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Google Trends Crisis Sentiment and Bank-Specific Conditions in Indonesian Deposit Dynamics

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Abstract

Background: Depositor confidence can respond rapidly to crisis-related information, while bank-specific conditions shape banks' capacity to retain funding. Digital search behavior provides a timely proxy for public attention that is not captured by conventional bank fundamentals alone.
Objective: This study examines whether Google Trends crisis sentiment and bank-specific conditions are associated with bank deposits in Indonesia and whether internal bank conditions moderate the relationship between digital sentiment and deposits.
Methods: A quantitative explanatory panel design uses quarterly observations from 35 publicly listed Indonesian banks over 2018–2023, yielding 840 bank-quarter observations. Six panel regression specifications were estimated using the Random Effects Model after panel-model selection tests. Google Trends indices for "financial crisis," "bank liquidation," and "failed bank" were combined with Net Interest Margin, Equity Ratio, Return on Assets, Cost to Income Ratio, and bank size.
Results: Crisis-related search intensity is negatively associated with deposits in several specifications, particularly for "financial crisis" and "failed bank." Bank size and Return on Assets are consistently positive, whereas Net Interest Margin and Equity Ratio are negative in several models. Selected interaction terms are significant, indicating that internal bank conditions can alter the deposit response to digital crisis sentiment.
Conclusion: The findings identify digital search intensity as a complementary behavioral signal for deposit dynamics and show that its effect depends partly on bank-specific conditions. The study contributes by integrating real-time crisis attention with bank fundamentals in a multi-model Indonesian panel setting, extending depositor-behavior analysis beyond either digital sentiment or internal financial ratios considered separately.

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INTRODUCTION

The COVID-19 pandemic exposed a dual response in depositor behavior: flight to liquidity through precautionary withdrawals and flight to quality through movement toward perceived safer banks or deposit instruments (Levine et al., 2021; Tran, 2022). Economic uncertainty and information asymmetry can weaken confidence in bank liquidity and reproduce mechanisms associated with bank runs (Duan et al., 2021; Wang et al., 2025). Beloglavec and Šebjan (2015) and Broekhoff (2024) similarly show that trust in financial institutions deteriorates during economic turmoil. In Indonesia, post-pandemic banking stability therefore cannot be evaluated solely through aggregate intermediation indicators; deposit growth, liquidity conditions, and the credibility of deposit protection remain jointly relevant to depositor confidence. This context makes it important to examine not only bank fundamentals but also fast-moving public attention that may precede changes in deposit behavior.

For regulators and banks, the post-pandemic problem is increasingly informational: financial conditions may remain sound while crisis narratives circulate rapidly through digital channels. Google Trends provides a standardized measure of relative search attention and can therefore complement conventional indicators by capturing when public concern intensifies around terms associated with banking distress.

The development of digital technology has changed the way people respond to various economic issues, including the financial crisis. One indicator that can now be used to measure public sentiment is Google Trends data that can record the volume of keyword searches related to issues in real time. As in the research of Mavragani and Gkillas (2020) and Habibdoust (2024), it provides evidence that the use of Google Trends to analyze public questions during the pandemic allows forecasts of people's behavior and conditions in response to the ongoing crisis. Furthermore, a study by Maddodi and Kunte (2024) specifically examined the implications of public research during COVID-19 on stock market predictions and concluded that spikes in interest related to stock market trends are associated with significant market movements. In addition, with the help of Google Trends in analyzing sentiments from various data sources can provide a broader picture of public feelings during the pandemic that reflects broader economic concerns and behaviors during important periods (Rathke et al., 2023). Therefore, researchers used the keywords “failed bank” “financial crisis” and “bank liquidation” as sentiments used to measure depositor fear.

Google Trends is a publicly available online tool developed by Google that collects and normalizes search query data from its search engine to provide an index of relative popularity in different geographic regions over time. According to Rech (2007) and Ullah (2026) the method underlying Google Trends involves adjusting the overall number of searches, locations and languages and sampling from many search queries sent by the Google Search engine.

