HOW FINTECH IS DOING INNOVATIONS AND EFFICIENCY IN THE BANKING SECTOR?

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ABSTRACT

Purpose - the purpose of the research is to examine the impact of fintech on bank efficiency in the Asian banking industry, where bank efficiency has been measured using the DEA (data envelopment analysis) approach for technical efficiency as a proxy. **Methodology -** the methodology of the research includes the sample consisting of 92 privatized commercial Asian banks from 2016-2022 and uses cross-country analysis. The panel regression models have been utilized, consisting of a fixed effect model. The model has run after the diagnostic check and the data validation has been satisfied with the stationary, serial autocorrelation, heteroscedasticity, homogeneity and multicollinearity issues. **Results -** The results show that fintech funding has a significantly positive effect on bank efficiency. Based on the results, it concludes that fintech funding is doing innovations using funding and improving efficiency in Asian banks. **Implication** - the implication derived from the empirical evidence of the study is that fintech funding brings innovations that positively consequence on bank efficiency in Asian banks. **Limitation -** the limitation of the study is that there was no data available before 2016 since fintech was a new technology during the time.

Keywords: Fintech, technical efficiency, data envelopment analysis, funding, banks.

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1. INTRODUCTION

A decade ago, Fintech emerged, with few startups gaining attention. Digital payments and mobile banking were growing but had not reached today's levels. A significant portion of consumers relied on traditional banks and cash transactions. Bitcoin was gaining attention as a digital currency but was absent from mainstream adoption.

That day, fintech regulation was limited compared to today; the concept of digital banks was relatively new, and AI (artificial intelligence) was not as advanced as it is now. However, fintech has seen significant growth and evolution over the past decade. It has transformed from a small sector to a mature, global financial industry, driven by technological advances, changing consumer preferences, and regulatory frameworks. The rise of digital banks has continued to offer online and mobile banking services, with AI, machine learning and blockchain becoming integral to fintech.

The favourable influence of Fintech on bank efficiency is likely to play a crucial role in driving growth and success as it continues to alter the banking industry. According to the previous studies, fintech innovation significantly improves bank profitability (Lee et al., 2021; Tian et al., 2019).

The bank efficiency is the ability to use sources efficiently, generate profits, and offer high-quality services. A bank's capacity is quantified to generate outputs with the least inputs and, impacts bank efficiency more strongly (Li et al., 2021; Hauner & Peiris, 2005) to enhance performance by reducing costs (Chhaidar et al., 2022; Kou et al., 2021).

Nowadays, fintech known as an improved technology disrupts transitional business models and transformation affect banking performance for several reasons. For example, Asian banks will aid customers in experiencing online services such as digital wallets, internet banking, and mobile apps, which make managing accounts and transactions more convenient around the clock. The service are easy to use and save money over time by automating services like online account registration and compliance, which lowers operating expenses to assists banks protect customer data and prevent fraud using AI, enhancing security via cloud computing to meet customer needs. Fintech transforms international payments, using blockchain technology, improving bank efficiency and bringing digital solutions to unbanked adults who lack access to banks, promoting financial inclusion, a vital component of fintech.

The fintech innovations approached by the banking industry, and encouraging unbanked adults (without accounts) to access banking services, as financial inclusion can provide access, usage, and quality financial services (Demirguc et al., 2022).

2. LITERATURE REVIEW

The theory of innovation acts as a relevant framework to realize the way that fintech is utilized by banks to generate higher profits while reducing costs. Accordingly, banks that pursue innovation tend to achieve higher profits and then apply the fintech, as an innovation in banking, to enhance profitability through cost reductions, and improving bank efficiency (Yang et al., 2021).

As depicted by Bahrainian banks, fintech adoption has a positive effect on the bank performance (Hannoon et al., 2021), different economic development levels and diverse contexts (Yoon et al., 2023). In contrast, Yudaruddin (2022) found that the presence of fintech startups negatively impacted bank performance in Indonesia. Haddad and Hornuf (2023) similarly reported a positive correlation between fintech startups and bank performance.

