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The impact of information technology adoption on bank efficiency: Evidence from listed Vietnamese banks

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ABSTRACT

In this study, we examined publicly listed commercial banks in Vietnam from 2014 to 2020 to investigate whether technology development has a non-linear effect on bank efficiency. We measured bank efficiency using Data Envelopment Analysis (DEA). The level of technological development was assessed using the Information Communication Technology (ICT) Index, which is published annually by the Vietnamese government. Consistent with our expectations, the results show an inverted U-shaped relationship between technological development and bank efficiency. This finding provides important insights for banks when planning and allocating their budgets for information and technology investments, particularly in the context of increasing digitalization in the banking sector.

1. Introduction

Bank efficiency is defined as the distance to a best-performance frontier that is not explained by statistical noise. An efficient banking system is important to ensure financial stability as well as the supply of sufficient credit for economic growth. Therefore, an established strand of literature has been developed to understand different determinants of bank efficiency. With the prominent development of technology, especially with the wave of digitalization, the banking industry has experienced a significant transformation in its operation. The application of technology is not only seen via the channels of service delivery, such as internet banking, mobile banking, etc., but also observed in the back-office tasks such as credit scoring, customer research, etc. The benefits of technology adoption could include creating new products and services to have the opportunity to reach more customers, eliminating physical boundaries in operations, and saving operating costs (Ungratwar et al., 2025). In addition, management is better thanks to abundant sources of management information and a smooth, timely, and effective reporting system, from which managers can make quick and accurate decisions. These benefits could contribute to improving bank efficiency. However, there are many challenges for the banking industry, such as high installation, maintenance, and training expenses when they update their technology to the latest advancement, as well as deal with digital crime such as cyber-attacks. These new challenges could hinder bank efficiency. Given this intuition, it is not clear how the adoption of technology could influence bank efficiency.

The evidence on the impact of technology adoption on the performance of the banking industry has produced mixed outcomes. Solow's (1987) hypothesis on the productivity paradox proposes that there is a non-linear connection between investment in information technology (IT) and productivity. Jiang et al. (2025) developed a model and reported that bank efficiency impacts business productivity by influencing agents' occupational selections; furthermore, enhancing technology adoption within the banking sector also contributes to the economy's long-term growth. Regarding empirical evidence, several studies indicate that implementing IT infrastructure in banks can lead to cost reduction, increased operational efficiency, improved service quality, and profitability (Ngo and Le, 2022; Gyau et al., 2024). Notably, Ren et al. (2024) analyzed the period from 2014 to 2020 concerning Chinese commercial banks and identified a substantial positive correlation between digital transformation and profit efficiency in these institutions. This correlation is mainly ascribed to the impact of digital transformation on enhancing revenue and minimizing expenses, hence increasing profit efficiency. In the context of the Vietnam's

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banking system, some studies report the positive association between technology investment and higher competitiveness and income diversification. Nevertheless, some studies report that overreliance on technology can lead to a bank's higher risk-taking (Li et al., 2025) and lower financial performance (Gupta et al., 2018) due to intensive investment in technology. A study of Uddin et al. (2020) documented the nonlinear effect of IT investment on banking sector profitability and stability. The result could be explained by the law of diminishing marginal returns; in other words, banks could reap the benefits of investing in technology only up to a threshold of investment, beyond which the investment yields lower benefits.

Vietnam provides a unique context for this investigation. Vietnam's banking system has experienced an ongoing robust digital transition in the past few years; several banks confirmed their long-term plan to adopt advanced digital technology with a higher investment budget. Nevertheless, due to the nature of the evolving technological capabilities and regulatory framework in Vietnam, the technological investment could be exposed to the risk of over-investment and or misallocation in digital technologies. This setting makes Vietnam an ideal setting to test whether the efficiency gains from technology follow a non-linear path. Taking into account the existing mixed evidence on the benefits of increased technological investment, this study aims to examine the impact of technological development on banks' efficiency. Specifically, given the law and prior evidence of the diminishing return of technology on banks' performance, we hypothesize that there is also a non-linear relationship between technology development and bank efficiency in Vietnam.

