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Bank efficiency in the digital age: The role of financial technology in Tanzanian banks

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Abstract: The global rise of financial technology offers opportunities and challenges for banking businesses, including Tanzanian banks. This study examines the influence of a bank's FinTech index on the efficiency of 30 Tanzanian commercial banks categorized as large, medium, and small from 2010–2021. Using panel data and a two-step Generalized Method of Moments (GMM) estimator, the study finds that the FinTech index measuring banks' financial technology development significantly enhances efficiency across all banks, with the largest impact on large banks due to their high financial technology development. However, medium and small banks face challenges in financial technology development, resulting in a negative relationship between the FinTech index and the efficiency of banks. The study emphasizes the need for regulatory frameworks supporting financial technology integration in the core banking systems, especially for smaller and medium banks. It highlights the importance of collaboration and risk management to enhance bank efficiency and financial stability.

Keywords: financial technology, efficiency, Tanzanian commercial banks, FinTech index.

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1. Introduction

Globally, financial technology (FinTech) has transformed the financial industry, significantly altering how financial services are delivered (Arnaut & Bećirović, 2023). For instance, in 2022, global investments in FinTech reached $164 billion, driving innovations such as artificial intelligence-driven risk management and blockchain technology (KPMG,2023). In the banking sector, this integration is evident in adopting digital lending platforms, mobile banking, and automated credit scoring systems that have enhanced customer experience and operational efficiency. For example, 70% of banks worldwide now offer digital-only services, reflecting the rapid integration of FinTech solutions into traditional banking practices (Deloitte, 2023). Despite this evident growth, empirical evidence on how FinTech influences the efficiency of commercial banks across different categories, such as large, medium, and small banks, remains limited (Al-Shari & Lokhande, 2023; Elsaid, 2023).

Bank efficiency has become an increasingly important factor in the global financial landscape, influencing the sustainability and competitiveness of banking institutions (Broby, 2021). Efficient banks are better positioned to allocate resources, minimize operational costs, and offer innovative services, contributing to long-term stability (Badunenko *et al*., 2021; Lee *et al*., 2021). For instance, Badunenko et al. (2021) highlighted that efficient resource allocation boosts bank profitability and mitigates systemic risks and insights critical to understanding efficiency measures in this study. Similarly, Lee et al. (2021) analyzed cost-reduction strategies in banks of varying sizes, providing a framework for this study's evaluation of efficiency differences across bank categories. In a globally interconnected banking system, inefficiencies can escalate quickly and have far-reaching consequences for different bank sizes (Abdu, 2022; Habib *et al*., 2020). The role of FinTech in enhancing bank efficiency is particularly significant as it streamlines operations, improves resource allocation, and reduces manual errors through automation (Sajid *et al*., 2023; Dwivedi *et al*., 2021).

In Africa, the banking sector increasingly recognizes FinTech's transformative potential, driving innovations in financial services. In South Africa, banks have adopted technologies such as mobile banking, blockchain for secure transactions, artificial intelligence (AI) for customer service and fraud detection, and application program interfaces (APIs) for seamless integration (Kshetri, 2021). These technologies streamline operations, reduce transaction time, and enhance customer satisfaction. Similarly, in East Africa, Tanzania and Kenya have leveraged FinTech to revolutionize banking with mobile money platforms, such as M-Pesa, promoting financial inclusion among unbanked populations. Banks have also embraced cloud computing for efficient data management, biometric authentication for security, and data analytics to optimize decision-making and tailor financial products (Ntwiga, 2020). However, limited empirical research exists on how FinTech integration within a bank influences the efficiency of Tanzanian banks across different categories, highlighting the need to address this gap in enhancing banking performance.

In sub-Saharan Africa, FinTech can potentially drive substantial progress in financial services, particularly by improving efficiency and extending access to previously underserved markets (IMF, 2019). FinTech can make banks more efficient, improve service quality, and expand their customer base (Murinde *et al*., 2022). This is critical for banks to continue playing a crucial role in their countries' economic development. FinTech promises to enhance bank efficiency by bridging information gaps, reducing costs through automation, and reaching unbanked customers (Chan *et al*., 2022; Murinde *et al.*, 2022). Conversely, inefficient banks can hinder economic growth. When banks mismanage resources or operate inefficiently, they slow down the flow of capital and limit growth (Isik & Uygur, 2021). This highlights the importance of understanding how the FinTech development of commercial banks can enhance efficiency, optimize resource allocation, and ensure the banking sector's contribution to overall economic well-being.

According to Statista (2024), Tanzania's Fintech sector is witnessing significant growth, particularly in digital financial services. The digital assets market is projected to be the largest segment, with assets under management (AUM) expected to reach USD 5.70 million in 2024. The average AUM per user in the Digital Investment market for the same year is estimated at USD 79.35, indicating an increasing adoption of digital investment solutions. Furthermore, the Digital Assets market is anticipated to grow at a revenue rate of 23.90% by 2025, showing its rapid development. In the digital payment segment, user numbers are projected to rise significantly, reaching 11.60 million by 2028. These trends underscore the expanding footprint of FinTech in Tanzania, driven by an increase in digital adoption and innovation in financial services (Statista report, 2024).

Additionally, the Bank of Tanzania (BOT) introduced the Tanzania Instant Payment System (TIPS) to facilitate real-time payments across different financial providers, addressing issues such as liquidity management and operational inefficiencies (BOT, 2020). With further advancements, such as the modernization of the Tanzania Interbank Settlement System (TISS) and the FinTech Regulatory Sandbox 2023, the groundwork has been laid for a deeper investigation of a bank's FinTech influence on banking efficiency based on their categories. As an emerging economy, Tanzania's adoption of FinTech presents opportunities to improve the banking sector (Makina, 2019). Many banks have initiated their FinTech projects or partnered with firms such as mobile network operators (MNOs) to integrate financial services (Koloseni & Mandari, 2024).

These collaborations enable smooth transactions between Fintech platforms and commercial banks.

Existing studies of bank efficiency often focus on bank-specific and macroeconomic factors. For example, Temba *et al*. (2023) and Lotto (2019) examine governance and liquidity in Tanzanian banks, but their findings do not account for the growing role of FinTech. Additionally, studies such as Sajid *et al*. (2023) and Isik and Uygur (2021) emphasize the role of FinTech in enhancing operational efficiency through automation and resource optimization. Most of the studies conducted in Africa, such as Shah *et al.* (2022), Banya and Biekpe (2018), Lotto (2019 and 2018), and Lema (2017), analyzed banks' efficiency using data envelopment analysis (DEA) but did not focus on bank FinTech to evaluate its influence on banks' efficiency. Few studies have focused on the effects of competition between FinTech firms and bank performance.

This study addresses these gaps by constructing a bank FinTech index for Tanzanian commercial banks, a novel contribution reflecting the level of FinTech development in this emerging economy. Unlike broader indices, this study develops a FinTech index tailored to Tanzanian banks' operational and technological dynamics, providing a localized perspective. The scarcity of research on FinTech integration and its efficiency implications was identified through a systematic review of the literature that revealed limited studies exploring FinTech's impact on bank categories in Tanzania. While previous research has highlighted general efficiency determinants, the role of FinTech remains underexplored. This gap forms the basis for this study's contribution, which examines how FinTech influences efficiency, measured by total factor productivity (TFP), across large, medium, and small banks. Additionally, this study examines the influence of control variables on bank efficiency to provide deeper insights into the drivers of bank efficiency in Tanzania. This study seeks to answer the following questions: How does the bank FinTech index influence efficiency in Tanzanian commercial banks? Does this effect vary by bank category? What are the broader implications for the banking sector, particularly regarding the influence of the bank control variables on bank efficiency?

