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Capital Buffer and Risk-Taking in Publicly Listed Banks in Indonesia: A Quantile Regression Approach

*Isrita Anelly [1], Abel Tasman [1]**

[1] Management Study Program, Faculty of Economics and Business
Padang State University, Padang, Indonesia
Correspondence: E-mail: abeltasman@fe.unp.ac.id.

ABSTRACT

This study aims to analyze the non-linear and heterogeneous effects of the relationship between capital buffers and risk-taking in public banks in Indonesia. This study uses a quantitative approach with secondary data from financial reports of 45 public banks in Indonesia during the 2020-2024 period, employing purposive sampling to select a sample of 225 observations. The analysis uses OLS panel data regression and quantile regression to test the effect of capital buffers on risk-taking across different levels of the bank risk distribution. The results of the study indicate that (1) capital buffers have a nonlinear U-shaped relationship with bank risk-taking, which indicates that increasing capital buffers at a certain level can reduce risk-taking, but after passing a certain turning point, increasing capital buffers actually encourages increased risk-taking, (2) the nonlinear effect is stronger in banks at lower risk-taking levels, thus indicating heterogeneity in the influence of capital buffers along the risk distribution, and the turning point of capital buffers tends to decrease across the risk-taking distribution, which means that banks with high risk levels tend to reach the threshold for changing risk behavior at lower capital buffer levels. These findings indicate that increasing capital requirements is not always effective in consistently suppressing risk-taking. The implications of this research suggest that capital policies need to be designed more adaptively, taking into account the risk characteristics of each bank, as implementing excessively high capital buffer requirements could potentially encourage banks to increase risk-taking, particularly at high-risk banks.

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1. INTRODUCTION

The banking industry plays a central role in the economic system through its financial intermediation function, namely, collecting, managing, and channeling funds to the productive sector (Nguyen, 2020) . In the Indonesian context, banking is a key pillar of the financial services sector with the largest asset contribution to the national financial system, making banking stability a very important factor for financial system stability and economic growth. (Tasman et al., 2019) . However, the characteristics of the banking business, which is highly dependent on leverage, maturity transformation, and exposure to various types of risks, make this industry vulnerable to instability disturbances. (Klemkosky, 2013) . In this context, bank risk-taking behavior is an important issue to consider because it is directly related to the bank's vulnerability to financial stress and the potential for systemic risk (Yuwonoputro & Syaichu, 2019) . Excessive risk-taking can increase the likelihood of bank failure, exacerbate financial system instability, and trigger broader systemic impacts (Sudarmanto et al., 2021; Tampubolon, 2006) . The experience of the 2007-2009 global financial crisis demonstrated that excessive risk-taking behavior is a major trigger of financial instability, prompting regulators to strengthen the prudential framework by increasing capital requirements (Verberi et al., 2023) .

Within the framework of modern banking regulation, capital buffers are viewed as a key instrument for strengthening bank resilience because they serve as a buffer capital above the regulatory minimum limit that can absorb unexpected losses and limit banks' tendency to take excessive risks (Noreen et al., 2016; Shim, 2019; Tasman et al., 2019) . Theoretically, the relationship between capital buffers and risk-taking can be explained through the moral hazard hypothesis, which states that increasing capital initially strengthens a bank's internal discipline because shareholders bear a greater proportion of losses, thus reducing the incentive to take excessive risks (Gupta & Jain, 2022; Kane, 1995) . However, this relationship is not always linear. At very high capital levels, additional buffers can actually encourage increased risk-taking because banks have a larger buffer and perceive a lower probability of bankruptcy (Calem & Rob, 1999 in Anginer et al., 2018; Hellmann et al., 2000) . Thus, capital buffers have the potential to have a nonlinear relationship to risk-taking, where increasing capital may reduce risk in the initial stage, but encourage increased risk after passing a certain threshold.

Empirical findings on the relationship between capital buffers and risk-taking also show mixed results. Several studies have found that higher capital buffers tend to reduce risk-taking by increasing loss-absorbing capacity and strengthening internal bank discipline (Abbas et al., 2021; Anginer et al., 2018; Salim & Suripto, 2023). Conversely, several studies have shown that increasing capital does not always reduce risk, and under certain conditions, even encourages banks to take greater risks due to moral hazard, regulatory arbitrage, and the drive to maintain profitability (Bitar et al., 2018; Ding & Sickles, 2018). Other studies also confirm that the effect of capital on risk is highly dependent on institutional conditions, governance, and bank characteristics (Klomp & Haan, 2012; Laeven & Levine, 2009) . Guidara et al. (2013), for example, found no significant relationship between *capital buffer* and *risk-taking* in Canadian banks. Meanwhile, Jiang et al. (2020) and Tu et al. (2025) show that the relationship is nonlinear, U-shaped, and differs across risk quantiles, indicating that the effect of capital buffers on risk-taking is heterogeneous. However, most previous studies have focused on a linear, average-based approach, thus failing to fully explain the heterogeneity of the effect of capital buffers across different levels of bank risk distribution, particularly in developing countries.

