BANK FAILURE DURING THE COVID-19 PANDEMIC: DO CAMEL RATING MATTER?

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ABSTRACT

This paper examines the risk of bank bankruptcy during the Covid-19 pandemic using logistic methods and logistic panels using data from Asia. After data cleaning, the total sample that meets the requirements consists of 1064 banks. Of the total sample, 19% were in the bankruptcy category. The results indicate that the eta capital ratio and the net interest income variable had a negative and significant effect. The credit risk variable, measured by NPL and non-operating cost variables, have a positive and significant effect. The positive coefficient results increase the risk of bankruptcy and vice versa. The liquidity and dependence on money market variables only affect the logistic model. For the dummy variable (D2020), the results are positive and significant, indicating that the impact of COVID-19 had significantly increased the risk of bankruptcy. This finding is robust even though it only includes company-level characteristic variables.

Keywords: Failure, COVID-19, CAMEL-rating, Logistic, Panel

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1. INTRODUCTION

The outbreak in Wuhan City, China, in 2019 created an extraordinary economic and humanitarian disaster and brought uncertainty to the sustainability of humanity in general and the economy in particular. The impact of the COVID-19 pandemic has been colossal. As of August 2023, the WHO has recorded 770,085,713 people infected with the COVID-19 virus. What is truly depressing is that the rate of mortality reached 6,956,173 deaths. Data on the actual number of infections and deaths is confirmed to be more than reported. In developing countries, statistical accuracy is rather poor. Actual number of cases and deaths may be 15% higher than reported. Many in-depth studies on the economic impact of this pandemic are comprehensive, such as those conducted by Barua (2020), Beck and Keil (2022). Its effects on the economy are decidedly adverse. Unlike these aforementioned studies, this paper examines the effect of the pandemic on the risk of bank bankruptcies. Economists believe every crisis, whether caused by health or economic mismanagement, always impacts the resilience of the banking system. This paper endeavours to examine the impact of the COVID-19 pandemic on bankruptcy risk in systematically important banking institution (SIBI) categories, namely banks with huge assets.

The global banking system was robust when facing the COVID-19 pandemic. This can be observed by the absence of failures of internationally active banks during the 2019-2021 pandemic. The resilience of the global banking system results from the Basel Committee, which always emphasizes large capital and good governance with sound risk management. Banking system resilience is also due to the government and central bank supporting the economy through various stimuli that indirectly support banks in their respective countries. The advantage is that the banking system continued providing essential financial services

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to the economy during this pandemic. Surprisingly, when the pandemic ended, Silicon Valley Bank, Signature Bank, and Credit Suisse went bankrupt (Reuter, 2023).

Banks as intermediary institutions, namely depository institutions and borrowers, are the first parties to directly feel the pandemic's impact. The business sector, which was the bank's primary debtor and the largest absorber of credit when the pandemic occurred, faced tremendous difficulties due to policies carried out by the government in the form of lockdowns or social restrictions. As a result, the COVID pandemic caused bank to experience difficulties. It has been realized that bank bankruptcies are considered a source of economic destabilization because of their role in the economy. Related to this risk, it is natural to conduct a study to elucidate the impact of COVID-19 on the economy and especially banking as a way to draw lessons in creating a robust banking system in the future. As is known, a pandemic like COVID-19 will be one of the sources of economic destabilization, and the impact of the 2019 COVID pandemic will not be the last.

An empirical study by Susanti et al. (2023) in Indonesia indicates a decline in performance in terms of ROA and ROE during the pandemic. This thus suggests a significant difference between the situation before and after the pandemic, except for the NPL. The NPL did not change because there was an obligation to restructure problem credits during the COVID-19 pandemic, and banks had to treat them as performing loans. During the pandemic, Hu and Zhang (2021) noticed that the decline in bank performance resulted in a decrease in bank output but this was not accompanied by a reduction in input and as a consequence, efficiency fell. Banks were unable to make cost-saving efficiency adjustments due to the pandemic. The deteriorating banking performance also occurred in corporations. In contrast, Boubaker, Le and Ngo (2023) found Islamic banks efficiency improved.

Using the financial performance of corporate companies worldwide, Hu and Zhang (2021) concluded that the impact of COVID-19 on company performance was excessive due to social restrictions and mobility. However, company performance was less significantly affected in countries with better healthcare systems, financial systems, and institutions. Regarding bank failures during the 2007-2009 global financial crisis (GFC), Cole and White (2012) confirm that bank failures during the GFC are no different from failures in the 1990s. They also concluded that the CAMELS variable is still relevant, especially regarding capital adequacy, asset quality, and liquidity as strong predictors of bank failure. This view is supported by Calice (2014), who states that the early warning system of bank failures using CAMEL-based data is still very accurate.
Cleary and Hebb (2016) used discriminant analysis to examine the sources of failure of 132 US banks from 2002–2009 found that CAMEL Types data can distinguish banks that failed from banks that did not with 92% accuracy. They found capital variables, loan quality and bank profitability as determinants of bankruptcy. Discriminant model with the three variables capital, asset quality and profitability produced prediction accuracy in the range of 90–95%. This model can help supervisory authorities distinguish healthy banks from banks having trouble.

