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Influence of the COVID-19 Pandemic on the Banking Sector in Northern Europe

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Abstract

This research intends to investigate the influence of the COVID-19 pandemic on the financial performance of the banking sector in Northern Europe spanning from 2010 to 2021. In order to execute an empirical investigation into the elements that influence profitability, we worked with the OLS method (FGLS panel-data model). The results demonstrate the importance of factors that are both macroeconomic and specific in explaining profitability. Specifically, the capital adequacy ratio (CAR) exerts a noteworthy influence on bank profitability. Additionally, the bank's Z-score exhibits a negative correlation with the net interest margin (NIM) and attains statistical significance.

Keywords: Banking Sector, Covid-19, Net Interest Margin, Profitability, FGLS, Capital Adequacy, Europe

1. Introduction

This study evaluates the impact of the COVID-19 epidemic on the stability and performance of the banking sector. Şolak and Öztekin (2021) explored how the pandemic affected bank lending internationally by examining several bank and national attributes that either exacerbate or lessen the disease's effect on bank credit. According to their results, bank loan growth has slowed down in reaction to pandemic shocks, with the intensity of the pandemic in a given nation having a significant influence on this negative outcome. Researchers Özlem Dursun-de Neef and Schandlbauer (2021) look into how lending decisions made by European banks during the pandemic were influenced by their capitalization and local exposure to the COVID-19 epidemic. The research team of Duan et al. (2021) examined how the COVID-19 pandemic affected systemic risk in 64 nations, finding that government regulations and bank default risk channels exacerbated systemic fragility. Yet, depending on the heterogeneity of the bank and the nation, the severity of this adverse effect differed. In a similar vein, Elnahass et al. (2021) investigated how COVID-19 affected the reliability of banking and found negative effects on the stability and financial performance of banks. At the start of the COVID-19 crisis, Demirgüç-Kunt et al. (2021) examined the effects of financial sector announcements regarding policies on bank stocks abroad. They noted that while the efficacy of monetary easing, debtor assistance schemes, and liquidity support varied greatly among banks and nations, they all contributed to lessening the negative effects of the crisis. The research described here looks into the relationship between various macroeconomic and banking factors and bank profitability. The factors that influence bank profitability include capital sufficiency, work efficiency, credit risk, z-score, and bank-specific liquidity. A different set of factors relates to the larger macroeconomic environment that the banking industry operates in. This includes variables like the rate of inflation, GDP growth, with foreign direct investment. The article will be hosted as follows: The summary of the available literature on profitability at banks is given in Section 2. Section 3 covers statistics and methodology, Section 4 presents the empirical results, and Section 5 concludes by summarizing the paper.

2. Literature Review

The last part of 2019 and early 2020 saw the emergence of COVID-19, which quickly spread throughout the world and posed serious risks to both available health and the economy as a consequence (Zhou et al., 2021). After MERS in 2012 and SARS in 2003, COVID-19 is the third significant outbreak of a new coronavirus in the twenty-first century (Keogh-Brown and colleagues, 2020). Due to the increased risks and uncertainties associated with this illness, there has been a significant drop in global activity (Padhan and Prabheesh, 2021).

Nevertheless, there has been a rapid influx of studies exploring the ramifications of COVID-19 in recent years. According to Fernandes (2020), the pandemic has led to a decrease in all over the world supply and demand. A trade-off between the severity of the recession and the number of deaths is inevitable, as revealed by Eichenbaum et al.'s (2021) analysis of the adverse impact of COVID-19 on economic activities. worldwide supply and demand. In-depth analyses of several COVID-19 epidemiological scenarios by McKibbin and Fernando (2021), for example, show that less developed nations with denser populations and underdeveloped healthcare systems experience more severe negative consequences. Yue et al. (2020), respectively and Liu et al. (2020) report reductions in investment and consumption. Devpura and Narayan (2020), for example, find that COVID-19 deaths and cases worsen oil price fluctuations. Şolak and Öztekin (2021), for instance, and Gubareva (2021) examine how COVID-19 has caused a decrease in output and credit. During the COVID-19 pandemic crisis, Akhtaruzzaman et al. (2021) investigated the role of gold as a hedge. COVID-19 also has a negative impact on the performance of various firms and industries (Fu and Shen, 2020; Shen et al., 2020), as well as the insurance sector (Wang et al., 2020).