This empirical gap becomes increasingly relevant to study in the context of Indonesian banking. Studies in Indonesia generally focus on the average effect of capital buffers on bank stability or risk-taking (Danarsari & Rokhim, 2018; Fauziah & Pangestuty, 2020; Salim & Suripto, 2023) , thus failing to fully capture the nonlinear dynamics and heterogeneity of influences at each risk level. However, preliminary data on publicly listed banks indicate that the relationship between capital buffers and risk-taking is not unidirectional. PT Bank Mandiri Tbk. (BMRI), for example, maintained a capital buffer in the range of 11-13% during 2020-2024, followed by a decrease in NPLs from 3.29% to 0.97%, indicating a stable relationship between capital strengthening and reduced credit risk. Conversely, PT Bank Pembangunan Daerah Banten Tbk. (BEKS) recorded a much higher capital buffer, above 26% to 36%, but still accompanied by a high NPL ratio, although it decreased from 22.3% to 7.53%. A different pattern was seen at PT Bank Amar Indonesia Tbk. (AMAR), which experienced a jump in its capital buffer from 37.43% to 118.3%, but its NPL remained in the high range of 6-10%. Meanwhile, PT Bank Harda Internasional Tbk. (BBHI) showed a significant increase in its capital buffer from 11.61% to 74.58% and was accompanied by a very low NPL ratio. On the other hand, PT Bank KB Bukopin Tbk. (BBKP) actually showed a relatively low capital buffer with a consistently high NPL ratio. This variation confirms that an increase in the capital buffer is not always followed by a consistent decrease in risk-taking, thus indicating that the effect of the capital buffer on risk-taking is not homogeneous and may vary at different risk levels.

To provide an initial empirical overview of this heterogeneity, Table 1 presents variations in capital buffers and NPLs in several publicly listed banks in Indonesia during the 2020-2024 period.

Table 1Capital Buffer and NPL Ratios of Several Publicly Listed Indonesian Banks in 2020-2024

Bank/Year	2020		2021		2022		2023		2024	
	BUF	NPL	BUF	NPL	BUF	NPL	BUF	NPL	BUF	NPL
PT Bank Mandiri Tbk. (BMRI)	11.9	3.29	11.6	2.81	11.46	1.88	13.48	1.02	12.1	0.97
PT Banten Regional Development Bank Tbk. (BEKS)	26.75	22.3	33.68	14.09	35.38	9.45	36.72	9.36	34.99	7.53
PT Bank Amar Indonesia Tbk. (AMAR)	37.43	6.93	21.85	6.58	74.52	6.09	74.52	9.23	118.3	10.25
PT Bank Harda Internasional Tbk. (BBHI)	11.61	2.76	40.82	0.52	71.53	0.01	75.35	0.08	74.58	0.81
PT Bank KB Bukopin Tbk. (BBKP)	4.08	10.2	12.26	10.66	11.08	6.56	19.05	9.56	8.38	9.06
Bank of India Indonesia Tbk. (BSWD)	37.49	4.95	90.07	9.08	119.4	9.07	84.54	6.28	80.58	6.02

Source: Annual Report, 2020-2024

Based on these variations, an empirical approach is needed that can capture both the nonlinear relationship and the heterogeneity of the influence of capital buffers on risk-taking, particularly in publicly listed banks in Indonesia, which have different characteristics of governance, transparency, and market exposure compared to non-listed banks. Therefore, this study aims to analyze the influence of capital buffers on risk-taking in publicly listed banks in Indonesia, emphasizing two main aspects: the nonlinear relationship and the heterogeneity of influence across risk distributions. This study uses panel quantile regression to test whether capital buffers have a nonlinear relationship with risk-taking and whether this influence differs across different levels of bank risk. This study contributes to the literature in three ways. First, it expands the study of the relationship between capital buffers and risk-taking in the context of developing countries, particularly Indonesia, which is still relatively limited. Second, this study addresses the limitations of previous studies by examining the heterogeneity of the influence of capital buffers across the bank risk distribution. Third, this study provides a methodological contribution through the use of panel quantile regression, which allows the identification of nonlinear dynamics and heterogeneity of influence that cannot be adequately explained by conventional linear models. Thus, this research is expected to provide academic contributions to the development of banking literature and provide practical input for regulators and bank management in formulating more effective capital policies to maintain financial system stability.