This paper aims to enrich our understanding of how the pandemic impacts the resilience of a bank, through its effects on prudential variables such as capital, credit risk and liquidity. It is known that banks that have strong capital with a very low credit risk position and with adequate liquidity ownership, are always able to endure a crisis, as proven in some earlier studies. Accordingly, we also examined the impact of the 2020 pandemic on banks' risk of failure.

2. LITERATURE REVIEW

2.1 CAMELS RATING

Browning (2019) said that the prudential aspect is essential when developing early warning systems in small banks in Europe, meaning that capital, credit risk, and liquidity are buffers for the survival of a bank. Referring to Nguyen, et al. (2020), CAMELS rating system is still Superior as an indicator of banking resilience. Le and Viviani (2018) conducted a comparative analysis of the precision of two conventional statistical methodologies and machine learning techniques in predicting bank failures. Using a sample of 3,000 U.S. banks, they identified credit quality, capital quality, operational efficiency, profitability, and liquidity as determinants of bank failure. They also found that better prediction results are produced by modern estimation techniques that use artificial neural network methods and k-nearest neighbors techniques.

Beutel, et al (2019) compared out-of-sample predictive performance from various early warning models for banking systemic crises using a sample of developed countries that included data from the past 45 years. They compared the benchmark logit approach with several machine-learning approaches recently proposed in the literature. Although machine learning methods often achieve very high sample fit, they perform better than logit approaches in recursive out-of-sample evaluation. Conventional logit models use available information quite efficiently and, for example, could predict the 2007/2008 financial crisis outside of samples applied in many countries. Logit models identify credit expansion, asset price spikes, and external imbalances as critical predictors of systemic banking crises in line with economic intuition.

Based on various studies that have been conducted, studies on bank bankruptcy can generally be grouped into two parts. The first part describes how bankruptcy hits a single system, namely banking as a whole that occur throughout the country. These studies generally concern financial failure that focus on the macroeconomic aspect of a country. Among these were studies by

Levy-Yeyati and Panizza, (2011), Frankel and Saravelos, (2012), Rose and Spiegel (2011), Dabrowski, Beyers and de Villiers (2016), Drehmann, and Juselius (2014) and Tamadonejad, *et al*. (2016)

Bank bankruptcies from the micro side use bank data only, and some include macroeconomic variables in modelling. It is interesting that this study group generally uses CAMELS variables. The studies include Martin (1977), Cole and Gunther (1995), Coles and Gunther (1998), Beck, Jonghe and Schepens (2013), Cole and White (2012), Calice (2014), Anggraeni et al (2020) and Cleary and Hebb (2016). In Indonesia, Mongid (2002) and Montgomery, Santoso and Besar (2005) are also in the same category.

It is common to use CAMELS information-based variables from bank financial statements to predict bank failures that occur in various countries. Jin and Kanagaretnam (2011) expand on data from CAMELS by including auditor quality and governance. They use auditor type, loan growth, Tier 1 capital ratio, proportion of securitized loans, and loan mix as predictors for bank failures with better predictive accuracy results. Currently, many banks carry out non-traditional activities to increase revenue. De Young and Torna (2013), who studied bank failures in the U.S., examined the impact of these non-traditional activities. They concluded that non-traditional banking activities contributed to the rise in failures of hundreds of U.S. commercial banks during the 2007-2009 financial crisis. Income from investment banking, insurance underwriting, and venture capital increases the likelihood of bank failure.

2.2 Capital

Zheng and Cronje (2019) examined the role of bank capital in moderating the relationship between bank liquidity creation and default risk in U.S. banks before, during and after the global financial crisis from 2003-2014. Given the important role of capital in the survival of banks, especially when asset values plummet and in reducing excessive risk-taking incentives, it turns out that liquidity creation is negatively related to bank failure risk moderated positively (i.e. strengthened) by (changes in) bank capital. In times of high liquidity risk, banks will accumulate more capital buffers as collateral against liquidity risk arising from liquidity creation. The higher the capital, the lower the probability of bank failure, increasing the bank's ability to create liquidity. The negative and significant relationship between the creation of bank liquidity and the risk of bank failure is especially true of small banks. The impact of changes in bank capital on the relationship between liquidity creation and the risk of bank failure is more pronounced during periods of financial crisis than in normal times. Cole and White (2012) concluded that capital adequacy is still strong predictors of bank failure during the 2007–2009 GFC. Downs, et al (2022) found that bank bankruptcies in America will decrease when capital ratio at higher and the effect would turn negative.

