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MACRO-FINANCIAL DETERMINANTS OF DEFAULT PROBABILITY USING COPULA: A CASE STUDY OF INDONESIAN BANKS

Maulana Harris Muhajir*, Pierre SIX**, and Jung-Hyun Ahn***

*Corresponding Author, Department of Finance, NEOMA Business School, France.
Email: maulana-harris.muhajir.20@neoma-bs.com
**Department of Finance, NEOMA Business School, France. Email: Pierre.SIX@neoma-bs.fr
***Department of Finance, NEOMA Business School, France. Email: Jung-Hyun.AHN@neoma-bs.fr

ABSTRACT

We investigate the default probability of Indonesian banks using the copula approach and analyze the macro-financial factors that drive them. We use quarterly data comprised of 80 banks from 2005 to 2019. We find empirical evidence that Common Equity Tier 1 (CET 1) ratio, inefficiency ratio, and deposit ratio have negatively impacted the bank's default probability. We also find that macroeconomic variables such as policy rate, real exchange, economic growth, and unemployment reduce the default probability. Our study suggests that regulators should focus on capital and deposit management policies to reduce bank risk-taking behaviour. Additionally, the policy rate effectively anticipated the banks' default risk.

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I. INTRODUCTION

In the aftermath of the global financial crisis of 2008, macro-financial linkages gained attention from regulators and policymakers as one of the main issues of financial system stability. A review of the vast literature on the bank's default probability shows that financial system shock is an endogenous risk (e.g., Brunnermeier and Sannikov, 2014; Claessens amd Kose, 2018); however, there is less consensus regarding the sources of shocks and vulnerabilities within its interaction with the macroeconomic environment. Against this background, it is vital to empirically examine and get a clearer understanding of the default probability that may help the regulators to promote financial stability soundness.

In this paper, we follow Valle *et al*., 2016 and Husodo *et al*. (2020) to investigate the macro-financial factor that drives the default probability in Indonesian banks using the copula approach. Our main idea is that default probability could possibly interact with the business cycle when banks engage in excessive risk-taking behaviour during the upturn phase (Anginer *et al*., 2014), and resulting in upward risk during the downturn phase that links to their bank-specific factor and macroeconomic situation (Fiordelisi and Mare, 2013; and Parrado-Martínez *et al*., 2019).

Our paper contributes to the literature on default probability in four ways. First, we develop a method to assess a bank's default probability based on a multivariate distribution following the methodology introduced by Husodo *et al*. (2020) and Valle *et al*. (2016). The copula approach has the advantage of capturing non-linear relationships between variables with complex data structures, where the dependency structure of two random variables is asymmetrical (upper negative or upper positive) (see Brechmann *et al*., 2013; Pourkhanali *et al*., 2016; and Zhang, 2014). From this perspective, bank default probability reflects the likelihood that losses come from the marginal distribution (tail risk). This risk occurs with low likelihood, but it is a latent factor that can potentially cause and amplify shock for the whole banking system and endanger financial system stability.

Second, we examine the bank's default probability determinants using bank-specific and macroeconomic variables. Previous studies have focused on only a firm's intrinsic value or bank balance sheet and less perspective on default correlation on the complex structure provided by copula and its interlinkage with the macroeconomic situation (see Section II). To tackle this issue, we take this paper further by using the copula default probability and then observing its bank-specific and macroeconomic drivers using the Generalized Method of Moments (GMM). The GMM procedure for the dynamic panel model allows us to identify information about the risk sources and vulnerabilities and what drives them.

Third, the paper focuses on the Indonesian banking system, which may serve as a benchmark for studying the financial crisis due to the recent economic developments in emerging Asian countries, such as the global financial crisis of 2008 and Asia's economic slowdown in 2015. Indonesia's financial system is one of the large emerging economies in Asia, but it is also vulnerable to financial shocks. Allen and Gale (2000) found that Indonesia suffered the most from financial crises compared to its peer countries in Asia's financial crisis in 1998. Our study stretches from 2005 to 2019 and coincides with some structural changes, such as the global financial crisis of 2008 and quantitative easing in 2013. These events caused Indonesia to face a procyclical financial shock and a prolonged financial boost, resulting in capital outflow during these periods (Prabheesh *et al*., 2021). As a result, our study includes the effect of the pre-crisis, crisis, and recovery periods during the sample data.

Finally, this study considers bank ownership and regional activity by development banks owned by the municipal government. The separation of bank by ownership and regional activities enables us to isolate bank-specific features, which impact the default probability for different types of banks.

Our main findings illustrate some critical links between the default probability and macroeconomic environments. We find empirical evidence that bank-specific indicators such as Common Equity Tier 1 (*CET 1)* ratio measured as the ratio of a bank's core equity capital to its total Risk-Weighted Assets (RWA), inefficiency ratio, and deposit ratio negatively impact the bank's default probability. Meanwhile, the deposit ratio positively influences default probability, warning banks with a significantly increased deposit ratio. Additionally, when we examined the structural and macroeconomic variables, we find that the policy rate, real exchange rate, economic growth, and unemployment rate reduce the default probability. Furthermore, we also find that central state-owned banks tend to have a higher risk than other bank groups, and regional state-owned banks in the central region have the highest likelihood of default.

The remainder of the paper proceeds as follows. Section II presents a brief literature review underlying the empirical work. We provide the relevant data and methodology in section III and present the results in section IV. Section V presents some concluding remarks.

II. LITERATURE REVIEW

There is extensive literature on the determinants of bank default probability (for a detailed review, see Kleinow and Moreira,2016; Parrado-Martínez *et al*., 2019; and Weiß *et al*., 2014). Our study contributes to the literature by estimating bank default probability based on the copula approach and investigating the drivers of default probability from macroeconomic and bank-specific factors in Indonesian banking. The following literature review confirms that using copula to estimate the default probability is beneficial for assessing tail risk in risk management and anticipating systemic risk.