Apart from sentiment using Google Trends, bank-specific internal factors such as Net Interest Margin (NIM) described by Hidayat et al. (2024) conveyed that the banking industry in Indonesia experienced considerable NIM fluctuations during the pandemic, which indicates that banks could manage their assets effectively. Banks with higher NIM are in a better position to offer competitive deposit rates during periods of uncertainty, this relationship illustrates that maximizing effective interest income management against costs can increase deposits, especially when banks face external pressures such as COVID-19. Another bank-specific factor explained in the research of Fecht et al. (2019) and Tümmler (2022) mentions that the German banking system explicitly controls the Equity Ratio as one of the key variables in deposit flow analysis. This study found that banks with a higher Equity Ratio (or better capitalized) tend to experience lower deposit outflows when there are concerns about bank stability. Furthermore, research by Fecht, Thum and Weber (2019) also and Tümmler (2022) highlighted that Equity Ratio is one of the factors used by depositors in assessing bank risk.

Behavioral finance explains how attention, perceived risk, and loss aversion shape financial decisions under uncertainty (Ranjan, 2025). In banking, trust and satisfaction influence loyalty and withdrawal behavior (Naatu et al., 2025; Narteh & Owusu-Frimpong, 2011). Digital search activity adds a real-time behavioral signal: Saputro et al. (2024) show that Google Trends can capture public concern about banking crises, allowing shifts in attention to be examined alongside observed deposit behavior.

The deposit in this study is the context of third-party funds, which are deposits placed by the public in banks, both individually and as business entities. Law No. 10 of 1998 concerning banking defines a bank as a business entity that collects funds from the public in the form of deposits and distributes them to the public. Werner (2016) and Egan et al. (2022) also emphasizes that savings are very important because they are a stable source of funding that banks convert into loans, effectively connecting savers with borrowers. High savings rates enable banks to extend more loans, thereby encouraging business expansion and stimulating economic growth (Egan et al., 2017, 2022).

Google Trends is a publicly available online tool developed by Google that collects and normalizes search query data from its search engine to provide a relative popularity index across different geographic regions over time (Priyarsono & Laelia, 2023). Academics are very interested in using Google Trends data as a theoretical tool to assess financial performance. Experts argue that internet search volume reflects investor sentiment and attention in real-time proxies for measuring market behavior and performance (Choi & Varian, 2012; Preis et al., 2013; Wu et al., 2023).

Bank-specific factors are factors that are unique or relevant to banking activities and performance and are not found in other industries. These factors provide a framework for assessing how well banks can manage their resources, generate income, and maintain their operations through effective risk-adjusted strategies. By influencing key operating results, these factors ultimately determine the ability of banks to do what they want to do to become exceptional banks. By influencing key operational outcomes, these factors ultimately determine a bank's ability to do what it takes to become an exceptional bank (Sinay et al., 2022).

However, this study focuses on Net Interest Margin (NIM) and Equity Ratio (ER), because NIM plays an important role in influencing the volume and stability of bank deposits. A higher NIM indicates that banks are effectively generating income from interest-bearing assets compared to their costs, in line with the research presented by Gounder and Sharma (2012) and Chand (2026) which states that when banks have a higher NIM, they can offer competitive interest rates to attract more deposits and maintain profitability.

In addition, the Equity Ratio has very important implications for attracting and retaining deposits. This is supported by research by Khawatida et al. (2024), which states that a higher Equity Ratio generally indicates greater stability and strength of the bank. Banks with a strong equity position are considered less risky, thereby increasing depositor confidence.

Previous studies address different parts of the depositor-confidence mechanism but rarely integrate them. Saputro et al. (2024) show that Google Trends can capture depositor fears and bank-related public attention in Indonesia. Fecht, Thum, and Weber (2019) and Tümmler, (2022) demonstrate that bank capitalization influences deposit reallocation under stability concerns, while Levine et al. (2021) and Tran, (2022) document heterogeneous depositor responses during COVID-19. These studies establish the relevance of digital attention, bank-specific resilience, and crisis behavior, respectively; however, none jointly tests whether crisis-related Google Trends signals interact with Net Interest Margin and Equity Ratio in explaining Indonesian bank deposits across the 2018–2023 period.

The study offers three forms of benefit. Theoretically, it extends depositor-behavior research by connecting digital attention with bank-specific conditions in a single explanatory framework. Practically, the findings can help bank management identify when public concern may require liquidity, communication, or depositor-retention responses. For OJK, Bank Indonesia, and LPS, the results indicate that search-based attention measures may serve as complementary early-warning information alongside prudential, liquidity, and deposit-insurance monitoring rather than as substitutes for official indicators.

The research gap is therefore interactional rather than merely descriptive. The novelty of this study lies in testing whether a real-time behavioral signal of crisis attention changes its association with deposits depending on bank-specific financial conditions, using three crisis-related search terms and six panel specifications. This design links behavioral finance and information-asymmetry arguments with observable bank fundamentals and allows digital sentiment to be interpreted as a conditional, rather than stand-alone, driver of deposit dynamics.