We examined thirteen listed commercial banks in Vietnam during the period of 2014- 2020 to address the research question. We measured bank efficiency using Data Envelopment Analysis (DEA). We measured the bank's technology development using the Information Communication Technology Index reported by the Vietnamese government annually. In line with our hypothesis, we document a non-linear relationship between technology development and bank efficiency in Vietnam. We also provide several robust tests, including alternative measures of bank efficiency and Tobit regression. The finding provides an important implication for proper investment planning in technology infrastructure by banks.

Our paper is organized as follows. Section 2 reviews related literature and develops our hypothesis. Section 3 presents our research methodology. Section 4 presents and discusses our results. Section 5 concludes our research.

2. Literature review and hypothesis development

The mathematical model of Jiang et al. (2025) shows that higher bank information technology (IT) acquisition is associated with a lower cost of bank intermediation, which leads to higher credit supply to small businesses. Regarding empirical evidence, several studies indicate that implementing IT infrastructure in banks can lead to cost reduction, increased operational efficiency, and improved service quality (Ngo and Le, 2022). The benefits could be derived from lower agency costs, and the positive association between technology adoption and bank efficiency has been found in different contexts, such as in the USA and India.

Nevertheless, some studies report that overreliance on technology can lead to banks' higher risk-taking, lower financial performance (Gupta et al., 2018) due to intensive investment in technology. With the focus on bank efficiency, several studies document weak or no evidence about the impact of technology adoption. An argument from a management perspective is that the success of technology adoption also depends on how technology is combined with the social and human factors to achieve organizational benefits. Another explanation developed by Carr (2003) is that technological development would increase a bank's competitiveness in the early phase of its adoption; due to the technology spillover effect over time, other competitors could access and employ similar technology, heightening market competition and lowering profits. Some empirical evidence suggests these arguments are feasible. Ho and Mallick (2010) provided empirical evidence to support this competition channel; specifically, the authors argued that the adoption and diffusion of ICT can lead to a negative network competition effect in the US banking system, which hinders their productivity and performance. Similarly, Martín-Oliver and Salas-Fumás (2008) explained that IT investments did not help Spanish banks improve their profits during the 1983–20003 period. Beccalli (2007) found that there is little association between technological innovation and the performance of European banks during the 1995–2000 period. Recently, Lee et al. (2023) also documented the negative impact of Fintech development on Chinese banks' efficiency.

The mixed evidence could be derived from the fact that most prior empirical studies model the impact of technology adoption on bank efficiency as a linear relationship. However, there are a few pieces of evidence that the impact of technology adoption could be non-linear. Specifically, Solow (1987) is concerned that if more investment is made in information technology, worker productivity may go down instead of up, the so-called "IT Productivity Paradox." Therefore, in line with this productivity paradox, we could hypothesize that there is a non-linear connection between investment in information technology (IT) and productivity. A recent study of Uddin et al. (2020) documented a nonlinear effect of IT investment to deal with cyber-attacks on banking sector profitability and stability. The result could be explained by the law of diminishing marginal return; in other words, banks could reap the benefits of investing in technology only up to a threshold of investment, beyond which the investment yields lower benefits. However, there have not been any empirical studies documenting the non-linear impact of technology adoption on bank efficiency. The existing context of the Vietnamese banking system could serve as a suitable context to examine whether this non-linearity exists. Vietnamese banks are at different stages of technology and digitalization. Given this heterogeneity, it is possible to observe some banks reaping benefits in the early stage of technology adoption while others experience the marginal benefits decline over time. Therefore, we develop our hypothesis as follows:

H1: There is a non-linear impact of technology adoption on bank efficiency in Vietnam.