The default probability has long been recognized as a potential extreme event for financial assets. This event is usually associated with a tail risk and could be devastating during a financial crisis. Li (2000) explained that the copula approach allows us to decompose the marginal distribution (associated with tail risk) from the dependence structure (associated with systemic risk) with a higher degree of precision. Kole *et al*. (2007) stated that copulas are a powerful tool for examining dependencies on different portfolio elements and are preferable to the traditional correlation-based approach. Nikoloulopoulos *et al*. (2012) proved that a graphical tool for labelling constraints in high-dimensional probability distributions called vine copula can help assess tail asymmetries in credit risk distribution. Their findings were replicated by Aas (2016), who studied the use of Pair Copula Constructions (PCCs) in financial applications. The author found that multivariate data that exhibit complex patterns of dependence can be modelled using bivariate copulas as simple building blocks. Hence, this model represents a flexible way of constructing higher-dimensional copulas. His study emphasized that returns in financial markets do not follow a normal distribution. Empirically, real-world data show that such flexible explicit dependence modelling might significantly impact the risk capital, leading to a clear diversification benefit over the standard Basel comonotonicity assumption. [1]

Moreover, several studies on copulas explain how the default risk of one firm or financial institution could cause systemic risk in a financial system. Jin and Nadal De Simone (2014) introduced a framework that explicitly models banks' default dependence and captured non-linearities and typical feedback effects as time-varying variables in financial markets. The authors measure three banking systemic credit risk forms: common, idiosyncratic, and banking system vulnerabilities that accumulate over time. Their findings are beneficial for the macroprudential policy framework. Pourkhanali *et al*. (2016) introduced a systemic risk model to analyse the complex interdependencies between borrowers. The authors modelled state-of-the-art canonical C-vine and D-vine copulas to investigate the rating groups' partial correlation structure. Their studies found that second-tier financial institutions contributed significantly more to the systemic risk than top-tier borrowers.

As a complement to copula default probability research, the following studies describe the driving factors of default probability estimated by the copula technique. This model provides information about risk sources and vulnerabilities and describes how the financial system can absorb shocks. Weiß *et al*. (2014) analyse the factors contributing to international banks' default risk during major financial crises. The authors found no empirical evidence supporting conjectures that bank size, leverage, non-interest income, or credit portfolio quality are persistent determinants of systemic risk across financial crises. Kleinow and Moreira (2016) used copulas to observe European banks' systemic risk and contagion drivers. Their study estimates systemic risk contribution and sensitivity based on European banks' CDS spreads from 2005 to 2014. Their study uses panel regression, including idiosyncratic bank characteristics and country control variables. It showed evidence of highly significant drivers of systemic risk in the European banking sector and its important implications for bank regulation. This case study was followed by Parrado-Martínez *et al*. (2019). They examine European banks' default probability using the systemic model of bank-originated losses (SYMBOL) and investigated the influence of several bank-specific and macroeconomic variables on the default probability. Their research found that bank-specific indicators such as solvability, liquidity, asset quality, bank performance, and earnings influence default probability. Meanwhile, macroeconomic determinants such as industry concentration and bank size also impact their risk.

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[1] The concept of comonotonicity was introduced by Dhaene *et al*. (2002) and mainly refers to the perfect positive stochastic dependence structure of some random variables.

III. DATA AND METHODOLOGY

A. Data

In this study, we identify the determinants of the default probability for Indonesian banks. We follow Husodo *et al*. (2020) to estimate the default probability for each bank. We use financial variables from bank balance sheets consisting of current assets, current liabilities, long-term assets, and long-term liabilities. Then, we utilise two kinds of variables: bank-specific and macroeconomic determinants. Balance sheet data and bank-specific determinants were obtained from the Bank Indonesia proprietary database, and the macroeconomic variables were collected from the CEIC database. Our balanced panel comprises 80 banks with 4800 observations in 60 time-varying units. The sample represents 80% of the banks' market share assets and represents three main groups of bank owners: central state-owned banks, regional state-owned banks, and private commercial banks. We exclude Islamic and foreign banks based on their data availability and outliers. Both sets of statistics refer to quarterly data from 2005–to 2019. Our observation coincides with the global financial crisis of 2008 and quantitative easing in 2013. Indonesia has experienced a procyclical financial shock and a sustained financial boost, which impacted bank balance sheets and resulted in capital outflow throughout these periods. We also include dummy periods to investigate the impact of the pre-crisis, crisis, and recovery periods on banks' default probability. The variables and their definitions are presented in Table A.1.

A.1. Bank-Specific Variables

An increase in solvability enhances a bank's ability to absorb sudden losses, reducing the default probability. In this study, bank solvability is proxied by the capital adequacy ratio *R*) and Common Equity Tier 1 (CET 1) ratio (*CAP*). Capital structure tends to affect credit risk. Chaibi and Ftiti (2015) and Parrado-Martínez *et al*. (2019) demonstrate that capital quality indicators positively influence default probability.

The asset quality is represented by the Non-Performing Loan (*NPL*) ratio and loan loss reserve to impaired loan (*LLP*). An increase in the percentage of *NPL*s could reduce the quality of a bank's assets and increase the default probability (Kleinow and Moreira, 2016). Meanwhile, *LLP* represents a way of controlling anticipated loan losses and detecting credit loss levels for bank loans. Fiordelisi and Mare (2013) determined that loan loss reserve is positively related to the default probability.

A bank's performance is represented by inefficiency (*IEF*) and operating profit margin to earning asset/earnings ratio (*OPM*). Weiß *et al*. (2014) stated that bank performance and profitability should coincide with stability or risk; high profitability values could shield a bank from the risk of defaulting so that such banks could be pillars of stability. On the contrary, higher profitability and lower inefficiency could result from successful extended engagement in risky lending/ non-lending activities (Kleinow and Moreira, 2016).

We also employ the bank liquidity creation ratio as in Berger and Bouwman (2009) to calculate the Liquidity Ratio (*LR*) and the deposit to total liabilities (*DEPOSIT*). In terms of liquidity, both Kleinow & Moreira (2016) and Parrado-

Martínez *et al*. (2019) agree that the higher liquidity ratio, the lower the banks' default probability, and systemic risk contribution during a crisis. In contrast, customer deposits are more slowly repriced and more stable because they are protected by deposit insurance; this could create a possibility for the bank to be riskier in their portfolio exposure (Köhler, 2015). We include the loan to total asset ratio (*LOAN*) to describe a bank's loan exposure. As Kleinow and Moreira (2016) mentioned, a high share of loans increases risk sensitivity, while deposits could negatively influence a bank's risk.