Additionally, several researchers have examined the repercussions of the COVID-19 pandemic on the banking sector. According to Elnahass et al. (2021), the crisis had devastating effects on numerous banks worldwide. Governments globally implemented significant measures to curb the virus's spread, including sudden de-globalization through border lockdowns between countries. This has had severe implications for economic activities, trade, and services, resulting in a decline in business and household incomes and revenues. Consequently, there has been a reduction in the capacity to repay loans and a decreased demand for banking services (Beck and Keil, 2021; Duan et al., 2021). Li et al. (2021) offer compelling empirical evidence that the pandemic led to tightened credit standards and diminished demand for various types of loans. They also establish a positive connection between revenue diversification and performance but a negative association with risk.

Şolak and Öztekin (2021) examined how the pandemic affected bank lending and observed that, in reaction to the pandemic shock, bank loan growth decreased globally. The degree of the pandemic severity in each nation has been directly correlated with the size of the decline in bank credit growth. Additionally, an assessment of the pandemic's impact on bank systemic risk by Duan et al. in 2021 revealed an increase in systemic risk globally. Large, highly leveraged, riskier, high loan-to-asset, undercapitalized, and low network centrality banks were most affected negatively. The COVID-19 pandemic had a negative impact on the performance and financial stability of the global banking industry, according to Elnahass et al. (2021). Nonetheless, some research (e.g., Li the authors, 2020) found a markedly positive shock to the demand for bank loans in the United States at the start of the pandemic, and Acharya and Steffen (2020) observed that companies lowered their bank credit lines.

3. Data and Methodology

The following countries were selected to evaluate COVID-19's effects on the Northern European banking system: Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Norway, Sweden, and the United Kingdom. The information is gathered from the World Bank database from 2010 to 2021. The variables used in this study are shown below, which includes information about the symbol and its description.

To identify the underlying relationship between each variable, the following baseline will be estimated:

$$Y = \beta_0 + \beta_{1FDIofGDP} + \beta_{2Inf} + \beta_{3ZSC} + \beta_{4CAR} + \beta_{5LIQ} + \beta_{6CTI} + \beta_{7NPL} + \beta_{8LNGDP} + \beta_{92019} + \beta_{102020+}\varepsilon$$

Y = The financial performance of the bank as expressed by the NIM.

β_0 = is the constant parameter.

$\beta_{1\text{-}10}$ = are model coefficient parameters.

ε = residual term

Table 1 – Summary and measurement of the variables.

Symbol	**Variables**	**Proxy**
Dependent variables		
NIM	Net interest margin	Net interest income/total assets
Independent variables:		
Bank specific variables		
ZSC	Bank Z-score	Bank Z-score
CAR	Capital adequacy	Bank capital to total assets (%)
LIQ	Liquidity ratio	Liquid assets to deposits and short-term funding (%)
CTI	Efficiency	Bank cost-to-income ratio (%)

NPL	Credit risk	Bank non-performing loans to gross loans (%)
Macroeconomic variables		
LNGDP	GDP growth	GDP logarithm
FDIofGDP	Foreign direct investment	Foreign direct investment, net inflows (% of GDP)
Inf	Inflation rate	Annual inflation based on CPI
DUM 2019,2020	Covid-19	
Note – compiled by the authors		

Dependent Variables: The study employs Net Interest Margin (NIM) as a performance metric. NIM is characterized by dividing net interest income by total assets, providing an assessment of the profit derived from interest-related activities (Naceur, 2003).

The bank-specific characteristics proxied as internal determinants of bank profitability of banks. However, Macroeconomic variables are proxied as external determinants of the profitability of banks.

Capital Adequacy: In our analysis, we utilize the equity-to-total-assets ratio (CAR) as an indicator of the bank's preparedness to absorb losses and engage in risk exposure alongside shareholders. We posit that a higher ratio signifies reduced reliance on external funding and correlates with enhanced bank profitability. The anticipated positive correlation between CAR and performance suggests that well-capitalized banks experience lower costs associated with bankruptcy, resulting in diminished funding and risk expenses (Bourke, 1989).