Cole and White (2012) support the CAMELS approach to assessing the safety and soundness of commercial banks. Iwanicz-Drozdowska, and Ptak-Chmielewska (2019) studied problem banks in Europe using 163 failed banks and 3566 healthy banks during 1990–2015, using factor analysis and cluster analysis, logistic regression. They concluded it was difficult to predict bank failure events using a set of CAMELS-like variables because the results were inaccurate. However, equity to total assets ratio (leverage) and loans to funding (liquidity) are the best variables for bankruptcy. Cleary and Hebb's (2016) study in applying data from CAMELS, succeeded in distinguishing between failed banks and surviving banks with bank capital (C). Browning (2019) and Le and Viviani (2018) support these findings. Browning (2019) said that the prudential aspect is essential when developing early warning systems in small banks in Europe, meaning that capital, credit risk, and liquidity are buffers for the survival of a bank.

2.3 Asset Quality

Cheong and Ramasamy (2019) stated that asset quality is significant as a differentiator between non-performing and sound banks, whereas credit risk reserves (LLRGL) in non-performing banks are relatively higher and significant. Efficiency is measured by showing a significant difference where the bank fails to have a lower ROA. For liquidity measured by ownership of liquid tools (LATA), it turns out that it is only significantly different one year before the onset of a crisis and after a crisis or when banks are in trouble. Banks tend to have the same liquidity as a result of management policies that maximize ownership of liquid tools. The logistic regression results found that capital had a negative and significant effect.

Meanwhile, asset quality has a positive and significant effect. For credit reserve indicators, the effect is not significant. ROA has a significant negative effect, and the efficiency measured from NIM has similarly a negative and significant effect. In contrast to other views, Wagner (2007) and Browning (2019) found that banks with large liquid assets are at high risk of failure. Cleary and Hebb's (2016) found that asset quality (A) as the most important determining factors. using various ratios. Cipollini and Fiordelisi (2012) demonstrate that credit risk, measured by the ratio of allowance for loan losses to total loans is good indicators of bank bankruptcy. Le and Viviani (2018) and Anggraeni et al. (2020) concluded that credit quality positive and significant.

Are there differences in the determinants of bank bankruptcy during normal times and crises? Cole and White (2012) concluded that bank failures during the 2007-2009 GFC were no different from failures in the 1990s when the economy was normal. The validity of CAMELS-based information for assessing bank bankruptcy risk is still valid, especially the aspects of asset quality, as predictor of bank failure during the 2007–2009 GFC. In contrast, Seelye and Ziegler (2020) stated that during the pandemic, credit risk did not show a significant increase so the risk of bank failure was not higher in banks representing 80% of total United States banking assets.

2.4 Earning

Cheong and Ramasamy (2019) concluded that variable earnings or income, both ROA and NIM, banks fail much lower and significantly. Cole and White (2012) concluded that bank failures during the 2007-2009 GFC were no different from failures in the 1990s when the economy was normal. Income or earning is strong predictors of bank failure during the 2007–2009 GFC. Downs, et al (2022) examined the determinants of bankruptcy of banks in America during the global financial crisis in 2007-2009 and they found that earning from real estate is positive and significant. Browning (2019) found that earning or profitability reduce the risk of bankruptcy. Le and Viviani (2018) and Anggraeni et al. (2020) added that operational efficiency and Profitability are significant variables for bankruptcy prediction.

2.5 Liquidity

The sustainability of the bank's business is highly dependent on its liquidity conditions. Liquidity here means the ownership of high-quality liquid equipment to fulfil deposit withdrawals by customers. In this context, liquidity needs are short-term because the structure of bank assets is generally long-term ownership of productive assets. On the other hand, the source of bank funds is generally short-term deposits that depositors can withdraw at any time. Therefore, banks must maintain sufficient liquidity at all times to anticipate the withdrawal of customer funds. According to Cheong and Ramasamy (2019), banks are theoretically very prone to liquidity risk because bank assets and liabilities always do not match, aka mismatch. Cooke, Koch, and Murphy (2015) include excessive mismatch risk as a problem. Alessi, and Detken (2011) support the role of liquidity on the failure.

A bank with long-maturing assets financed mostly with short-term liabilities is vulnerable to withdrawals and liquidity risks that can lead to bankruptcy. This result is supported by Le, and Viviani (2018) that liquidity ownership reduces bankruptcy. Liquidity risk is one of the most difficult risks to manage and can instantly lead to bank bankruptcy. Many measures are used to measure bank liquidity, including the ratio of liquid assets to total deposits and total liquid assets to assets. Fungacova, Turk and Weill (2021) mentioned that banks that create excessive liquidity will be at risk of failure. Cipollini and Fiordelisi (2012) demonstrate that liquidity risk, measured by the ratio of liquid assets to total assets, is significant to bank failure. Browning (2019), and Cole and White (2012) concluded that the liquidity variable is a strong predictor of bank failure during the Global Financial Crisis (GFC) in 2007–2009. In contrast, Downs, et al (2022) found that Liquidity does not have a significant effect on bankruptcy.