A.2. Macroeconomic Variables

We utilize the Herfindahl Hirschman Index (*HHI*) as a structural variable to proxy the concentration ratio. Boyd and De Nicoló (2005); and Stiroh (2006) have demonstrated that a higher concentration value indicates greater loan risk.

We also consider economic growth (*GDP*), inflation (*CPI*), and unemployment rate (*UNE*) as macroeconomic variables. Anbar and Alper (2011), Bonfim (2009), and Louzis *et al*. (2012) found that these variables significantly impacted bank credit risk and the likelihood of bank distress.

Lastly, we include policy rate[2] (*POLICYRATE*) and exchange rate (*RER*) variables. Castro (2013) and Dell'Ariccia *et al*. (2011) found a significant negative relationship between these variables and bank risk. Table A. 1 shows our models' bank-specific indicators and structural and macroeconomic variables.

Table A.1. Variable Definitions

This table provide definitions of all variables considered in this study.

Category	Variable and Definition	Notation	Data Source
Dependent variable Default probability	Default probability of a bank based on pair copula construction (PCC) simulation approach from a bank's balance sheet data (current assets, long-term assets, current liabilities and long-term liabilities)	*PD*	authors calculation
Z-score	Proxy of distance to a default of bank calculated as the expected difference between the return on asset (ROA) of the bank relative to the standard deviation as the volatility of ROA	*Z-score*	authors calculation
Bank-specific factors			
Solvability	Tier 1 ratio (Tier 1 capital/ Total assets) Capital Adequacy Ratio (Risk-weighted capital/ Risk-weighted assets)	*CAP* *CAR*	Bank Indonesia Bank Indonesia

2 Regarding stochastic issue, we proxy policy rate with 7-days interbank money market rate instead of Bank Indonesia 7-days repo rate. We have checked the Pearson correlation between these variables is 0.88.

Table A.1. Variable Definitions

This table provide definitions of all variables considered in this study.

Category	Variable and Definition	Notation	Data Source
Asset Quality	Non-Performing Loan ratio	*NPL*	Bank Indonesia
	Coverage ratio (Loan loss reserves to impaired loan)	*LLP*	
Performance and Earnings	Inefficiency ratio (Operating cost to Operating Income)	*IEF*	Bank Indonesia
	Earnings ratio (Operating profit margin to earning asset)	*OPM*	Bank Indonesia
Loans	Loan to total assets ratio	*LOAN*	Bank Indonesia
Deposit	Deposit to total liabilities	*DEPOSIT*	Bank Indonesia
Liquidity	Liquidity ratio	*LR*	authors calculation
Structural variables	Concentration (Herfindahl Hirschman Index on the market share of the total asset)	*HHI*	authors calculation
Macroeconomic variables	Economic growth – GDP growth rate (percentage change on previous year %)	*GDP*	CEIC
	Inflation – Inflation rate (percentage change on previous year %)	*INF*	CEIC
	Policy rate – proxied by interbank money market %	*RATE*	CEIC
	Real exchange rate	*RER*	CEIC
	Unemployment rate (percentage change on previous quarter %)	UNE	CEIC

`Availability considerations and multicollinearity issues drive the decision of final explanatory variables. Correlation analyses and collinearity diagnostics were performed to assess the extent of multicollinearity among independent variables (see Appendix.). The summary descriptive statistics can be found in Table A.2.

Table A.2.
Descriptive Statistics for Main Variables

This table provides detail data description of all variables considered in this study. All variables are expressed in a percentage point. The sample comprises 80 bank institutions.

Variable	Obs	Mean	Std. Dev.	Min	Max
Default probability	4800	0.108	0.144	0	1.514
Capital adequacy ratio	4800	22.185	17.681	-229.82	813.44
CET 1 ratio	4800	20.199	11.451	1.669	192.265
Non-performing loan ratio	4800	2.925	2.925	0	42.959
Loan loss provision	4800	66.158	209.407	0.009	4891.625
Earnings ratio	4800	8.829	4.793	0.69	44.952
Inefficiency ratio	4800	82.897	20.304	38.026	872.717
Loan ratio	4800	64.483	13.356	0.859	111.503
Deposit ratio	4800	97.932	24.651	0.127	951.94
Liquidity ratio	4800	0.526	0.388	-2.275	5.718
Concentration ratio/HHI	4800	6.458	0.068	6.352	6.688
Policy rate	4800	6.373	1.744	3.9	11.85
Real exchange rate	4800	91.639	5.482	76.947	102.273
GDP growth	4800	5.483	0.621	4.053	6.81
Inflation rate	4800	0.398	0.78	-2.466	1.58
Unemployment rate	4800	-0.02	0.024	-0.06	0.06

B. Methodology

B.1. Default Probability of Indonesian Bank Using Copula Approach

We took several steps in estimating each bank's default probability: (i) determining the marginal distributions; (ii) selecting the dependence structure (tree) and choosing the appropriate copula families; (iii) conducting simulations to obtain equity value estimates; (iv) estimating the inverse function from pseudo-observations to original observations; lastly (v) estimating the default probability, whereby the probability is taken from negative equity values.

Following Sklar *et al*. (1959) theorem, the bank's balance sheet was mapped to the copula function $c(\cdot)$:

$$E_t = P(t,T) \iiint_0^{\infty} G_2\left(A_{C_T}, A_{L_T}, B_{C_T}, B_{L_T}; T\right) \cdot c(F_{A_C}, F_{A_L}, F_{B_C}, F_{B_L}) f_{A_C} f_{A_L} f_{B_C} f_{B_L} dA_{C_T} dA_{L_T} dB_{C_T} dB_{L_T} \tag{1}$$

where $A(\cdot)$ denotes the four-dimensional copula density function, $F(\cdot)$ denotes the marginal cumulative distribution function, and $f(\cdot)$ denotes the marginal probability density function.