2. METHODS

a. Types, Objects, Population and Research Samples

This study uses a quantitative approach with a causality design to analyze the nonlinear relationship and heterogeneity between capital buffers and risk-taking. This quantitative approach was chosen because this study aims to empirically test the relationship between variables through numerical measurements and statistical analysis (Sugiyono, 2013) . The subjects of this study are public banks listed on the Indonesia Stock Exchange (IDX) between 2020 and 2024.

The study population included all publicly listed banks on the Indonesia Stock Exchange (IDX) during the observation period, using a purposive sampling technique with the following criteria: publicly listed banking companies listed on the IDX in 2020-2024, providing complete annual reports and financial data during the study period, and possessing the required data for all research variables. Based on these criteria, 45 banks with a total of 225 observations were obtained. The data used were secondary data in the form of annual reports and financial statements collected through archival research methods. Secondary data are research data sources obtained and recorded by other parties, in other words, data obtained by researchers indirectly through intermediaries (Indriantoro & Supomo, 2018) .

b. Operational Definition and Measurement of Variables

To avoid differences in interpretation of the variables used in this study, the operational definitions and measurement indicators of each research variable are presented in Table 2.

Table 2 Research Variables and Operational Definitions

Variables	Indicator	Formula	Scale	Source
Dependent Variable				
Non-Performing Loan (NPL) Ratio	Ratio of *non-performing loans* to *gross loans*	NPL $=\frac{Non\ Performing\ Loan}{Total\ Gross\ Loan}$	Ratio	(Jiang et al., 2020)
Z-Score	ROAit is return on assets, σROAit is standard deviation	$Z-score_{it}=\frac{ROA_{it}+CAR_{it}}{\sigma ROA_{it}}$	Ratio	(Jiang et al., 2020)

	of ROAit, and CARit is the ratio of total equity to total assets.			
Independent				
***Capital buffer* (BUF)**	The difference between the capital held by the bank and the minimum capital ratio set by the regulator	BUF = Bank CAR – Minimum CAR	Ratio	(Jiang et al., 2020)
Squared *capital buffer* (BUF2)	Quadratic estimation of *the capital buffer*	$BUF_{it} = BUF_{it}^2$	Ratio	(Jiang et al., 2020)
Control				
Bank size (SIZE)	Bank size based on the natural logarithm of total assets	SIZE = Ln *Total assets*	Ratio	(Jiang et al., 2020)
Market discipline (CID)	The bank's deposit fee is the interest fee paid on the total deposit account.	CID $=\frac{interest\ expense}{Deposit}$	Ratio	(Jiang et al., 2020)
Cost efficiency (CIR)	Cost efficiency is the ratio of operating expenses to operating income	CIR $=\frac{operational\ expenses}{operational\ income}$	Ratio	(Jiang et al., 2020)
GDP growth	Annual real GDP growth	GDP $=\frac{GDP_t-GDP_{t-1}}{GDP_{t-1}}$	Ratio	(Jiang et al., 2020)
Annual Inflation Rate	Growth of the consumer price index last year compared to the following year	INF $=\frac{CPI_t-CPI_{t-1}}{CPI_{t-1}}$	Ratio	(Jiang et al., 2020)

c. Analysis Techniques

The analysis technique used in this study is the panel data quantile regression analysis technique with the help of computer application software, namely the Stata17 program. Panel data quantile regression is combined with Ordinary Least Squares (OLS) regression as a comparison to see the differences in the estimation results on the average and at various points of the distribution of the dependent variable. The quantile regression approach was chosen because it is more robust against heteroscedasticity and outliers, and is able to estimate the influence of independent variables on various quantiles of the distribution of the dependent variable that cannot be adequately explained by the mean-based estimation approach. (Koenker, 2004; Yanuar et al., 2017) .

3. RESULTS AND DISCUSSION

a. Descriptive Analysis

Descriptive statistical analysis is used to provide an overview of the characteristics of the research data through measures of central tendency and data dispersion, such as the average value (mean), variance, minimum value, maximum value, range, and data distribution reflected by skewness and kurtosis (Ghozali, 2018) . This study uses panel data consisting of a combination of time series and cross-sectional data for five years (2020-2024) from 45 sample banks, with a total of 225 observations analyzed. This is also the final sample size in this study. A descriptive summary of the risearch variables for the 2020-2024 period is presented in table 3.