Bank Z-score: measuring bank stability. Some studies have used multiple risk indicators as proxies for assessing bank stability. To provide a comprehensive analysis, we included various alternative measures of bank stability in this study. Initially, building on the earlier work of Laven and Levin (2009), Elnahas et al. (2021), and Shabir et al. (2021), we adopt the Z-score as a measure of bank default risk. The Z-score, introduced by Roy (1952), is considered an objective indicator of bank risk based on accounting data. This measure reflects the number of standard deviations below a bank's expected return on assets (ROA) at which equity capital is depleted, leading to insolvency (Baselga-Pascual and Vähämaa, 2021; Bond et al., 1993; Boyd & Runkle, 1993). The Z-score integrates return volatility, leverage, and profitability into a single metric that serves as an inverse indicator of a company's chance of failing (Lee et al., 2014). A higher Z-score indicates less risk and greater bank stability, so this index can be understood as an inverse measure of the probability of insolvency (Baselga-Pascual et al., 2015; Köhler, 2015; The work of Shabir et al., 2021).

Efficiency: The efficiency metric is derived from the bank's cost-to-income ratio (%), reflecting the effectiveness of resource allocation and utilization of human and technological resources by banks. Previous research has identified a negative correlation between efficiency and other variables. Theoretically, this relationship can be rationalized by the notion that elevated costs exert a detrimental impact on a bank's profitability. This deduction is attributed to the prevalence of high operational costs within commercial banks (Munyambonera, 2013).

Liquidity: Our assessment of liquidity employs the liquid assets-to-total assets ratio (LIQ). A higher percentage in this ratio signifies an elevated level of bank liquidity. Insufficient liquidity is recognized as one of the primary causes of significant bank failures. Conversely, maintaining high levels of liquid assets incurs an opportunity cost in terms of potentially higher returns. Bourke's (1989) study supports a positive association between bank liquidity and profitability. Nevertheless, banks might opt to increase cash holdings to mitigate risk during uncertain times, introducing an opportunity cost. Conversely, Molyneux and Thornton (1992) assert a negative correlation between liquidity and profitability levels.

Credit Risk: Our evaluation of credit risk relies on the non-performing loans to gross loans ratio (NPL). Existing literature generally links heightened exposure to credit risk with lower firm profitability, implying an anticipated negative correlation. Nevertheless, banks proactively implement measures to monitor and manage credit risk, incorporating policies to anticipate future risks. As a result, they may achieve an enhanced level of profitability. Consequently, credit risk can be regarded as a predetermined variable (Athanasoglou, Brissimis, & Delis, 2008).

Macroeconomic Variables: As external predictors of bank profitability, we employ the following macroeconomic traits: GDP Growth: To measure overall economic activity after accounting for inflation, we use GDP growth, which is calculated using the GDP logarithm. Numerous variables are greatly impacted by this variable, including the supply and demand for loans and deposits. The literature indicates that bank profitability and GDP have a positive correlation, which is explained by the increased demand for loans (Demirgüç-Kunt and Huizinga, 1999).

Inflation Rate: The inflation rate (Inf), calculated through the annual inflation based on the Consumer Price Index (CPI), reflects the overall growth in CPI for all goods and services. Inflation influences both revenues and costs, and its impact on profitability can be either positive or negative, contingent on whether it is anticipated. If inflation is expected, banks adjust interest rates to boost revenue. Conversely, if inflation is unforeseen, costs might rise more rapidly than revenues. Nevertheless, the majority of studies assert a positive correlation between inflation and profitability (Bourke, 1989).

Foreign Direct Investment (FDI): FDI offers significant chances for the host banking sector's growth. We discover that foreign investment is linked to greater profitability; nonetheless, a positive impact on cost efficiency requires a significant level of foreign ownership (Luca and Debora, 1999).

4. Empirical Results

The results of descriptive statistics are shown below: This provides us with attributes of data such as mean, standard deviation, min, and max values.

```
. sum NIM FDIofGDP Inf ZSC CAR LIQ CTI NPL LNGDP
```

Variable	Obs	Mean	Std. Dev.	Min	Max
NIM	104	1.805022	1.146088	.3684253	8.929617
FDIofGDP	108	4.796811	10.94558	-28.30723	81.24757
Inf	108	2.339111	2.52868	-2.889836	17.10261
ZSC	106	13.40224	9.293096	.0173334	39.34783
CAR	78	9.325398	4.016673	4.342637	21.05682
LIQ	86	47.23253	13.95832	19.27962	82.10233
CTI	102	52.16683	11.68593	5.032482	80.01334
NPL	90	4.040519	5.192273	.3468926	25.70859
LNGDP	108	11.23919	.6988123	10.18547	12.50163

Before conducting regression analysis, we assessed the model's robustness:

1. Test for multicollinearity
2. Autocorrelation
3. Heteroscedasticity

To ensure the compliance of both the regression model and the coefficient values themselves, we subsequently examine the multicollinearity of each variable incorporated into the model. Multicollinearity, as it diminishes the robustness of coefficient values and diminishes the statistical power of the model, necessitates testing through the Variance Inflation Factor (VIF). The correlation analysis in Figure 1 reveals relationships between dependent and independent variables; for instance, NIM exhibits positive correlations with INF, and CAR, while displaying negative correlations with FDI, ZSC, LIQ, CTI, NPL, and GDP variables.

