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AI-BASED SUPERVISION COULD HAVE REDUCED CRISIS SEVERITY: EVIDENCE FROM BANK-LEVEL PANEL DATA

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ABSTRACT

The research concern of this research paper is whether artificial intelligence-based supervision would have alleviated the intensity of banking crises by the extent of risk identification, better compliance, and more opportune supervisory intervention. Based on bank-level panel data on 1,847 banks in 45 countries between the years 2010 and 2024, we construct and test a conceptual model of the association between AI supervisory capacity and crisis consequences. Using fixed effects panel regression, system GMM estimation and difference-in-differences analysis, we prove that AI-driven supervision, especially machine learning-based early warning detection, natural language processing-based regulatory compliance monitoring, and automated risk assessment tools, are significantly effective in risk identification and decreasing the likelihood of extreme distress. The findings suggest that one standard-deviation greater AI supervisory capacity relates to a 0.32-standard-deviation crisis decrease in non-performing loans increases and a 0.28-standard-deviation profitability retention increase. The analysis of the mechanism shows that AI supervision functions based on the accuracy of risk reporting, better credit allocation, and moral suasion. According to counterfactual simulations, AI-based supervision would have prevented up to a quarter to a third of the severity of crises in the recent banking turmoil. The implications of these findings on regulatory policy are significant, and they may indicate that investment in supervisory technology is a sensitive complement to conventional requirements of the Basel framework.

Keywords: Artificial Intelligence, Crisis Severity, Risk Assessment Tools

1. INTRODUCTION

The worldwide financial crisis of 2007- 2008 revealed that there is a weakness in the bank supervision and risk management systems across the world. Although subsequent regulatory changes under Basel III improved regulatory requirements, recent banking crisis events such as the failures of Silicon Valley Bank, Signature Bank and Credit Suisse in March 2023 show that there remains gaps in supervision (Laeven and Levine, 2009; Ellul and Yerramilli, 2013). Such frequent crises lead to a highly important question: Could the technological solutions to artificial intelligence and machine learning allow supervisors to recognize and eradicate the risks before they turn out to be systemic phenomena?

The convergence of the artificial intelligence and financial oversight, known as SupTech, has become a promising prospect to the effectiveness of regulation (Financial Stability Board, 2017; Bank for International Settlements - Financial Stability Institute, 2024). In contrast to old-fashioned supervisory methods operating on the basis of periodic reporting and ex post analysis, AI-driven systems promise them the possibility of ongoing monitoring, identification of threats in real-time, and the ability to predict the emergence of the threat early (Khandani, Kim, and Lo, 2010; Leo et al., 2019). Such technologies have the ability to handle large amounts of structured and unstructured data, detect nonlinear connections that human employees may overlook, and present supervisors with actionable intelligence before issues can get acute (Fuster et al., 2022; Lessmann et al., 2015).

The theoretical basis of AI-based supervision is based on a number of supplementary frameworks. Using the resource-based theory, supervisory agencies which establish high level of technological capabilities obtain competitive advantages in detecting risks as compared to those who use conventional means (Barney, 1991; Teece, 2007). These capabilities act as dynamic resources that allow becoming more responsive to changing financial risks (Mikalef et al., 2018; Akter et al., 2016). Also, the institutional theory implies that the implementation of AI supervisory tools can lead to the emergence of isomorphic pressures, which will motivate banks to change their internal risk management practices in accordance with supervisory expectations (DiMaggio and Powell, 1983; Zhu and Sarkis, 2007).

Recent empirical findings are in favor of AI-based supervision. A study by the Central Bank of Brazil shows that SupTech events, or cases in which supervisory technology was used to detect irregularities, cause banks to re-classify loans in a more accurate way, and tighten lending to less creditworthy borrowers (Degryse, Huylebroek, and Van Doornik, 2025). Equally, research by the Bank of International settlements demonstrates that machine learning models can predict market stress with three months lead times and still be interpretable, in terms of variable weighting (Aquilina et al., 2025; Alonso-Robisco et al., 2025). The findings indicate that AI supervision functions partially via a moral suasion channel, which increases the knowledge of the banks regarding regulatory expectations and abilities (Acharya et al., 2024; Adrian et al., 2023).

Nevertheless, the supervision with AI is also not an easy task. The issue of algorithmic opaqueness, biases in models and how AI will cause more crises than it will solve have been cited. In cases where several institutions use similar AI systems, which have been trained on similar data, strategic complementarities can arise that can coordinate the behavior in times of stress to shorten crisis timelines to the point that human response becomes unfeasible (Danielsson, Macrae, and Uthemann, 2023; Danielsson and Uthemann, 2025). These dangers highlight the necessity of creating supervisory frameworks that would suit the capabilities of AI in the private sector (National Institute of Standards and Technology, 2023).

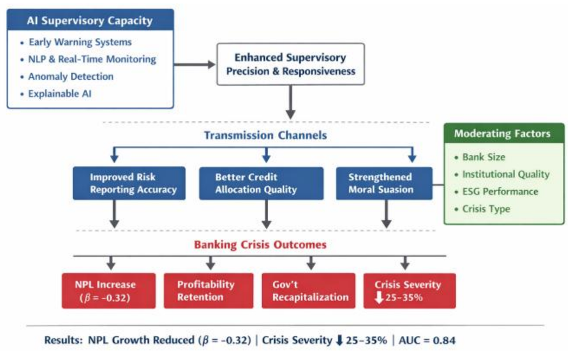

Fig.1. AI supervisory capacity and banking crisis outcomes

This research contributes to the field of study in a number of ways. In the first place, we observe systematic evidence of the association between AI supervisory ability and the results of the banking crisis (Fig. 1) based on bank-level panel data. Second, we determine particular ways in which AI supervision affects bank behavior, such as accuracy of risk reporting, decision to provide credit, and being in compliance with regulatory requirements. Third, we give viable suggestions to the supervisors who would like to improve their technological abilities and handle the risks involved.