Table 3: Summary of Descriptive Statistics

Variable	Obs	Mean	Elementary School	Min.	Q (10)	Q (90)	Max.
NPL	225	0.032	0.025	0	0.010	0.058	0.223
Z	225	0.011	0.029	-0.037	-0.003	0.034	0.188
BUF	225	0. 267	0. 225	0.025	0.101	0.503	1,619
BUF2	225	0. 122	0. 269	0.0006	0.010	0.253	2,622
SIZE	225	17,747	1,656	14,595	15,894	19,828	21.61
CID	225	0.055	0.061	0.008	0.024	0.082	0.740
CIR	225	0. 921	0.335	0.417	0 .659	1,123	2,879
GDP	225	0.034	0.028	-0.0206	-0.021	0.053	0.053
INF	225	0.026	0.015	0.0157	0 .016	0.055	0.055

Source: Sata17 Data Processing 2026

Based on Table 3, this study used 45 publicly listed banks with a total of 225 observations during the 2020-2024 period. Descriptive statistics show that bank risk-taking, as proxied by NPL, averaged 3.2% with a standard deviation of 2.5%, indicating considerable variation in credit risk across banks. The minimum NPL value of 0% indicates banks with excellent credit quality, while the maximum value of 22.3% reflects high credit risk in some banks. The data distribution is also quite wide, with the 10th quantile at 1% and the 90th quantile at 5.8%, indicating heterogeneity in risk-taking across bank groups. Meanwhile, the Z variable, the inverse of the Z-score, averaged 1.1% with a standard deviation of 2.9%, indicating relatively high variation in bank stability. The minimum value of -3.7% and maximum of 17.4% indicate that the level of bank insolvency risk in the sample is quite varied. The distribution of NPLs and the inverse Z-score, which tend to be skewed to the right with a thick right tail, indicates that the distribution of risk-taking is asymmetric, thus supporting the use of a quantile approach to capture the heterogeneity of the risk distribution.

The capital buffer (BUF) has an average value of 26.7% with a standard deviation of 22.5%, indicating that the sample banks generally have relatively high levels of buffer capital, although with considerable variation. The minimum value of 2.5% indicates banks with limited buffer space, while the maximum value of 161.9% reflects very high capital accumulation in some banks. The 10th and 90th quantile values are 10.1% and 50.3%, respectively, indicating a fairly wide distribution of capital buffers across banks. The squared capital buffer variable (BUF^2) has an average of 12.2% with a standard deviation of 26.9%, indicating fairly strong nonlinear variation in the distribution of capital buffers and supporting the test of a nonlinear relationship between capital buffers and risk-taking.

The bank size (SIZE) variable, measured by the natural logarithm of total assets, has a mean value of 17.747 with a standard deviation of 1.656. The minimum value of 14.594 and the maximum value of 21.610 indicate a significant size difference between small and large banks in the sample. The market discipline (CID) variable has a mean value of 5.4% with a standard deviation of 6.0%, indicating a significant variation in the cost of funds across banks. The minimum value of 0.8% and the maximum value of 74.0% indicate that the market discipline pressures faced by banks vary widely. The cost efficiency (CIR) variable has a mean value of 92.0% with a standard deviation of 33.5%, indicating that bank operational efficiency remains relatively variable, with some banks exhibiting a significant level of inefficiency.

In terms of macroeconomic conditions, gross domestic product (GDP) growth averaged 3.4% with a standard deviation of 2.7%, while the inflation rate (INF) averaged 2.6% with a standard deviation of 1.5%. The minimum GDP value of -2.1% and the maximum of 5.3% indicate fluctuations in the economic cycle during the study period, primarily due to post-pandemic economic pressures. Meanwhile, relatively stable inflation indicates that macroeconomic conditions during the observation period tended to be under control. Overall, descriptive statistics show significant variation in both internal bank characteristics and external conditions, thus supporting the use of a panel quantile regression approach to capture the heterogeneity of the influence of capital buffers on bank risk-taking.

b. Inductive Analysis

1) Chow Test

The Chow test is used to determine the most appropriate estimation model between the Common Effect Model (CEM) and the Fixed Effect Model (FEM). If the probability value is greater than 0.05, the Common Effect Model is selected. Conversely, if the probability value is less than 0.05, the Fixed Effect Model is deemed more appropriate, and testing is continued with the Hausman test. Based on the results of data processing using Stata17, the following results were obtained.