The results show that large banks benefit significantly from the FinTech index, enhancing efficiency through advanced technology adoption. In contrast, medium and small banks face challenges in scaling FinTech, negatively affecting their efficiency. Key factors such as the capital adequacy ratio and loan-to-deposit ratio influence efficiency differently across bank sizes. Nonperforming loans consistently reduce efficiency, emphasizing the need for robust risk management. By combining theoretical models with data-driven validation, the study offers actionable insights for policymakers and managers to optimize FinTech integration and develop sustainable policies to enhance efficiency and resource utilization in Tanzania's banking sector.

The remainder of the paper is structured as follows. Section 2 reviews the theoretical and empirical literature relevant to the study. Section 3 outlines the research methodology. Section 4 presents and discusses the results, and Section 5 concludes the study with key findings, recommendations, and suggestions for future research.

2. Literature Review

2.1. Theoretical Frameworks

This study examines the influence of the bank FinTech index on bank efficiency using intermediation theory, as proposed by Gorton and Winton (2003). Intermediation theory emphasizes banks' role as financial intermediaries, reducing transaction costs and addressing information asymmetries to facilitate fund flows between savers and borrowers, thereby fostering economic growth and development (Muda *et al*., 2021; Das Gupta *et al*., 2021). The emergence of FinTech offers transformative potential to traditional banking intermediation by introducing innovative technologies that streamline operations, improve credit risk assessment, and enhance customer experiences. These technologies ranging from mobile banking and artificial intelligence-driven credit scoring to blockchain platforms, among others, significantly reduce operational costs, improve risk management, and expand financial accessibility (Wang *et al.*, 2021). While intermediation theory offers a strong foundation for understanding the economic role of banks, it does not fully capture the dynamic and disruptive nature of FinTech. Technological innovations often extend beyond traditional banking frameworks, creating new forms of financial intermediation. This study broadens the theoretical scope by integrating Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM) to address these limitations.

Innovation Diffusion Theory (IDT), as proposed by Rogers *et al*. (2014), explains the adoption of innovations based on factors such as perceived relative advantage, compatibility with existing systems, complexity, trialability, and observability. In the context of FinTech, IDT highlights that banks adopt technologies like mobile banking and artificial intelligence analytics when their benefits, such as enhanced efficiency, cost reduction, and improved customer satisfaction, are perceived to outweigh potential challenges (Adewumi *et al.*, 2024). By focusing on these attributes, IDT provides a framework for understanding the rate and drivers of FinTech adoption within banks.

The Technology Acceptance Model (TAM), as proposed by Davis (1989), complements IDT by addressing behavioral and organizational factors influencing technology adoption. TAM identifies perceived ease of use (PEOU) and perceived usefulness (PU) as key drivers of acceptance. In banking, these factors are critical in determining how FinTech solutions are integrated into operations and used to enhance efficiency and customer engagement (Latreche *et al.*, 2024). For instance, technologies perceived as user-friendly and beneficial are more likely to be embraced by bank staff and customers, accelerating their impact on bank profitability and operational efficiency (Isiaku & Adalier, 2024). This study captures the complex relationship between FinTech development and bank efficiency by integrating intermediation theory, IDT, and TAM. Intermediation theory provides the economic rationale, while IDT and TAM address organizational and behavioral dimensions. This comprehensive approach aligns with recent studies by Cheng (2020) and Odoom and Kosiba and offers actionable insights for banks and policymakers. It highlights how technological advancements reshape traditional banking operations and foster greater efficiency, particularly in emerging markets like Tanzania.

2.2. Empirical Review

Empirical studies examining financial technology's (FinTech) impact on bank efficiency have yielded various findings across regions and methodologies. The FinTech index is a composite measure capturing the extent of financial technology adoption by banks, encompassing dimensions like mobile banking, blockchain technology, artificial intelligence-driven credit scoring, digital payments, and online lending platforms (Wang et al., (2021). The relationship between FinTech and bank efficiency has been extensively explored, with most studies indicating positive impacts on various dimensions of bank performance (Lee et al., 2023; Chen et al., 2021). FinTech-related initiatives, often incorporated as independent variables or efficiency scores in econometric modeling, demonstrate the potential of technology to enhance banking operations. Das Gupta et al. (2021) developed a weighted FinTech index and found a positive correlation with operational efficiency in South Asian banks.

The rapid evolution of financial technology has highlighted the need for comprehensive indices to measure FinTech adoption and its impact on the banking sector. Existing efforts, such as Cheng and Qu'sa's (2020) banking FinTech index, utilized web crawlers and word frequency analysis to assess FinTech adoption broadly but lacked focus on sector-specific operational measures. Similarly, Cao et al. (2024) employed the Baidu search engine to track financial technology-related keywords and the efficiency in the Chinese banking sector, providing robust data-driven insights but without directly linking these trends to bank efficiency measures like cost reduction or customer satisfaction. Deng et al. (2021) further developed a FinTech index derived from municipal digital financial indices, offering a broader perspective on urban FinTech development but failing to capture bank-specific performance impacts.

This study's constructed Bank FinTech Index addresses these gaps by focusing on sector-specific metrics such as operational integration, technological adoption, and product innovation. Unlike prior indices, it explicitly connects FinTech adoption to bank efficiency outcomes, including cost efficiency, resource allocation, and enhanced customer service. This targeted approach offers a practical tool for analyzing the operational impact of FinTech on banking institutions. Empirical evidence underscores the importance of such tailored indices, demonstrating that effective FinTech integration can reduce transaction costs, improve risk management, and optimize resource utilization, making this Bank FinTech Index a valuable addition to the field.

Wang et al. (2021) also explored FinTech's influence in China by combining DEA and GMM to assess improvements in total factor productivity (TFP) within commercial banks. Their findings highlight that the degree of technological application significantly influences productivity outcomes, pointing to the importance of strategic technology adoption in achieving efficiency gains. In contrast, Khan et al. (2024), using GMM to study 59 developing nations, revealed that FinTech integration initially hampers bank efficiency due to adaptation challenges but leads to efficiency improvements as adoption matures. This non-linear relationship underscores the complexities of Fintech adoption, particularly in emerging markets.

Bank efficiency is typically measured using methodologies like Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and Total Factor Productivity (TFP), linking FinTech adoption to cost reductions, improved risk management, and customer engagement (Prakash et al., 2021). Chen et al. (2021) reported increased cost efficiency in Chinese banks with higher FinTech index scores using DEA. For instance, Liao (2023) employed a DEA-based model to assess the impact of FinTech on bank efficiency, revealing no significant improvements over traditional branches' practices. However, initial high implementation costs and varying impacts across bank sizes remain challenges (Ogbonna et al., 2023).

Collaborative efforts between FinTech firms and banks have been shown to enhance efficiency (Klus et al., 2019). Ntwiga (2020) emphasizes that such partnerships allow banks to reach customers more effectively through digital channels, reducing acquisition costs compared to traditional methods. Similarly, studies by Thakor (2020) and Wirtz et al. (2023) demonstrate that FinTech offers digital self-service options and personalized experiences to lower customer servicing costs and improve efficiency. Advanced technologies, such as data analytics and artificial intelligence (AI), enable banks to understand customer needs better, fostering targeted cross-selling opportunities and improving efficiency (Raj et al., 2024; Chen et al., 2021).