3. METHODOLOGY

We apply the logit and the logit panel methodologies to examine the effect of the CAMEL variable on the probability of bank failure. The definition of bankruptcy or bank failure in this research does not follow a single criterion but rather multiple criteria. The dependent variable is a dummy variable that has a value of 1 if the bank fails and 0 if otherwise. We define a failed bank if ROA<0.0025, CAR<0.08, NPL>5%, or if the bank is taken over by another party and closed by the authorities. This definition aligns with previous research on the determinants of bank failure during the global financial crisis (GFC) (Anggraeni et al. (2020).

3.1 The Sample and Variable Selection

Table 1: Samples Bank Failure

Year	Sample	Failure	Failure Ratio
2017	173	28	0,16
2018	179	27	0,15
2019	179	33	0,18
2020	179	57	0,32
2021	178	34	0,19
2022	176	28	0,16
Total	1064	207	0,19

Sources: Author's Calculation

The banks in this research sample belong to the Systematically Important Banking Institutions (SIBI) category that operate globally. The sample comprises only banks in the commercial and retail categories. The basis for selecting the sample is the largest assets as of 2022. There are 250 selected banks, and if the data are unavailable, the bank will then be excluded from the analysis for a particular year, thus resulting in an unbalanced panel. Of the 30 countries whose banks are included in the largest bank category in this study, the banks come from Europe; the Euro area being the largest, with 212 observations, followed by America with 144 observations and China, with 101 observations. Russia, with five banks, has the fewest bank observations. In total, there are 1064 bank observations.

Table 2: Samples Distribution by Country / Region

Number	Country	Banks	Failed	Rate	Number	Country	Banks	Failed	Rate
1	Arab Emirate	18	0	0%	16	Kuwait	6	0	0%
2	Australia	12	0	0%	17	Malaysia	24	2	8%
3	Brazil	22	0	0%	18	Norway	6	0	0%
4	Canada	18	1	6%	19	New Zealand	6	0	0%
5	Swiss	24	0	1%	20	Poland	6	1	17%
6	China	102	0	0%	21	Qatar	6	0	0%
7	Denmark	23	0	1%	22	Russia	5	0	0%
8	Euro	212	0	0%	23	Saudi Arabia	12	0	0%
9	UK	35	17	49%	24	Sweden	30	0	0%
10	Hong Kong	24	2	8%	25	Singapore	6	0	0%
11	Indonesia	12	0	0%	26	Thailand	24	0	0%
12	Israel	24	0	0%	27	Turkey	6	0	0%
13	India	48	26	54%	28	Taiwan	77	7	9%
14	Japan	84	56	67%	29	USA	144	8	6%
15	Korea	24	1	4%	30	South Africa	24	1	4%
Total							1064	207	19%

This research covers the observation period from 2017 to 2022 to provide a comprehensive picture of bank conditions before, during, and after the COVID-19 crisis. The variables used in this study represent the CAMEL Rating, specifically for capital (C) using the variables CAR and ETA, and for management using variables related to the funding strategy, namely Wholesale funds/total funds (WSFTF). The variables net interest income (NIIAA) and non-operating profit ratio (NNOEA) are used for earnings. We apply NPL and loan loss reserves (LLRGL) to assess asset quality while liquidity is measured by Liquid assets/total assets. Definitions and measurements follow the following definitions:

Table 3: Variables, Definition and Expected Results

No	Variable		Definition of the Variable	Expectation to Failure
1.	FAILURE	F2	Dummy for failed =1 , 0= Survived	
2.	CAR	X_1	Capital/Risk Weighted assets (C)	Negative
3.	ETA	X_2	Equity to Total Deposit Ratio (C)	Negative
4.	NPL	X_3	Problem loan/total loan (A)	Positive
5.	LLRGL	X_4	Loan Loss Reserve / total loan (C)	Negative/Negative
6.	NNOEA	X_5	Operating profit- total profit/total asset (E)	Negative/positive
7.	NIIA	X_6	Net Interest Income/Total asset (E)	Negative
8.	WSFTF	X_7	Wholesale funds/total fund (L)	Negative/positive
9.	LATA	X_8	Liquid asset / total asset (L)	Positive / Negative

3.2 The Empirical Model

The model for bank failure is derived from the corporate bankruptcy literature. Early warning of failure can be modelled as follows:

$$F2 = Pi = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + e$$

Because the dependent variable is dichotomous, (1 represents a failed bank and 0 represents a surviving bank), the appropriate estimation model for this study is the Logit model. The Logit model estimates the probability of failure ranging from 0 to 1. Using a Logit model enables the assessment of results using standard regression procedures to determine the significance level and gauge the probability of bank failure. Estimation is conducted using Stata with limited dependent variables applied through logistic regression.

4. RESULT AND DISCUSSION

A general description of the variables used in this study is summarized in Table xxx. From the total eligible sample of 1064, the average bankruptcy rate was 19.5%. This indicates that almost 20% of banks in the sample are categorized as banks experiencing problems related to capital, profit, and credit risk. The average value of the capital variable, measured through the ratio of equity to total assets (ETA), is 7.7%. This suggests that, on average, banks in the SIFI category have only 7.7% capital with the remaining 92% financed through debt. Interestingly, while some banks have capital levels up to 18% of their assets, others have as little as 2%.