In addition, studies by other researchers showed that fintech efficiently affects banks (Pham et al., 2023; Lee et al., 2017; Li et al., 2021; Klimontowicz, 2019; Lee et al., 2023; Banna et al., 2023). Pham et al., (2023) analyzed the impact of fintech on bank efficiency in China and Vietnam, finding a positive response from Vietnamese banks to financial technology. Lee et al. (2021) also showed that fintech innovations enhance bank efficiency, while Li et al. (2021) indicated that fintech development is critical for improving bank efficiency. Klimontowicz (2019) analyzed fintech innovations' effect on bank efficiency in Europe, reporting improved efficiency from adopting such innovations. However, Lee et al. (2023) used the DEA-Malmquist model and found fintech development negatively influenced commercial banks' overall efficiency, suggesting that fintech integration may reduce efficiency across banking operations.

On the other hand, Banna et al. (2023) explore the relationship between fintech-based inclusive finance and bank efficiency, demonstrating a positive impact. Their study employed the DEA approach for efficiency measurement alongside regression analysis, highlighting that leveraging fintech for inclusive financial services positively contributes to banks' efficiency.

RQ1. What is the influence of fintech funding on bank efficiency, using bank-level criteria.
RQ2: What is the impact of fintech funding on bank efficiency, using macro-level factors.

Table 1: Literature matrix

Variables	Measurement	Data	Citations	Expected Significant
Bank Efficiency (DV)	DEA Approach	Eikon DataStream	Arrawatia, et at. (2015), Cava et al. (2016), Abdulahi et al. (2023), Banya and Biekpe (2017), Banna et al. (2023), Lee et al. (2023), Lee et al. (2021), Pham et al. (2023), Tan et al. (2017), Noor et al. (2020).	Positive
Fintech (IV)	Funding as a proxy	CB Insights and Crunchbase	Lee et al. (2021), Lee et al. (2023), Farouk and Kabiru (2015), Li et al. (2017), Sapulette et al. (2021), Banna et al. (2023), Pham et al. (2023), Lee et al. (2021), Yoon et al. (2023).	Positive
Macro Variables				
GDP growth	Economic growth	WDI of WB and IMF	Arrawatia, et at. (2015), Trujillo-Ponce (2012), Garcia and Guerreiro (2016), Abdulahi et al. (2023), Saleh and Alaallah (2022), (2022) and Goswami	Positive

			et al. (2019).	
Inflation	CPI Index as a proxy	WDI of WB and IMF	Trujillo-Ponce (2012), Garcia and Guerreiro (2016), Saleh and Alaallah (2022).	Negative
Interest rate	Lending rate	WDI of WB and IMF	Saleh & Alaallah (2022) and Goswami et al. (2019).	Positive
Covid-19	Covid-19 is also a dummy variable that takes the binary number 1 for Covid-19 period, and 0 otherwise.	Binary number for the years 2020-2022	Hill (2021), ("Digital finance and inclusion in the time of COVID-19," 2021), Al-Khawaja et al. (2023), and Sapulette et al. (2021).	Positive/Negative
Bank Level Variables				
Liquidity Risk	The ratio of Total Loans to Total Deposits	Eikon DataStream	Abdulahi et al. (2023), Batir et al. (2017), Repkova (2015), Tan et al. (2017), Dahiyat (2016), Marozva (2015), Banya and Biekpe (2017), Goswami et al. (2019).	Negative/Positive
Credit Risk	Total loan to total asset ratio	Eikon DataStream	Abdulahi et al. (2023), Banya and Biekpe (2017), Adusei (2016), Sharma et al. (2015), Salim et al. (2016) and Goswami et al. (2019),), Sang and Anh (2023).	Positive/Negative
Bank Size	Total Asset	Eikon DataStream	Abdulahi et al. (2023), Anwar (2019), Otero et al. (2020), Sakouvogui and Shaik (2020), (2018); Banya & Biekpe (2017), Li et al. (2017), Goswami et al. (2019), Sang and Anh (2023).	Positive/Negative
Level of Capitalization	The ratio of equity divided by total assets	Eikon DataStream	Repkova (2015), Batir et al. (2017), Adusei (2016) and Goswami et al. (2019).	Positive
NPL	Non-performing loan	Eikon DataStream	Ferreira (2022); Gaur & Mohapatra (2020) and Phung et al. (2022)	Negative

3. METHODOLOGY

3.1 Determination of Sample and Data

There are 15 Asian countries with financially sound banks that have funding for financial technology in this research study. The IMD Global Index features sixteen countries, of which

Cambodia is lacking adequate data. As a result, included seven commercial banks from each country, with data covering the period from 2016 to 2022. Additional banks were included in the countries with the fewest banks and countries with more fintech funding. As a result, 92 banks from 15 Asian countries were sampled for the study between 2016 and 2022, resulting in a total of 644 observations. Table 2 shows the banks in Asia.