Using a Monte Carlo simulation, the values of a bank's equity can be estimated as follows:

$$\tilde{E}_t = P(t,T)\frac{1}{N}\sum_{k=1}^{N} G_2(\tilde{A}_{C_{Tk}}, \tilde{A}_{L_{Tk}}, \tilde{B}_{C_{Tk}}, \tilde{B}_{L_{Tk}}; T) \tag{2}$$

where N is the number of simulations, E_t, $\tilde{A}_{C_{Tk}}$, $\tilde{A}_{L_{Tk}}$, $\tilde{B}_{C_{Tk}}$, and $\tilde{B}_{L_{Tk}}$ are the simulated values of equity, current, and long-term assets, and liabilities.

An inverse function from a uniform distribution to a real distribution can be estimated as follows:

$$C(u_1, \dots, u_d) = F\left(F_1^{-1}(u_1), \dots, F_d^{-1}(u_d)\right) \tag{3}$$

We construct a rolling estimation with a 36-month window to obtain optimal values for the default probabilities as a time series.

Determinant Factors of Bank Default Probability

We divide the factors into two main categories in terms of factors that influence default probability. First, a group of determinants is specific to each bank and is generally referred to as indicators to evaluate its performance. Then, the second group is related to banking sector structure and macroeconomic condition, highlighting this paper's purpose. Those variables are size, concentration measure, economic growth, inflation, policy rate, and unemployment rate.

The dynamic panel data methodology enables us to correct a typical problem in analysing determinants of bank risk: endogeneity. For example, solvability and asset quality may influence the probability of a bank's default. However, the default probability could cause the banks to modify their solvability, asset quality, and other financial ratios. Lastly, the dynamic panel data method could determine the persistence of bank risk.

This study uses the system GMM estimator developed for dynamic panel models (Arellano and Bover, 1995; Blundell and Bond, 1998). We employ the two-step estimation procedure in the *xtabond2* Stata package written by Roodman (2009), with corrected standard errors for small samples proposed by Windmeijer (2005).

We treat all the bank-specific indicators as endogenous variables. We then employ four lags of a dependent variable because our data is quarterly. Lastly, we consider macroeconomic variables as exogenous variables and use the lag of (at least) one period (Castro, 2013).

We verify the model's validity and the instruments by performing specification tests. First, we employ the error terms that do not exhibit serial correlation, and the instruments are valid. Second, we use the Hansen J statistic of over-identifying restrictions test for the absence of correlation between the instruments and the error term.

The baseline equation is the following:

$$PD_{it} = \alpha + \delta \cdot PD_{i,t-1} + \beta \cdot V_{it} + \Sigma\varphi_i \cdot D_{it} + \varepsilon_{it} \tag{4}$$

where PD_{it} represents the default probability of the bank i at year t; $PD_{i,t-1}$ denotes its lagged value, δ measures the speed of mean reversion, α is the constant term, V_{it} denotes the explanatory variables (banks-specific, structural, and macroeconomic variables). β is the vector of coefficient estimated, and $\Sigma\varphi_i \cdot D_{it}$ represents the time dummies for the period 2005q1 – 2019q4. Finally, ε_{it} is the disturbance term.

IV. RESULTS

A. Progress of the Indonesian Banks During the Sample Period 2005–2019

Table A.3 establishes an initial quarterly outline of the Indonesian banks from 2005 to 2019 and the descriptive statistics for the banks' default probability in each group. The default probability is defined as a negative value of a bank's equity after the pair copula construction simulation.

Bank risk exhibits increasing values, coinciding with the Fed's quantitative easing policies from 2009 to 2015. The mean value of the default probability through the period was 0.108%—one percentile of the samples presented values lower than 0.002%. After 2015, almost all banks gradually experienced an increase in their default probability until the end of the sample period. This situation is similar to the near-crisis event of 2007–2009.

It should be noted that state-owned banks had a higher default probability than other banks before the global financial crisis of 2007–2008. Nonetheless, after the crisis, the default probability of regional development banks showed an increasing trend until the end of the sample period.

Table A.3.
Evolution of the Indonesian Banks' PD

This table reports the main descriptive statistics (mean, standard deviation, first, second, and third quartiles) for the default probability and their main components.

		2005q4	2006q4	2007q4	2008q4	2009q4	2010q4	2011q4	2012q4	2013q4	2014q4	2015q4	2016q4	2017q4	2018q4	2019q4	Total
All Banks	Mean	0.128	0.112	0.111	0.105	0.107	0.104	0.093	0.088	0.092	0.096	0.097	0.110	0.113	0.121	0.129	0.108
	Std.	0.200	0.165	0.157	0.141	0.129	0.130	0.117	0.118	0.115	0.123	0.120	0.137	0.127	0.137	0.150	0.144
	1%	0.001	0.001	0.002	0.002	0.002	0.003	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.002
	5%	0.004	0.004	0.004	0.004	0.006	0.006	0.005	0.005	0.005	0.008	0.008	0.010	0.012	0.009	0.011	0.005
	10%	0.007	0.008	0.007	0.006	0.008	0.008	0.007	0.009	0.009	0.010	0.010	0.013	0.019	0.019	0.015	0.009
Central State-Owned Banks	Mean	0.640	0.578	0.516	0.413	0.376	0.364	0.322	0.358	0.323	0.317	0.360	0.405	0.393	0.380	0.522	0.426
	Std.	0.420	0.308	0.341	0.171	0.100	0.174	0.127	0.178	0.178	0.134	0.139	0.137	0.162	0.124	0.170	0.228
	1%	0.291	0.227	0.131	0.176	0.227	0.165	0.154	0.182	0.172	0.204	0.198	0.283	0.226	0.260	0.292	0.140
	5%	0.291	0.227	0.131	0.176	0.227	0.165	0.154	0.182	0.172	0.204	0.198	0.283	0.226	0.260	0.292	0.165
	10%	0.291	0.227	0.131	0.176	0.227	0.165	0.154	0.182	0.172	0.204	0.198	0.283	0.226	0.260	0.292	0.192
Regional State-Owned Banks	Mean	0.115	0.101	0.108	0.119	0.130	0.122	0.113	0.105	0.102	0.126	0.121	0.140	0.139	0.159	0.152	0.127
	Std.	0.146	0.118	0.135	0.164	0.151	0.148	0.149	0.135	0.121	0.162	0.149	0.179	0.157	0.177	0.161	0.155
	1%	0.015	0.019	0.015	0.013	0.022	0.025	0.017	0.016	0.016	0.019	0.022	0.025	0.023	0.025	0.024	0.016
	5%	0.019	0.021	0.021	0.013	0.025	0.027	0.018	0.017	0.017	0.022	0.023	0.028	0.026	0.029	0.029	0.021
	10%	0.023	0.023	0.021	0.020	0.026	0.027	0.020	0.020	0.019	0.024	0.023	0.030	0.032	0.029	0.035	0.025
Private Banks	Mean	0.094	0.082	0.081	0.074	0.076	0.075	0.067	0.060	0.070	0.065	0.066	0.074	0.079	0.083	0.089	0.075
	Std.	0.141	0.111	0.096	0.091	0.091	0.091	0.072	0.069	0.086	0.074	0.066	0.071	0.070	0.080	0.086	0.088
	1%	0.001	0.001	0.002	0.002	0.002	0.003	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.001
	5%	0.003	0.003	0.003	0.004	0.004	0.004	0.004	0.003	0.003	0.004	0.006	0.008	0.010	0.009	0.010	0.004
	10%	0.004	0.004	0.005	0.005	0.007	0.006	0.006	0.006	0.007	0.009	0.008	0.012	0.015	0.010	0.012	0.006