3. Research method

3.1. Model specification

To examine the impact of technological adoption on bank efficiency, we adopt the following model:

$$Eff_{jt} = \beta_o + \beta_1 L.ICT_{jt} + \beta_2\ L.Size_{jt} + \beta_3\ L.CAP_{jt} + \beta_4\ L.LDR_{jt} + \varphi_j + \sigma_t + \varepsilon_{jit} \quad (1)$$

$$Eff_{jt} = \beta_o + \beta_1 L.ICT_{jt} + \beta_2\ \beta_1 L.ICT_{jt\_square} + \beta_3 L.Size_{jt} + \beta_4\ L.CAP_{jt} + \beta_5\ L.LDR_{jt} + \varphi_j + \sigma_t + \varepsilon_{jit} \quad (2)$$

where, Eff_{jt} is the efficiency score for bank *j* in year *t*. ICT_{jt} proxies for the technology development of each bank and were collected from the annual Vietnam ICT report. The ICT index is constructed based on four components, including grades for technical capacity, ITC-related personnel capacity, applications used in banks' internal operations, and online service platforms offered to customers. In Eq. 1, we establish the baseline impact of ICT on banks' efficiency, while in Eq. 2, we specifically test our hypothesis of a non-linearity by adding the square term of the ICT index. In line with standard banking literature (Nguyen et al., 2023; Ngo and Le, 2022), we include a set of bank-level control variables, including bank size, equity capital to proxy for the strength of capital, loan to deposit ratio to proxy for liquidity, and returns on assets to proxy for profitability. The full list of variables and their definitions is provided in Table 1. The summary statistics of all variables are reported in Table 2.

In this regression model, all control variables are lagged for one year to mitigate the potential endogeneity problem (i.e. reverse causality); φ_j accounts for the bank firm fixed effect; σ_t accounts for the year fixed effect; ε_{jit} is the error term. We employ robust standard errors to obtain unbiased standard errors.

3.2. Variables

DEA is a non-parametric method to estimate the efficiency score of DMUs relative to an estimated frontier (Rashidi et al., 2026). The frontier serves as the benchmark, comprising DMUs with best practices to convert input into outputs. The efficiency of each DMU can be calculated once the frontier is constructed by comparing the distances from the points that are below the frontier to the points on the frontier. We adopt the Variable Return to Scale and input-oriented DEA model as developed by Banker et al. (1984). Let us assume a group of *n* bank *j* transforms *m* inputs (*x*) into *s* outputs (*y*). For the bank under examination (O'), the input-oriented efficiency estimator (θ_o) can be estimated by solving the following linear programming:

$$\text{TE} = \min \theta_o \quad (3)$$

subject:

$$\sum_{j=1}^{n} z_j\, x_{vj} \leq \theta_o x_o \qquad v = 1,2,\ldots,m \quad (4)$$
$$\sum_{j=1}^{n} z_j\, y_{rj} \geq y_o \qquad r = 1,2,\ldots,s \quad (5)$$
$$z_j \geq 0 \qquad j = 1,2,\ldots,n \quad (6)$$
$$\sum_{j=1}^{n} z_j = 1 \quad (7)$$

where, z_j denotes the weights to be determined by the program for observation *j*.

The linear program is solved *n* times to determine the efficiency score, one for each bank in the sample. A measure of θ_o = 1 indicates that the bank is on the frontier or being technical efficient. Otherwise, a measure of θ_o < 1 (i.e., the bank is below the efficient frontier), indicating that the current inputs can be further reduced to achieve optimization. In short, higher θ_o scores indicate greater efficiency. By including a convexity constraint (i.e., restriction (5)), we account for variable returns-to-scale effects (VRS).

Following prior literature (Ngo and Le, 2022), as banks serve as financial intermediaries, we specify that the two outputs include (i) gross loans and (ii) total investment securities; and the three inputs include (i) deposits, (ii) physical assets, and (iii) personnel. The selection of inputs and outputs follows the intermediation approach, which views banks primarily as financial intermediaries that transform deposits and other resources into loans and investments. Gross loans and total investment securities are used as outputs because they represent the main earning assets. On the input side, deposits are included as the primary funding source that banks use intermediary, while physical assets capture the capital and infrastructure needed to deliver services and adopt new technologies. Personnel, in turn, reflects human capital—an essential driver of both operational efficiency and customer service quality. This input–output structure is particularly relevant in the Vietnamese context, where traditional intermediation activities remain central to bank operations even as digitalization progresses. The detailed measurement is provided in Table 1.