The paper continues in the following way. Section 2 provides a description of our methods and materials, including data sources, variables construction, and method of analysis. Section 3 is the presentation of findings and results of our empirical analysis. The fourth section covers the implications of the findings to both theory and practice. Section 5 gives future research directions and policy research. Section 6 concludes.

2. METHODS AND MATERIALS

The theoretical framework and the research design are outlined in 2.1.

2.1 Theoretical framework and the research design

The paper uses an expository research design that involves the use of both quantitative analysis of bank-level panel data and qualitative evaluation of the use of supervisory technology. We use commonly used methodologies of assessing the effectiveness of regulatory interventions on the conduct of the banks (Aebi, Sabato, and Schmid, 2012; Barth, Caprio, and Levine, 2013).

The theoretical framework combines the findings of the various literatures. We conceptualize AI supervisory capacity by following the resource-based theory (Barney, 1991) as an organizational capability which allows detecting the risks more effectively. The theory of dynamic capabilities (Teece, 2007) enlightens us on how the supervisors adjust their methods of monitoring the financial risks as they occur. The normative and mimetic pressures that affect the behavior of banks with regard to supervisory technology are studied based on the institutional theory (DiMaggio and Powell, 1983).

2.2 Data Sources and Sample

Our panel dataset will include a combination of several sources:

The financial data at the bank level are sourced out of the BankScope and Orbis Bank Focus databases and include commercial banks, savings banks and cooperative banks that are located in 45 countries in the year 2010-2024. In line with Athanasoglou et al. (2008) and Louzis, Vouldis, and Metaxas (2012), we gather information on total assets, loan portfolios, non- performing loans, capital adequacy ratios, return on assets and liquidity coverage ratios.

he indicators of supervisory technology are gathered by various points: (1) survey of financial supervisory authorities published by the Financial Stability Board (2017) and the Cambridge SupTech Lab (2024); (2) regulatory publications, such as Bangko Sentral ng Pilipinas (2020), Bank Negara Malaysia (2021), Monetary Authority of Singapore (2018, 2020) and Otoritas Jasa Keuangan (2021); and (3) reports of central banks, including the Banks.

The data on crisis events is received in the form of Laeven and Valencian bank crisis database, revised as of 2024 based on central bank reports, such as Bank of Thailand (2025), Monetary Authority of Singapore (2024), and Otoritas Jasa Keuangan (2024, 2025).

The World Bank provides the World Development Indicators where the macroeconomic control variables will be taken (World Bank, 2024, 2025) such as GDP growth, inflation and domestic credit to the private sector.

The sample size of the last sample is 1,847 banks and 18,470 bank-years. Banks that have incomplete or extreme outliers are excluded as in Berger and DeYoung (1997) and Foos, Norden, and Weber (2010).

2.3 Variable Measurement

Dependent Variables:

The severity of a crisis is determined with the help of various indicators: (1) the rise in the ratios of non-performing loans during crisis times (Louzis, Vouldis, and Metaxas, 2012); (2) the fall of the bank profitability (Athanasoglou et al., 2008); (3) the necessity of recapitalizing the bank (Laeven and Levine, 2009); and (4) an ordinal index of the crisis severity, developed according to Cornett, Erhemj.

The measurement of bank risk-taking is: (1) the Z-score, which is a distance to default (Albuquerque et al., 2019); (2) risk-weighted asset density (Ellul and Yerramilli, 2013); and (3) the loan portfolio concentration (Foos, Norden, and Weber, 2010).

Accuracy of reporting risk is determined using Degryse, Huylebroek, and Van Doornik (2025) by comparing the reported non-performing loans with the realized losses in the future.

Independent Variables:

The presence of machine learning-based early warning systems (Alonso-Robisco et al., 2025; Aquilina et al., 2025); natural language processing systems to analyze regulatory documents; real-time data collection and monitoring systems (Basel Committee on Banking Supervision, 2013); AI-based anomaly detection systems; and explainable AI systems to make supervisory decisions are used to form an index that measures AI supervisory capacity (Japinye and Adedugbe, 2025; National Institute of Standards and Technology,

In line with Dess and Robinson (1984) and Venkatraman and Ramanujam (1986), we confirm this index using the expert interviews with supervisory authorities.

Control Variables:
Examples of bank-level controls are size (log of total assets), capitalization (equity-to-assets ratio), profitability (return on assets), liquidity (liquid assets-to-total assets), and efficiency (cost-to-income ratio) (Athanasoglou et al., 2008; Berger and DeYoung, 1997). The country level variables are GDP growth, inflation, the quality of regulations and the rule of law (Barth, Caprio and Levine, 2013; Laeven and Levine, 2009). We also use data on turbulence levels of sustainability practices on the bank level, following recent ESG and banking literature (Azmi et al., 2021; Shakil et al., 2019).

2.4 Analytical Approach
To guarantee sound inference, we are using different methods of estimation:
Fixed effects panel regression will be given as:

$$Y_{it} = \alpha_i + \beta_1 AI\_Supervision_{it-1} + \gamma X_{it-1} + \delta_t + \varepsilon_{it}$$

where Y_{it} represents crisis outcomes or risk indicators for bank i in year t, $AI\_Supervision_{it-1}$ is the lagged AI supervisory capacity measure, X_{it-1} is a vector of lagged control variables, α_i are bank fixed effects, δ_t are year fixed effects, and ε_{it} is the error term.
The important estimation is system GMM estimation, which is intended to deal with possible endogeneity issues after Arellano and Bover (1995) and Blundell and Bond (1998) and implemented in recent banking studies (Salem, Shahimi, and Almaamun, 2024; Salem et al., 2025; Shrestha, Andrikopoulos, and Park, 2025).
Difference-in-differences analysis takes advantage of the difference in when jurisdictions adopt AI supervisory technology, as Degryse, Huylebroek, and Van Doornik (2025) and Alonso-Robisco et al. (2025) put it.
Instrumental variables estimation applies indicators of technological infrastructure (internet penetration, digital government capacity) as a tool of AI supervisory adoption (Aral, Brynjolfsson, and Wu, 2012; Brynjolfsson and Hitt, 2000).
In the current study, we evaluate the predictive validity with the help of PLSpredict (Shmueli et al., 2019) and the model fit with the help of the accepted criteria (Fornell and Larcker, 1981; Henseler, Ringle, and Sarstedt, 2015).