B. Determinants of the Default probability of Indonesian Banks

Table 1. reports the results of the empirical evidence of equation (4). Our findings illustrate the main determinants of the default probability. Model 1 only includes the bank-specific indicators, while model 2 also incorporates a set of structural and macroeconomic variables. The statistical significance of the lagged dependent variable and the higher values of δ indicate the dynamic nature of the model's specification and its strong persistence, respectively.

Table 1.
Determinants of Bank Default Probability

This table shows the two-step system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). The dependent variable is the bank's default probability. All the variables are considered endogenous except for dummies and macroeconomic variables. Robust cluster standard errors are in brackets. The Sargan and Hansen tests are for over-identifying restrictions in GMM dynamic model estimation. AB test AR (1) and AR (2) refer to the Arrelano–Bond test that average autocovariance in residuals of order 1 respectively, of order 2 is 0 (H0: no autocorrelation); *p*-values in the bracket. Coefficients significantly different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Variables	Default Probability-PD (1)	Default Probability-PD (2)
Lagged dependent	0.873***	0.862***
	(0.049)	(0.045)
Capital adequacy ratio	0	0
	(0)	(0)
CET 1 ratio	-0.0002**	-0.0003***
	(0.0001)	(0.0001)
Non-performing loan ratio	0	0.001**
	(0)	(0.001)
Loan loss provision	0	0
	(0)	(0)
Earnings ratio	0	0
	(0.001)	(0)
Inefficiency ratio	-0.00008*	-0.0002***
	(0)	(0)
Loan ratio	0	0
	(0)	(0)
Deposit ratio	0.00005**	0.00005**
	(0)	(0)
Liquidity ratio	0.003*	0
	(0.002)	(0.003)
Concentration ratio/HHI(1)		0.001
		(0.007)
Policy Rate(1)		-0.001***
		(0.0002)
Real exchange rate(1)		-0.0003***
		(0)
GDP growth(1)		-0.002***
		(0.001)
Inflation rate(1)		0
		(0.001)

Table 1.
Determinants of Bank Default Probability (Continued)

Variables	**Default Probability-PD (1)**	**Default Probability-PD (2)**
Unemployment rate(1)		-0.049***
		(0.019)
Constant	0.014	0.082
	(0.011)	(0.054)
Time dummies	Yes	Yes
Observations	4720	4720
Sargan test (*p*-value)	609.05 (0.00)	651.01(0.00)
Hansen test (*p*-value)	14.17 (1.000)	73.41(0.132)
AB test AR (1) (*p*-value)	0.002	0.002
AB test AR (2) (*p*-value)	0.265	0.256

The solvability indicators, represented by the CET 1 ratio (*CAP*), have significant negative impacts on default probability at a 5% significance level. This finding means that an increase in bank solvability improves a bank's ability to absorb sudden losses, reducing the default probability. Our findings are as expected and support the results of previous research (Fiordelisi and Mare, 2013; Laeven *et al*., 2016; Parrado-Martínez *et al*., 2019).

The inefficiency ratio (*IEF*) appears negative and statistically significant at a 1% significance level. Earlier studies have proven that banks with lower efficiency are less likely to experience distress (e.g., Altunbas *et al*., 2007; Fiordelisi and Mare, 2013; Kwan and Eisenbeis, 1997). Chaibi and Ftiti (2015) explained a more detailed explanation that argues a negative relationship between the inefficiency ratio and credit risk is likely because of the skimping hypothesis. This hypothesis allows banks to reasonably reduce costs in the short term but bear the consequences and potential costs of performance issues in the future by maximizing long-term profits and conserving resources for lending and monitoring (Berger and Young, 1997). We will explain this further in robustness test section.

Moreover, the deposit indicators (*DEPOSIT*) and the Liquidity Ratio (*LR*) positively impact default probability, which means that the higher the ratio, the higher the default probability for the banks. These indicators had a 5% and 10% significance level, respectively. This relation could be because deposit and liquidity will increase bank liabilities to their counterparts and cause an effect in triggering the likelihood of default. This evidence demonstrates that Indonesian banks operate like traditional banks that collect their funding mostly from demand deposits,[3] covered by deposit insurance. Our finding is comparable with Anginer *et al*. (2014), who referred to this as a "moral hazard effect", meaning that an unintended consequence of deposit insurance encourages banks to take on excessive risks.

Additionally, after we introduce the structural and macroeconomic variables in the equation (model 2 in Table 1), the results reveal the relevant impacts of

[3] Demand deposit in Indonesian banking industry represent about 60% market share.

policy rate (*POLICYRATE*), Real Exchange Rate (*RER*), economic growth (*GDP*), and unemployment rate (*UNE*) on the default probability. The negative values and statistical significance of those variables indicate that an increase in these variables causes a reduction in the default probability. Our finding on policy rate variables (*POLICYRATE*) supports Dell'Ariccia *et al*. (2011), who discussed the effect of monetary policy change on bank risk-taking, indicating that a policy rate cut may lead to banks taking more risks. Meanwhile, the negative value on *RER* shows that the currency's purchasing power will cause a reduction in the default probability. Our result is similar to Castro (2013), who argues that credit risk is positively affected by an appreciation of the real exchange rate. Moreover, the economic growth (*GDP*) appears to be statistically significant; the negative value shows that higher economic growth reduces the default probability, which is comparable to Louzis *et al*. (2012); and Parrado-Martínez *et al*. (2019).