Table 4 Results of the Chow Test of NPL Panel Data

sigma_u	.02185664
sigma_e	.01295238

rho	.74009265
F test that all u_i=0: F(44,173) = 11.81	Prob>F = 0.0000

Source: Sata17 Data Processing 2026

Table 5 Results of the Chow Panel Data Z Test

sigma_u	.03190718
sigma_e	.0214501
rho	.68873312
F test that all u_i=0: F(44,173) = 4.26	Prob > F = 0.0000

Source: Sata17 Data Processing 2026

The probability value is 0.0000 < 0.05, meaning the selected model is the Fixed Effect Model (FEM). Therefore, a Hausan test is necessary.

2) Hausman test

The Hausman test is used to select between a Fixed Effect Model and a Random Effect Model. If the probability is >0.05, the Fixed Effect Model is used, whereas if it is <0.05, the Random Effect Model is selected.

Table 6 Hausman NPL Test Results

Test Of H0: Difference in Coefficients not Systematic	
chi2(7) =	(bB)'[(V_b-V_B)^(-1)](bB)
=	22.48
Prob > chi2 =	0.0021

Source: Sata17 Data Processing 2026

Table 7 Hausman Z Test Results

Test Of H0: Difference in Coefficients not Systematic	
chi2(7) =	(bB)'[(V_b-V_B)^(-1)](bB)
=	59.65
Prob > chi2 =	0.0000

Source: Sata17 Data Processing 2026

Based on Table 000, the Hausman test shows a probability value of 0.0021 in the NPL equation and 0.0000 in the Z equation, both of which are less than 0.05. These results indicate that the Fixed Effect Model (FEM) is the most appropriate model to use.

3) Classical Assumption Test

a) Multicollinearity

To determine whether multicollinearity exists in a model, a decision guideline based on the VIF value can be used. If the VIF value is greater than 10, there is strong multicollinearity between the independent variables. The results of the multicollinearity test using VIF are presented in table 8.

Table 8 Results of VIF Multicollinearity Test

Variable	VIF	1/VIF
buff_c	9.45	0.105851
buff2	9.27	0.107921
circle	5.1	0.195979
info	4.39	0.228042
GDP	3.12	0.320873
cid	1.79	0.558999
size_c	1.76	0.567313
Mean VIF	4.98	

Source: Sata17 Data Processing 2026

The results of the multicollinearity test show a VIF value < 10, meaning there is no multicollinearity between the independent variables.

b) Heteroscedasticity

A heteroscedasticity test is performed to determine whether the residual variance is constant (homoscedasticity). If the p-value is significant at the 5% level, the model is indicated to have heteroscedasticity.

Table 9 Heteroscedasticity Test Results

Model	p-value	Conclusion
NPL & Z Panel Data	0.0000	There is heteroscedasticity

Source: Sata17 Data Processing 2026

c. Panel Data Regression Test

The panel data regression estimation results indicate that the Fixed Effect Model (FEM) is the most appropriate model based on the model selection test. Furthermore, ordinary least squares (OLS) regression estimation is performed as a comparison with the quantile regression approach.

Table 10 Results of Panel Data Fixed Effect OLS Regression

Fixed Effect

	NPL	Z
BUFF	-0.045**	-0.032
	(0.019)	(0.032)
BUFF2	0.047***	0.014
	(0.012)	(0.021)
SIZE	-0.0004	0.005
	(0.004)	(0.007)
CID	0.017	-0.018
	(0.019)	(0.032)
CIR	0.0005	-0.047***
	(0.004)	(0.007)
GDP	-0.119***	-0.068
	(0.045)	(0.073)
INF	0.006	-0.154
	(0.066)	(0.109)
R2	0.1968	0.2476
F-Statistic	6.06***	8.13***
Observation	224	225

Source: Sata17 Data Processing 2026

Based on Table 10 in the NPL equation, the capital buffer (BUF) has a negative and significant effect at the 5% level (β = -0.045), indicating that increasing the capital buffer tends to reduce bank risk-taking. Meanwhile, the squared coefficient of the capital buffer (BUF^2) has a positive and significant effect at the 1% level (β = 0.047), indicating a nonlinear U-shaped relationship between the capital buffer and risk-taking. This finding indicates that increasing the capital buffer at the initial stage can suppress credit risk, but after passing a certain threshold, the effect reverses, increasing risk-taking. In the inverse Z-score equation, the capital buffer (BUF) has a negative effect and BUF^2 has a positive effect, but both are insignificant, so the nonlinear pattern has not been proven strong on insolvency risk.