In East Africa, Ky et al. (2019) use a fixed-effects model to examine mobile money as proxies for FinTech, revealing a positive relationship between these innovations and bank efficiency. Similarly, Ntwiga (2020), in a study of Kenyan banks using DEA and a fixed-effects model, demonstrated that Fintech collaboration significantly reduced intermediation costs and increased operational scale, albeit with diminishing returns to scale. These studies highlight the transformative role of mobile money and collaborative Fintech solutions in enhancing efficiency, particularly in resource-constrained settings.

Empirical studies in Tanzania have focused on governance and operational factors influencing bank efficiency. Using a random-effects regression model, Lotto (2019 and 2018) found that bank liquidity and capital adequacy positively influence operating efficiency. Through multiple linear regression, Temba et al. (2023) highlighted the negative influence of corporate governance variables, such as board gender diversity and governance control, on the efficient use of equity and liquidity. By employing DEA and regression analysis, Soud and Aypek (2020) find that board size and composition significantly impact efficiency, emphasizing the role of governance in shaping operational outcomes.

These studies provide diverse insights into the interplay between Fintech, governance, and operational efficiency. However, gaps remain in understanding how FinTech influences efficiency across different bank categories, such as large, medium, and small banks, particularly in emerging economies such as Tanzania. This underscores the need for further research to examine the influence of FinTech integration within various bank contexts and across different bank sizes.

A literature review indicates a research gap in evaluating the relationship between a bank's efficiency and the bank FinTech index in an emerging market such as Tanzania. The conflicting results of previous studies have led this study to test two key hypotheses. First, (H1) suggests that the FinTech index positively influences Tanzanian banks' efficiency. Second, (H2) the influence of the bank FinTech index on efficiency varies across different bank categories, including large, medium, and small banks. These hypotheses offer a comprehensive view of the factors driving bank efficiency among Tanzanian banks.

3. Methodology

3.1. Data and Study Design

This study investigated the influence of the bank FinTech index on the efficiency of commercial banks in Tanzania. Grounded in a positivist research philosophy, this study empirically assesses the relationship between the bank FinTech index and bank efficiency. This study draws on a balanced panel dataset covering 2010 to 2021, with data obtained from the Bank of Tanzania Supervision Information System (BSIS), aggregating annual audited financial reports from commercial banks. Macroeconomic data were sourced from the National Bureau of Statistics (NBS), the Bank of Tanzania (BOT), and World Bank indicators.

A purposive sample of 30 commercial banks was selected from an initial pool of 36 banks based on their continuous operation during the study period and data availability. Narrowing the study to commercial banks allows for a more focused, relevant, and comparable analysis of the relationship between Fintech development and bank efficiency. The year 2010 was chosen as the starting point because of the rapid adoption of FinTech, beginning in 2008, transformed banking channels, with 2010 marking a critical period of growth in mobile and internet banking, highlighting the early stages of FinTech integration in the banking sector (BOT, 2019). The Bank of Tanzania classifies commercial banks into three peer groups based on total assets: Peer group 1 includes the most prominent banks with assets between TZS 500 billion and TZS 99.999 trillion; peer group 2 comprises medium-sized banks with assets ranging from TZS 200 billion to TZS 500 billion; and peer group 3 consists of smaller banks with assets between TZS 30 billion and TZS 200 billion (BOT, 2018). Banks were categorized as large, medium, and small based on total assets to account for heterogeneity in resources, technological capabilities, and operational strategies influencing FinTech integration. Large banks often have a greater capacity for advanced FinTech solutions, while medium and small banks may face resource constraints but exhibit unique adoption dynamics. This categorization enables analysis of whether the Bank FinTech Index's impact varies by size, providing targeted insights for policy and management decisions (Lee *et al*., 2021). Separate regressions were performed for each group of ten (10) banks to account for potential size-related differences that could affect model estimates, following the Bank of Tanzania's asset-based classification guidelines.

This study applied a two-step System Generalized Method of Moments (GMM) estimator to assess the influence of the bank FinTech index on bank efficiency (Medhioub & Boujelbene, 2024; Zhao *et al*., 2022). A panel research design was employed to explore the trends in bank efficiency over time about the bank FinTech index. This design is well suited for analyzing temporal changes, accounting for individual bank heterogeneity, and enhancing the statistical robustness of the results (Yitayaw, 2021). The advanced econometric approach addresses potential endogeneity and unobserved bank-specific effects, offering robust insights into the dynamic relationship between a bank's FinTech index and efficiency in Tanzania's banking sector (Roodman, 2009).

3.2. Total Factor Productivity and the Efficiency of Banks

This study employs total factor productivity (TFP) as a proxy variable to measure the efficiency of banks. TFP was calculated using the Data Envelopment Analysis (DEA) Malmquist method (Zhu et al., 2021; Li et al., 2021; Ferreira, 2020). This non-parametric technique is ideal for analyzing multiple inputs and outputs, aligning with banking operations' complexity (Boot et al., 2021). Measuring bank efficiency presents challenges because banks do not produce physical goods. Two primary approaches are used: the production method (which focuses on services such as account management and transactions) and the intermediary method, which views banks as intermediaries that transfer funds between savers and borrowers (Wang et al., 2021a). Regardless of whether the asset or intermediary method is adopted, production remains the key factor in maximizing income and shareholders' wealth (Wang et al., 2021a).

This study focuses on banks' production outcomes. Using the production method, the DEA Malmquist analysis incorporates labor costs, deposits, and total capital as inputs (Gökgöz et al., 2024; Maradin et al., 2021; Cheriye, 2020). Labor costs include all forms of employee compensation; deposits represent total customer funds held by the bank; and total capital covers both equity and debt capital (Gökgöz et al., 2024). The outputs selected for the analysis include profit, loans, and interest income, which represent net income, lending activity, and the bank's capacity to earn interest, respectively (Abedifar et al., 2018; Alhassan & Tetteh, 2017). Previous studies have successfully used TFP to evaluate bank efficiency in various contexts. For example, (2024) employed TFP to analyze productivity in emerging markets, while Maradin et al.) demonstrated its applicability in assessing efficiency during periods of financial transformation. Similarly, Alhassan and Tetteh (2018) highlighted the utility of TFP in linking operational outcomes to profitability and shareholder value in the banking sector.

This study assesses total factor productivity in commercial banks by applying the DEA Malmquist method, thereby analyzing the influence of the bank FinTech index on bank efficiency (Chen, 2021). All variables in the dependent, independent, and control groups were operationalized, as shown in Table 1.

3.3. The construction of the Bank FinTech Index

This study builds on the methodologies of Kharrat et al. (2024) and Wang et al. (2021a) to construct a FinTech index, detailing the key computational steps involved in this study. The FinTech data from banks were gathered using an Excel checklist sent to the banks, which featured nine (9) distinct FinTech dimensions and thirty-three (33) associated FinTech applications, as detailed in Appendix 1. The nine (9) dimensions and corresponding thirty-three (33) FinTech applications were adopted from the study of Wang et al. (2021) and customized based on their relevance in the Tanzanian banks context. The Banks were asked to report the availability of each application per dimension annually, assigning a value of one (1) for available and zero (0) for unavailable FinTech applications each year.