Table 2: Sample Distribution of Commercial Banks 2016-2022

S/N	Country Name	Sample (commercial bank)	Observations	%
1	India	10	70	10.86
2	China	10	70	10.86
3	Malaysia	8	56	8.69
4	Saudi Arabia	8	56	8.69
5	Thailand	7	49	7.60
6	UAE	7	49	7.60
7	Qatar	7	49	7.60
8	Jordan	7	49	7.60
9	Philippine	6	42	6.52
10	Indonesia	6	42	6.52
11	Taiwan	5	35	5.43
12	Hong Kong	3	21	3.26
13	Singapore	3	21	3.26
14	Japan	3	21	3.26
15	South Korea	2	14	2.17
	Full sample	92	644	100

3.2 Variable Measurement

Bank efficiency (Dependent variable)

In selecting input and output variables for assessing bank efficiency, Berger and Humphrey (1997) assert that there is no standardized guidelines. Various criteria exist, such as the production, intermediation, value-added, and operating approaches. Since banks are often viewed as intermediaries, the intermediation approach is commonly employed in empirical studies for efficiency evaluation. This method, as highlighted by Noor et al. (2020), allows for effective assessment. Bank efficiency can be measured using a data envelopment analysis (DEA) approach, where input (cost) and output (profit) variables estimate technical efficiency. DEA is frequently applied in studies addressing bank efficiency. In this research, the efficiency of banks in Asian countries was evaluated using DEA. Cava et al. (2016) applied the DEA technique to calculate efficiency scores with specific input and output variables. Similarly, Abdulahi et al. (2023) used the CRS method to analyze bank efficiency and influencing factors, utilizing input variables like interest expenses, deposits, and total fixed assets, and output variables such as interest revenue, non-interest income, and total loans. Under the CRS concept, if all inputs are increased by a certain amount, the output will rise proportionately, based on the idea of constant returns to scale. This research employs the same methodology as previously mentioned.

Using the DEAP software to evaluate the data, a technical efficiency score is computed under DEA (Software, 2019). The ability of a decision-making unit (DMU) to maximize output from a given input is measured by its technical efficiency (TE). According to Cooper et al. (2006), TE may be computed as follows using the ratio of the total of weighted outputs to the sum of weighted inputs:

$$\text{Min } \theta_j = \frac{\sum_{r=0}^{s} u_{ra} y_{ra}}{\sum_{i=0}^{m} v_{ia} x_{ia}} \qquad \text{.........(i)}$$

where "v" and "u" stand for input and output weights, respectively, and "x" and "y" stand for inputs and outputs, "q" and "p" stand for the number of inputs and outputs, respectively, and '' θ_j " denotes the DMU's efficiency. Table 3.1 presents the variables utilizing the Intermediation Approach (Abdullahi et al., 2023):

Table 3: Input and Output Variables

Observations	**Variables**
Output Variables:	644
Interest Income	644
Non-Interest Income	644
Loan	644
Input Variables:	644
Interest Expenses	644
Deposits	644
Fixed-Assets	644

The following table 3 shows the efficiency scores of the DEA model, which is used to measure the bank's technical efficiency from 2016 to 2022 where average efficiency is estimated out of 100.

Table 4: Summary of efficiency scores

	Technical Efficiency/TE (%)						
	2016	2017	2018	2019	2020	2021	2022
Number of efficiencies	51	43	38	45	43	46	49
Number of inefficiencies	41	49	54	47	49	46	43
Number of banks	92	92	92	92	92	92	92
Average efficiency	65.37	64.55	60.75	66.17	72.25	70.67	76.77

According to Table 4, technical efficiency (TE) assumptions, the number of inefficient Asian banks is 43 in 2022, 49 in 2016, 47 in 2019, 54 in 2018, 47 in 2019, 49 in 2020, and 56 in 2021 because of below average while others are above average considered as efficient banks. From 2016 to 2022, banks' average efficiency scores were below 100%, at 65.37%, 64.55%, 60.75%, 66.17%, 72.25%, 70.67%, and 76.77%, respectively. indicates that the average technical efficiency of banks may be increased by 34.63%, 35.45%, 39.25%, 33.83%, 27.75%, 29.33%, and 23.23%, in that order. Asian banks should thus keep a careful eye on the variables that affect technical efficiency, such as growing loan volume, interest income, and deposits while cutting expenses using fintech innovations.