3.3. Sample

To obtain the best homogeneity in the production function, we only sampled the listed commercial banks in Vietnam, specifically 26 listed commercial banks whose financial and ICT data are consistently reported during the examined period. The examined period is from 2014 to 2020, which corresponds to the availability of Vietnam's ICT report for these banks. Due to the impact of the COVID-19 pandemic, the report was not launched for 2021 but only resumed in 2022. Due to this data gap, we intentionally limit our time frame before the Covid 19 pandemic.

The descriptive summary of the variables is provided in Table 2.

Table 1: Variables description

Variables	Definition
	DEA's inputs to compute the dependent variable (Eff)
W1	Cost of funds = Total interest expenses/total customer deposits
W2	Cost of physical capital = Overhead expenses net of personnel expenses /total assets
W3	Cost of labor = Personnel expenses/total assets
Q1	Output = Gross loans
Q2	Output = Total securities
	Independent variables
ICT	ICT index
SIZE	SIZE= Natural logarithm of total assets
LDR	Loan deposit ratio = Gross loans/total customer deposits
CAP	Equity ratio = Total equity/total assets
ROA	ROA= Net profit/total assets

Table 2: Descriptive summary

Variables	N	Mean	SD	Min	Max
Eff	182	0.8250	0.1192	0.4771	0.9680
ICT	182	0.5058	0.1191	0.2527	0.7762
SIZE	182	33.2903	0.9068	31.2375	35.3720
CAP	182	0.0815	0.0280	0.0382	0.1711
LDR	182	0.9345	0.5180	0.7117	2.7840
ROA	182	0.0109	0.0074	-0.0070	0.0324

As seen in Table 2, the average efficiency score (Eff) of the sampled banks is 0.8250; this implies that banks, on average, can improve their costs by about 18% relative to the best-performing bank in the sample. The ICT variable has a mean of 0.5058 and a standard deviation of 0.2527, meaning that the level of technology adoption among the sample banks varies considerably. On average, the sampled banks have an average size of 33.29, an equity capital ratio of 8.15%, a loan to deposit ratio of 93.45%, and profitability of around 10.9%. The correlation matrix provided in Table 3 implies that multi-collinearity is not an issue as the correlation scores among variables are all well below 0.8.

Table 3: Pair-wise correlation among variables

	Eff	ICT	SIZE	CAP	LDR	ROA
EFF	1					
ICT	0.12	1				
SIZE	0.204	0.4338***	1			
CAP	-0.1939	0.1311	-0.1865**	1		
LDR	-0.2068	0.1787	-0.1765	-0.0053	1	
ROA	-0.2565**	0.2471**	0.2523***	0.5021***	0.1153***	1

***: p<0.01; **: p<0.05

4. Results and discussion

4.1. Baseline results and discussion

Columns 1 and 2 of Table 4 present the results from estimating Eq. 1 with OLS-Fixed effect regression; column 1 is without the year fixed effect while column 2 is with the year fixed effect. As seen in column 2, the ICT index positively and significantly increases bank efficiency with a coefficient of 0.365 and a significance level of 5%. The initial result implies that technology adoption could help to increase bank efficiency. This finding is in line with most prior studies about confirming the benefits of technology adoption, such as cost reduction, increased operational efficiency, and improved service quality (Ngo and Le, 2022).

Column 3,4 reports the estimation of Eq. 2, where the square of the ICT index is also included. Take column 4 as the baseline result, we can see that the coefficient of ICT is 1.253 (at 1% significance level) while the coefficient of its squared value (ICT_sqr) is -0.824* (at 10% significance level). In other words, the ICT index also exerts a positive and significant impact on bank efficiency, but the squared value of the ICT index exerts a negative and marginally significant impact on bank efficiency. The result implies that technology adoption at first could contribute to higher bank efficiency; nevertheless, at a higher level of technology adoption, further technology investment would adversely impact bank efficiency. The finding lends support to several hypotheses initially postulated by Solow (1987) in his argument about "IT Productivity Paradox," which predicts that technology adoption would yield benefits to a certain level, and at a higher level of adoption, the marginal benefit will start to decline. The finding provides an important implication on the ideal level of technological development for banks. Regarding other control variables, the loan deposits ratio negatively influences bank efficiency, meaning that banks with a lower liquidity level often have lower efficiency. In column 1, we can see evidence of the positive impact of the equity capital ratio on bank efficiency.