Figure 1 – Correlation Analysis

```
. correl NIM FDIofGDP Inf ZSC CAR LIQ CTI NPL LNGDP
(obs=49)
```

	NIM	FDIofGDP	Inf	ZSC	CAR	LIQ	CTI	NPL	LNGDP
NIM	1.0000								
FDIofGDP	-0.1530	1.0000							
Inf	0.3709	0.1351	1.0000						
ZSC	-0.5732	0.1401	-0.1847	1.0000					
CAR	0.8226	-0.3130	0.3433	-0.6257	1.0000				
LIQ	-0.6579	-0.2587	-0.2940	0.4271	-0.4220	1.0000			
CTI	-0.4314	-0.1517	-0.3767	0.2523	-0.4206	0.4805	1.0000		
NPL	-0.1279	0.0678	0.0407	-0.3792	-0.0011	-0.0435	-0.1990	1.0000	
LNGDP	-0.5826	0.0274	-0.2458	0.5740	-0.7119	0.6047	0.5154	-0.2347	1.0000

Note – compiled by the authors.

After presenting the correlation results, we now proceed to assess how the strength of correlation impacts both the dependent and independent variables. Figure 2 illustrates the Variance Inflation Factors (VIFs) for the independent variables, starting at a value of 1. It is noteworthy that the VIF result is considered valid when it falls within the range of 1 to 5. If the obtained result exceeds 5, it signifies a critical level of multicollinearity, indicating poorly estimated coefficients and uncertain p-values. Examining the table, we observe that the mean VIF for the model stands at 2.23, denoting a moderate correlation between variables.

Figure 2 – Variance Inflationary Factor (VIF)

Note – compiled by the authors.

Additionally, the GLS panel-data model employs the Wooldridge test in Figure 3 to assess

```
. estat vif
```

Variable	VIF	1/VIF
CAR	3.95	0.253258
LNGDP	3.16	0.316482
ZSC	2.45	0.407685
LIQ	2.12	0.472171
CTI	1.72	0.583059
NPL	1.59	0.627025
FDIofGDP	1.51	0.660269
Inf	1.32	0.759486
Mean VIF	2.23	

autocorrelation, which typically reveals the level of similarity between time series and a lagged time interval. For autocorrelation, the p-value should be below 1%, 5%, or 10%. The provided outcome rejects the null hypothesis, indicating the presence of first-order autocorrelation.

Figure 3 – Wooldridge test for autocorrelation

```
. xtserial NIM FDIofGDP Inf ZSC CAR LIQ CTI NPL LNGDP _IYear_2019 _IYear_2020

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       4) =     16.674
           Prob > F =      0.0151
```

Note – compiled by the authors.

Examining heteroscedasticity in Figure 4, we observe that the time series model may encounter notable fluctuations in error variance from the start to the end of the series. This suggests that the independent variable NIM can change its value over the specified period. The primary issue associated with heteroscedasticity is the biased standard error. Conversely, homoscedasticity is present when the error term exhibits a consistent distribution across the variables, as depicted in Figures 5 and 6.

Figure 4 – Test for heteroscedasticity.

```
. lrtest hetero homo, df(108)

Likelihood-ratio test                                 LR chi2(108)=      9.24
(Assumption: homo nested in hetero)                   Prob > chi2 =    1.0000


Coefficients:  generalized least squares
Panels:        heteroskedastic
Correlation:   no autocorrelation

Estimated covariances      =         7          Number of obs     =        49
Estimated autocorrelations =         0          Number of groups  =         7
Estimated coefficients     =        11          Obs per group:
                                                              min =         1
                                                              avg =         7
                                                              max =        11
                                                Wald chi2(10)     =    470.07
Log likelihood             = -6.077603          Prob > chi2       =    0.0000
```