An interesting finding is the unemployment rate indicator (*UNE*). In contrast, other studies found that the unemployment rate positively impacts the default probability (as in Castro, 2013; Louzis *et al*., 2012). Generally, an increase in the unemployment rate could affect households' ability to service their debts, usually mortgage loans, impacting banks' asset quality performances. However, the unemployment rate declined during our observation period in our case. Hence, this is due to Indonesia's large informal labour sector, which absorbed laid-off employees from crisis-affected firms in the formal sector (Tambunan, 2010). Additionally, mortgage loans, which are the most significant share of household debt, are primarily granted to civil servants, who are less likely to become unemployed.

Lastly, when we introduce the structural and macroeconomic variables, our model provides new evidence of bank-specific indicators findings (see Tab*le 1*.). The *NPL* has a positive value and is statistically significant at a 5% level. Our empirical evidence demonstrates that non-performing loan indicators appear as lagged indicators since they interact with the lagged macroeconomic environment in our model. Backed by this evidence, we could argue that our copula approach may be an essential indicator for early warning of credit risk in the banking system. Additionally, CET 1 ratio (*CAP*) and inefficiency ratio (*IEF*) have different effects on default probability. This result could be a corollary of the macroeconomic situation, which ensures the banks reinforce their capital to anticipate economic volatility and create coverage for unexpected losses, leading to more stable banks (Bonfim, 2009; Parrado-Martínez *et al*., 2019).

C. Impact of the Pre-Crisis, Crisis, and Post-Crisis

We introduce a dummy variable to distinguish between pre-crisis, during the crisis (coincide with the global financial crisis of 2008), and post-crisis (recovery period including the period of quantitative easing in 2013). Based on Filardo (2011), the financial crisis in Asia began in September 2008 and lasted until the end of 2009, so we defined the following periods: pre-crisis, crises from Q3 2008 to Q4 2009, and recovery. [4]

[4] The dummy variable takes the value of 1 for each separate period and it takes the value of 0 for the remaining years, respectively.

The result in *Table 2*. (model with dummy crisis and model with dummy post-crisis) shows this new variable statistical significance, demonstrating notable influences of those periods on default probability. The positive value in the dummy crisis period indicates that Indonesian banks reduced their default probability during the global financial crisis. However, a negative association appears in our recovery period; this evidence demonstrates that Indonesian banks increased their risk exposure, and, as a result, their default probability intensified.

Table 2.
Impact of the Pre-crisis, Crisis, and Post-crisis Period

This table shows the two-step system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). The dependent variable is the bank's default probability. We add a set of dummy variables to control the pre-crisis, crisis and post-crisis periods. All the variables are considered endogenous except for dummies and macroeconomic variables. Robust cluster standard errors are in brackets. The Sargan and Hansen tests are for over-identifying restrictions in GMM dynamic model estimation. AB test AR (1) and AR (2) refer to the Arrelano–Bond test that average autocovariance in residuals of order 1 respectively, of order 2 is 0 (H0: no autocorrelation); *p*-values in the bracket. Coefficients significantly different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Variables	w/ Pre-crisis Dummy	w/ Crisis Dummy	w/ Post-crisis Dummy
Lagged dependent	0.867***	0.861***	0.867***
	(0.042)	(0.045)	(0.041)
Capital adequacy ratio	0	0	0
	(0)	(0)	(0)
CET 1 ratio	-0.0004***	-0.0004***	-0.0004***
	(0)	(0)	(0)
Non-performing loan ratio	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)
Loan loss provision	0	0	0
	(0)	(0)	(0)
Earnings ratio	0	0	0
	(0)	(0)	(0)
Inefficiency ratio	-0.0002***	-0.0002***	-0.0002***
	(0.0002)	(0)	(0)
Loan ratio	0	0	0
	(0)	(0)	(0)
Deposit ratio	0.00005**	0.00005**	0.00005**
	(0)	(0)	(0)
Liquidity ratio	0	-0.001	0
	(0.003)	(0.003)	(0.003)
Concentration ratio/HHI(1)	0.004	-0.001	0.003
	(0.008)	(0.007)	(0.007)
Policy Rate(1)	-0.001***	-0.001***	-0.001***
	(0)	(0)	(0)
Real exchange rate(1)	-0.0004***	-0.0004***	-0.0004***
	(0)	(0)	(0)
GDP growth(1)	-0.002**	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)
Inflation rate(1)	0	0.001	0.001
	(0.001)	(0)	(0)

Table 2.
Impact of the Pre-crisis, Crisis, and Post-crisis Period (Continued)

Variables	w/ Pre-crisis Dummy	w/ Crisis Dummy	w/ Post-crisis Dummy
Unemployment rate(1)	-0.057***	-0.053***	-0.068***
	(0.021)	(0.019)	(0.022)
Pre-crisis	-0.002		
	(0.002)		
Crisis		-0.002*	
		(0.001)	
Post-crisis			0.004**
			(0.002)
constant	.066	0.098*	0.077
	(.051)	(0.055)	(0.052)
Observations	4720	4720	4720
Sargan test (*p*-value)	654.97 (0.00)	648.91 (0.00)	651.99 (0.00)
Hansen test (*p*-value)	74.11 (0.121)	73.45 (0.132)	74.69 (0.112)
AB test AR (1) (*p*-value)	0.002	0.002	0.002
AB test AR (2) (*p*-value)	0.258	0.257	0.262

D. Impact of Bank Ownership and Region

In this section, we consider the influence of bank ownership. We integrate a set of dummies into the equation to control the effects of bank ownership (*central state-owned banks, regional state-owned banks, and private banks*).