d. Hypothesis Testing

1) t-test

A t-test was conducted to examine the influence of each independent and control variable on risk-taking individually. The following are the t-test results:

Table 11 Results of the NPL t-Test

NPL	Coefficient	Std. err.	t	P>t	[95% conf.	interval]

BUF	-0.04506	0.019403	-2.32	0.021	-0.08335	-0.00676
BUF2	0.047266	0.01249	3.78	0	0.022614	0.071918
SIZE	-0.00043	0.004415	-0.1	0.923	-0.00914	0.008287
CID	0.016614	0.019526	0.85	0.396	-0.02193	0.055153
CIR	0.000466	0.004162	0.11	0.911	-0.00775	0.008681
INF	0.006898	0.065836	0.1	0.917	-0.12305	0.136843
GDP	-0.11943	0.044603	-2.68	0.008	-0.20747	-0.03139
_cons	0.028713	0.005069	5.66	0	0.018708	0.038717

Table 12 Results of the Z t-Test

Z	Coefficient	Std. err.	t	P>t	[95% conf.	Interval]
BUF	-0.03222	0.032132	-1	0.317	-0.09564	0.031201
BUF2	0.014182	0.020684	0.69	0.494	-0.02664	0.055009
SIZE	0.004725	0.007312	0.65	0.519	-0.00971	0.019157
CID	-0.01796	0.032336	-0.56	0.579	-0.08178	0.045868
CIR	-0.04732	0.006893	-6.87	0.000	-0.06092	-0.03372
INF	-0.15441	0.109029	-1.42	0.159	-0.36961	0.060786
GDP	-0.06835	0.073866	-0.93	0.356	-0.21414	0.077447
_cons	0.059946	0.008394	7.14	0.000	0.043377	0.076514

Based on Table 11, the results of the Fixed Effect Model regression show that the capital buffer (BUF) has a significant negative effect on risk-taking as proxied by NPL (coef. -0.045; sig. 0.021), while the squared capital buffer (BUF^2) has a significant positive effect (coef. 0.047; sig. 0.000). These results indicate a non-linear U-shaped relationship with a turning point of 0.479, thus H1 is accepted.

In the inverse Z-score model, the capital buffer and its square show coefficient directions consistent with a U-shaped pattern, but both are not statistically significant, so the non-linear relationship has not been proven strong in this proxy.

2) F test

The F test is used to test whether the independent variables jointly influence the dependent variable.

Table 13 Results of simultaneous test (F test) on NPL

Corr(u_i,x) = 0.0500	F(7,173) = 6.06
	Prob > F = 0.0000

Table 14 Results of simultaneous test (F test) on z

Corr(u_i, Xb) = -0.7353	F(7,173) = 8.13
	Prob > F = 0.0000

Based on Table 13 and Table 14, the Prob > F value of 0.0000 < 0.05 indicates that the capital buffer, bank-level control variables, and macroeconomic control variables simultaneously have a significant effect on risk-taking, both as proxied by NPL and inverse Z-score in public banks in Indonesia, so that the research model is declared suitable for use.

3) Coefficient of Determination (R2)

The coefficient of determination is used to measure the extent to which the independent variables in the model can explain the variation in the dependent variable (risk-taking). Based on the test results, the R-squared (within) value in the NPL model of 0.1552 indicates that the capital buffer, bank-level control variables, and macroeconomic control variables are able to explain 15.52% of the variation in risk-taking, while the remaining 84.48% is influenced by other factors outside the model. Meanwhile, the Z-score model obtained a value of 0.2473, which means that the variables in the model explain 24.73% of the variation in risk-taking, and the remaining 75.27% is influenced by other factors outside the study.

e. Quantile Regression Test

Quantile regression tests are used to analyze variations in the influence of capital buffers on risk-taking at various distribution levels. In this study, the Fixed Effect Model is used as the baseline with a two-step estimator approach. (Canay, 2011) .