Fintech (Independent variable)

Some research has utilized fintech as an independent variable, employing various proxies such as investment, R&D spending, and deal frequency (Lee et al., 2021). Other studies (Lee et al., 2023; Li et al., 2017; Sapulette et al., 2021) sourced data from CB Insights and Crunchbase, treating fintech as an independent variable proxied by fintech news. Certain fintech indices, like the innovation index, enhance innovation capacity. However, since the fintech development index and innovation index do not directly address bank efficiency, might be represent other factors contributing to increased innovation.

Since 2010, fintech investment has surged, particularly in countries with greater innovation potential (Bank for International Settlements, 2021). However, R&D costs, which cover various development forms, only partially support innovation in banks and do not fully encompass fintech in the industry. The study uses funding as a proxy, making funding value a crucial metric for assessing fintech developments in banks.

Bank level factors

Empirical studies by Abdulahi et al. (2023), Repkova (2015), and Tan et al. (2017) demonstrate a positive impact of liquidity risk on bank efficiency. Conversely, Dahiyat (2016) and Marozva (2015) indicate a negative effect of liquidity risk on efficiency, leading to the hypothesis that liquidity risk is inversely associated with bank efficiency.

The relationship between bank size and efficiency is debated in empirical studies. Research by Abdulahi et al. (2023), Anwar (2019), Otero et al. (2020), and Sakouvogui and Shaik (2020) suggests banks with a larger asset base exhibit higher operational efficiency.

Credit risk findings are ambiguous. Studies (Abdulahi et al., 2023; Banya & Biekpe, 2017; Adusei, 2016; Sharma et al., 2015) show credit risk positively relates to technical efficiency, while Salim et al. (2016) found an inverse relationship between credit risk management and bank performance. Sang and Anh (2023) note that both bank size and credit risk positively affect profitability.

The link between capitalization and technical efficiency has yielded mixed results. Repkova (2015) found a positive correlation, while Batir et al. (2017) reported an opposing trend. Ferreira (2022) and Gaur and Mohapatra (2020) highlight that banks with high profitability and economic growth tend to have fewer non-performing loans (NPLs), indicating a strong negative correlation between NPLs and profitability.

Macroeconomic factors (control variables)

To account for banks and cross-country heterogeneity, the study considered several variables frequently used as control variables in the bank efficiency literature. Economic growth influences bank profitability (Trujillo-Ponce, 2012; Garcia & Guerreiro, 2016). Their results indicate that real GDP growth had a significant negative effect on bank profitability before and after the financial crisis. Saleh and Alaallah (2022) and Arrawatia et al. (2015) also revealed a positive relationship between the interest rate, economic growth, and bank performance. In prior studies above, CPI has been used as a measure of inflation, and the study also uses the same measure. The external determinant of inflation rates influences bank profitability (Trujillo-Ponce, 2012). Garcia and Guerreiro (2016) indicated that real inflation rates had a significant negative effect on bank profitability. The COVID-19 epidemic has had a transformative impact on the financial services industry, particularly in China. Hill (2021) and Al-Khawaja et al. (2023) observed that the crisis prompted a notable shift in consumer behaviour towards online and mobile financial services. ("Digital finance and inclusion in the time of COVID-19," 2021) highlighted that the pandemic acted as a catalyst for accelerating the process of financial digitization.