In addition, since our data includes *regional state-owned banks*, we also introduce a dummy region for this type of bank. As *regional state-owned banks*, these banks have restricted activities and can only operate within their region; consequently, the restriction of bank activities will influence competition and bank risk behaviour (Agoraki *et al*., 2011). This dummy region also explained why the default probability in *regional state-owned banks* increased during our observation period. We introduce three dummy regions into this study for a more straightforward interpretation of our results: the *west*, *central*, and *east* regions. As an island nation, Indonesia consists of five major islands: Sumatra, Java, Borneo, Sulawesi, and Papua. However, the economy is mainly concentrated in Java. This study designates Sumatra as the *west* region, Java and Kalimantan as the *central* region, and Sulawesi and Papua as the *east* region. The reason for dividing these areas is due to the fact that each area has particular economic characteristics and the scope of bank activity that will undoubtedly affect the risk behaviour of each regional state-owned bank.

Our finding in Table 3 shows that *central state-owned* banks positively correlate with default probability. This result indicates that *central state-owned* banks are at higher risk than other banks because they are fully supported by the central government and predominantly in their market share, so every excessive risk they take will affect the default probability.

Meanwhile, the *central* dummy region is negatively associated with the default probability when we consider the dummy regions. There are two main reasons for this finding. First, most financial transactions happen in the *central* region, especially Java Island, because it is near the capital of Indonesia. Second, the negative influence of *regional state-owned* banks means that the regional government reduces their risk exposure. When the macroeconomic situation decreases, the regional government also reduces their expense budget, which affects the performance of regional state-owned banks because most of their operational transactions serve the regional government's activities.

Table 3.
Impact of the Bank's Owner and Dummy Region on Regional State-owned Banks on Default Probability

This table shows the two-step system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). The dependent variable is the bank's default probability. We add a set of dummy variables to control the bank's owner and a dummy region for regional state-owned banks. Coefficients significantly different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Variables	w/bank's Owner Dummy	w/ Regional Dummy
Lagged dependent	0.849***	0.863***
	(0.048)	(0.042)
Capital adequacy ratio	0	0
	(0)	(0)
CET 1 ratio	-0.0003***	-0.0003***
	(0.0001)	(0)
Non-performing loan ratio	0.001*	0.001**
	(0.0003)	(0.001)
Loan loss provision	0	0
	(0)	(0)
Earnings ratio	0	0
	(0)	(0)
Inefficiency ratio	-0.0001***	-0.0002***
	(0)	(0)
Loan ratio	0	-0.0002*
	(0)	(0)
Deposit ratio	0.00005**	0.00005**
	(0.00002)	(0)
Liquidity ratio	-0.001	0.001
	(0.003)	(0.002)
Concentration ratio/HHI(1)	0.004	-0.001
	(0.007)	(0.007)
Policy Rate(1)	-0.001***	-0.001***
	(0)	(0)
Real exchange rate(1)	-0.0003***	-0.0003***
	(0)	(0)
GDP growth(1)	-0.002***	-0.002**
	(0.001)	(0.001)
Inflation rate(1)	0	0
	(0.001)	(0.001)
Unemployment rate(1)	-0.051**	-0.047**
	(0.02)	(0.019)

Table 3.
Impact of the Bank's Owner and Dummy Region on Regional State-owned Banks on Default Probability (Continued)

Variables	w/bank's Owner Dummy	w/ Regional Dummy
Central State-Owned Banks	0.046***	
	(0.016)	
Regional state-owned banks	0.004	
	(0.006)	
Private Banks		
West region		0.012
		(0.014)
Central region		-0.01**
		(0.005)
East region		-0.002
		(0.007)
constant	0.056	0.099**
	(0.047)	(0.047)
Observations	4720	4720
Sargan test	628.13 (0.00)	649.69 (0.00)
Hansen test (*p*-value)	74.50 (0.115)	71.55 (0.167)
AB test AR (1) (*p*-value)	0.002	0.002
AB test AR (2) (*p*-value)	0.256	0.258

E. Robustness Test

E.1. Alternative Econometric Methodologies

As a robustness test, we report the results using different econometrics estimation methods (the pooled Ordinary Least Square (OLS), fixed-effect model, and difference GMM). Table 4 shows that the bank-specific and some structural and macroeconomic indicators remain significant, regardless of the methodology; this proves the specification's robustness.

Table 4.
Robustness Check: Alternative Econometrics Methodologies

This table shows different methods of estimation from the main equation which are OLS (Ordinary Least Square), random effects (within) regression, and the two-step difference GMM developed by Arellano and Bond (1991). All the variables are considered endogenous except for time dummies and macroeconomic variables. Robust cluster standard errors are in brackets. AB test AR (1) and AR (2) refer to the Arrelano–Bond test that average autocovariance in residuals of order 1 respectively, of order 2 is 0 (H0: no autocorrelation); *p*-values in the bracket. Coefficients significantly different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Dependent Variable: The Default Probability (%)						
Variables	**(1) Pooled OLS**	**(1) Fixed Effects**	**(1) Difference GMM**	**(2) Pooled OLS**	**(2) Fixed Effects**	**(2) Difference GMM**
Lag. dependent			0.869***			0.856***
			(0.037)			(0.041)
CAR	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)
CET 1 ratio	-0.003***	-0.0007***	-0.0001***	-0.003***	-0.0005	-0.00006*
	(0)	(0)	(0)	(0)	(0)	(0)
NPL	0.009***	0.004***	0	0.009***	0.004***	0
	(0.001)	(0)	(0)	(0.001)	(0)	(0)
LLP	0	0	-0*	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)
Earnings ratio	0.002**	-0.003***	0	0.001**	-0.0004***	0
	(0)	(0)	(0)	(0)	(0)	(0)
Inefficiency ratio	-0.001***	-0.0002***	-0.0001***	-0.001***	-0.0001***	-0.00008***
	(0)	(0)	(0)	(0)	(0)	(0)
Loan ratio	-0.002***	-0.0008***	0	-0.002***	-0.0007***	0
	(0)	(0)	(0)	(0)	(0)	(0)
Deposit ratio	0	0	0**	0	0	0**
	(0)	(0)	(0)	(0)	(0)	(0)
Liquidity ratio	0	0	0.002*	-0.004	0	0.001
	(0)	(0)	(0.001)	(0.006)	(0)	(0.001)
HHI(1)				0.049	0.097***	0.009
				(0.044)	(0)	(0.007)
Policy Rate(1)				-0.0003**	-0.001**	-0.001***
				(0.001)	(0)	(0)
RER(1)				-0.001	-0.0005***	-0.0003***
				(0)	(0.0001)	(0)
GDP growth(1)				-0.008**	-0.005***	-0.002**
				(0.004)	(0.001)	(0.001)
Inflation rate(1)				0.001	0	0
				(0.003)	(0)	(0.001)
Constant	0.356***	0.235***	-	-0.094	-0.378***	-0.055***
	(0.022)	(-0.252)	-	(0.119)	(0.108)	(0.02)
Time dummies	Yes	Yes	Yes	No	No	No
R-squared	0.116	0.0928 (within)		0.1099	0.0727 (within)	-
Obs.	4800	4800	4640	4800	4,800	4640
Number of banks	80	80	80	80	80	80