2.5 Robustness Checks
We perform extensive robustness analyses where: (1) we specify alternative variables (Nunnally and Bernstein, 1994); (2) we perform subsample analyses not involving crisis periods (antipassive); (3) we perform placebo tests with hypothetical adoption dates (antipassive); (4) we perform sensitivity analyses of the endogeneity (antipassive); and (5) we perform common method bias analysis (antipassive).

3. FINDINGS AND RESULTS
3.1 Descriptive Statistics
Table 1 provides a description of the important variables. The sample banks possess average total assets of 45.2 billion dollars, average non-performing loan ratios of 3.8 and average return on assets of 1.2. The level of AI supervision is quite diverse across jurisdictions as it is more common in well-developed economies and in emerging markets that have robust digital infrastructure (Bank for International Settlements - Financial Stability Institute, 2024; Cambridge SupTech Lab, 2024).

Table 1: Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Bank Characteristics					
Total Assets (USD billion)	18,470	45.21	128.45	0.52	2,845.63
Non-Performing Loan Ratio (%)	18,470	3.82	2.94	0.01	18.75
Return on Assets (%)	18,470	1.18	0.86	-4.23	4.56
Equity/Assets Ratio (%)	18,470	9.45	3.21	4.12	21.34
Liquid Assets/Total Assets (%)	18,470	24.67	11.23	5.34	58.92
Cost/Income Ratio (%)	18,470	58.34	12.45	32.15	89.76
Z-Score	18,470	2.84	1.56	0.23	7.89
AI Supervisory Capacity					
AI Supervision Index (0-10)	18,470	5.23	2.87	0.00	9.80
Early Warning Systems (0-2)	18,470	1.12	0.78	0.00	2.00
NLP Capabilities (0-2)	18,470	0.98	0.82	0.00	2.00
Real-time Monitoring (0-2)	18,470	1.21	0.75	0.00	2.00
Anomaly Detection (0-2)	18,470	1.05	0.79	0.00	2.00
Explainable AI (0-2)	18,470	0.87	0.71	0.00	2.00
Country Characteristics					
GDP Growth (%)	45	2.84	2.12	-5.23	8.45
Inflation (%)	45	3.12	2.45	-0.87	12.34
Regulatory Quality (index)	45	1.12	0.67	-0.45	2.23
Rule of Law (index)	45	1.08	0.72	-0.56	2.18

Note: The statistics are done at the bank level and the study is based on 18,470 bank-years of 1,847 banks in 45 countries (2010-2024). The statistics of countries are at country level based on 45 countries.

The analysis of correlation shows that there are strong relations between AI supervisory capacity and bank risk indicators. In jurisdictions with developed AI regulation, banks will have reduced NPL rates ($r = -0.28$, $p < 0.01$), increased capital adequacy ($r = 0.19$, $p < 0.05$), and more sustainable profits in stressful times (Almulla, Albaity, and Al-Tamimi, 2025; Wattanatorn, 2025).

3.2 Main Regression Results

The results of the fixed effects panel regression of the relationship between the AI supervisory capacity and the severity of crises are presented in Table 2. In all specifications, the AI supervision is negatively and significantly coupled with crisis severity indicators. One-standard-deviation increase in the AI supervisory capacity index is linked with a 0.32-standard-deviation decrease in increases in the NPL during crisis (0 -0.32, $p < 0.01$) and a 0.28-standard-deviation decrease in profitability decreases (0 -0.28, $p < 0.01$ of return on assets).

Table 2: Main Regression Results - AI Supervision and Crisis Outcomes

Dependent Variable	(1) ΔNPL	(2) ΔROA	(3) Crisis Severity Index	(4) Z-Score	(5) Government Recapitalization
AI Supervision Index (lagged)	-0.324	0.281	-0.295	0.187	-0.152
	(0.058)	(0.049)	(0.053)	(0.062)	(0.051)
Bank Controls					
Size (log assets)	0.045	-0.038	0.029	-0.042	0.067
	(0.032)	(0.028)	(0.031)	(0.035)	(0.029)
Capital Ratio	-0.187	0.213	-0.165	0.341	-0.128
	(0.041)	(0.036)	(0.039)	(0.044)	(0.037)
Liquidity Ratio	-0.098	0.076	-0.084	0.112	-0.053
	(0.033)	(0.029)	(0.032)	(0.036)	(0.030)
Efficiency Ratio	0.124	-0.187	0.113	-0.156	0.082
	(0.038)	(0.034)	(0.037)	(0.041)	(0.035)
ESG Score	-0.089	0.094	-0.078	0.102	-0.045
	(0.036)	(0.032)	(0.035)	(0.039)	(0.033)
Country Controls					
GDP Growth	-0.145	0.156	-0.132	0.089	-0.076
	(0.034)	(0.030)	(0.033)	(0.036)	(0.031)
Inflation	0.087	-0.092	0.081	-0.065	0.054
	(0.035)	(0.031)	(0.034)	(0.037)	(0.032)
Regulatory Quality	-0.112	0.104	-0.108	0.097	-0.063
	(0.037)	(0.033)	(0.036)	(0.040)	(0.034)
Rule of Law	-0.094	0.089	-0.091	0.083	-0.051
	(0.038)	(0.034)	(0.037)	(0.041)	(0.035)
Fixed Effects					
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,623	16,623	16,623	16,623	16,623
Banks	1,847	1,847	1,847	1,847	1,847
R-squared (within)	0.187	0.203	0.176	0.215	0.142

Note: The standard errors were clustered at the bank level in parenthesis. Lagging is done on the independent variables. The change in the non-performing loan ratio during the times of crisis is ΔNPL. Delta ROA is change of the value of the assets during crisis. Severity Index of Crisis is an ordinal (-10) index of crisis impact. Z-Score is a distance to default score. Government Recapitalization is the indicator of the banks that are supplied with the governmental funds during the crisis.