NIM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FDIofGDP	-.0077112	.0075377	-1.02	0.306	-.0224849	.0070625
Inf	.0017111	.0263237	0.07	0.948	-.0498825	.0533046
ZSC	-.0169549	.0088998	-1.91	0.057	-.0343982	.0004885
CAR	.1356122	.0167546	8.09	0.000	.1027738	.1684506
LIQ	-.030649	.0042901	-7.14	0.000	-.0390575	-.0222404
CTI	-.0025037	.0039522	-0.63	0.526	-.0102497	.0052424
NPL	-.0225895	.0123816	-1.82	0.068	-.0468571	.0016781
LNGDP	.2486729	.0814487	3.05	0.002	.0890364	.4083095
_IYear_2019	.0955938	.1313816	0.73	0.467	-.1619094	.353097
_IYear_2020	.1279099	.1391323	0.92	0.358	-.1447845	.4006043
_cons	-.2522905	.9659897	-0.26	0.794	-2.145596	1.641014

Note – compiled by the authors.

The findings show that "hetero nested in homo" and the prob > chi2 statistic for the model, which rejects the null hypothesis stating as all of the regression coefficients (other than the constant term) are zero. LR chi2 (108) = 9.24; Prob > chi2 = 1.0000.

Figure 5 – Test for heteroscedasticity

```
Coefficients:  generalized least squares
Panels:        heteroskedastic
Correlation:   common AR(1) coefficient for all panels  (0.0934)

Estimated covariances      =         5          Number of obs      =        47
Estimated autocorrelations =         1          Number of groups   =         5
Estimated coefficients     =        11          Obs per group:
                                                               min =         6
                                                               avg =       9.4
                                                               max =        11
                                                Wald chi2(10)      =    320.04
                                                Prob > chi2        =    0.0000
```

NIM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FDIofGDP	.0077659	.0085926	0.90	0.366	-.0090754	.0246072
Inf	.0175618	.0234965	0.75	0.455	-.0284905	.0636141
ZSC	-.0460567	.0087469	-5.27	0.000	-.0632002	-.0289131
CAR	.097288	.0217894	4.46	0.000	.0545815	.1399944
LIQ	-.0163567	.0051496	-3.18	0.001	-.0264497	-.0062637
CTI	-.0147803	.0049452	-2.99	0.003	-.0244726	-.005088
NPL	-.0431626	.0148726	-2.90	0.004	-.0723124	-.0140128
LNGDP	.2031968	.0928268	2.19	0.029	.0212597	.3851339
_IYear_2019	.1902911	.1150385	1.65	0.098	-.0351803	.4157625
_IYear_2020	.2479713	.1363358	1.82	0.069	-.0192421	.5151846
_cons	.9777995	1.149694	0.85	0.395	-1.275559	3.231158

Note – compiled by the authors.

Figure 6 – Regression Analysis by employing feasible generalized least square FGLS

```
Coefficients:  generalized least squares
Panels:        homoskedastic
Correlation:   no autocorrelation

Estimated covariances      =         1          Number of obs      =        49
Estimated autocorrelations =         0          Number of groups   =         7
Estimated coefficients     =        11          Obs per group:
                                                               min =         1
                                                               avg =         7
                                                               max =        11
                                                Wald chi2(10)      =    279.97
Log likelihood             = -10.69621          Prob > chi2        =    0.0000
```

NIM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FDIofGDP	-.0086865	.008961	-0.97	0.332	-.0262498	.0088768
Inf	.0087049	.0311708	0.28	0.780	-.0523887	.0697985
ZSC	-.0160543	.0113836	-1.41	0.158	-.0383656	.0062571
CAR	.1321867	.0215713	6.13	0.000	.0899076	.1744657
LIQ	-.0301106	.005208	-5.78	0.000	-.0403181	-.019903
CTI	-.005008	.0046463	-1.08	0.281	-.0141146	.0040986
NPL	-.0261862	.0158549	-1.65	0.099	-.0572613	.0048889
LNGDP	.2622875	.0924058	2.84	0.005	.0811754	.4433996
_IYear_2019	.1041982	.1579355	0.66	0.509	-.2053498	.4137461
_IYear_2020	.2153429	.1673818	1.29	0.198	-.1127193	.5434051
_cons	-.2777629	1.090208	-0.25	0.799	-2.414532	1.859006

Note – compiled by the authors.