METHOD

This study employed a quantitative explanatory research design using quarterly panel data to test the relationship between Google Trends crisis sentiment, bank-specific conditions, and bank deposits in Indonesia. The population comprised Indonesian banks that were publicly listed before the observation period. Purposive sampling was applied to retain banks with continuous quarterly data for 2018–2023 and to exclude banks that merged or changed identity during the study period; 35 banks met these criteria, producing 840 bank-quarter observations. The dependent variable was bank deposits (third-party funds). The focal explanatory variables were Google Trends indices for "financial crisis," "bank liquidation," and "failed bank," together with Net Interest Margin (NIM) and Equity Ratio (ER). Return on Assets (ROA), Cost to Income Ratio (CIR), and total assets are included as control variables.

Model selection followed standard panel-data logic. The Chow test evaluates pooled versus fixed effects, the Hausman test evaluates fixed versus random effects, and the Lagrange Multiplier test evaluates pooled versus random effects. The combined test results supported the Random Effects Model for the final specifications. This approach accommodates unobserved bank-level heterogeneity while estimating the association of time-varying search attention and bank characteristics with deposits.

The measurement instruments were source-specific. Google Trends supplied normalized relative search-interest indices for the three crisis terms using a consistent geography and quarterly time aggregation. Bank deposits and financial ratios were obtained from OJK/Indonesian Banking Statistics, bank financial statements, and S&P Capital IQ. Microsoft Excel was used for initial data cleaning and matching, while Stata 17 was used for panel estimation. Data collection proceeded by downloading each source series, standardizing bank identifiers and quarter labels, checking missing and duplicate observations, matching the digital-search series to each bank-quarter record by period, and constructing a balanced analytical panel for the eligible banks.

$$Y_{i,t}\beta_1\text{krisiskeu}_{i,t} + \beta_2\text{SpesifikbankNIM}_{i,t} + \beta_3\text{Control}_{i,t} + \beta_4(\text{krisiskeu}_{i,t}x\ \text{Spesific}bankNIM_{i,t})\text{lnDeposit\_it} = \alpha + \beta 1\ \text{FinancialCrisis\_t} + \beta 2\ \text{NIM\_it} + \beta 3(\text{FinancialCrisis\_t} \times \text{NIM\_it}) + \gamma\text{Controls\_it} + \text{u\_i} + \varepsilon\text{\_it} \quad (1)$$

$$Y_{i,t}\beta_1 krisiskeu_{i,t} + \beta_2 SpesifikbankER_{i,t} + \beta_3 Control_{i,t} + \beta_4(krisiskeu_{i,t}x\ SpesificbankER_{i,t})lnDeposit\_it = \alpha + \beta 1\ BankLiquidation\_t + \beta 2\ NIM\_it + \beta 3(BankLiquidation\_t \times NIM\_it) + \gamma Controls\_it + u\_i + \varepsilon\_it \quad (2)$$

$$Y_{i,t}\beta_1 likuibank_{,t} + \beta_2 SpesifikbankNIM_{i,t} + \beta_3 Control_{i,t} + \beta_4(likuibank_{i,t}x\ SpesificbankNIM_{i,t})lnDeposit\_it = \alpha + \beta 1\ FailedBank\_t + \beta 2\ NIM\_it + \beta 3(FailedBank\_t \times NIM\_it) + \gamma Controls\_it + u\_i + \varepsilon\_it \quad (3)$$

$$Y_{i,t}\beta_1 likuibank_{,t} + \beta_2 SpesifikbankER_{i,t} + \beta_3 Control_{i,t} + \beta_4(likuibank_{i,t}x\ SpesificbankER_{i,t})\text{lnDeposit\_it} = \alpha + \beta 1\ \text{FinancialCrisis\_t} + \beta 2\ \text{ER\_it} + \beta 3(\text{FinancialCrisis\_t} \times \text{ER\_it}) + \gamma\text{Controls\_it} + \text{u\_i} + \varepsilon\text{\_it} \quad (4)$$

$$Y_{i,t}\beta_1 gagalbank_{,t} + \beta_2 SpesifikbankNIM_{i,t} + \beta_3 Control_{i,t} + \beta_4(gagalbank_{i,t}x\ SpesificbankNIM_{i,t})lnDeposit\_it = \alpha + \beta 1\ BankLiquidation\_t + \beta 2\ ER\_it + \beta 3(BankLiquidation\_t \times ER\_it) + \gamma Controls\_it + u\_i + \varepsilon\_it \quad (5)$$

$$Y_{i,t}\beta_1 gagalbank_{,t} + \beta_2 SpesifikbankER_{i,t} + \beta_3 Control_{i,t} + \beta_4(gagalbank_{i,t}x\ SpesificbankER_{i,t})lnDeposit\_it = \alpha + \beta 1\ FailedBank\_t + \beta 2\ ER\_it + \beta 3(FailedBank\_t \times ER\_it) + \gamma Controls\_it + u\_i + \varepsilon\_it \quad (6)$$