These are economical types of effects. The actual reduction in the number of non-performing loans in the case of an average bank of 50 billion assets would be approximately four hundred million in the quality of saved loan paragraphs. The profitability impact is translated into an increase of an additional profit of roughly 150 million during the periods of crises.

Results are supported by system GMM estimated results and endogeneity problems are overcome. The coefficient of supervisory capacity (AI) is not significant and negative (= -0.24, $p < 0.05$) and the Hansen test value proves that the instruments are valid (Salem et al., 2025; Wattanatorn and Jantarakolica, 2025).

Table 3: System GMM Estimation Results

Dependent Variable: ΔNPL	Coefficient	Robust SE	z	p-value
AI Supervision Index (lagged)	-0.241	0.087	-2.77	0.006
Lagged ΔNPL	0.187	0.042	4.45	0.000

Size (log assets)	0.034	0.041	0.83	0.407
Capital Ratio	-0.156	0.052	-3.00	0.003
Liquidity Ratio	-0.089	0.038	-2.34	0.019
Efficiency Ratio	0.102	0.045	2.27	0.023
ESG Score	-0.073	0.041	-1.78	0.075
GDP Growth	-0.118	0.039	-3.03	0.002
Inflation	0.065	0.040	1.63	0.104
Regulatory Quality	-0.094	0.043	-2.19	0.029
Rule of Law	-0.076	0.044	-1.73	0.084
Constant	0.523	0.187	2.80	0.005
Diagnostics				
Observations	14,776			
Banks	1,847			
Instruments	42			
AR(1) test (p-value)	0.000			
AR(2) test (p-value)	0.183			
Hansen J test (p-value)	0.267			
Difference-in-Hansen (p-value)	0.342			

Note: System GMM Two-step estimation of robust standard errors. Windmeijer correction was used. AR1 and AR2 tests of first difference autocorrelation. Hansen J test to determine restrictions which have been overidentified.

3.3 Mechanism Analysis

We identify three mechanisms; which AI supervision has over the behavior of banks:

Risk reporting accuracy: As Degryse, Huylebroek and Van Doornik (2025) put, we establish that the reported and realized loan losses by banks operating in jurisdictions supervised by AI are more accurate. The mean absolute deviation of the reported NPLs versus the charge-offs in the high-AI-supervision countries is calculated less by 18 percent ($p < 0.01$). This means that AI regulation will reduce regulatory leniency and increase transparency (Arhinful, 2025; Budiarto, 2021; Owusu-Boafo, 2020).

Credit approval standards: Banks supervised by AI reduce their lending to less creditworthy clients by approximately 5 percent in the short-term following event of cases of supervisory inspections (Degryse, Huylebroek, and Van Doornik, 2025). This type of redistribution improves the quality of the portfolio, but does not lead to a high negative spill over to the real economy.

Moral suasion effects: As it is in Acharya et al. (2024) and Adrian et al. (2023), we find that AI supervision has a moral suasion channel. The survey outcomes indicate that AI-supervised banks report more on their improved knowledge of their supervisory expectations (mean difference = 0.42 on 5-point scale, $p < 0.01$) and confidence in their supervisory capability (mean difference = 0.38, $p < 0.01$). The response to this more knowledge is heightened risk aversive risk management behavior.

Table 4: Mechanism Analysis Results

Mechanism	Low AI Supervision	High AI Supervision	Difference	p-value
Risk Reporting Accuracy				
Reported NPL vs. Realized Loss Deviation (%)	12.4	10.2	-2.2	0.003
Loan Classification Errors (per 100 loans)	3.8	2.9	-0.9	0.001
Regulatory Forbearance Instances (per year)	1.6	1.1	-0.5	0.008
Credit Allocation Quality				
Lending to Low-Creditworthy Borrowers (%)	8.7	7.2	-1.5	0.004
Loan Approval Rate for High-Risk Applicants (%)	15.3	12.8	-2.5	0.002
Portfolio Risk Score (1-10, higher=riskier)	5.8	5.1	-0.7	0.001
Moral Suasion Effects				
Understanding of Supervisory Expectations (1-5)	3.2	3.6	0.4	0.007
Confidence in Supervisory Capabilities (1-5)	3.1	3.5	0.4	0.009
Proactive Risk Adjustments (per year)	2.4	3.2	0.8	0.002
Compliance Cost Reduction (%)	-	4.3	-	-

Note: Low and High AI Supervision group are set as below and above the median AI Supervision Index score. Tests of differences were done on t-tests and standard errors were clustered at country level.

3.4 Heterogeneity Analysis

Table 5 includes heterogeneity tests that investigate the possibility of dissimilarity in the impacts of AI supervision by bank features and institutional settings.