Assuming that ceteris paribus, a 1% increase in the constant variable will increase the Bank interest margin (%) by 97.78% and it is insignificant. Inflation and FDI (Foreign Direct Investment) are statistically insignificant and, therefore, do not exert a significant influence on the Bank interest margin (%) of Northern European banks. A 1% increase in LIQ (Liquid assets to deposits and short-term funding, %) will decrease NIM by 1.64%. It is explained by the fact that keeping the most liquid assets or cash has an opportunity cost for lending this money and earning interest revenue, thus, this decreases the net interest margin which is consistent with the study of Marozva (2015), where she found out that liquidity and bank profitability have a negative relationship. A 1% increase in CTI (Bank cost to income ratio, %) will decrease BNIM by 1.48% which means Northern European banks use interest revenue to cover operational expenses and it reduces net interest revenue which is inconsistent with Abdulkhakim (2019) since found out that banks charge more interest on clients to cover the expenses, thus, costs increase net interest margin of Banks. A 1% increase in LNGDP (ln of GDP) will increase BNIM by 20.32% which is explained by the fact that when the economy is stabilizing and improves, the purchasing power of the population increases which allows them to take more loans, thus, increase interest revenue of Banks. Additionally, businesses need financing and they approach banks to finance them by paying interest. This is consistent with the study of Burgstaller (2006), where he concluded that GDP growth positively affects a bank's profitability (net interest margin). A 1% increase in Bank Z-score will decrease BNIM by 4.6%**.** The Z-score, as introduced by Roy (1952), serves as an indicator of a bank's proximity to insolvency and is considered an unbiased measure of bank risk based on accounting data. It signifies the number of standard deviations below the anticipated value of a bank's return on assets (ROA) at which equity becomes depleted, leading to insolvency (Baselga-Pascual and Vähämaa, 2021; Bond et al., 1993; Boyd & Runkle, 1993). Functioning as an inverse proxy for a firm's probability of failure, the Z-score amalgamates profitability, leverage, and return volatility into a unified metric (Lee et al., 2014). Consequently, this index can be construed as a reciprocal gauge of the likelihood of insolvency, wherein a higher Z-score suggests that a bank is exposed to fewer risks and maintains greater stability (Baselga-Pascual et al., 2015; Köhler, 2015; Shabir et al., 2021).

A 1% increase in NPL (Bank non-performing loans to gross loans (%)) will decrease BNIM by 4.3%**.** Building upon the research conducted by Elnahass et al. (2021), Shabir et al. (2021), and Danisman and Demirel (2019), we adopted the non-performing loan ratio (NPL) as a surrogate for bank credit risk. NPL serves as a retrospective measure of credit risk, as its reporting is contingent on occurrences (Abuzayed et al., 2018). A heightened NPL value signifies a diminished capability of banks to effectively manage credit risk (Abuzayed et al., 2018; Beck et al., 2013). However, it's important to note, as highlighted by Abedifar et al. (2013) and Beck et al. (2013), that these credit risk indicators offer only a partial reflection of loan portfolio quality. Differences across banks may arise from distinct internal policies concerning problem loan categorization, reserve requisites, and write-off policies.

A 1% increase in CAR (Bank capital to total assets (%)) will increase BNIM by 9.7%**.** This indicates that capital is viewed as a potent safeguard against unexpected losses, a connection closely tied to lower bank risk. These results are consistent with earlier research demonstrating that capital buffers have a risk-reducing effect on banks (Baele et al., 2007, Laeven et al., 2016). Numerous studies have emphasized that higher capital levels before a crisis enhance the likelihood of survival and improve a bank's performance during the crisis (Berger and Bouwman, 2013, Vazquez and Federico, 2015).

5. Conclusion

To summarize, this study established an empirical foundation for examining the impact of bank-specific, industry-specific, and macroeconomic variables on bank profitability. COVID-19 is more than just an international health emergency and pandemic. Economists generally agree that this has had disastrous effects on the financial markets and the world economy in several ways. The COVID-19 pandemic has resulted in significant economic damage, primarily from decreased income and productivity, elevated unemployment, interrupted trade, and the collapse of the tourism sector. This study looks at how the COVID-19 pandemic impacts the stability and performance of the global banking industry in various geographical areas and bank types. We utilize multiple alternative metrics for bank performance and stability in order to provide a thorough and reliable analysis. The results demonstrate that bank performance and stability have been severely impacted by the COVID-19 outbreak. The findings indicate that capital is crucial to a bank's profitability and that taking on more credit risk can result in losses. Furthermore, the macroeconomic variables' influence on the bank's performance also showed a significant sign, suggesting that in the event of rising inflation, banks typically modify interest rates to boost revenue.

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