4.2. Robust tests

In this section, we perform three additional robustness checks of our baseline findings. Firstly, as bank efficiency is measured by the DEA ranges from 0 to 1. Given this range, OLS-FE could yield biased results. Therefore, in columns 1 and 2 of Table 5, we provide a robust check with the use of Tobit as our estimation method. As seen in these columns, the results are quantitatively similar to the baseline reported in Table 4. Second, the efficiency scores obtained from the DEA approach applied in the baseline results suffer from an upward bias, meaning that those scores relative to the frontier are too optimistic. To correct this potential bias, we apply a biased-corrected procedure as described in Simar and Wilson (2000) and Badunenko and Mozharovskyi (2016).

Specifically, a bias factor for each hotel firm is estimated using a smoothed bootstrapping procedure with 1,000 replications; then subtracted from the original efficiency scores estimated in the baseline. This process provides us with the bias-corrected efficiency score (BC_Eff). The results are presented in columns 4 and 5 of Table 5.

Table 4: The impact of technology adoption on bank efficiency (OLS- FE regression)

	(1)	(2)	(3)	(4)
VARIABLES	Eff	Eff	Eff	Eff
L.ict	0.460*	0.365**	1.860***	1.253**
	(0.220)	(0.130)	(0.419)	(0.552)
L.ict_squared			-1.353***	-0.824*
			(0.344)	(0.450)
L.size	-0.063	-0.037	-0.023	0.016
	(0.077)	(0.198)	(0.062)	(0.184)
L.cap	4.949**	1.517	5.135**	2.747
	(1.846)	(2.909)	(1.988)	(2.951)
L.ldr	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
L.roa	0.781	0.122	0.173	-0.308
	(3.637)	(3.636)	(2.821)	(2.903)
Constant	2.343	1.800	0.616	-0.309
	(2.524)	(6.578)	(1.996)	(6.157)
Observations	182	182	182	182
R-squared	0.537	0.707	0.673	0.744
Number of id bank	26	26	26	26
Year FEs	No	Yes	No	Yes
Firm FEs	Yes	Yes	Yes	Yes

(1): Baseline OLS fixed-effects regression without year fixed effects; (2): OLS fixed-effects regression with year fixed effects; (3): OLS fixed-effects regression including the squared ICT term (testing non-linearity), without year fixed effects; (4): OLS fixed-effects regression including the squared ICT term, with year fixed effects (baseline specification for hypothesis testing); Robust standard errors in parentheses; ***: p<0.01; **: p<0.05; *: p<0.1

Finally, to ease the concern of potential endogeneity due to the inclusion of bank-level variables in the model, we adopt the System-GMM estimation developed by Arellano and Bover (1995) and Blundell and Bond (1998). The System-GMM allows us to use the lagged explanatory variables as instruments rather than employing external instrument variables. As can be seen in columns 5 and 6 of Table 5, the results are qualitatively like the baseline result, confirming the non-linear relationship between technological adoption and bank efficiency.