Table 4: Variable description

Variable	Obs	Mean	Std. Dev.	Min	Max
F2	1064	.1945489	.3960392	0	1
ETA	1064	7.697727	2.809337	2.08	18.32
CAR	1064	18.01697	11.84677	8.87	136.2
NPL	1064	2.698778	3.248457	.01	39.97
LLRGL	1064	2.354135	2.310892	0	27.38
WSFTF	1064	13.71438	14.88441	.01	94.18
NNOEA	1064	.1920197	.2812182	-1.98	2.8
NIIAA	1064	2.180368	1.623788	-.1	15.78
LATA	1064	16.95445	10.34944	.28	70.7

Table 4 shows 19% of samples are in the failed category. The capital adequacy ratio according to regulations, ranged from a minimum of 8.87% to a maximum of 136%, with an average of 18%. Banks generally operated above the regulatory 8.8%. However, considering the evolution of capital requirements under Basel III, capital levels below 10% is included in the minimum category. In terms of credit risk measured by NPL, the average was 2.7%. In comparison, the average credit risk allowance (LLRGL) is 2.35% which is smaller than the NPL value. This also suggests an overall inadequacy in allowance provision relative to the NPL as experienced. For variable liquidity, as measured by liquid assets to total assets (LATA), the average is 16.96% with significantly varied distribution, with the highest reaching 71% while the lowest at below 1%. In general, banks in the SIFI category exhibit relatively high ownership of liquid assets.

Table 5: Pearson Correlation

Variable	F2	CAR	ETA	NPL	LLRGL	NNOEA	NIIAA	WSFTF	LATA
F2	1.0000								
CAR	-0.0350	1.0000							
ETA	-0.3182***	-0.0498	1.0000						
NPL	0.2037***	-0.0918***	0.1174***	1.0000					
LLRGL	0.0327	-0.1028***	0.3005***	0.7929***	1.0000				
NNOEA	-0.1720***	-0.0448	0.3153***	-0.2514***	-0.0156	1.0000			
NIIAA	-0.2577***	-0.1123***	0.5763***	0.1882***	0.4893***	0.5027***	1.0000		
WSFTF	0.0355	0.1092***	-0.1625***	-0.0215	-0.1550***	-0.0002	-0.0916***	1.0000	
LATA	0.2245***	0.0525*	-0.2468***	-0.0284	-0.0728**	-0.1283***	-0.2712***	0.1826***	1.0000

Notes: *** p<.01, ** p<.05, * p<.1.

We also conducted a correlation analysis among the variables used in this study. Generally, the relationship between variables in this study is consistent with theoretical expectations. The relationship between bankruptcy and capital, whether measured by ETA or CAR, shows consistently negative correlations. ETA specifically shows a negative correlation of -0.34, while CAR similarly exhibits a negative but weaker correlation of -0.04. This indicates that higher capital adequacy ratios correspond to lower probabilities of bankruptcy. Interestingly, ETA demonstrates a stronger negative correlation with bankruptcy risk compared to the regulatory capital adequacy ratio (CAR). This suggests that ETA serves more effectively as buffer against bank risk.

Both NPL and Loan Loss Reserve Gross Loan (LLRGL) show contrasting results for credit risk. An increase in NPL correlates positively with an escalation in bankruptcy risk, thus indicating that NPLs exhibit stronger predictive power for such risk relative to the allowance ratio. This is natural since NPL is a regulatory metric while allowances are subjected to management decision. However, an increase in credit risk invariably increases the probability of failure. Conversely, the liquidity ratio shows a positive correlation of 0.24, which suggests that any increase in liquidity ownership will lead to an increase in bankruptcy risk. This indicates that banks heavily reliant on liquid assets may face lowered profitability, where such assets become a burden for banks.

Non-operating profit or loss (NNOEA) has a negative correlation of -0.187, which means that the higher the NNOEA, the lower the risk of bankruptcy. However, if the bank experiences losses in very large non-operational costs, the risk of bankruptcy will increase. Meanwhile, net interest income (NIIA) has a negative correlation of -0.273, which suggests that every increase in interest income will reduce the risk of bankruptcy. Conversely, dependence on wholesale or non-retail funds will increase the risk of bankruptcy due to the high-interest rate volatility and high liquidity risk.

In this study, we modelled the influence of internal bank variables on bankruptcy risk during the COVID-19 pandemic with the use of four models: OLS-based Logistic Model and the Data Panel-based Logistic Model, each with or without year dummies. The findings consistently highlight the effect of capital ratios, credit risk ratios and liquidity on the likelihood of bank bankruptcies. The model is detailed in Table 6.