3.3 Analytical Method

In the section, the study uses several variables from the table-4 above to estimate an empirical model:

Regression models

$$Beffi_{jt} = \alpha + \beta_1 FT_{jt} + \beta_2 Bsize_{jt} + \beta_3 LiqRisk_{jt} + \beta_4 CRisk_{jt} + \beta_5 Lcap_{jt} + \beta_6 NPL_{jt} + \mu_{jt} \quad \ldots\ldots (1)$$

$$Beffi_{jt} = \alpha + \beta_1 FT_{jt} + \beta_2 Bsize_{jt} + \beta_3 LiqRisk_{jt} + \beta_4 CRisk_{jt} + \beta_5 Lcap_{jt} + \beta_6 NPL_{jt} + \beta_7 GDPgrowth_{jt} + \beta_8 CPI_{jt} + \beta_9 IRate_{jt} + \beta_{10} Covid_{jt} + \mu_{jt} \quad \ldots\ldots (2)$$

Where *$Beffi_{jt}$* denotes bank efficiency, FT as Fintech, Bsize as bank size, LiqRisk as liquidity risk, CRisk as credit risk, Lcap as level of capitalization, NPL as non-performing loan, GDPgrowth as real GDP growth, CPI as consumer price index, IRate as interest rate, Covid as binary variable, j as number of banks, t as a year, α as intercept, β_1 - β_{10} as slope parameters, μ as error, unobservable, residual

Raw data examination and preparation

The results of descriptive statistics on raw data under the equation 2 are presented in table 4.

Table 5: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
Bank Efficiency (Beffi)	644	0.680	0.233	0.198	1.000
Fintech (FT)	644	255.103	1093.592	0.000	10700
Competitiveness (Com)	644	27.309	15.37684	1.000	58.000
Liquidity Risk (LiqRisk)	644	1.038	1.816	0.211	28.750
Credit Risk (CRisk)	644	35611.51	147234.40	1.363	165.00
Bank Size (Bsize)	644	593285.2	360.000	676.100	3.450
Level of Capitalization (Lcap)	644	0.122	0.101	0.007	1.000
Non-Performing Loan (NPL)	644	3177.775	8006.53	2.19	73838.08
GDP Growth (GDPgrowth)	644	0.029	0.038	0.095	0.087
Interest Rate (IRate)	644	0.021	0.020	-0.025	0.081
Consumer Price Index (CPI)	644	0.052	0.025	0.008	0.118
COVID-19	644	0.284	0.451	0.000	1.000

The descriptive statistics (table 5) above using raw data show more than three standard deviations, indicating a significant variation in the variables. Particularly, the variables with very high standard deviations—fintech, country competitiveness, credit risk, bank size, and non-performing loans—as well as very large ranges between their minimum and maximum values, stand out from the others. Thus, data filtering is required. STATA is used for both graphical and non-graphical approaches to check for outliers. The total number of observations drops to 613 once the high standard deviation data is filtered, and each variable's fluctuation has come to less than one standard deviation.

Diagnostic check

The data pass the tests for endogeneity, heteroskedasticity, autocorrelation, multicollinearity, and normality, as shown by the findings shown in Table 6 suggests that there is no significant multicollinearity among the variables and that the distribution of the dataset is consistent with normality assumptions. Consequently, the accuracy of these data points may be trusted by researchers, which improves the dependability of any further statistical analysis and conclusions.

Table 6: Diagnostic Check

	Unit-root test based on ADF test	VIF for multicollinearity	Breusch-Godfrey LM test for autocorrelation	Breusch-Pagan test for heteroskedasticity	Durbin-Wu-Hausman test for endogeneity	FE model selection using Hausman
Model 1	Results are normal since $p<0.05$	Range = 1.04-3.29	p-value = 0.0568	p-value = 0.250	p-value = 0.615	$P<0.01$
Model 2	Results are normal since $p<0.05$	Range = 1.04-3.29	p-value = 0.060	p-value = 0.129	p-value = 0.615	$P<0.01$

Unit-root test based on ADF test

Unit-root tests based on the ADF method (Islem, 2017) show normality for all variables. Additionally, the VIF test for collinearity reveals no multicollinearity among the variables.

Auto-correlation and Heteroskedasticity Tests

The results of the autocorrelation test using the Breusch-Godfrey LM test and the heteroskedasticity test using the Breusch-Pagan test indicate that for models 1-2, the p-values are not statistically significant, showing no autocorrelation. The heteroskedasticity test also shows p-values greater than 0.05, suggesting no significant evidence of heteroskedasticity.

The endogeneity test

The endogeneity test was conducted to avoid inconsistent OLS estimation, as endogeneity can correlate treatment and outcome, complicating causal interpretation. The Durbin-Wu-Hausman test showed non-significant p-values, indicating that variables are exogenous. Therefore, models 1-2 do not have any endogeneity issues.