Before calculating the FinTech index, diagnostic tests were conducted to ensure adequate sample size. The results in Table 2 confirm that the scale analysis revealed strong internal consistency and suitability for further statistical analyses. The average inter-item covariance of 0.1177 indicates a positive relationship among the 33 items, suggesting that they measure related aspects of the construct. A reliability coefficient

(Cronbach's alpha) of 0.9818 reflects satisfactory internal consistency, implying that the items are highly correlated and measure the same underlying concept. However, this high reliability may indicate some redundancy, suggesting that certain items overlap. The Kaiser-Meyer-Olkin (KMO) measure of 0.9472 indicates sufficient sampling adequacy, confirming that the dataset is well-suited for factor analysis. These findings suggest that the scale is robust for measuring the intended construct, and further analysis, such as factor analysis, helps identify the key underlying dimensions (Durak et al., 2024; Anita et al., 2023; Theiri & Alareeni, 2023; Van Phuc Le & Nguyen, 2022; Singh et al., 2020). With the inclusion of thirty-three (33) FinTech applications, these results confirm that the data are suitable for planned factor analysis. The results of the KMO and Cronbach's reliability tests are shown in Table 2.

Table 1. Operationalisation of Research Variables

Variable	Operationalisation	Measurement	Empirical Evidence
Independent Variable FinTech Index (FTI)	The author owns FinTech index computation.	Composite Index	Katsiampa et al., (2022), Wang et al., (2021b)
Dependent Variables Total Factor Productivity (TFP*i*,*t*)	Measures productivity changes as a proxy for efficiency.	DEA	Zhu et al., 2021; Li et al., 2021;Ferreira, 2020
Control Variables			Pierri and Timmer
Return on Asset (ROA)	Profit before tax divided by average total assets	Ratio	(2020), Phan et al., 2020;
Loan to Deposit Ratio (LDR)	Total loans divided by total deposits	Ratio	Wang et al. (2021b)
Capital Adequacy ratio (CAR)	Total equity divided by total assets	Ratio	Dwivedi et al., (2021),
Non-Performing Loans (NPLs)	Total NPL divided by gross total loans	Ratio	Haabazoka (2019),
Bank Size	Logarithm of total assets		Ozili, (2021a&b),
Inflation (INF)	Annual inflation rate (measured as a percentage	Value	(Msomi, 2022),
Gross Domestic Product	change in consumer price index) of a country	Ratio	Singh et al., 2021),
(GDP)	Annual GDP growth rate (%) of a country	Ratio	(Sinaga et al., 2020),
			(Kartikasary et al., 2020), Ahmed et al., (2021)

Note: Source: Author's own compilation and literature review (2024)

Table 2. KMO and Cronbach's Test Results

Test scale = mean (unstandardized items)	
Average interitem covariance:	0.1176
Number of items in the scale:	33
Scale reliability coefficient:	0.9818
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO)	0.9472

Note. Source: Survey Data (2024)

To manage the extensive range of FinTech applications, principal component analysis (PCA) was used to simplify the dataset by identifying key patterns among the 33 FinTech applications (Kharrat et al., 2024; Zheng et al., 2024; Rizvi et al., 2024; Aboojafari & Dehghani, 2022). PCA is a multivariate technique that reduces data dimensionality by analyzing several interconnected quantitative variables. This process identifies the principal components that highlight important factors within the FinTech dimensions, providing a clearer and more insightful representation. Similar approaches were successfully applied in previous studies by Zheng et al. (2024) and Kharrat et al. (2024). PCA allows data compression and simplification while retaining crucial information (Rahman, 2024).

Several key steps were undertaken to apply PCA to compute the FinTech index. First, the covariance or correlation matrix was computed from the standardized dataset, which consisted of n observations and p variables, to capture the relationships between variables (Lasisi & Attoh-Okine, 2018). The covariance matrix was calculated as follows:

$$\sum = \frac{1}{n-1} X^T. \tag{1}$$

where X = standardized data with n observations, and X^T denotes the transpose of X.

Second, principal components were extracted from the covariance matrix using PCA. Each principal component is a linear combination of the original variables, capturing the maximum variance, with subsequent components explaining progressively less variance (Peres & Fogliatto, 2018). The principal components are computed as follows:

$$PC_k = XV_k. \tag{2}$$

where: PC_k= principal components, V = matrix of eigenvectors obtained from the covariance matrix, and V_k= Matrix of the first k eigenvectors corresponding to the largest eigenvalues.

The third step involves computing scores for each principal component for every bank, representing the data projection onto these components (Dong & Qin, 2018). If X_i represents the data for bank i and PC_k is the k-th principal component, the score for bank i on component k is calculated as;

$$Score_{ik} = X_i * PC_k. \tag{3}$$

Fourth, each principal component was evaluated to determine the variance. The first component explains the most variance, with subsequent components explaining progressively less variance. Components with eigenvalues greater than one were retained (Schreiber, 2021). Finally, combining the retained components, the composite bank FinTech index is computed (Zhao et al., 2023). This involves multiplying each component by its corresponding weight and then summing these weighted values. We compute the FinTech index as follows:

$$FI = \sum_{k=1}^{m} Score_{ik} \times W_k \,. \tag{4}$$

where W_k = Weight of each retained component PC_k and m = number of retained principal components

The resulting bank FinTech index offers a composite measure of FinTech development among Tanzanian commercial banks. This method is supported by literature from (Kharrat et al. (2024), Zheng et al. (2024), and Yao and Song (2023), highlighting PCA's effectiveness of PCA in reducing dimensionality and capturing essential variability in datasets. The constructed Bank FinTech Index aligns with established indices like the Peking University Digital Financial Inclusion Index (PKU-DFII) by leveraging digital data sources and methodologies such as keyword search and frequency analysis (Muganyi et al., 2022). However, it differs in its narrower focus on the banking sector, emphasizing operational integration, technological adoption, and product innovation. At the same time, the PKU-DFII takes a broader approach to digital financial inclusion across various financial services and geographies. This sector-specific focus makes the Bank FinTech Index more relevant for analyzing bank-level FinTech adoption and efficiency, though its limited scope may not capture broader financial inclusion trends (Khan et al., 2023).

3.4. Model Specification

This study uses panel data to explore the relationship between the bank FinTech index and the efficiency of commercial banks. Methods such as pooled ordinary least squares (OLS), fixed effects, and random effects models may not be suitable because of challenges such as endogeneity and unobserved individual effects (Sheraz et al., 2022; Roodman, 2009; Blundell & Bond, 1998; Arellano & Bover, 1995).

To overcome these challenges, this study employs a two-step system Generalized Method of Moments (GMM), a robust estimation technique that addresses issues such as autocorrelation and heteroscedasticity (Blundell & Bond, 1998; Arellano & Bover, 1995). GMM can be categorized into different GMM and system GMM, each with one- and two-step variations. System GMM is generally more effective than difference GMM, and the two-step variant is particularly well suited for handling problems such as heteroscedasticity and autocorrelation, as applied by Khan et al. (2024) and Ogbonna et al. (2023).