Table 5: Robustness tests

Bank efficiency (Eff)	Tobit regression	Tobit regression	BC_Eff	BC_Eff	System-GMM	System-GMM
	(1)	(2)	(3)	(4)	(5)	(6)
L.ict	0.365***	1.253***	0.365**	1.253**	0.540*	6.058**
	(0.094)	(0.399)	(0.130)	(0.552)	(0.268)	(2.752)
L.ict_squared		-0.824**		-0.824*		-5.329*
		(0.337)		(0.450)		(2.638)
L.size	-0.037	0.016	-0.037	0.016	0.106**	0.093
	(0.135)	(0.129)	(0.198)	(0.184)	(0.044)	(0.143)
L.cap	1.517	2.747	1.517	2.747	2.170***	0.859
	(1.849)	(1.908)	(2.909)	(2.951)	(0.671)	(5.167)
L.ldr	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.roa	0.122	-0.308	0.122	-0.308	-9.321	0.848
	(2.659)	(2.348)	(3.636)	(2.903)	(8.610)	(21.786)
Constant	1.901	-0.179	1.800	-0.309	-3.073*	-4.029
	(4.437)	(4.280)	(6.578)	(6.157)	(1.676)	(5.265)
Observations	182	182	182	182	182	182
R-squared	-	-	0.707	0.744	-	-
Number of id bank	26	26	26	26	26	26
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; ***: p<0.01; **: p<0.05; *: p<0.1

5. Conclusions

In the digital age, organizations, including banks, have made huge investments in advanced technology, which is expected to revolutionize their business and sharpen their competitiveness in the market. However, given the law of diminishing returns, any excessive investment would eventually lead to an adverse impact. In this study, we conducted an analysis of thirteen publicly traded commercial banks in Vietnam from 2014 to 2020 to test whether there exists a non-linear impact of technology development on bank efficiency. We assessed bank efficiency by the utilization of Data Envelopment Analysis (DEA). We assessed the progress of the bank's technological advancement by utilizing the Information Communication Technology Index, which is published by the Vietnamese government on a yearly basis. Consistent with our prediction, we observe an inverted-U-shaped association between technological advancement and banking efficiency in Vietnam.

This finding has significant implications for both the regulator and commercial banks. For the central bank, the inverted-U relationship suggests that policies should encourage digital investment up to an efficiency-enhancing threshold while preventing excessive or duplicative spending that erodes performance. This can be achieved through benchmarking digital adoption relative to bank size, promoting shared infrastructure (e.g., payment platforms, credit information systems), and strengthening capacity-building initiatives to ensure technology is used strategically. For banks, the results highlight the need to adopt value-based digital strategies. Banks should treat technology as a strategic resource rather than a race for modernization; investments should be guided by efficiency-enhancing use cases. Specifically, banks should routinely assess the marginal returns of additional IT spending as well as identify the thresholds of excessive investment. This could involve internal audits of digital project outcomes, linking them directly to operational efficiency and profitability metrics.

List of abbreviations

AI	Artificial intelligence
BC_Eff	Bias-corrected efficiency score
CAP	Equity ratio, measured as total equity divided by total assets
DEA	Data Envelopment Analysis
DMU	Decision-making unit
Eff	Bank efficiency score estimated using Data Envelopment Analysis
FE	Fixed effects
FinTech	Financial technology
ICT	Information and Communication Technology
ICT index	Composite index measuring the level of information and communication technology development
ICT_sqr	Squared term of the information and communication technology index
IT	Information technology
L.	Lagged value of a variable by one period
L.cap	Lagged equity capital ratio
L.ict	Lagged information and communication technology index
L.ict_squared	Lagged squared value of the information and communication technology index
L.ldr	Lagged loan-to-deposit ratio
L.roa	Lagged return on assets
L.size	Lagged bank size
LDR	Loan-to-deposit ratio, measured as gross loans divided by total customer deposits
OLS	Ordinary least squares
OLS-FE	Ordinary least squares with fixed effects
Q1	Output variable representing gross loans
Q2	Output variable representing total securities
ROA	Return on assets, measured as net profit divided by total assets
SD	Standard deviation
SIZE	Bank size, measured as the natural logarithm of total assets
System-GMM	System Generalized Method of Moments estimator
TE	Technical efficiency
Tobit	Tobit regression model for censored dependent variables
VRS	Variable returns to scale
W1	Cost of funds, measured as total interest expenses divided by total customer deposits
W2	Cost of physical capital, measured as overhead expenses net of personnel expenses divided by total asset
W3	Cost of labor, measured as personnel expenses divided by total assets

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Arellano M and Bover O (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68(1): 29-51. https://doi.org/10.1016/0304-4076(94)01642-D

Badunenko O and Mozharovskyi P (2016). Nonparametric frontier analysis using Stata. The Stata Journal, 16(3): 550-589. https://doi.org/10.1177/1536867X1601600302

Banker RD, Charnes A, and Cooper WW (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30(9): 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Beccalli E (2007). Does IT investment improve bank performance? Evidence from Europe. Journal of Banking & Finance, 31(7): 2205-2230. https://doi.org/10.1057/9780230591981

Blundell R and Bond S (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1): 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8

Carr NG (2003). IT doesn't matter. Harvard Business Review, 81: 41-49.