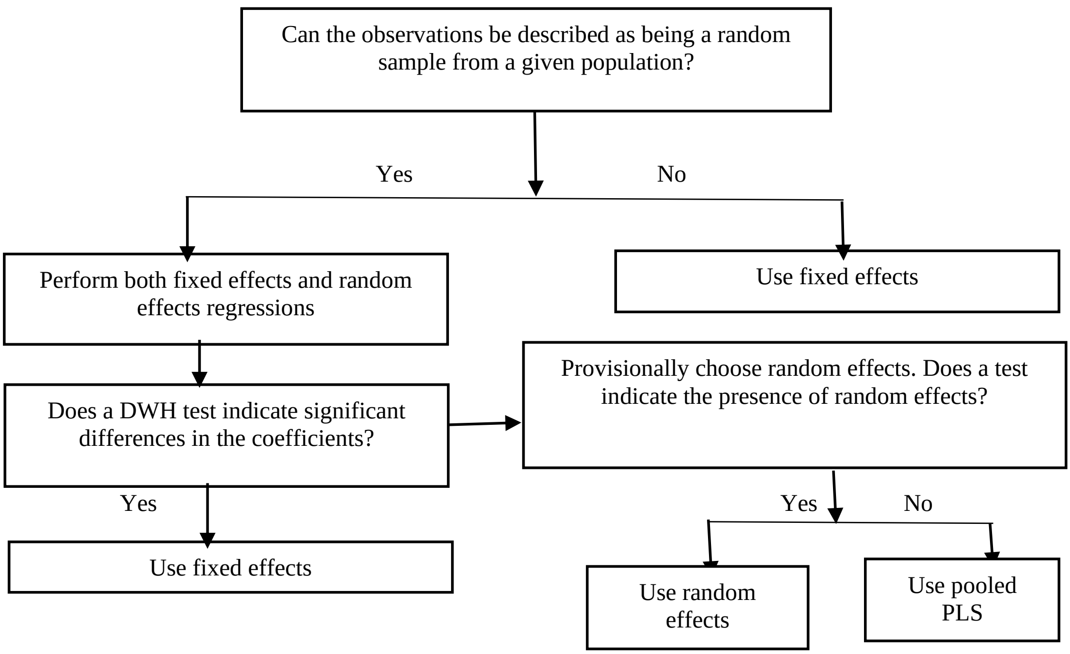
Model Selection Fixed-Effect (FE)

Previous studies (Farouk & Kabiru, 2015) examined the impact of fintech investments on bank performance using a panel data regression model. Li (2022) investigated the effects of fintech innovation on bank risk management with panel data. In this research, panel data was used to select the appropriate regression model—whether pooled, fixed effects (FE), random effects (RE), or ordinary least squares (OLS)—through a systematic process. The results of the selection are presented in Chapter 4. To ensure the analysis is suitable for pooled or panel data, the Breusch-Pagan Lagrange Multiplier (BPLM) tests were conducted before proceeding with FE or RE. The baseline estimations using OLS and RE models are included in the Appendix.

Dougherty (2016) and Torres-Reyna (2007) state that the Hausman test is used to determine whether to select FE or RE regression, while the Breusch-Pagan LM test identifies whether to use

RE or OLS. Similarly, the Hausman test helps choose between fixed effects and random effects regression models, providing a clear evaluation of model quality (Ceesay & Moussa, 2022). The first step in selecting the appropriate regression model for panel data is determining if the observations are drawn from a random sample. If samples are, a fixed-effects model is preferred; otherwise, both fixed and random effects should be assessed. The Lagrange multiplier approach (LM) is then used to choose between the random-effects model and the pooled OLS model. The Durbin–Wu–Hausman (DWH) test evaluates the fixed-effect and random-effect models (Hoang & Thanh, 2023; Nguyen & Nguyen, 2012). Additionally, a test for random effects existence is conducted; if detected, the random-effects model is applied; if not, the pooled OLS model is utilized in Figure 1.