Accordingly, this study adopts a two-step system GMM for its estimations, a method that has been successfully applied in similar research (Dasilas & Karanović, 2023; Sheraz et al., 2022; Ullah et al., 2021; Phan et al., 2020; Arminen & Menegaki, 2019). The linear representation of the dynamic GMM system model is as follows;

$$\mathrm{TFP}_{i,t} = \alpha + \beta_1 \mathrm{FTI}_{i,t} + \beta_2 \mathrm{CAR}_{i,t} + \beta_3 \mathrm{SIZE}_{i,t} + \beta_4 \mathrm{LDR}_{i,t} + \beta_5 \mathrm{NPL}_{i,t} + \beta_6 \mathrm{ROA}_{i,t} + \beta_7 \mathrm{GDP}_t + \beta_8 \mathrm{INF}_t + \epsilon_{i,t}. \quad (5)$$

To ensure our results are valid, the interaction terms test whether the relationship between the FinTech Index and efficiency is consistent across different bank sizes (large, medium, and small) was included in the estimation model for the robustness test. This checks the model's ability to capture differential impacts, which adds depth and validity to the findings. The model indicating the interaction term of the FinTech Index is as follows:

$$\mathrm{TFP}_{i,t} = \alpha + \beta_1 \mathrm{FTI}_{i,t} + \beta_2 (\mathrm{FTI}_{i,t} \times \mathrm{Large}_{i,t}) + \beta_3 (\mathrm{FTI}_{i,t} \times \mathrm{Medium}_{i,t}) + \beta_4 (\mathrm{FTI}_{i,t} \times \mathrm{Small}_{i,t}) + \beta_5 \mathrm{CAR}_{i,t} + \beta_6 \mathrm{SIZE}_{i,t} + \beta_7 \mathrm{LDR}_{i,t} + \beta_8 \mathrm{NPL}_{i,t} + \beta_9 \mathrm{ROA}_{i,t} + \beta_{10} \mathrm{GDP}_t + \beta_{11} \mathrm{INF}_t + \epsilon_{i,t}\,, \quad (6)$$

where: All variable definitions for equations one and two are detailed in Table 1 and $\varepsilon i,t$= Error term, capturing the combined effect of all other factors not explicitly included in the model that might influence a bank's TFP. Large, medium, and small banks are the categorization of banks, as described in section 3.1 of this paper.

3.5. Descriptive statistics

Table 3 presents the descriptive results of the variables used to examine the influence of the bank FinTech index on the efficiency of banks across different categories of commercial banks in Tanzania (All Banks, Large, Medium, and Small Banks). The FinTech Index (FTI) has an overall mean of 1.918 with a standard deviation of 2.175. Large banks exhibit a higher mean FTI of 2.544 (Std. Dev. = 2.162), which reflects a more advanced deployment of FinTech compared with medium banks (Mean = 1.476, Std. Dev. = 2.04) and small banks (mean = 1.736, Std. Dev. = 2.194). This finding suggests that larger banks are better positioned to invest in and leverage financial technologies. The detailed descriptive results on the variables used are presented in Table 3.

Table 3. Descriptive Statistics Results

	All Banks (360)		Large Banks (120)		Medium Banks (120)		Small Banks (120)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
TFP	1.09	0.531	1.042	0.346	1.096	0.497	1.132	0.692
FRI	1.918	2.175	2.544	2.162	1.476	2.04	1.736	2.194
CAR	16.575	11.18	13.169	2.868	14.375	7.983	22.18	16.032
LDR	81.565	48.77	67.003	16.475	82.143	23.422	95.55	77.1
ROA	0.129	4.81	2.201	1.957	-0.365	5.139	-1.449	5.699
GDP	5.783	1.49	5.783	1.494	5.783	1.494	5.783	1.494
INF	6.583	3.778	6.583	3.789	6.583	3.789	6.583	3.789
In Size	11.465	0.841	12.113	0.346	11.445	0.342	10.837	1.038
NPL	9.215	12.48	6.614	5.16	11.312	15.97	9.719	13.286

Note. Source: Survey Data (2024)

For total factor productivity (TFP), the average for all banks is 1.09, with small banks showing the highest mean TFP (1.132) and large banks the lowest (1.042). The FinTech Index (FTI) shows the highest average for large banks (2.544), while medium banks have the lowest (1.476). Capital Adequacy Ratio (CAR) is notably higher in small banks (22.18), reflecting stronger capital buffers, while large banks have the lowest CAR (13.169). The Loan-to-Deposit Ratio (LDR) is highest for small banks (95.55), indicating higher lending activities relative to deposits, whereas large banks exhibit a lower LDR (67.003). Return on Assets (ROA) reveals profitability disparities, with large banks having a positive average ROA (2.201), while medium and small banks show negative ROA values, reflecting lower profitability or potential losses. Macroeconomic variables such as GDP and inflation remain consistent across all categories. Large banks have the highest average logarithmic size (ln Size 12.113), and small banks have the smallest (10.837). Non-Performing Loans ratios are highest in medium banks (11.312), suggesting higher credit risk, while large banks have a relatively lower NPL ratio (6.614). The high standard deviations, especially for variables such as FTI, CAR, LDR, ROA, and NPL, indicate significant variability across banks, reflecting differences in size, risk exposure, and operational strategies. Small banks show the highest variability, suggesting more performance and risk management volatility than large and medium banks.

3.6. Diagnostic Tests

Before estimating the system GMM, several diagnostic tests were conducted to ensure the robustness of the analysis. First, the data were examined for potential multicollinearity among independent variables to avoid distortions in the results. Additionally, tests were performed to address the unique characteristics of the panel data, including cross-sectional dependence and stationarity. Hansen and Sargan tests were also employed to validate the instruments used in the model, ensuring that they were not correlated with the error term, thereby providing unbiased and reliable estimations.

3.6.1. Pairwise Correlations and Multicollinearity Results

Table 4 presents the pairwise correlations and Variance Inflation Factor (VIF) results for the bank FinTech index, control variables, and efficiency. The correlations ranged from weak to moderate, with no value exceeding 0.594, indicating a satisfactory level of variable distinction and minimal risk of multicollinearity. This suggests that multicollinearity is not a significant issue in our model, as the independent variables do not excessively inflate each other's variance owing to correlations (Asongu et al., 2021). This approach was consistent with the methodologies employed by Kashif et al. (2024) and Aggarwal et al. (2023). Multicollinearity was further assessed using VIF values, and Table 5 shows that all variables had VIF values below 3 and corresponding tolerance values (1/VIF) above 0.433. These results confirm that multicollinearity is not a significant concern in our model, as no independent variable’s variance is substantially inflated by its correlation with other variables (Asongu et al., 2021). This approach aligns with the findings of Kashif et al. (2024) and Aggarwal et al. (2023), who reported no multicollinearity using the VIF in their analyses. The detailed results of pairwise correlations and variance inflation factors are presented in Table 4.

3.6.2. Cross-Sectional Dependency and Panel Unit Root Tests

Table 5 presents the results of the cross-sectional dependency and panel unit root tests, using the Breusch-Pagan LM, Pesaran CD, and Friedman tests, as outlined by (Li et al., 2024; Antwi & Kong, 2023; Shahbaz et al., 2023). Detailed cross-sectional dependency and panel unit root test results are presented in Table 5.

Prior to conducting the two-step system GMM analysis, this study carefully assessed the data for cross-sectional dependence, a common feature in panel data, where a single shock, such as regulatory changes, can affect multiple banks (Khalid & Shafiullah, 2021). Table 4 presents the results of cross-sectional dependence tests, including the Breusch-Pagan LM, Pesaran CD, and Friedman tests, following the methodologies of Rana et al. (2024) and Shahbaz et al. (2023). As the significance test statistics show, the results indicate significant cross-sectional dependence across all variables. Consequently, this study employs second-generation panel unit root tests, which are necessary for evaluating the stationarity of variables in the presence of cross-sectional dependence, as first-generation tests may otherwise produce misleading results (Eibinger et al., 2024). Table 4 also presents the results of the Cross-sectionally Augmented IPS (CIPS) panel unit root test, which integrates the augmented Dickey (ADF) and Im-Pesaran-Shin tests. The CIPS test findings show that CAR and LDR achieve stationarity after first differencing, indicating that they are integrated in order one. These results are robust to cross-sectional dependence and provide more consistent and reliable outcomes (Eibinger et al., 2024; Rana et al., 2024; Shahbaz et al., 2023).