Model equation

$$Q_r(RISK_{it}|X_{it}) = \alpha + \beta_{1\tau}BUF_{it} + \beta_{2\tau}BUF_{it}^2 + \gamma_\tau B_{it} + \theta_\tau M_t + \varepsilon_{\tau it}$$

This quantile regression equation is used to analyze the variation in the influence of capital buffer on risk-taking at various levels of risk distribution. The equation $Q_r(RISK_{it}|X_{it})$shows the quantile $\tau$of the quantile regression function; $RISK_{it}$is the risk-taking of bank i in year t; $BUF_{it}$is the capital buffer of the bank; $BUF_{it}^2$is the quadratic form of BUF_{it}; $B_{it}$is the set of bank-level control variables; $M_t$is the set of annual macroeconomic control variables, and $\varepsilon_{\tau it}$is the error. Following *the quantile regression literature*, this study sets six quantiles, namely τ= {0.1, 0.25, 0.5, 0.75, 0.8, 0.9} to determine the effect of covariates between the conditional distributions of bank *risk-taking*.

Table 15 Results of NPL Quantile Regression Test

NPL Dependent Variable						
	Quantile					
	0.1	0.25	0.50	0.75	0.80	0.90
buff_c	-0.063***	-0.039***	-0.048***	-0.039***	-0.039***	-0.025**
	0.021	0.011	0.009	0.013	0.013	0.011
buff2	0.055***	0.045***	0.047***	0.045***	0.048***	0.035***
	0.016	0.009	0.007	0.010	0.010	0.008
size_c	0.000	0.001	0.000	0.000	0.000	-0.001
	0.001	0.001	0.001	0.001	0.001	0.001
cid	-0.026	0.018	0.012	0.001	0.001	0.017
	0.026	0.014	0.011	0.016	0.016	0.013
circle	-0.012**	-0.003	-0.001	0.010***	0.013***	0.014***

	0.005	0.003	0.002	0.003	0.003	0.003
info	0.072	-0.007	-0.031	-0.020	-0.025	-0.045
	0.115	0.061	0.048	0.070	0.072	0.058
GDP	-0.092	-0.062*	-0.063**	-0.111***	-0.125***	-0.168***
	0.063	0.034	0.027	0.038	0.040	0.032
_cons	0.027	0.026	0.029	0.027	0.026	0.032
	0.006	0.003	0.003	0.004	0.004	0.003
Pseudo-R	0.139	0.118	0.121	0.213	0.244	0.340
Observation	225	225	225	225	225	225

Table 16 Results of the Z Quantile Regression Test

Dependent Variable Z						
	Quantile					
	0.1	0.25	0.50	0.75	0.80	0.90
buff_c	-0.036	-0.023*	-0.030***	-0.019**	-0.017	-0.020
	0.054	0.012	0.006	0.009	0.013	0.045
buff2	0.021	0.009	0.014***	0.007	0.005	0.010
	0.041	0.009	0.005	0.007	0.010	0.035
size_c	0.006*	0.006***	0.005***	0.005***	0.005***	0.004
	0.003	0.001	0.000	0.001	0.001	0.003
cid	-0.063	-0.023	-0.009	-0.013	-0.014	-0.022
	0.066	0.015	0.007	0.011	0.016	0.055
circle	-0.061***	-0.050***	-0.044***	-0.037***	-0.037***	-0.029***
	0.013	0.003	0.001	0.002	0.003	0.011
info	-0.068	-0.020	-0.005	-0.052	-0.036	-0.046
	0.292	0.065	0.033	0.050	0.072	0.244
GDP	-0.121	-0.079**	-0.076***	-0.080***	-0.098**	-0.162
	0.161	0.036	0.018	0.028	0.039	0.134
_cons	0.062	0.056	0.053	0.052	0.054	0.054
	0.016	0.004	0.002	0.003	0.004	0.013
Pseudo-R	0.5322	0.5681	0.5519	0.4517	0.419	0.304
Observation	225	225	225	225	225	225

Based on the quantile regression results in Table 15, the capital buffer (BUF) variable has a significant negative effect on risk-taking (NPL) at all tested percentiles (10, 25, 50, 75, 80, and 90), indicating that increasing the capital buffer will reduce bank credit risk. However, the magnitude of the effect varies across quantiles, with a stronger effect seen in banks in the lower tail than in the upper tail, indicating heterogeneity of influence. The squared capital buffer (BUF^2) variable is also significant with a negative sign at all percentiles, indicating a non-linear, U-shaped relationship between the capital buffer and risk-taking.