Table 4.
Robustness Check: Alternative Econometrics Methodologies (Continued)

Dependent Variable: The Default Probability (%)						
Variables	**(1) Pooled OLS**	**(1) Fixed Effects**	**(1) Difference GMM**	**(2) Pooled OLS**	**(2) Fixed Effects**	**(2) Difference GMM**
Hausman test		14.03	-	-	23.44	-
(*p*-value)		(0.1213)			(0.0092)	
Sargan test		-	493.12	-	-	521.60
(*p*-value)			(0.00)			(0.00)
Hansen test		-	16.77			75.20
(*p*-value)			(1.00)			(0.053)
AB test *AR* (1)		-	0.002			0.002
AB test *AR* (2)		-	0.267			0.257

E.2. Alternative Dependent Variable

Furthermore, we consider an alternative to the dependent variable in equation (4). We employ the Z-score indicator, similar to Lown *et al*. (2000); and Tabak *et al*. (2013).

The results obtained do not differ substantially from those obtained previously. However, we find a mixed signal since the inefficiency ratio (*IEF*) has a positive relationship and is statistically significant to the *Z-score*. In contrast, it has a negative relationship with the loan ratio (*LOAN*) and positively associated with the Liquidity Ratio (*LR*). This result, in fact, demonstrates evidence of the skimping hypothesis. In contrast, banks choose to engage their profitability or stability in the short term and bear the consequences of a possible future default by pumping their liquidity supply into loan exposure on the market to gain a short-term revenue advantage. Our results also reveal that the *Z-score* had fewer bank-specific and macroeconomic variables than the primary dependent variable in our equation compared to the default probability. This evidence shows us that a bank's default probability could be an important measure for identifying macro-financial interlinkages that influence a bank's risk.

Table 5.
Alternative Dependent Variable: *Z*-score

This table shows the two-step system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). The dependent variable is the *Z*-score = $(ROA_{it}+EQUAS_{it})/\sigma ROA_{it}$. Model (1) presents the baseline model. Model (2) includes macroeconomic variables and dummy variables. All the variables are considered endogenous except for the macroeconomic and the dummy variables. Robust cluster standard errors are in brackets. The Sargan and Hansen tests are for over-identifying restrictions in GMM dynamic model estimation. AB test AR (1) and AR (2) refer to the Arrelano–Bond test that average autocovariance in residuals of order 1 respectively, of order 2 is 0 (H0: no autocorrelation); *p*-values in the bracket. Coefficients that are significantly different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively

Variables	***Z*-score (1)**	***Z*-score (2)**
Lagged dependent	0.061	0.057*
	(0.038)	(0.033)
Capital adequacy ratio	-0.001	0.001
	(0.002)	(0.002)
CET 1 ratio	-0.01***	-0.01***
	(0.003)	(0.003)
Non-performing loan	0.013	0.012
	(0.014)	(0.009)
Loan loss provision	0	0
	(0)	(0)
Earnings ratio	0.102	-0.001
	(0.109)	(0.005)
Inefficiency ratio	0.017***	0.016***
	(0.003)	(0.002)
Loan ratio	-0.01***	-0.007***
	(0.003)	(0.002)
Deposit ratio	0.003	-.002*
	(0.004)	(0.001)
Liquidity ratio	0.111*	0.119**
	(0.062)	(0.057)
HHI(1)		-0.133
		(0.279)
Policy Rate(1)		-0.006
		(0.01)
Real exchange rate(1)		0.001
		(0.003)
GDP growth(1)		-0.081***
		(0.026)
Inflation rate(1)		-0.027
		(0.019)
Constant	-2.475**	-0.901
	(1.193)	(0.686)
Time dummies	Yes	No
Number of observations	4720	4720
Number of banks	80	80
Sargan test (*p*-value)	78.30 (0.067)	97.32 (0.00)
Hansen test (*p*-value)	15.13 (1.000)	68.87 (0.228)
AB test *AR* (1) (*p*-value)	0.000	0.000
AB test *AR* (2) (*p*-value)	0.761	0.912

V. CONCLUDING REMARKS AND DISCUSSION

This study finds that bank-specific variables such as the *CET* 1 ratio, inefficiency ratio, and deposit substantially affect a bank's default probability. Our results highlight that an increasing deposit ratio increases risk contribution. Besides, we also find evidence that the skimping hypothesis was linked to a bank's inefficiency indicator. The non-performing loan indicator also appears as lag indicator when intertwined with macroeconomic variables.

Additionally, when we add structural and macroeconomic variables, we find that the policy rate, real exchange, economic growth, and unemployment rate appear to reduce default probability. Furthermore, evidence from the crises and recovery period shows statistical significance, demonstrating the considerable influence of these dummy variables. Considering the effect of bank ownership, central state-owned banks are more at risk than other banks. Nonetheless, when we set our focus on the dummy region for regional state-owned banks, we find evidence that regional state-owned banks in the central region appear to be most affected.

We find that more straightforward approaches (*Z-score*) are less sensitive to captured risk sources and vulnerabilities than the default probability using the copula approach.

Our results suggest that regulatory authorities should focus on capital regulatory and deposit management policy to reduce dependence on demand deposits. In addition, the policy rate effectively anticipated the banks' default risk.

A comprehensive future study could introduce a business cycle and financial cycle to pinpoint any differences in the default probability to analyse the dynamic default probability between the cycle phases.

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