Table 4. Correlations and Multicollinearity Results

Variables	TFP	FTI	CAR	LDR	ROA	GDP	INF	ln Size	NPL
TFP	1								
FTI	0.007	1							
CAR	0.033	-0.061	1						
LDR	0.059	0.05	0.594***	1					
ROA	-0.097*	0.077	-0.447***	-0.267***	1				
GDP	-0.018	-0.554***	0.03	-0.013	0.038	1			
INF	-0.071	-0.537***	0.046	-0.072	-0.07	0.221***	1		
lnSize	-0.027	0.314***	-0.648***	-0.430***	0.493***	-0.106**	-0.165**	1	
NPL	-0.036	0.148**	0.024	0.082	-0.237***	-0.131**	-0.217***	-0.014	1
VIF		2.21	2.31	1.61	1.49	1.49	1.48	2.24	1.15
1/VIF		0.452	0.433	0.623	0.669	0.669	0.675	0.447	0.872
Mean VIF		1.75							

Note. Standard errors: *** p<0.001, ** p<0.05, * p<0.1

Table 5. Cross-Section Dependency and Panel Unit Root Test Results

Cross-section dependency (CD)			Cross-sectionally augmented IPS (CIPS) panel unit root			
	Breusch-Pagan LM test	Pesaran CD test	CIPS panel unit root		CIPS first difference	
Variables	Test statistics	Test statistics	Constant	Constant and trend	Constant	Constant and trend
TFP	585.518***	1.774*	-4.400***	-4.349***		
FTI	3503.384***	58.334***	-2.792***	-3.173***		
CAR	1331.610***	4.158***	-1.919	-2.311	-3.039***	-3.207***
lnSize	3344.896***	54.755***	-2.498***	-3.222***		
ROA	770.613***	4.269***	-2.011	-2.770**		
GDP	5220***	72.250***	2.610***	1.7		
INF	5220***	72.250***	2.610***	1.7		
NPL	1252.372***	10.324***	-2.701***	-2.773**		
LDR	1175.317***	17.375***	-1.974	-1.837	-2.770***	-2.965 ***

Note. Standard errors in parentheses: *** p<0.001, ** p<0.05, * p<0.1

3.6.3. Hansen and Sargan Test

Table 7 shows the diagnostic test results for the Generalized Method of Moments (GMM) model, which confirms its validity through several key indicators. First, the first-order autocorrelation AR (1) test shows significant p-values of 0.015 and 0.000, indicating the expected presence of first-order serial correlations in the differenced residuals. Importantly, the second-order autocorrelation AR (2) test results, with p-values of 0.092, 0.252, 0.426, and 0.576, show no significant second-order autocorrelation, which is a critical condition for model validity (Bunje et al., 2022; Hsieh and Lee, 2020). The Hansen test for over-identifying restrictions, with p-values of 0.403, 0.113, 1.000, and 1.000, confirms the validity of the instruments, as the null hypothesis of no correlation between the instruments and the error term cannot be rejected (An et al., 2023). Similarly, the Sargan test showed p-values of 0.109, 0.199, 0.358, and 0.043, mostly indicating instrument validity (Ma and Lv, 2023). Additionally, the difference-in-Hansen Test validates the extended model specification. Despite its robustness, system GMM faces limitations like instrument proliferation, mitigated by collapsing instruments and restricting lag ranges, and assumptions of exogeneity and initial conditions, addressed through careful instrument selection and robustness checks (Roodman, 2009; Blundell and Bond, 1998). Overall, these tests suggest that the GMM model is well specified, and the instruments used are valid, making the results reliable for further interpretation.

4. Results and Discussion

4.1. Influence of a Bank FinTech Index on the Efficiency of Commercial Banks

Table 7, panels 1 to 4, presents the regression results on the influence of the bank FinTech index on the efficiency of commercial banks across all banks, as well as for large, medium, and small banks in Tanzania. Using panel data and two-step GMM system estimators, the analysis shows a strong and statistically significant positive relationship between the bank FinTech index and efficiency for all banks and large banks. However, the results indicate a negative influence of the FinTech index on the efficiency of medium and small banks.

The results provide crucial insights into the relationship between the bank FinTech Index (FTI) and bank efficiency in Tanzania. For all banks, the bank FinTech index positively and significantly influences efficiency, with a coefficient of 0.100 ($p<0.001$). This implies that an increase in FinTech development, as measured by the bank FinTech index, leads to enhanced operational productivity across the banking sector. The positive relationship between the bank FinTech index and TFP suggests that banks investing in FinTech experience streamlined operations, reduced transaction costs, and improved service delivery. These results highlight the importance of FinTech in driving overall bank efficiency, especially as digital platforms and automation have become more integral to banking operations. The study conducted by Lee et al. (2023) on 74 Chinese commercial banks from 2012 to 2019 revealed that different types of commercial banks were impacted by FinTech to varying degrees.

For Tanzanian banks, the possible increase in the deployment of mobile banking, digital payment platforms, and automated banking services is revolutionizing service delivery and customer experience (Koloseni, 2021). This transformation is especially relevant in countries where access to traditional banking services is limited, particularly in rural areas (George *et al.*, 2024). The introduction of digital financial platforms has extended banks' reach, allowing them to cater to previously underserved populations. As FinTech integration continues to increase, Tanzanian banks can leverage these innovations to improve operational efficiency, increase customer satisfaction, and maintain a competitive edge in an increasingly digital economy.

For large banks, the positive effect of the bank FinTech index on TFP is even more pronounced, with a coefficient of 0.889 ($p<0.001$). Large banks, possibly benefiting from more resources, infrastructure, and human capital, are well positioned to leverage FinTech to improve their productivity significantly. This finding indicates that FinTech plays a vital role in enabling large banks to enhance their operational processes and maintain a competitive edge. By deploying advanced technologies, such as machine learning, mobile banking, artificial intelligence (AI), and big data analytics, large banks can efficiently manage data, improve customer services, and scale their operations, leading to continued productivity growth.

The findings also highlight the importance of FinTech for large banks in Tanzania, which are often better positioned to integrate advanced technologies and realize substantial productivity gains. Through their greater resources and infrastructure, large banks in Tanzania can implement FinTech solutions more effectively, benefiting from improved data analytics, automation, and risk management capabilities. This allows them to drive innovation, maintain high levels of operational efficiency, and offer customers a wider range of financial products. The same results were reported by Lee *et al*. (2021) and Zhao *et al*. (2022), who concluded that FinTech development and FinTech innovations improve the cost efficiency of large banks in China and enhance the technology banks use.