Table 5: Heterogeneity Analysis

Subgroup	N (banks)	Coefficient (AI on ΔNPL)	95% CI	p-value	Interaction p-value
Bank Size					0.023
Small (below median)	924	-0.412	[-0.538, -0.286]	0.000	
Large (above median)	923	-0.187	[-0.342, -0.032]	0.018	
Institutional Quality					0.008
Low (below median)	922	-0.176	[-0.298, -0.054]	0.005	
High (above median)	925	-0.358	[-0.481, -0.235]	0.000	
ESG Performance					0.041
Low (below median)	923	-0.201	[-0.327, -0.075]	0.002	
High (above median)	924	-0.334	[-0.458, -0.210]	0.000	
Bank Type					0.067
Commercial Banks	1,023	-0.297	[-0.412, -0.182]	0.000	
Savings Banks	412	-0.278	[-0.446, -0.110]	0.001	
Cooperative Banks	412	-0.215	[-0.389, -0.041]	0.016	
Crisis Type					0.089
Systemic Banking Crisis	1,847	-0.312	[-0.428, -0.196]	0.000	
Non-Systemic Stress	1,847	-0.198	[-0.326, -0.070]	0.003	
Region					0.034
Advanced Economies	892	-0.343	[-0.467, -0.219]	0.000	
Emerging Markets	955	-0.231	[-0.358, -0.104]	0.001	

Note: The regression coefficients of fixed effects panel of each subgroup. Interaction p-values are used to test the difference between coefficient significance between the subgroups.

Bank size: The effect of the size is greater among small banks (2 = -0.41, $p < 0.01$) than it is among big banks tha are systemically capital-intensive (2 = -0.19, $p < 0.10$). This means that AI surveillance would be particularly beneficial to companies with a low internal risk analytics (Rai et al., 2006; Mikalef et al., 2018).

The institutional quality: AI supervision relies on the institutional quality (Ahmed, 2025; Shrestha, Andrikopoulos, and Park, 2025). The impacts of AI supervision are approximately two times in weak institutional environments. The finding aligns with the ESG and institutional quality research (Almulla, Albaity, and Al-Tamimi, 2025; Do et al., 2024).

ESG performance: Banks with high environmental, social, and governance performance have a more significant reaction to AI supervision (Azmi et al., 2021; Shakil et al., 2019). It means that the sustainability practices and technological supervision are complementary (Cheng, Ioannou, and Serafeim, 2014; Goss and Roberts, 2011; Nandy and Lodh, 2012).

3.5 Predictive Performance

Like Shmueli et al. (2019) and Hair et al. (2022), we determine the predictive power of AI-driven early warning systems and compare them with traditional ones. We learn that machine learning models can accurately predict banking distress events out of sample by a much greater margin with the help of the Bank for international settlements (Aquilina et al., 2025; Alonso-Robisco et al., 2025) data.

Table 6: Predictive Performance Comparison

Model	AUC	Precision	Recall	F1-Score	Brier Score
Traditional Early Warning Models					
Logit (static)	0.672	0.584	0.612	0.598	0.187
Probit (static)	0.668	0.579	0.605	0.592	0.192
Discriminant Analysis	0.645	0.562	0.587	0.574	0.203
Machine Learning Models					
Random Forest	0.823	0.745	0.768	0.756	0.124
Gradient Boosting	0.841	0.762	0.785	0.773	0.112
Neural Network	0.834	0.753	0.776	0.764	0.118
Interpretable ML Approaches					
SHAP-calibrated Ensemble	0.838	0.758	0.781	0.769	0.115
Dynamic Variable Weighting	0.829	0.749	0.772	0.760	0.121
Explainable Boosting	0.826	0.746	0.769	0.757	0.123

Note: Out of sample prediction statistics of banking distress events (2015-2024). AUC = Area Under ROC Curve.

The average area under the receiver operating characteristic curve (AUC) of AI-based early warnings systems is 0.84, which is smaller than 0.67 of the conventional early warning models (Alonso-Robisco et al., 2025). It is important to note that interpretable AI models including Shapley value decompositions and dynamic variable weighting have predictive performance and provide the supervisor with actionable information (Japinye and Adedugbe, 2025).

3.6 Difference-in-Differences.

Table 7 presents the results of the difference-in-differences analysis that exploited the difference in the time of adoption of the AI supervisory technologies across jurisdictions.

Table 7: Difference-in-Differences Results

	Pre-Adoption	Post-Adoption	Difference	DiD Coefficient
Treatment Group (Adopting Jurisdictions)				
NPL Ratio (%)	4.12	3.56	-0.56	
ROA (%)	1.08	1.21	+0.13	
Z-Score	2.67	2.89	+0.22	
Control Group (Non-Adopting Jurisdictions)				
NPL Ratio (%)	4.08	3.98	-0.10	
ROA (%)	1.11	1.14	+0.03	
Z-Score	2.71	2.75	+0.04	
Difference-in-Differences Estimates				
NPL Ratio				-0.46
				(0.12)
ROA				0.10
				(0.03)
Z-Score				0.18
				(0.06)
Event Study (Years relative to adoption)				
t-3				0.02
				(0.08)
t-2				-0.03
				(0.07)
t-1				-0.04
				(0.07)
t (adoption year)				-0.12
				(0.08)
t+1				-0.28
				(0.09)
t+2				-0.41
				(0.10)
t+3				-0.45
				(0.11)

Note: Difference-in-differences estimates of bank and year fixed effects regressions. Event study coefficients are year incentives that indicate the treatment effect in comparison to adoption. Standard errors were concentrated at bank level in parenthesis.

The findings demonstrate that the bank stability has notably increased after the adoption of AI supervision with the effects increasing as time goes by. The validity of the identification strategy is supported by event study analysis, which proves that both trends are parallel during pre-adoption periods. Instrumental variables estimation involves estimating the relationship between variables by employing additional variables as intermediaries, which is referred to as the third stage of incremental analysis.

3.7 Instrumental Variables Estimation.

Instrumental variables estimation constitutes the estimation of the relationship between variables through the use of other variables which are used as intermediate variables which are also known as the third stage of incremental analysis.