Before estimation, panel-model specification tests were conducted to determine the appropriate estimator. The Chow, Hausman, and Lagrange Multiplier tests were interpreted jointly to distinguish pooled, fixed-effects, and random-effects specifications. Diagnostic checks were then used to assess whether the selected estimator was suitable for inference. Based on these tests, the Random Effects Model was used for the six regression specifications reported below.

Research conducted by Saputro et al. (2024) further strengthened the predictive ability of Google Trends data related to bank deposits. The study found a link between the search term "financial crisis" on Google and depositor behavior, suggesting that increased search activity around economic instability may increase depositor fear and influence their decision to withdraw or reduce deposits (Saputro et al., 2024). Their research contributes empirical evidence to the idea that consumer behavior can be analyzed in advance through digital search patterns, reflecting real-time sentiments that could potentially guide banking activities.

H1a: There is a relationship between Google Trends with the keyword "financial crisis" and bank deposits in Indonesia.

Research conducted by Hanson et al. (2024) provides insight into how the popularity of search queries about bank stability correlates with observable shifts in deposit behavior, aligning with the psychology behind consumer fears and responses to financial uncertainty. This highlights the capacity of Google Trends to effectively portray consumer sentiment and predict deposit outflows amid concerns over banking issues, including liquidation.

H1b: There is a relationship between Google Trends with the keyword “bank liquidation” and bank deposits in Indonesia.

In a financial crisis, media coverage and public discourse about bank failures may exacerbate depositor anxiety. Although specific references to how panic affects depositor behavior are not supported by Venugopal (2023), (as their study focuses more on systematic factors regarding large banks), the link between public sentiment and financial instability is well documented in the broader literature and supports the discussion here (Venugopal, 2023). This reflects a self-reinforcing cycle where news of bank failures prompts immediate and protective financial actions from consumers. H1c: There is a relationship between Google Trends with the keyword “bank failure” and bank deposits in Indonesia.

A solid NIM is essential for sustainable growth within the bank. Emphasize that banks with consistent NIM growth can better position themselves to invest in profitable opportunities and increase their operational capacity, while simultaneously ensuring the financial health of depositors (Chand et al., 2026; Gounder & Sharma, 2012). This synergistic relationship facilitates long-term deposit retention and growth.

H2a: there is a relationship between bank-specific factors (Net Interest Margin) and bank deposits in Indonesia.

In addition, Khatib et al. (2023) illustrate the positive impact of a good Equity Ratio on return on equity, which correlates with deposit growth, because banks that are considered stable are more likely to attract resources. The importance of the Equity Ratio goes beyond profitability. This is supported by research by Rida et al. (2026), which notes that economic factors such as inflation and interest rates can directly affect the Equity Ratio, which is significant in attracting depositors to make deposits. H2b shows the relationship between bank-specific factors (Equity Ratio) and bank deposits in Indonesia.

The study in Sudrajat and Sumiyati (2019) and Abu Al-Haija et al., (Abu Al-Haija et al., 2026) indicates that consumer interest assessed through Google Trends metrics can be linked to banks' ability to attract deposits. They showed that consumer behavior indicators often precede changes in banking conditions, which suggests that banks with positive online sentiment may experience higher deposit growth. Furthermore, research by Kunwar and Jnawali (2023) also indicated that bank-specific factors, including Equity Ratio and NIM, significantly affect banks' total profitability, which in turn impacts deposit levels. Their empirical results from Nepalese banks illustrate that better capital adequacy (i.e. higher Equity Ratio) correlates with higher Net Interest Margin, which is related to the attractiveness of banks to depositors.

H3a there is an interaction relationship between Google Trends and keywords (financial crisis, bank liquidation and failed bank) on bank deposits in Indonesia.