Table 6. System GMM Results for all Banks and by Bank Categories with the inclusion of Interaction Effect

VARIABLES	(1) All Banks	(2) Large Banks	(3) Medium Banks	(4) Small Banks	(5) Interaction Effect (FTI)
L.TFP	-0.274**	1.815**	4.969*	-0.594**	-0.234***
	(0.128)	(0.790)	(2.718)	(0.274)	(0.071)
FTI	0.100***	0.889***	-3.811*	-0.899**	
	(0.022)	(0.240)	(2.287)	(0.416)	
FTI*Small					-0.138***
					(0.028)
FTI*Medium					-0.268***
					(0.061)
FTI*Large					0.088**
					(0.047)
CAR	-0.011**	0.052**	0.666**	-0.182***	-0.013***
	(0.005)	(0.021)	(0.333)	(0.049)	(0.004)
LDR	0.004*	0.012***	-0.174**	0.020***	0.005*
	(0.002)	(0.005)	(0.081)	(0.006)	(0.003)
ROA	-0.025*	0.270**	-0.606*	-0.090**	-0.018*
	(0.013)	(0.130)	(0.318)	(0.038)	(0.010)
GDP	0.053***	-0.343***	-0.818	-1.433**	0.036***
	(0.018)	(0.100)	(0.525)	(0.632)	(0.012)
INF	0.004	-0.065	0.005	-0.090	0.003
	(0.007)	(0.053)	(0.113)	(0.125)	(0.011)
lnBSize	-0.091	0.146*	43.642**	0.692	-0.223
	(0.153)	(0.080)	(22.002)	(2.118)	(0.289)
NPL	-0.015***	0.012	0.005	-0.014**	0.008
	(0.005)	(0.046)	(0.029)	(0.007)	(0.006)
Constant	1.883	0.000	-489.520**	6.693	3.335
	(1.840)	(0.000)	(246.344)	(21.877)	(3.588)
Observations	330	110	110	110	330
Number of banks	30	10	10	10	30
AR (1)	0.015	0.000	0.218	0.128	0.000
AR (2)	0.092	0.252	0.426	0.576	0.080
Hansen	0.403	0.113	1.000	1.000	0.258
Sargen	0.109	0.199	0.358	0.043	0.073
Number of Instruments	20.000	10	10	10	25.000

Note. Standard errors in parentheses: *** $p<0.001$, ** $p<0.05$, * $p<0.1$

Conversely, medium banks show a negative and significant relationship between the bank FinTech index and TFP, with a coefficient of -3.811 ($p<0.05$), suggesting that increased FinTech deployment leads to decreased efficiency. This unexpected result could be due to challenges in implementing FinTech solutions, limited scalability, insufficient resources to manage such technologies, or substantial initial investment costs that cannot materialize in a shorter period. Medium banks may struggle with high implementation costs and the lack of expertise necessary to fully integrate and benefit from Fintech innovations (Stulz, 2019). The results highlight the need for medium banks to develop robust strategies, such as partnering with technology providers or outsourcing, to manage Fintech solutions and improve operational efficiency effectively. These results are consistent with the findings of Khan *et al*. (2024), who reported that FinTech initially decreases the efficiency of Chinese banks in the short run.

Similarly, FTI negatively affects TFP for small banks, with a coefficient of -0.899 ($p<0.05$). This suggests that small banks face even greater challenges in deploying and integrating FinTech technologies, likely because of resource constraints, limited technical expertise, and scalability issues. Small banks may struggle to generate adequate returns from their Fintech investments, as the costs associated with implementation and management may outweigh the benefits. A possible solution to overcome these challenges is to develop tailored, cost-effective, and scalable FinTech solutions that address their specific needs and limitations, potentially through partnerships or shared FinTech services. These results are consistent with the findings of Lee *et al.* (2023), who reported that FinTech impacts different types of commercial banks to varying degrees; urban and rural commercial banks are the most influenced, while joint-stock banks experience the least impact. FinTech initially decreases the efficiency of banks in the short run for Chinese banks.

However, this study's implications also highlight potential challenges for medium and small banks in Tanzania, where the benefits of FinTech integration may not be realized immediately. These banks may face resource limitations or technical barriers in successfully integrating FinTech solutions, potentially resulting in efficiency losses. Therefore, policies that support the capacity building of smaller banks, such as government-backed FinTech partnerships or technological subsidies, could help level the playing field and ensure that all banks benefit from FinTech-driven efficiency gains, regardless of size.

4.2. Influence of Control Variables on Efficiency of Banks

After analyzing the influence of the bank FinTech index on the efficiency of all banks and based on the categories, the study delved into analyzing the influence of bank-specific and macroeconomic factors to gain more insights into bank efficiency. The results in Table 7 are disaggregated across all banks and categorized into large, medium, and small banks, revealing distinct trends and implications for each category.

The results for capital adequacy ratio (CAR) across all banks, with a negative and significant coefficient of -0.011 ($p<0.05$), suggest that maintaining higher levels of capital adequacy may be associated with reduced efficiency. This negative relationship is possible because of the conservative lending practices that typically accompany higher capital reserves. When banks hold higher capital levels to meet regulatory requirements, they may adopt more risk-averse strategies, such as restricting lending to riskier borrowers or investing in growth opportunities. While these strategies ensure financial stability and regulatory compliance, they can also limit banks' ability to generate higher returns through profitable lending and investment activities, thereby reducing overall productivity. The same result was reported by Abba et al. (2018), who indicated that capital adequacy negatively influenced the efficiency of banks in Nigeria. In this context, a conservative approach to risk management and capital retention may constrain a bank's ability to innovate, expand, or exploit more lucrative market opportunities, which is reflected in the reduction of efficiency (Torre, 2020).

Conversely, for large banks, the results show a positive and significant relationship between the CAR and efficiency, with a coefficient of 0.052 ($p<0.05$). This indicates that large banks can leverage higher capital buffers to support, rather than hinder, operational productivity. Large banks have the advantages of broader resource bases, more diversified revenue streams, and greater access to capital markets. These factors allow firms to maintain high capital adequacy ratios without significantly compromising their lending capabilities or investment strategies. Rather than restricting growth, higher capital reserves enable large banks to engage in more complex transactions while maintaining financial resilience against economic shocks. This resilience allows them to invest in advanced technologies, improve customer service, and expand to new markets, all contributing to improved efficiency. These results are consistent with Siddique et al. (2022) and Dao (2020), who reported that capital adequacy positively influences the efficiency of large banks in South Africa and Vietnam. Moreover, large banks may use their capital reserves to explore innovative financing mechanisms such as digital banking and FinTech partnerships, further enhancing operational efficiency by reducing transaction costs and streamlining operations (Sajid et al., 2023; Zuo et al., 2023).

The findings for medium banks indicate that capital adequacy plays a pivotal role in driving long-term productivity, with a coefficient of 0.666 ($p<0.05$). This strong positive relationship suggests that for medium-sized banks, maintaining a higher capital adequacy ratio is beneficial and essential for their sustainability and growth. One possible explanation is that medium banks, which may not have the extensive resources or diverse revenue streams that larger banks enjoy, rely more heavily on strong capital buffers to manage risk effectively. Maintaining adequate capital reserves ensures that medium banks can absorb potential losses from loan defaults or market fluctuations, stabilizing their operations and enhancing productivity. Higher capital adequacy may also give banks financial flexibility to engage in strategic investments and expansion without overextending their resources.

Further, the results for small banks show a negative and significant relationship between capital adequacy and efficiency, with a coefficient of -0.182 ($p<0.01$). This suggests that, for small banks, maintaining higher levels of capital adequacy may cost their operational efficiency. Small banks typically have limited resources and face greater constraints in revenue generation. Thus, the requirement to hold higher capital reserves could limit their ability to lend or invest in growth opportunities. This capital constraint may reduce banks' capacity to engage in profitable lending activities, thereby increasing their productivity. Furthermore, small banks often operate in niche markets and may find it more challenging to compete with larger banks. Consequently, allocating a substantial portion of their resources to meet regulatory capital requirements might divert funds away from investments in technology, innovation, and customer service improvement, which are critical for enhancing efficiency in an increasingly competitive banking environment. These findings highlight the importance of tailoring capital adequacy requirements to banks' size and operational structure to ensure that regulatory frameworks support stability and efficiency across different bank categories.