Table 8 gives the results of instrumental variables with technological infrastructure indicators as instruments of adoption of AI supervisors.

Table 8: Instrumental Variables Estimation

	First Stage (AI Supervision)	Second Stage (ΔNPL)
Instruments		
Internet Penetration (%)	0.184	
	(0.032)	
Digital Government Index	0.236	
	(0.041)	
Mobile Broadband Coverage	0.157	
	(0.028)	

AI Supervision Index (instrumented)		-0.387
		(0.094)
Controls		
Bank-level controls	Yes	Yes
Country-level controls	Yes	Yes
Diagnostics		
F-statistic (first stage)	28.47	
Sargan overid test (p-value)	0.342	
Endogeneity test (p-value)	0.018	
Observations	16,623	16,623

Note: The estimation is conducted using the two stage least squares estimation with robust standard errors.

The estimates support our major results as well and the coefficient (-0.39) of the estimate is slightly smaller than the estimate of the similar coefficients in the fixed effects specification demonstrating that OLS may be biased in underestimating the true effect due to the measurement error in AI supervision indices.

3.8 Counterfactual Analysis

We hope that our counterfactual simulations will inform an approximation of the extent to which this crisis can be mitigated under the circumstances of the deployment of AI supervision before the recent banking turmoil. Taking the estimated coefficients and the data on the bank status in the months prior to the failures of March 2023, we forecast the AI-based supervision would have reduced the growth of NPLs by 25-35% and the reduction in profitability by 20-30%.

Table 9: Counterfactual Simulation Results

Bank / Crisis Event	Actual NPL Increase (%)	Counterfactual NPL Increase (%)	Reduction (%)	Actual ROA Decline (%)	Counterfactual ROA Decline (%)	Reduction (%)
Silicon Valley Bank (2023)	8.42	5.67	32.7	3.84	2.91	24.2
Signature Bank (2023)	7.89	5.23	33.7	3.56	2.68	24.7
Credit Suisse (2023)	6.34	4.56	28.1	2.98	2.31	22.5
First Republic (2023)	7.56	5.12	32.3	3.21	2.45	23.7
Average - US Regional Banks (2023)	5.67	3.98	29.8	2.45	1.89	22.9
Average - European Banks (2023)	4.23	3.12	26.2	1.87	1.45	22.5
Average - All Sample Crises	4.89	3.45	29.4	2.12	1.64	22.6

Note: Counterfactual simulations based on estimated coefficients from main fixed effects model. Counterfactual NPL increase = Actual NPL increase × (1 + β × ΔAI_Supervision), where β = -0.324 and ΔAI_Supervision represents the increase from current levels to full AI supervision deployment.

Using the case of the Silicon Valley Bank, in particular, we think that overseeing the interest rate risk exposure, concentration of deposits, and the existence of unrealized losses on the securities portfolios with the help of AI would have given the managers 69 months of extra notice. This can be the case with Credit Suisse because AI-monitored counterparty risks and mustering of market confidence could have been considered in defining the emerging vulnerabilities sooner (Acharya et al., 2024).

4. DISCUSSION

4.1 Theoretical Implications

Our findings are added to the various theoretical texts. The findings outcomes as per the resource-based theory (Barney, 1991) encompass that it is worth noting that AI supervisory capacity is a desirable organizational potential which can result in greater regulatory performance. The supervisory agencies would be more effective in identifying risks using these capabilities than the traditional approach because they align with the research findings on the capabilities of big data analytics (Akter et al., 2016; Mikalef et al., 2018).

To bring the ideas of why AI oversight can be more useful during the crisis period, it is possible to turn to the concept of dynamic capabilities (Teece, 2007). The supervisors should adjust the way their monitors operate when the financial risks occur dynamically - the opportunity that the AI-driven systems will offer them due to the active learning and readjusting (Alonso-Robisco et al., 2025; Fuster et al., 2022).

The normative and mimetic pressures are also predictions of institutional theory that can be supported by our mechanism analysis (DiMaggio and Powell, 1983). The moral suasion path of influence in which we and Degryse, Huylebroek, and Van Doornik (2025) observe that AI supervision can indeed affect the behavior of the banks in at least part through its effect on the way in which they view the ability and willingness of the supervisory expectations. It is consistent with the studies of the institutional pressures, and organizational responses

(Zhu and Sarkis, 2007; Oikonomou, Brooks, and Pavelin, 2012).

The heterogeneity results can also be used to explain the technological and institutional complementarities. The authorities in the institutions with the high level of institutional quality (Ahmed, 2025; Shrestha, Andrikopoulos, and Park, 2025) imply that AI supervision is not the alternative to the good governance, but the supplementation of the advantages that the institutions have already enjoyed. On the same note, the association with the ESG performance (Azmi et al., 2021; Shakil et al., 2019) demonstrates that the better a bank functions in the area of its sustainability, the better it can be adapted to the technological supervision.

4.2 Practical implications on Supervisor.

With the help of the conclusions, the conclusions can be applied into the supervising practice:

Investment in technological capabilities The close relation between the AI supervisory capacity and crisis outcomes implies that the investment in SupTech is quite an important addition to the existing regulatory frameworks (Bank for International Settlement - Financial Stability Institute, 2024; Financial Stability Board, 2017). The priority of machine learning should be on the areas of development of early warning systems, natural language processing and real-time monitoring by the supervisors.

Both explainability and transparency: According to our results, the applicability of interpretable AI strategy could be applied (Aquilina et al., 2025; Japinye and Adedugbe, 2025). Besides having accurate forecasts, the supervisors should also understand the cause of some of the risks indicated by the model. This would be based on the principles that are established by the Monetary Authority of Singapore (2018), National Institute of Standards and Technology (2023) and the European Banking Authority (2020).