RESULTS AND DISCUSSION

Result

Researchers conducted a Chow test to indicate if the model that fits the research is the Fixed Effect Model or the Common Effect Model. The test results on the research model showed a p-value of 0.0000 which indicated that the researcher rejected H0, so the model used was the Fixed Effect Model (FEM). Researchers conducted the Hausman test to indicate if the model that fits the research is the Random Effect Model or the Fixed Effect Model. The test results of the research model showed a p-value of 0.9996 which indicated that the researcher rejected H0, so the model used was the Fixed Effect Model (FEM). Researchers conducted a Chow test to indicate if the model that fits the research is the Random Effect Model or the Common Effect Model. The test results on the research model showed a p-value of 0.0000 which indicated that the researcher accepted H0, so the model used was the Common Effect Model (CEM).

The results of the three tests conducted show that the most appropriate estimation method is the Random Effects Model, so this study uses the Random Effects Model in running the regression. Furthermore, researchers ran 3 classic assumption tests, namely the heteroscedicity, multicollinearity and autocorrelation tests with the results indicating heteroscedicity problems but no autocorrelation and multicollinearity problems. The sixth estimation model used in this research is the Random Effects Model. This test wants to see the effect of independent and control variables on the dependent variable, where there is this study is the volume of deposits (deposits) represented by the notation Y. The following are the results of the study:

Table 1

Regression Test Results Model 1

Obs	840		
R-Square Within	0.8376		
lndeposit	Coef.	Robust Std. Error	P>| z |
Lnkrisis	-0.0322	0.00629	0.000*
Nim	-0.02849	0.008765	0.001*
Cir	-5.89E-06	2.06E-05	0.775
Lnttalasset	1.039576	0.013328	0.000*
ROA	0.007953	0.00148	0.000*
Lnkrisisxnim	0.003329	0.001328	0.012*

Source: Processed by the researcher

The table above is the regression result using the Random Effects Model method with this study using 840 observation s from 35 banks and is able to explain about 83.7% of the variation in deposits, based on the R-squared within value of 0.8376. This model is very good in capturing the dynamics of third party fund collection in Indonesian banking. From the analysis, the keyword financial crisis (lnkrisis) significantly has a negative impact on deposits, where each one-unit increase in the crisis variable will reduce log deposits by 0.0322. This finding is consistent with theory and the results of previous studies which state that financial crisis keywords generally reduce public confidence in banks, resulting in a decrease in third party funds. The Net Interest Margin (nim) variable also shows a negative and significant effect, where a one-unit increase in NIM decreases log deposits by 0.0082. This negative effect indicates that an increase in interest margin is not always followed by an increase in third party funds, possibly because customers are more sensitive to risk or other factors outside of interest rates.

Control variables such as Cost to Income Ratio (cir) which reflects the operational efficiency of banks also have a negative and significant effect. Every one unit increase in CIR (decreasing efficiency) will decrease log deposits by 0.0035. Low efficiency makes banks less attractive to depositors, as it indicates suboptimal operational management. Likewise, the Log Total Assets variable (lnttlasset) is the variable with the strongest and highly significant effect. Every one unit increase in log total assets will increase log deposits by 0.9396. This confirms that larger banks in terms of assets tend to be able to collect more third party funds, as bank size is often an indicator of trust and stability for customers. Return on Assetss (ROA) also has a positive and significant effect. Each increase of one unit of ROA will increase log deposits by 0.0832. High profitability increases public confidence to place funds in the bank. The interaction variable Lnkrisisxnim shows a positive coefficient of 0.003329 and is significant at the 5% level. The positive coefficient of 0.003329 also indicates that this moderating effect significantly weakens the negative effect of the independent variables (lnkrisis and nim) on the deposit variable (lndeposit).

Table 2

Regression Test Results Model 2

Obs	840		
R-Square Within	0.8483		
lndeposit	Coef.	Robust Std. Error	P >| z |
Lnkrisis	-0.00631	0.004915	0.199
Equity Ratio	-1.66676	0.195573	0.000*
Cir	-2.3E-05	1.43E-05	0.106

Obs	840		
Lnttalasset	0.971594	0.00984	0.000*
ROA	0.008812	0.001031	0.000*
Lnkrisisxer	0.035256	0.028435	0.215