Table 6: Regression Result

Variable	Logistic (OLS)		Panel Logistic	
	LOGIT1	LOGIT2	PANEL1	PANEL2
ETA	-.322***	-.339***	-.512***	-.443***
CAR	-.0178	-.0213	-.0294	-.0194
NPL	.526***	.591***	.691***	.521***
LLRGL	-.254*	-.331**	-.156	-.00121
NNOEA	1.97***	2.34***	3.29***	2.38***
NIIAA	-1.66***	-1.7***	-2.37***	-2.24***
WSFTF	-.0224**	-.0241***	-.00802	-.0103
LATA	.0266**	.0287**	.02	.0192
y18	-.206		-.405	
y19	.477		.604	
y20	1.42***		2.24***	
y21	.413		.583	
y22	.131		.117	
_cons	2.31***	2***	2.49*	2.82**
lnsig2u				
_cons			1.73***	1.42***
Pseudo R-Squared	0.379	0.351	0.425	0.415
LR chi2	289.50	263.44	289.50	63.68
Log likelihood	-354.08287	-367.11296	-354.08287	-310.88197
chibar2(01)			127.33	112.46

Legend: * p<.05; ** p<.01; *** p<.001

4.1 Logistic – OLS Result

The LOGIT1 model is a simple logistic regression model used to examine bankruptcy risk. The CAR coefficient for the model is -0.018 which is not significant. The CAR coefficient for LOGIT2 is similarly negative at -0.021 and is also not significant. Conversely, for the ETA variable, both LOGIT1 and LOGIT2 have fairly similar coefficients of -0.322 and -0.339 respectively that are significant at 1% confidence. These results show that ETA has better information content than CAR in predicting bankruptcy risk. They also suggest that ETA shows more robust predictive power for bankruptcy risk compared to CAR. The simplicity in ETA's calculation renders it less susceptible to circumvention risk. In contrast, such risk is inherent in the regulatory-based CAR, which relies on asset risk weights. The findings of this study are consistent with those of Browning (2019), Downs et al. (2022), Le and Viviani (2018), Cole and White (2012), Anggraeni, et al (2020), and Iwanicz-Drozdowska and Ptak-Chmielewska (2019), that established capital as a critical buffer to the survival of banks. Zheng and Cronje (2019) similarly confirmed that capitalization reduces excessive risk-taking.

NPL and loan loss reserve ratio (LLRGL) are used to measure credit risk. In the LOGIT1 model, the NPL coefficient value is 0.526 while in LOGIT2 model it increases to 0.591, both significant at 1%. Conversely, LLRGL in LOGIT1 produces a significant coefficient of -0.254 and in LOGIT2 it increases to -0.33, also significant at 1%. These results indicate that higher NPLs increase the risk of bankruptcy for banks, while credit risk reserves (LLRGL) mitigate bankruptcy risk. These results establish NPL as a robust measure of credit risk that affect bank failure whereas LLRGL indicates prudent practice in credit management. These findings are consistent with Browning (2019), Le and Viviani (2018), Cheong and Ramasamy (2019), Cole and White (2012), and Cipollini and Fiordelisi (2012) which underlines the role of asset quality, especially credit risk, in bank survival.

The variable wholesale funds to total funds (WSFTF), as representative of management strategy, produces negative coefficient values in both LOGIT1 (-0.224) and LOGIT2 (-0.241) models. This is contrary to expectations, especially during crisis, where dependence on non-retail funds typically heightens bankruptcy risk. However, for this study period, stable interbank interest rates reduced the risk of bankruptcy. Recent bank failures experienced by Signature Bank, Silicon Valley Bank (SVB), First Republic Bank, Western Alliance, Credit Suisse and Silvergate Bank in 2023, were mainly due Fed interest rate hikes which underline the importance of limiting risk-taking incentives for bank CEOs (DeYoung, Peng, and Yan, 2013; Boyallian and Ruiz-Verdú, 2018).

The NNOEA variable in the LOGIT1 model produces a coefficient of 1.97, significant at 1%, while LOGIT2 model produces a positive coefficient of 2.34. These results suggest that increase in *non-operating expenses* will elevate the risk of bankruptcy. NNOEA, which represents the difference between operating profit and reported real profit, clearly establishes that increased non-operational costs will elevate bankruptcy risk.

The NIIAA is an earnings indicator that exhibits negative and significant coefficients in all models. This indicates that higher NIIAA will reduce the risk of bankruptcy for banks by boosting their income. These results follow Le and Viviani (2018), Cheong and Ramasamy (2019), Anggraeni et al (2020) and Cole and White (2012), which state that income and profits are a buffer for the survival of a bank. Conversely, De Young and Torna (2013) state that earnings from non-traditional activities increase the risk of bankruptcy.

These results are consistent with Le and Viviani (2018), Cheong and Ramasamy (2019), and Cole and White (2012), who state that income and profits act as a buffer for the survival of a bank. De Young and Torna (2013) maintain that earnings from non-traditional activities increase the risk of bankruptcy. The variable net interest rate (NIIA) results in aligning with the expectations of both LOGIT1 and LOGIT2 models, both of which have negative and significant coefficients. This suggests that with every increase in interest margins, the likelihood of survival for the bank increases.