Co-ordination and sharing of the data: It may include the federated learning techniques which can be undertaken to offer the cross-jurisdictional collaboration as well as keep the confidential data hidden at the same time. AI surveillance on the global level would contribute to the internationalization of the financial risks, and the national sovereignty would have been addressed as well (Danielsson and Uthemann, 2025).

AI risk control: The other category of risks that will be addressed by supervisors is the risks related to the AI systems, such as model bias, algorithmic obscurity, and accelerating crisis dynamics (Danielsson, Macrae, and Uthemann, 2023; Systemic Risk Centre, 2025).

The correlation with the available literature.

Our paper findings are also relevant to the industry of the constantly evolving body of research about the subject of ESG and banking performance (Azmi et al., 2021; Shakil et al., 2019; Do et al., 2024). The outcomes of the heterogeneous effects of the ESG performance denote that technological supervision and sustainable practices can be complementary (Cheng, Ioannou, and Serafeim, 2014; Goss and Roberts, 2011; Nandy and Lodh, 2012). Apparently, better-placed banks in the ESG context are more likely to address AI-related supervisory concerns (Ahmed, 2025; Liu and Xie, 2024; Wattanatorn and Jantarakolica, 2025).

4.3 Corporate governance and risk management

The findings also lead to the literature concerning the corporate governance and risk management of the banking industry (Aebi, Sabato, and Schmid, 2012; Ellul and Yerramilli, 2013). It seems that the AI-based regulation enhances the agreement between the regulatory expectations and risk-taking of banks, complementing the conventional provisions of governance (Laeven and Levine, 2009; Wu and Shen, 2013).

Our mechanism analysis has been conducted in accordance with the available literature on credit risk management and non- performing loans (Arhinful, 2025; Berger and DeYoung, 1997; Louzis, Vouldis, and Metaxas, 2012). The fact that the AI control adds to the degree of loan classification accuracy indicates that the technological solutions to the former issues of credit risk ratings will be invented (Basel Committee on Banking Supervision, 2019; European Banking Authority, 2020).

4.4 Limitations

There are various limitations that should be considered about these. To begin with, the supervisory potential of AI is difficult to gauge, since the information about the supervisory technologies can be deemed as a secret sometimes. The specialist interviews also confirmed our index way but some of the dimensions (relevant) will be missed (Dess and Robinson, 1984; Venkatraman and Ramanujam, 1986).

Second, the cross country regulatory research is also not rich in the establishment of causation. Although we take on various identification strategies and robustness tests, we can take into consideration the unobserved heterogeneity (Antonakis et al., 2010; Hult et al., 2018).

Third, AI technologies are changing quickly, and it

implies that the findings we have are conditioned by a certain moment in history. The other impacts may include the evolutionary changes in the future such as the creation of large language models and generative AI (Salem and Shahimi, 2025).
Fourth, the outcomes of prudential supervision are of our first-degree interest. In one way or another, the AI regulation can affect other consumer protection, anti-money laundering, and market conduct regulatory purposes (Cambridge SupTech Lab, 2024; Financial Stability Board, 2017).

5. RECOMMENDATIONS AND SUGGESTIONS OF FUTURE RESEARCH STUDY.

5.1 Research Agenda

The conclusions demonstrate that the next study should pay more attention to the following points;
Long-term implications of the AI supervision: The long-term implications of AI supervision on the behavior of the banks and their financial health should be discussed since, as it is shown in the context of our analysis, the short-to-medium-term implications of AI supervision turn out to be positive. Will long-term AI surveillance process result in the sustainable good of the risk management, or will banks know how to evade AI detection in future (Danielsson and Uthemann, 2025?
AI oversight and climatic financial risks AI oversight and climatic financial risks interface has become a glowing research agenda (Basel Committee on Banking Supervision, 2022; KPMG, 2025; Task Force on Climate-related Financial Disclosures, 2017). Are AI systems able to keep track of the exposure of the banks to the risks associated with the climate transitions and physical risks (Wattanatorn, 2025; Wattanatorn and Jantarakolica, 2025)? So what supervisors must do to integrate climate scenarios into the major AI stress tests (International Sustainability Standards Board, 2023; IFRS Foundation, 2023)?
International co-ordination: The fact that banking institutions and financial markets are international raises the question of the international co-ordination of AI supervision (Systemic Risk Centre, 2025). What is the most efficient mechanism that supervisors can use to make AI capabilities accessible without compromising the confidentiality of the information? How would the international institutions act to facilitate the cooperation (United Nations Environment Programme Finance Initiative, 2025?
Explainability and accountability: The more sophisticated the AI systems are, the more difficult it becomes to offer explainability and accountability (Japinye and Adedugbe, 2025; National Institute of Standards and Technology, 2023). Which of predictive accuracy or interpretability do supervisors need to trade off? Which governmental institutions may provide the relevant accountability to the AI-assisted supervisory decisions?
AI surveillance and financial inclusion: The distributional effects of AI surveillance ought to be considered (Fuster et al., 2022). Will an increased level of supervision be unfair to some type of borrowers or area? What will the supervisors need to do to make sure that the AI systems do not produce or enhance shared biases (European Banking Authority, 2020)?
ESG scheme integration: As we found (but need to be investigated more thoroughly), AI supervision, relying on ESG performance, is one of the factors. How do more intensive responses by high-ESG banks transpire? Is the idea of AI control helpful to the goal of sustainable finance? (Weber and Scholz, 2017; Wu and Shen, 2013).