Source: Processed by the researcher

The regression model uses 840 observations from 35 banks and can explain about 84.8% of the overall variation in deposits, based on the overall R-squared value of 0.8483. The analysis shows that bank size (log total assets/lnttlasset) and profitability (ROA) have a positive and significant effect on deposits. Each one-unit increase in log total assets increases log deposits by 0.9716, while a one-unit increase in ROA increases log deposits by 0.0888. This finding confirms that larger and more profitable banks tend to be able to collect more deposits, as size and profitability are often indicators of trust and stability for customers. On the other hand, Equity Ratio has a negative and highly significant effect, where every one unit increase in Equity Ratio decreases log deposits by 1.6668. This may reflect a trade off between funding from equity and third party funds, or a more conservative bank preference in raising funds. Furthermore, the variables of lnkrisis and Cost to Income Ratio have a negative and insignificant effect. The interaction variable Lnkrisisxer shows a positive coefficient of 0.035256 and is not significant at the 5% level. The positive coefficient of 0.035256 also indicates that this moderating effect weakens the insignificant negative effect of the independent variables (lnkrisis and Equity Ratio) on the deposit variable (lndeposit).

Table 3

Regression Test Results Model 3

Obs	840		
R-Square Within	0.8388		
lndeposit	Coef.	Robust Std. Error	P >| z |
Lnlikuidasi	-0.01868	0.005451	0.001*
NIM	-0.01342	0.007774	0.084
Cir	-3.12E-06	2.08E-05	0.881
Lnttalasset	1.026703	0.012544	0.000*
ROA	0.008892	0.00148	0.000*
Lnlikuidasixnim	0.001179	0.001197	0.324

Source: processed by the researcher

This regression model uses 840 observations from 35 banks and can explain about 83.9% of the overall deposit variable, based on the R-squared value of 0.8388. The analysis shows that bank size (log total assets/ lnttlasset) and profitability (ROA) have a positive and highly significant effect on deposits. Each one-unit increase in log total assets increases log deposits by 1.0267, while a one-unit increase in ROA increases log deposits by 0.0089. This finding confirms that larger and more profitable banks tend to be able to collect more deposits, as size and profitability are often indicators of trust and stability for customers. On the other hand, the keyword bank liquidation (lnlikiudasi) has a negative and significant effect at the 5% level, where every one unit increase in the liquidation variable will decrease log deposits by 0.0187. This indicates that bank liquidation events markedly reduce public confidence in banks and result in a decline in deposits. Net Interest Margin (NIM) also shows a negative and insignificant effect where every one unit increase in NIM tends to decrease log deposits by 0.0134. This negative effect may indicate that an increase in interest margin is not always followed by an increase in third party funds, possibly because customers are more sensitive to risk or other factors outside the interest rate. Variables such as operational efficiency do not show a significant effect on deposits. The interaction variable Lnlikuidasixnim shows a positive coefficient of 0.001179 and is not significant at the 5% level. The positive coefficient of 0.001179 also indicates that this moderating effect weakens the insignificant negative effect of the independent variables (lnlikuidasi and nim) on the deposit variable (lndeposit).

Table 4
Regression Test Results Model 4

Obs	840		
R-Square Within	0.8482		
lndeposit	Coef.	Robust Std. Error	P >| z |
Lnlikuidasi	-0.00658	0.004411	0.136
Equity Ratio	-1.60466	0.173771	0.000*
Cir	-2.3E-05	1.43E-05	0.109
Lnttalasset	0.975035	0.008932	0.000*
ROA	0.00879	0.00102	0.000*
Lnlikuidasixer	0.026872	0.02485	0.28

Source: processed by the researcher

The regression model uses 840 observations from 35 banks and can explain about 84.8% of the overall variation in deposits, based on the overall R-squared value of 0.8482. The analysis shows that bank size (log total assets/lnttlasset) and profitability (ROA) have a positive and highly significant effect on deposits. Each one-unit increase in log total assets increases log deposits by 0.9705, while a one-unit increase in ROA increases log deposits by 0.0088. This finding confirms that larger banks tend to be able to collect more deposits, as size and profitability are often indicators of trust for customers. On the other hand, Equity Ratio has a negative and highly significant effect, where every one unit increase in Equity Ratio decreases log deposits by 1.6047. This reflects the trade-off between funding from equity and third party funds. Furthermore, variables such as bank liquidation and Cost to Income Ratio do not show a significant effect on deposits. Other variables such as bank liquidation (lnlikiudasi) and operational efficiency (CIR) do not show a significant effect on deposits. Thus, the keywords bank liquidation, Cost to Income Ratio (CIR), and the interaction of liquidation with Equity Ratio are not proven to be the main determinants in attracting third party funds. The interaction variable Lnlikuidasixer shows a positive coefficient of 0.026872 and is not significant at the 5% level. The positive coefficient of 0.026872 also indicates that this moderating effect weakens the insignificant negative effect of the independent variables (liquidation and Equity Ratio) on the deposit variable (lndeposit).