Figure 1: Regression model selection procedure for panel data adapted from (Dougherty, 2016, p.421)



4. RESULTS AND DISCUSSION

4.1 Result: Fixed-Effect Model

In the research, panel data regression model has been applied since prior study (Farouk & Kabiru, 2015) is the most relevant. The following table-6 represents the results:

Table 7: Panel data regression model
DV= Bank efficiency (Beffi) and IV= Fintech (logFT)

Independent Variables	Model 1	Model 2
logFT	0.015**	0.026***
	(0.006)	(0.007)
logLiqRisk	0.055	0.062
	(0.029)	(0.032)
logCRisk	0.078	0.131
	(0.158)	(0.168)
logBsize	0.187***	-0.033
	(0.071)	(0.089)
logLcap	1.97***	1.69***
	(0.454)	(0.531)
logNPL	0.158***	0.096**
	(0.033)	(0.039)
logGDPgrowth		0.052***
		(0.016)
logIRate		-0.179***
		(0.036)
logCPI		0.015
		(0.014)
Covid		0.033**
		(0.012)
Constant	-1.000***	-0.137
	(0.342)	(0.446)
Observation	613	613
R-squared	12.580	12.300
F-statistics	12.380	12.880
Prob (F-Statistic)	(0.000) ***	(0.000) ***

Notes: Standard errors are in parentheses and p-values in square brackets.
* p < 0.10; ** p < 0.05; *** p < 0.01

4.2 Discussion

Model 2 indicates that the bank's efficiency will decline by 0.137 units if all variable coefficient values are set to zero (0). According to the findings in Table 7, each variable is described as follows:

The results show that fintech (FT) has a significant positive effect (p<0.01) on bank efficiency. Holding other independent variables constant, a 1% increase in FT funding boosts bank efficiency by 0.026 units in Model 2. It means that an increase in fintech correlates with improved bank efficiency. Farouk and Kabiru (2015) demonstrated the positive impact of IT investment on bank performance using bank-level factors, while Yudaruddin (2022) examined the positive effects of fintech startups on bank performance. The study finds that the value of fintech financing positively influences bank efficiency, aligning with previous research (Lee et al., 2023; Fang et al., 2022; Liao, 2023) investigating how fintech development affects bank efficiency in Taiwan and China through various methodologies. These findings can assist banks in developing fintech policies and making strategic decisions to enhance efficiency and streamline services.

Fintech funding has driven innovation in Asia's banks, allowing them to disrupt traditional business models, improve operational effectiveness, and reach a broader customer base. Financial inclusion has also increased access to basic services for underprivileged populations, potentially leading to more profitable, accessible, and convenient banking in Asia.

However, fintech in Asian banks is lagging, hindering improvements in bank efficiency. With a wider client base, lower operating costs, and advanced technology, fintech substantially impacts bank efficiency. Policymakers should encourage Asian banks to adopt technological innovations.

The report also shows that fintech has a significant positive effect ($p<0.05$) on bank efficiency when considering only bank-level factors in Model 1, indicating a 1% increase in fintech funding improves bank efficiency by 0.015 units. The regression models provide strong evidence to support the hypotheses, implying that fintech adoption positively contributes to the technical efficiency of Asian banks. In simpler terms, banks that invest in fintech tend to operate more efficiently.

The report examines the impact of fintech on bank efficiency with regard to bank-level factors: liquidity and credit risk have an insignificant ($p>0.05$) positive impact on efficiency. Capitalization levels have a significant ($p<0.01$) positive effect on bank efficiency at both bank and macro levels, with a 1% increase in capitalization raising technical efficiency by 1.69 units at the macro level and 1.97 units at the micro level, suggesting that higher capitalization leads to better bank efficiency. Additionally, bank size significantly ($p<0.05$) affects efficiency at the bank level, where a 1% increase in size raises efficiency by 0.187 units in Model 1, assuming other variables remain constant. The finding is consistent with previous research (Repkova, 2015).

Unexpectedly, NPL has a significantly ($p>0.05$) positive effect on bank efficiency, differing from earlier studies (Ferreira, 2022; Gaur & Mohapatra, 2020; Phung et al., 2022), potentially due to income generated from interests and penalties on defaulted loans, which may exceed management costs.
On the other hand, the report also examines the impact of fintech funding on bank technical efficiency by considering broader macro-level factors. GDP growth has a significantly positive relation with bank efficiency ($p<0.01$), indicating that a 1% increase in GDP will raise bank efficiency by 0.052 units, assuming other variables remain constant. These findings align with prior studies (Saleh & Alaallah, 2022; Goswami et al., 2019).