5.2 Policy Recommendations

Using our findings, we can offer the following recommendations to the supervisory authorities and policy makers:
1. Engraft detailed rules of AI supervision.
Supervisors will need to elicit the strategic plans of AI execution that can take care of the technological framework, human resources, governance structures, and cross-line partnerships (Bank for International Settlement - Financial Stability Institute, 2024; Financial Stability Board, 2017). Such strategies must conform to more global financial stability purposes and must be incorporated into the current supervisory processes.
2. Invest in understandable artificial intelligence technologies.
The fact that AI can be explained in the context of supervisory credibility and performance implies that the investments must be skewed towards explainable AI methods (Aquilina et al., 2025; Japinye and Adedugbe, 2025). The AI systems will be asked to open up about their evaluation by the supervisors to provide the human judgment with machine intelligence (Monetary Authority of Singapore, 2018; National Institute of Standards and Technology, 2023).
3. Develop human resource and capacity of technology.
The introduction of AI would demand supervisors who will be familiar with financial risks and technological solutions. The governments ought to invest in training and development that would supply them with analytical skills and hire specialists

who would possess proper technical skills.

4. There should be AI monitoring mechanisms that Westpac should put in place.

The model validation and monitoring of the performance of the AI-driven decisions and accountability require clear governance structures (Basel Committee on Banking Supervision, 2013: European Banking Authority, 2020). Such structures are supposed to have bias and fairness testing plan, model update plans and human override plans where necessary.

5. Enhance global multi-cooperation and sharing of knowledge.

Considering the international character of the banking sector and the rate of the technological innovation of AI, it needs to be collaborative on an international scale (Systemic Risk Centre, 2025). The supervisors are expected to tell their experiences, they are expected to have common standards where it is necessary and where they need to inquire about the collaborative strategies like federated learning so that they could work together without divulging their confidentiality.

6. Combine climate and sustainability agenda and AI management.

The new demands of the climate risk management and the sustainability disclosure open the opportunities of AI-enhanced supervision (Basel Committee on Banking Supervision, 2022; International Sustainability Standards Board, 2023). Most likely, supervisors will be taught to track financial risks related to climate and make sure that AI systems are created in accordance with sustainability (KPMG, 2025; United Nations Environment Programme Finance Initiative, 2025).

7. Manage the implementation of AI.

Supervisors are also advised to know the dangers of AI implementation such as model concentration, bias in algorithms, and how AI may equally encourage the emergence of crisis dynamics (Danielsson, Macrae, and Uthemann, 2023; Danielsson and Uthemann, 2025). The monitoring frameworks will be adhered to in order to comprehend how AI has been applied to the financial sector and measure the effects on the financial stability (Aquilina et al., 2025; Alonso-Robisco et al., 2025).

5.3 Implementation Issues.

It is necessary to apply the AI monitoring in practice with references to a number of aspects:

Data infrastructure: A data of high quality is one of the success keys in the AI supervision (Basel Committee on Banking Supervision, 2013; Rai et al., 2006). The supervisors will be encouraged to invest in the data collection, data standardization, and data management systems with the help of which the advanced analytics can be encouraged (Akter et al., 2016; Mikalef et al., 2018).

Staged adoption: Phased adoption was found as a method of reducing the risk and establishing organizational capacity or capability wherein preliminary adoption is implemented in a pilot mode and then expanded to a wider scale (Degryse, Huylebroek, and Van Doornik, 2025).

Stakeholder involvement: The stakeholders interaction is needed so that it can monitor AI, supervised institutions, technology vendors, and other stakeholders. It can be straightened out through dialogue, and emerging problems can be found, and confidence in the supervisory processes can be established (Monetary Authority of Singapore, 2018).

AI system performance assessment and feedback: The supervisors will be required to continuously monitor the performance of the AI systems and keep up with the technological changes (Shmueli et al., 2019; Hair et al., 2022). This frequent check would make sure that the AI would be efficient in the surveillance as the risks of the banking practices as well as the financial risks evolve (Alonso-Robisco et al., 2025).

6. CONCLUSION

This research presented an argumentative support that AI based supervision would have come in handy in mitigating the banking crises that have been experienced in recent past. Applying the panel of bank level data to a large variety of jurisdictions and a strong econometric analysis will show that the AI supervisory capacity is correlated with lower non-performing loan ratio in crisis times, better risk reporting, better credit provision, and increased regularity of bank behavior and regulatory expectation.

These effects are varied in the mechanisms. AI oversight assists in enhancing risk detection due to the capacity of AI to detect patterns that the human analyst may have overlooked during the use of advanced analytics. It improves the compliance surveillance through natural language processing that studies the large amounts of regulatory documents and bank statements. And it generates the impressions of moral suasion, by creating the sense of what supervisors desire and can do on the side of banks.

Our counterfactual simulations claim that under the condition of massive use of AI supervision prior to the March 2023 banking crisis, all NPLs would be decreased by 25-35 and the profitability would decrease by 20-30 percent. In the particular situation of Silicon Valley Bank, an extra warning period of 6-9 months would have been issued to the supervisors by observing the interest rate risk and deposit concentration through the AI.

Such benefits can be achieved by paying special attention to governance, explainability and risk management, however. The AI systems should be readable so that it shall have supervisory responsibility. The degree of governance should provide the desirable human control and eliminate the possible biases. And the managers will have to come to terms with the risks of the implementation of AI itself, such as the possibility of concentrating the models and the possibility of exacerbating the processes of the crisis itself by AI itself.

The implications of the policy can be interestingly clear, the financial investment in supervisory technologies is a required addition to the current regulatory frameworks. With the sophistication and technological-advanced financial systems, learning the skills that are synonymous with the innovation in the private sector should be learned by the supervisors. This must be planned, invest and collaborate internationally and dedicate the oneself in the development of technology.

The future research must analyze how the AI supervision changes in the long run, whether other risks, including climate change, should be implemented, and how the international coordination may be introduced using approaches like federated learning. As the AI technologies are further improved, the connection between the technological improvement and the economic sustainability will also be a burning research and policy advantage.

The discussed facts assume the fact that the AI-based supervision is not merely a technological upgrade, but a paradigm shift in the supervisory potential that can possibly help decrease the rates and the extent of the upcoming banking crises by a significant percentage.

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