Table 5
Regression Test Results Model 5

Obs	840		
R-Square Within	0.8388		
lndeposit	Coef.	Robust Std. Error	P >| z |
Lngagal	-0.02822	0.00514	0.000*
NIM	-0.02573	0.007371	0.000*
Cir	-1.7E-05	2.07E-05	0.426
Lnttalasset	1.044101	0.013622	0.000*
ROA	0.008078	0.001474	0.000*
Lngagalxnim	0.003059	0.00111	0.006

Source: processed by the researcher

The regression model uses 840 observations from 35 banks and can explain about 83.9% of the overall variation in deposits, based on the overall R-squared value of 0.8388. The analysis shows that bank size (log total assets/lnttlasset) and profitability (ROA) have a positive and highly significant effect on deposits. Each one-unit increase in log total assets increases log deposits by 1.0440, while a one-unit increase in ROA increases log deposits by 0.0088. This finding confirms that larger and more profitable banks tend to be able to collect more deposits, as size and profitability are often indicators of trust and stability for customers. On the other hand, the keywords bank failure, Net Interest Margin (NIM), and operational efficiency (CIR) have a negative and significant effect on deposits. Each one-unit increase in the bank failure variable decreases log deposits by 0.0282, each one-unit increase in NIM decreases log deposits by 0.0257, and each one-unit increase in CIR decreases log deposits by 0.0002. This negative effect indicates that bank failure events, increased interest margins, and low operational efficiency can reduce public confidence to deposit funds in banks. The interaction variable Lngagalxnim shows a positive coefficient of 0.003059 and is significant at the 5% level. The positive coefficient of 0.003059 also indicates that this moderating effect significantly weakens the negative effect of the independent variables (lngagal and nim) on the deposit variable (lndeposit).

Table 6
Regression Test Results Model 6

Obs	840		
R-Square Within	0.8486		
lndeposit	Coef.	Robust Std. Error	P >| z |
Lngagal	-0.00509	0.004205	0.227
Equity Ratio	-1.81574	0.18125	0.000*
Cir	-2.4E-05	1.43E-05	0.088
Lnttalasset	0.958867	0.010259	0.000*
ROA	0.009037	0.001024	0.000*
Lngagalxer	0.05067	0.024893	0.042*

Source: processed by the researcher

Discussion

The regression model uses 840 observations from 35 banks and is able to explain about 84.9% of the overall variation in deposits, based on the overall R-squared value of 0.8486. The analysis shows that bank size (log total assets/ lnttlasset) and profitability (ROA) have a positive and highly significant effect on deposits. Each one-unit increase in log total assets increases log deposits by 0.9589, while a one-unit increase in ROA increases log deposits by 0.0094. This finding confirms that larger and more profitable banks tend to be able to collect more deposits, as size and profitability are often indicators of trust and stability for customers.

On the other hand, Equity Ratio has a negative and highly significant effect, where every one unit increase in Equity Ratio decreases log deposits by 1.8157. This reflects a trade-off between funding from equity and third party funds, or a more conservative bank preference in raising funds. Furthermore, the Cost to Income Ratio (CIR) variable shows a negative effect that is close to significant at the 10% level, where every one unit increase in CIR (decreasing efficiency) will decrease log deposits by 0.00024. Low efficiency makes banks less attractive to depositors, although the effect is relatively small. Furthermore, the variable with the keyword lngagal does not show a significant effect. Furthermore, the variable with the keyword lngagal does not show a significant effect. The interaction variable Lngagalxer shows a positive coefficient of 0.05067 and is significant at the 5% level. The positive coefficient of 0.05067 also indicates that this moderating effect weakens the insignificant negative effect of the independent variables (lngagal and Equity Ratio) on the deposit variable (lndeposit).

Across the six models, the results reveal a consistent three-part pattern. First, crisis-related Google Trends variables are negatively associated with deposits in several specifications, indicating that heightened public attention to financial distress can coincide with weaker deposit accumulation. Second, bank size and ROA show the most stable positive associations with deposits, suggesting that scale and profitability remain important confidence signals. Third, NIM and Equity Ratio are negative in several specifications, while selected interaction terms are significant. The interaction results indicate that digital crisis sentiment is not independent of bank conditions: its association with deposits changes according to the internal financial position of the bank.

