal of Financial Economics*, 142, 46–68. <https://doi.org/10.1016/j.jfineco.2021.05.052>
- Pan, W. F., Wang, X., Wu, G., & Xu, W. (2021). The COVID-19 pandemic and sovereign credit risk. *China Finance Review International*, 11, 287–301. <https://doi.org/10.1108/CFRI-01-2021-0010>
- Pfeffer, J., 2019. Size and composition of corporate boards of directors: The organization and its environment, in: *Corporate Governance: Values, Ethics and Leadership*. pp. 53–64. <https://doi.org/10.2307/2393956>
- Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. *Review of Corporate Finance Studies*, 9, 622–655. <https://doi.org/10.1093/rcfs/cfaa012>
- Rizwan, M. S., Ahmad, G., & Ashraf, D. (2022). Systemic risk, Islamic banks, and the COVID-19 pandemic: An empirical investigation. *Emerging Markets Review*, 51, 100890. <https://doi.org/10.1016/j.ememar.2022.100890>
- Robinson, T. J. (2003). Multilevel analysis: Techniques and applications. *Journal of the American Statistical Association*, 98(462), 496.
- Shabir, M., Jiang, P., Wang, W., & Işık, Ö. (2023). COVID-19 pandemic impact on banking sector: A cross-country analysis. *Journal of Multinational Financial Management*, 67, 100784. <https://doi.org/10.1016/j.mulfin.2023.100784>
- Tevfik Kartal, M. (2020). The behavior of sovereign credit default swaps (CDS) spread: Evidence from Turkey with the effect of Covid-19 pandemic. *Quantitative Finance and Economics*, 4, 489–502. <https://doi.org/10.3934/qfe.2020022>
- The New York Times. (2020) Live stock market tracker during coronavirus pandemic. Available at: <https://www.nytimes.com/2020/04/07/business/stock-market-today->
- Twum, A. K., Agyemang, A. O., & Sare, Y. A. (2022). Revisiting credit risk and banks performance of China's commercial banks before and after Covid 19 pandemic. *Journal of Corporate Accounting & Finance*, 33, 16–30. <https://doi.org/10.1002/jcaf.22539>
- World Health Organization. (2020). Z WHO clinical management of severe acute respiratory infection (SARI) when COVID-19 disease is suspected. Who. (2020) 2019:12. <https://doi.org/10.15557/PiMR.2020.0003>
- Xue, F., Li, X., Zhang, T., & Hu, N. (2021). Stock market reactions to the COVID-19 pandemic: The moderating role of corporate big data strategies based on Word2Vec. *Pacific-Basin Finance Journal*, 68, 101608. <https://doi.org/10.1016/j.pacfin.2021.101608>
- Zhang, J., Yin, Y., & Zhang, L. (2019). Determinants of loan securitization in Chinese banking: Cost-benefit-based analysis. *Pacific-Basin Finance Journal*, 57, 101060. <https://doi.org/10.1016/j.pacfin.2018.08.014>

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APPENDIX A: VARIABLE DESCRIPTION

Variable	Definition	Source
COVID19	COVID-19 pandemic – Confirmed deaths growth ($\log(1 + \text{death cases in current week}) + \log(1 + \text{death cases in previous week})$)	(Demir & Danisman, 2021; Hale et al., 2020)
NPLs	Credit risk – Non-performing loan divided by the bank's total assets.	Datastream Eikon
SIZE	Bank size – natural logarithm of the bank's total assets	Datastream Eikon
LEVERAGE	Financial leverage – Total debt scaled by total assets	Datastream Eikon
MTB	Market-to-book value – market value divided by the book value of equity. High MV/BV = high market valuation.	Datastream Eikon
ROEQUITY	Return on equity	Datastream Eikon
MVEQUITY	Market value of equity – market value of equity in the natural logarithm form. The higher value of LogMV implies a higher current market valuation.	Datastream Eikon
TOBIN-Q	Tobin's Q – scales the bank's debt and equity market value by the book value of equity. Higher value = higher forward-looking market valuation.	Datastream Eikon
DIVINCOME	Total non-interest income divided by total income	Datastream Eikon
ECON_INDEX	The economic support index is computed as the mean value of the individual two-component policy response indicators that pertain to the economic response. The range of the variable under consideration extends from 0 to 100.	(Hale et al., 2020)
STR_INDEX	The stringency index encompasses the degree of rigor exhibited by government measures in response to the COVID-19 outbreak. It is computed as the mean of the nine constituent policy response indicators of containment and closure. The numerical values are delineated within the range of 0 to 100.	(Hale et al., 2020)
GOV_INDEX	The collective mean of six imperative measures of country governance: Government effectiveness, corruption, political stability, the rule of law and regulatory quality, and voice and accountability.	World Bank
GDP	Natural logarithm of gross domestic products per capita	World Bank
INFLATION	The annual inflation rate is the percentage variation in the consumer Price index.	World Bank

APPENDIX B: DESCRIPTIVE STATISTICS FOR THE U.S., EUROPE, AND CHINA

	U.S.				Europe				China			
	N	Mean	Median	SD	N	Mean	Median	SD	N	Mean	Median	SD
COVID19	3,204	−0.1344	−0.2017	1.3622	1,269	0.9840	1.0020	1.5692	486	−1.6838	−1.6530	0.9804
NPLs	3,204	0.0845	0.0252	0.0870	1,269	0.0648	0.0150	0.0845	486	0.0213	0.0033	0.0472
SIZE	3,204	6.7760	6.6460	0.8537	1,269	7.5790	7.5100	0.9081	486	8.2450	8.0700	0.6373
LEVERAGE	3,204	0.0621	0.0406	0.0649	1,269	0.2581	0.2317	0.1582	486	0.5116	0.5173	0.0416
MTBOOK	3,204	1.0610	1.0200	0.3601	1,269	0.7296	0.6200	0.4599	486	0.6528	0.6300	0.3694
ROEQUITY	3,204	9.8180	9.8700	4.6931	1,269	6.5560	6.3400	5.5321	486	10.0500	10.560	3.6011
MVEQUITY	3,204	0.5747	0.5637	0.0992	1,269	0.6530	0.6552	0.1233	486	0.7909	0.7800	0.0565
TOBIN-Q	3,204	0.5245	0.5225	0.1341	1,269	0.6913	0.7032	0.1230	486	0.8454	0.8398	0.0655
DIVINCOME	3,204	0.2150	0.1960	0.1293	1,269	0.3741	0.3761	0.1499	486	0.1231	0.1157	0.0512
ECON_INDEX	3,204	7.8890	8.0000	1.3700	1,269	19.390	20.500	2.3904	486	6.4444	7.0000	1.0668
STR_INDEX	3,204	3.7780	4.0000	0.4158	1,269	3.8890	4.0000	0.3143	486	3.8890	4.0000	0.3145
GOV_INDEX	3,204	1.0134	1.0268	0.0341	1,269	0.7183	0.7152	0.0255	486	0.2478	0.2478	0.0000
GDP	3,204	0.8466	0.9632	1.7469	1,269	0.4802	0.1393	1.9751	486	1.3760	1.3000	1.7472
INFLATION	3,204	2.8611	2.0329	2.0670	1,269	1.7381	1.3801	1.4107	486	1.9910	1.7820	1.6267

Note: This table provides a comprehensive description of the variables employed, with separate data for each country under examination. The continuous variables undergo winsorization at the respective 1st and 99th percentiles. Appendix A defines all variables.