Liquidity ratios indicate positive and significant coefficient in both models. In LOGIT1, the LATA coefficient in is 0.0266 and significant at 1%. LATA in LOGIT2, has a coefficient of 0.0287, and also significant at 1%. The result suggests that excessive liquidity, despite provision for safety with central bank support, as in the COVID-19 pandemic crisis, will constrain banks' profit through curtailing lending or high-yield investments (Browning, 2019; Le and Viviani, 2018; Cheong and Ramasamy, 2019; Cooke, Koch, and Murphy, 2015; Zheng and Cronje, 2019; Cole and White, 2012; Iwanicz-Drozdowska and Ptak-Chmielewska, 2019; Cipollini and Fiordelisi, 2012). According to Cheong and Ramasamy (2019), liquidity ratios are only effective one year before a bank experiences a crisis. The positive coefficient of LATA supports Wagner (2007), who stated that excessive liquidity increases the risk of bankruptcy.

In the LOGIT1 model with year dummies, the regression results show a negative coefficient in 2018 indicating reduced banking risk as compared to 2017. However, 2019 results show increased bank bankruptcy risk. The constant value experienced the largest increase in 2020, which rose by 1.3 and was significant at 1% indicating elevated bankruptcy risk during the COVID-19 pandemic. The findings are consistent with earlier reports which highlight the adverse economic impact due to the pandemic (Barua, 2020); Beck and Keil, 2022). In 2021, while COVID-19 was still ongoing, there was a decrease in the coefficient compared to 2020, but it still remained positive. In 2022, the decline was quite significant, indicating that banks were starting to succeed in managing risks related to the COVID-19 outbreak, showing signs of recovery.

4.2 Logistic – PANEL Results

This study estimated the bankruptcy model by regression of the panel data. Two models were developed; one that include year dummies (PANEL 1) and one without (PANEL 2). The results for the panel data regression, including year dummy (PANEL1) are as follows: ETA has a negative effect with a coefficient of -0.512 and -0,433, both being significant at 1%. Meanwhile, the CAR variable has a negative coefficient of -0,294 and -0,0194 and both are not significant. The results are consistent with the findings of Browning (2019), Downs et al. (2022), Le and Viviani (2018), Cole and White (2012), Anggraeni et al (2020), and Iwanicz-Drozdowska and Ptak-Chmielewska (2019) that capital serves as a buffer for the survival of a bank. Zheng and Cronje (2019) inferred that capital reduces excessive risk-taking.

The NPL variable's effect is positive at 0.691 and significant at 1%. For the credit loss risk reserve (LLRGL) variable, the coefficients are -0.156 and -0.001, with both being not significant. For liquidity ratio (LATA), the results are positive at 0.2000 and 0.0192 and both are also not significant. The effect of the time variable shows that the dummy value in 2020 is 1.9 and significant at 1%.

In general, the results are consistent with previous estimation methods that used ordinary logistics. The logistic panel model (PANEL2) yielded an ETA variable coefficient of -0.443 and was significant at a 1% confidence level. Result of the CAR variable was negative -0.019 and was not significant. For the NPL, the result was positive 0.691 and significant at 1%. The credit risk reserve variable (LLRGL) obtained a coefficient of -0.001 which was not significant.

From the logistic panel models for the management variable measured by WSFTP, the result is negative and not significant. The findings are consistent with DeYoung, Peng, and Yan (2013) and Boyallian and Ruiz-Verdú (2018) who underline the importance of limiting risk-taking incentives by bank CEOs. For earnings measured with NNOEA, the results are positive and significant. Conversely, the net interest rate (NIIAA) produces negative and significant results.

The results consistently reveal that capital measured by ETA has a negative and significant effect while the CAR ratio has a negative but not significant effect. For credit risk (NPL), all models produce positive and significant results. This indicates that the higher the NPL, the greater the risk of increase in bankruptcy. Conversely, credit risk reserves (LLRGL) produce negative coefficients for all models, although the logistic panel models show non-significant effects.

The NNOEA variable on PANEL1 produces a coefficient of 0.329 and is significant at 1%, while PANEL2 produces a coefficient of 2.380 which is also significant at 1%. These results are consistent with those of previous models. For WSFTF variables, although the results were consistent with the LOGIT model, they were not significant in the panel regression model. Meanwhile, for the net interest income variable (NIIAA), regression results were -2.37 and -2.24 and both were significant at 1%. Both panel regression models yielded similar coefficients, suggesting that the results were generally consistent across all models

Conversely, liquidity variable (LATA) obtained a coefficient figure of 0.042 and was significant at 1%. Consistency also occurs for liquidity ratios where all produce the same conclusions, i.e. positive and significant. Banks that make efforts to reduce liquidity risk by increasing the number of liquid equipment will face the risk of increasing bankruptcy because of the *opportunity costs* incurred, namely the lower ability to provide credit and get higher income. The positive coefficient of LATA supports Wagner (2007), which stated that excessive liquidity increases the risk of bankruptcy.