In some models that include interactions between digital sentiment keywords and internal bank factors, such as the interaction of the keyword “financial crisis” with NIM in Model 1 and the interaction of the keyword “failed bank” with NIM in Model 5, the results are significant. This indicates that internal bank conditions, especially Net Interest Margin (NIM), can strengthen or weaken the impact of public sentiment on the dependent variable. Meanwhile, in models that include Equity Ratio (capital to asset ratio), this variable is always significant, confirming the importance of bank capital in maintaining stability or customer confidence. However, the interaction between the digital sentiment keyword and Equity Ratio is only significant in Model 6 (interaction of "failed bank" with Equity Ratio), suggesting that under certain conditions, the level of bank capital may moderate the impact of negative sentiment towards banks. Overall, the results of this analysis confirm that both internal bank factors (such as NIM, total assets, ROA, and Equity Ratio) and the digital sentiment of the public (as reflected by the search volume of certain keywords) play an important role in influencing the dependent variable of the study. The results of this analysis reinforce the importance of considering the dynamics of public behavior as seen from digital data, in addition to internal bank financial factors, in the analysis of banking deposit stability or behavior. The results of this study also reinforce the principles of behavioral finance in the context of banking depositor behavior in Indonesia. This is relevant to Saif-Alyousfi (2024) research where banks must understand consumer psychology amid economic change. Then with the results of negative digital sentiment having a significant effect on this study, it reflects the emotion of fear (fear behavior) dominating the financial decisions of depositors in situations of economic change or crisis.

The negative digital-sentiment results are consistent with Saputro et al. (2024), who show that Google Trends can capture depositor fears in Indonesia, and with Levine et al. (2021) and Tran (2022), who document depositor responses to crisis conditions. The findings also fit behavioral-finance and information-asymmetry arguments: when depositors face incomplete information about bank resilience, search activity can reflect heightened attention and loss aversion, increasing sensitivity to adverse signals. However, the negative NIM and Equity Ratio coefficients in several models differ from a simple signaling expectation that stronger margins or capitalization should uniformly attract deposits. One interpretation is that the deposit response reflects funding-structure trade-offs and heterogeneous bank strategies rather than a direct confidence effect alone.

The practical implication is differentiated by stakeholder. Bank management can incorporate crisis-related search intensity into liquidity and communication monitoring, especially when internal indicators suggest greater sensitivity to deposit outflows. OJK and Bank Indonesia can treat digital attention as a complementary high-frequency signal alongside prudential and liquidity indicators. LPS can use similar signals to inform depositor-communication and confidence-monitoring strategies, while recognizing that search data measure attention rather than verified solvency risk.

The significant interaction terms deepen this interpretation. They indicate that crisis attention operates conditionally: identical increases in search intensity need not produce the same deposit response across banks with different NIM or Equity Ratio profiles. This conditional effect links digital-finance evidence to bank-run theory by showing how public attention can interact with balance-sheet characteristics before or during perceived stress.

In addition, this study shows that bank-specific factors such as Net Interest Margin (NIM) and Equity Ratio in some models have a negative effect on deposits (H2a and H2b), which is contrary to the initial hypothesis that internal bank performance will increase depositor confidence. Analysis of the interaction between digital sentiment and bank-specific factors (H3a) shows that internal bank conditions such as NIM and Equity Ratio can moderate the impact of negative sentiment on deposits, although this moderating effect is relatively small. This finding confirms the importance of integration between digital data as an indicator of public sentiment and bank-specific factors in the analysis of banking deposit behavior.

CONCLUSION

This study addresses whether Google Trends crisis sentiment and bank-specific conditions are associated with bank deposits in Indonesia. Across six Random Effects Model specifications for 35 listed banks during 2018–2023, crisis-related search intensity is negatively associated with deposits in several models, while bank size and ROA show consistently positive associations. NIM and Equity Ratio are negative in several specifications, and selected interaction terms are significant, indicating that internal bank conditions can modify the relationship between digital crisis attention and deposit dynamics.

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AUTHOR CONTRIBUTION STATEMENT

All authors contributed to the development of this study, including conceptualization, research design, methodology, data collection, data processing, formal analysis, interpretation of findings, manuscript preparation, critical revision, and approval of the final version of the manuscript. Muhammad Iqbal Maulana, as the corresponding author, was primarily responsible for coordinating the research process, conducting the analysis, and preparing the manuscript. Permata Wulandari contributed to the research framework development, validation of analysis, interpretation of results, and critical review of the manuscript. Both authors have read and approved the final manuscript.

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