Conversely, interest rates and inflation demonstrate a significantly negative relationship with bank efficiency ($p<0.01$), which contradicts previous findings (Saleh & Alaallah, 2022). Interestingly, COVID has a significant positive relationship with bank efficiency ($p<0.05$), indicating that a 1% increase in fintech funding will enhance bank efficiency by 0.033 units, consistent with earlier research (Hill, 2021).

The report highlights that the relationship between the value of fintech funding and bank technical efficiency had not been widely studied before, bringing innovative elements to the research. Consequently, the findings suggest that fintech funding positively influences the technical efficiency of Asian banks.

Additionally, the study explored various bank-level and macro-level factors, shedding light on their effects on technical efficiency. These findings provide valuable insights for both the banking industry and policymakers regarding how to leverage fintech-based cutting-edge technologies in Asian banks.

5. CONCLUSION

Fintech funding has improved bank efficiency across regions, but Asia's funding remains low, leaving many consumers underbanked. Advanced technologies that are user-friendly and customized at a lower cost can lead to higher operational efficiency for these consumers. While fintech has transformed the banking industry globally, Asian banks continue to lag, resulting in diminished efficiency.

Over the past decade, innovations such as AI, cloud computing, and blockchain have revolutionized banking worldwide. However, due to limited fintech funding, Asian banks face ongoing challenges in efficiency. If continue to operate under traditional business models, the risk falling further behind as other regions experience rapid growth in fintech.

Therefore, Asian banks must adopt fintech to enhance resource allocation, reduce manual interventions, improve customer experiences, and expand access to banking services. The includes leveraging technologies like AI and blockchain.

The study offers valuable insights for policymakers, banking stakeholders, and investors regarding the benefits of fintech. It contributes to the existing literature on the relationship between fintech funding and bank technical efficiency using the DEA approach. Future research should expand by incorporating different fintech proxies, extending dataset periods, and focusing on the financial services sector.

Research Implications

The empirical evidence from the study indicates that fintech funding positively affects bank efficiency in Asia. By implementing fintech innovations, banks can provide efficient digital financial services to SMEs and consumers, making banking services more accessible and inclusive while also reducing overhead costs, thereby enhancing bank efficiency.

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APPENDIX

OLS AND RANDOM-EFFECT (RE) RESULTS OF MODELS 1-2

Table i: Appropriate model 1

Independent Variables	Breusch-Pagan LM test for RE	Hausman Test for FE
Model 1 (RE)	0.000 $Chi^2 = 258.67$	
Model 1 (FE)		0.040 $Chi^2 = 18.97$

Table ii: The result for Panel data regression model (OLS) on the relationship between bank efficiency and fintech starting from year 2016-2022 for Asia's banks.

DV= Bank efficiency (Beffi) and IV= Fintech (logFT)

Independent Variables	***Model 1***
logFT	0.009 (0.337)
logLiqRisk	0.082 (0.001) ***
logCRisk	0.505 (0.000) ***
logBsize	-0.054 (0.118)
logLcap	0.217 (0.063)
logNPL	0.119 (0.000) ***
logGDPgrowth	0.042 (0.022) **
logIRate	-0.181 (0.000) ***
logCPI	0.026 (0.146)
COVID	-0.035 (0.156)
Constant	-0.144 (0.234)
Observations	613
R-squared	0.2784
F-stat/Wild test	17.050
Prob (F-Statistic)	(0.000) ***

Notes: p-values in square brackets. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table iii: The result for Panel data regression model (RE) on the relationship between bank efficiency and fintech starting from year 2016-2022 for Asia's banks.

DV= Bank efficiency (Beffi) and IV= Fintech (logFT)

Independent Variables	***Model 1***

logFT	0.024 (0.002) ***
logLiqRisk	0.069 (0.005) ***
logCRisk	0.342 (0.006) ***
logBsize	-0.057 (0.053)
logLcap	0.227 (0.153)
logNPL	0.110 (0.000) ***
logGDPgrowth	0.057 (0.000) **
logIRate	-0.207 (0.000) ***
logCPI	0.022 (0.111)
COVID	-0.011 (0.516)
Constant	-0.051 (0.742)
Observations	613
R-squared	0.2269
F-stat/Wild test	140.66
Prob (F-Statistic)	(0.000) ***

Notes: p-values in square brackets. * p < 0.10; ** p < 0.05; *** p < 0.01