Table 19 Turning Point Capital buffer

Turning point *capital buffer*						
Quantile						
	0.1	0.25	0.5	0.75	0.8	0.9

NPL	0.56%	0.44%	0.52%	0.43%	0.40%	0.36%
Z	0.87%	1.24%	1.04%	1.44%	1.65%	1.06%

The turning point calculation results show a higher value at the lower quantile (0.56% at the 10th quantile) and a lower value at the higher quantile (0.36% at the 90th quantile), indicating that high-risk banks in the upper tail are more sensitive to changes in capital buffers than banks in the lower tail. This finding is consistent with Jiang et al., (2020) , who stated that there is a threshold at which an increase in capital buffers can reverse the direction of the effect on risk-taking. Differences in turning points at each quantile indicate variations in optimal CAR across bank groups. Banks in the upper tail (high-risk) have a lower turning point, so changes in risk-taking behavior can occur at a smaller capital buffer level than banks in the lower tail. This indicates that high-risk banks are more sensitive to changes in capital buffers.

f. Discussion

This study aims to examine the effect of capital buffers on risk-taking in publicly traded banks in Indonesia using a quantile regression approach. The results show that the capital buffer (BUF) has a negative and significant effect on risk-taking, while the squared capital buffer (BUF^2) has a positive and significant effect, indicating a non-linear U-shaped relationship. These findings support the first hypothesis and are consistent with Jiang et al. (2020) , who stated that at a certain level, capital buffers reduce risk-taking, but after exceeding the optimal point, they actually encourage increased risk-taking.

Theoretically, these results can be explained through Moral Hazard Theory, which states that at low capital buffer levels, banks tend to increase risk-taking due to regulatory pressures and the risk of failure. However, as capital buffers increase, these risks decrease, leading banks to become more conservative. After a certain point, increasing capital buffers actually encourages banks to take higher risks, as they perceive greater security and greater flexibility in seeking profits.

Furthermore, the quantile regression results indicate that the effect of capital buffers on risk-taking is heterogeneous across all levels of the risk distribution. The effect is stronger for low-risk banks (lower-tail) than for high-risk banks (upper-tail), thus the second hypothesis is also accepted. This finding indicates differences in bank sensitivity to changes in capital buffers, contradicting some findings by Jiang et al. (2020) who stated higher sensitivity for high-risk banks.

These differences can be explained by bank characteristics, where high-risk banks tend to be more subject to regulatory oversight, thus limiting their risk-taking behavior adjustments. Conversely, low-risk banks are more flexible in responding to changes in capital, thus exhibiting greater sensitivity. Furthermore, the study also shows that the turning point varies across quantiles, confirming that the inflection point of the capital buffer's influence is not constant. High-risk banks have a lower turning point than low-risk banks, resulting in more rapid changes in risk-taking behavior. In other words, a capital buffer level that is still effective in suppressing risk-taking in one group of banks may not have the same effect in another group. This finding confirms that the non-linear relationship between capital buffers and risk-taking is not only general but also varies according to the distribution of bank risk. These differences in turning points indicate that banks with different risk characteristics have varying rates of behavioral adjustment in response to capital changes.

Overall, these findings indicate that the relationship between capital buffers and risk-taking is not only non-linear but also heterogeneous across the risk distribution. This finding confirms that capital buffers are not an instrument that automatically and consistently reduces risk-taking. The effectiveness of capital buffers depends heavily on the level of capital held by banks and their risk position within the risk-taking distribution. Therefore, the quantile regression approach is better able to capture the dynamics of bank behavior than averaging approaches such as OLS, as it provides a more comprehensive picture of the variation in bank responses to different levels of risk. Therefore, quantile regression is more appropriate for explaining the dynamics of bank risk-taking behavior, which is complex, asymmetric, and varies across risk groups.

4. CONCLUSION

Based on the data analysis and discussion, it can be concluded that the capital buffer has a negative and significant effect on risk-taking, as proxied by NPL, meaning that the higher the capital buffer, the lower the risk-taking. However, the square of the capital buffer shows a positive and significant effect, indicating a nonlinear U-shaped relationship, where after a certain point, an increase in the capital buffer can actually increase risk-taking. Meanwhile, the inverse Z-score proxy shows an insignificant effect of the capital buffer, making its influence more consistent in explaining credit risk than insolvency risk.

The quantile regression results also show that the effect of capital buffers is heterogeneous across risk distribution levels, with a stronger effect on reducing risk-taking for low-risk banks than for high-risk banks. Furthermore, the lower turning point value for high-risk banks indicates that this group is more sensitive to changes in capital buffers. Overall, these findings confirm that the relationship between capital buffers and risk-taking is not linear, and capital policy cannot be applied uniformly across banks.

For future research, it is recommended to use a broader measure of risk-taking and add variables such as governance and ownership structure for more comprehensive analysis. For regulators and banks, these results demonstrate the importance of establishing optimal capital buffers based on each bank's risk profile to avoid potential moral hazard and maintain financial system stability.

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