Gupta SD, Raychaudhuri A, and Haldar SK (2018). Information technology and profitability: Evidence from Indian banking sector. International Journal of Emerging Markets, 13(5): 1070-1087. https://doi.org/10.1108/IJoEM-06-2017-0211

Gyau EB, Appiah M, Gyamfi BA, Achie T, and Naeem MA (2024). Transforming banking: Examining the role of AI technology innovation in boosting banks financial performance. International Review of Financial Analysis, 96: 103700. https://doi.org/10.1016/j.irfa.2024.103700

Ho SJ and Mallick SK (2010). The impact of information technology on the banking industry. Journal of the Operational Research Society, 61(2): 211-221. https://doi.org/10.1057/jors.2008.128

Jiang S, Rebucci A, and Zhang G (2025). Banking on technology: Bank technology adoption and its effects. National Bureau of Economic Research, Cambridge, USA. https://doi.org/10.3386/w33551

Lee CC, Ni W, and Zhang X (2023). FinTech development and commercial bank efficiency in China. Global Finance Journal, 57: 100850. https://doi.org/10.1016/j.gfj.2023.100850

Li C, Li Y, Xu Y, and Sun G (2025). Research on the impact of financial technology on risk-taking of commercial banks. Research in International Business and Finance, 76: 102804. https://doi.org/10.1016/j.ribaf.2025.102804

Martín-Oliver A and Salas-Fumás V (2008). The output and profit contribution of information technology and advertising investments in banks. Journal of Financial Intermediation, 17(2): 229-255. https://doi.org/10.1016/j.jfi.2007.10.001

Ngo T and Le T (2022). Impact of information and communication technology on banking efficiency: The Vietnamese experience. In: Nguyen DK (Ed.), Handbook of banking and finance in emerging markets: 238-253. Edward Elgar Publishing, Cheltenham, UK. https://doi.org/10.4337/9781800880900.00020

Nguyen QTT, Ho LTH, and Nguyen DT (2023). Digitalization and bank profitability: Evidence from an emerging country. International Journal of Bank Marketing, 41(7): 1847-1871. https://doi.org/10.1108/IJBM-03-2023-0156

Rashidi SF, Olfati M, Mirjalili S, Grosan C, Platoš J, and Snášel V (2026). A hybrid DEA–fuzzy clustering approach for accurate reference set identification. Machine Learning with Applications, 23: 100818. https://doi.org/10.1016/j.mlwa.2025.100818

Ren X, Song K, Zhu K, and Yang X (2024). Does digital transformation increase bank profit efficiency? Evidence from China. Pacific-Basin Finance Journal, 86: 102388. https://doi.org/10.1016/j.pacfin.2024.102388

Simar L and Wilson PW (2000). Statistical inference in nonparametric frontier models: The state of the art. Journal of Productivity Analysis, 13: 49-78. https://doi.org/10.1023/A:1007864806704

Solow R (1987). We'd better watch out. New York Times Book Review, 36.

Uddin MH, Mollah S, and Ali MH (2020). Does cyber tech spending matter for bank stability? International Review of Financial Analysis, 72: 101587. https://doi.org/10.1016/j.irfa.2020.101587 **PMid:38620708 PMCid:PMC7486648**

Ungratwar S, Sharma D, and Kumar S (2025). Mapping the digital banking landscape: A multi-dimensional exploration of fintech, digital payments, and e-wallets, with insights into current scenarios and future research. Humanities and Social Sciences Communications, 12(1): 1064. https://doi.org/10.1057/s41599-025-05186-z