4.3 Robustness Test

To ensure the consistency of relationship between the independent and dependent variables, we conducted a robustness test by comparing the research results from the models used. Results are generally consistent when using different estimation models, but the conclusions are generally similar. For the ETA variable, the results were negative, significant, and consistent across all models. The CAR variable results were negative and not significantly consistent across all models. The NPL variable results are positive and significant in all models. For credit risk reserve (LLRGL), the result was negative and significant for logit model and negative but not significant for the panel model. The liquidity (LATA) variable results are positive and significant on logit models, but for panel models, the results are positive but not significant. The non-operating income (NNOEA) variable results were positive and significant in all models.

Tabel 7: Robustness Check

Variable	LOGISTIC		PANEL LOGISTIC	
	LOGIT1	LOGIT2	PANEL1	PANEL2
ETA	Negative /Significant	Negative /Significant	Negative /Significant	Negative /Significant
CAR	Negative /Not Significant	Negative /Not Significant	Negative /Not Significant	Negative /Not Significant
NPL	Positive/Significant	Positive/Significant	Positive/Significant	Positive/Significant
LLRGL	Negative /Significant	Negative /Significant	Negative /Not Significant	Negative /Not Significant
YEARS	Positive/Significant	Positive/Significant	Positive/ Not Significant	Positive/ Not Significant
NNOEA	Positive/Significant	Positive/Significant	Positive/Significant	Positive/Significant
WSFTF	Negative /Significant	Negative /Significant	Negative /Not Significant	Negative /Not Significant
NIIAA	Negative /Significant	Negative /Significant	Negative /Significant	Negative /Significant
y18	Negative /Not Significant		Negative /Not Significant	
y19	Positive/ Not Significant		Positive/ Not Significant	
y20	Positive/Significant		Positive/Significant	
y21	Positive/ Not Significant		Positive/ Not Significant	
y22	Positive/ Not Significant		Positive/ Not Significant	

Meanwhile, for dependence on wholesale or interbank funds (WSFTF), the results were negative and significant for the logit model. However, the logit panel model's results were negative and insignificant. For net interest income (NIIAA), the result was negative and significant. An interesting result found in all models, is that the dummy variable of 2020 produced positive and significant results. Since the year was during the COVID-19 pandemic the study established that 2020 was a difficult period for banks that has resulted in increasing the risk of bankruptcy. This result supports Barua (2020), Beck and Keil (2022) regarding the negative impact of the pandemic. An empirical study by Susanti, et al (2023) in Indonesia further maintained a declining trend in bank performance in terms of ROA and ROE during the pandemic. This suggests a significant difference in bank performance before and after the pandemic, except for the NPL. The NPL remained unchanged since there was an obligation to restructure credit during the COVID-19 pandemic.

5. CONCLUSION

The COVID-19 pandemic has triggered a global crises to human welfare and has become the source of unparalleled human suffering. The global economies in general, have experienced negative growth. All efforts have focused on preventing disease transmission at any cost. The impact of the pandemic on banking has been intense: profits have decreased drastically, credit growth has been negative, credit risk has increased, and several banks have experienced diminished capital due to losses resulting from the COVID-19 pandemic.

This paper empirically examines the impact of COVID-19 on bank bankruptcy with a sample of banks, comprising 200 of the largest in the world, known as Systematically Important Banking Institutions (SIBI), with focus on the retail and commercial categories. A logistic model is adopted to predict bank failure using financial ratios reflecting the CAMEL rating.

We obtained interesting results from the study, namely that the CAMEL-rating aspect is generally still quite powerful in identifying bankruptcies experienced by banks. The capital variable (C), as measured by ETA, produces a negative and significant coefficient. This thus suggests that the higher the ETA ratio, the lower the risk of bankruptcy facing the bank. Meanwhile, the asset quality (A) credit risk has a positive and significant coefficient. This means that the higher the NPL, the higher will be the risk of bankruptcy.

With the management strategy aspect (M), the study discovered that the reliance on short-term funds from non-deposit sources reduced the risk of bankruptcy. This is attributed to the drastic increase of global liquidity which consequently became cheap following the Global Financial Crisis. For the earnings variable (E), the greater the non-operating profit (NNOEAA), the higher the risk of bankruptcy. This suggests that banks whose non-operating costs are high and are not accompanied by high non-operating income will more likely end in bankruptcy. Meanwhile, the interest margin has a negative and significant effect, which suggests that the ability to obtain a net interest margin reduces the risk of bankruptcy.

For liquidity (L), holding too many liquid assets increases the risk of bankruptcy. The year dummy was positive and significant in 2020, indicating an increase in the risk of bankruptcy during the pandemic. The results of this study confirm the relevance of CAMEL rating t for bank bankruptcy analysis. It means financial data is still relevant as Beaver et al (2005).
A weakness of this research is the need for the inclusion of economic variables and the full impact of the pandemic. For further research this aspect needs to be addressed in order to ascertain the impact of COVID-19 and draw lessons as preparation in facing similar risks in the future.

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