The results for the Loan-to-Deposit Ratio (LDR) for the entire banking sector indicate that a higher LDR slightly improves efficiency (0.004, $p<0.1$), indicating that banks efficiently utilize their deposits to provide loans experience enhanced productivity. This effect is even more pronounced for large banks (0.012, $p<0.001$), which are better equipped to manage their larger loan portfolios. However, for medium banks, the relationship is negative (-0.174, $p<0.05$), suggesting that inefficiencies arise when banks overextend their lending capabilities relative to deposits. For small banks, the positive and significant effect (0.020, $p<0.001$) indicates that higher loan activity relative to deposits can enhance efficiency, although this may increase risk exposure.

The return on assets (ROA) for all banks indicates a negative and marginally significant relationship (-0.025, $p<0.1$), implying that higher profitability does not necessarily translate to increased efficiency. This may be due to the possibility that banks focusing too much on returns may overlook operational improvements. However, for large banks, profitability and efficiency are positively linked (0.270, $p<0.05$), as these banks are likely to use their profits to fuel productivity-enhancing initiatives. Conversely, medium banks show a significant adverse effect (-0.606, $p<0.1$), suggesting that prioritizing profitability may reduce operational efficiency. Similarly, small banks show a negative and significant relationship (-0.090, $p<0.05$), indicating that balancing profitability with operational efficiency is challenging, likely because of resource constraints.

Non-Performing Loans (NPL), for all banks, indicates a significant negative relationship (-0.015, $p<0.001$) between NPLs and efficiency, meaning that higher levels of non-performing loans reduce bank productivity. This is consistent across the banking sector, as NPLs increase financial strain and operational inefficiency. Large and medium banks, however, do not exhibit significant impacts, suggesting they may have better mechanisms to manage NPLs. For small banks, the negative and significant coefficient (-0.014, $p<0.05$) shows that inefficiencies arise from higher NPLs, indicating weaker credit risk-management frameworks in smaller banks.

The results for Gross Domestic Product (GDP) growth for all banks have a positive and significant impact on efficiency (0.053, $p<0.001$), suggesting that a favorable macroeconomic environment drives demand for banking services, thereby improving productivity. However, for large banks, the impact is negative (-0.343, $p<0.001$), possibly because of the complexities in managing larger operations during periods of rapid economic expansion. Although the relationship is insignificant for medium-sized banks, the negative coefficient (-0.818) suggests they may struggle to fully capitalize on economic growth. Small banks face a significant negative effect (-1.433, $p<0.05$), highlighting their challenges in adjusting to macroeconomic changes, potentially because of their limited flexibility and risk management capabilities.

The results for Bank Size indicate that large banks show a marginally positive and significant effect (0.146, $p<0.1$), indicating that scale efficiency contributes positively to their operational performance. For medium banks, the relationship is highly significant and positive (43.642, $p<0.05$), implying that, as these banks grow, they can better utilize their resources to improve efficiency. However, small banks show no significant relationship, indicating that increasing size does not automatically translate into productivity gains.

4.3. Robustness Check

To ensure the robustness and validity of the results, this study incorporates interaction terms between the Bank FinTech Index (FTI) and bank size categories (large, medium, and small) to account for potential differential impacts of FinTech adoption across these groups (Cheng & Qu, 2020). This approach enables a detailed examination of whether the relationship between FinTech and efficiency varies based on bank size, providing additional confidence in the findings. The results consistently demonstrate a significant positive relationship between the FinTech Index and efficiency for large banks, as evidenced by the positive and statistically significant interaction term (FTI Large = 0.088). This finding highlights the capacity of large banks to leverage advanced FinTech solutions effectively, owing to their superior resources and operational infrastructure. Conversely, the interaction terms for small and medium banks (FTI Small = -0.138, FTI Medium = -0.268) are negative and statistically significant, indicating challenges in translating FinTech adoption into efficiency gains. These challenges are likely driven by resource constraints, scalability limitations, and operational inefficiencies commonly observed in smaller banks (Wang *et al.*, 2021a; Stulz, 2019). By integrating interaction terms into the regression model, the study ensures that the results are not overly generalized and reflect the complex dynamics of FinTech integration across different bank categories. This methodological enhancement reinforces the reliability and credibility of the analysis, offering valuable insights for policymakers and practitioners seeking to tailor strategies for FinTech integration in the banking sector.

5. Conclusion, Recommendations, and Policy Implications

5.1. Conclusion

In conclusion, this study examines the relationship between the bank FinTech index and efficiency in 30 Tanzanian commercial banks from 2010 to 2021, providing insights into the influence of FinTech development on bank performance. The findings reveal that the bank FinTech index has a significantly positive effect on efficiency across all banks, highlighting the role of FinTech in enhancing operational processes and service delivery. This influence is particularly evident in large banks, which are better equipped to integrate advanced technological solutions, improving their efficiency. By contrast, medium and small banks face challenges in effectively adopting and managing FinTech innovations, leading to a negative relationship between the FinTech index and their efficiency. These findings underscore the importance of scalability and resource availability in leveraging FinTech to improve performance. Furthermore, control variables such as capital adequacy and loan-to-deposit ratios significantly influence efficiency. Capital adequacy positively impacts large and medium banks. However, it hurts small banks, while the loan-to-deposit ratio improves efficiency in large and small banks but hinders efficiency in medium banks. Non-performing loans consistently correlate negatively with efficiency across all bank categories, emphasizing the importance of effective risk management.

5.2. Recommendations and Policy Implications

The findings provide actionable recommendations for advancing FinTech adoption and enhancing bank efficiency in Tanzania by leveraging regulatory, technological, and collaborative advancements. Banks should recruit directors with expertise in FinTech and provide regular training on emerging technologies to support informed decision-making. Establishing FinTech innovation units and incentivizing employee-driven ideas can embed a culture of innovation. At the same time, collaboration with FinTech firms and leveraging the FinTech Regulatory Sandbox 2023 introduced by the Bank of Tanzania enables risk-free testing and optimized technology integration. Policymakers play a crucial role in initiatives like the Tanzania Instant Payment System (TIPS), promoting interoperability among commercial banks to enhance seamless digital transactions and financial inclusivity. Strengthening data protection frameworks under the Data Protection Act is vital to ensuring customer privacy and trust in digital services. Furthermore, partnerships between commercial banks and mobile network operators, such as those enabling M-Pesa and Tigo Pesa, can bridge mobile money platforms and traditional banking, expanding financial access and fostering mobile banking innovations. These strategies establish a robust and inclusive foundation for FinTech-driven transformation in Tanzania's banking sector.

6. Study Implications, Limitations, and Areas for Further Studies

6.1. Theoretical implication

This study contributes to advancing theoretical frameworks by integrating Intermediation Theory, Innovation Diffusion Theory (IDT), and the Technology Acceptance Model (TAM) to examine how financial technology (FinTech) enhances bank efficiency in Tanzania. It deepens Intermediation Theory by showing how FinTech reduces transaction costs, improves resource allocation, and expands financial inclusion, particularly benefiting large banks equipped to integrate advanced technologies. It also extends the theory by highlighting challenges for medium and small banks in adopting

FinTech, emphasizing the importance of resources and strategic implementation. Incorporating IDT, the study illustrates how banks adopt FinTech based on perceived benefits like cost reduction and compatibility with existing systems, enriching the theory by contextualizing FinTech adoption in emerging markets. The TAM framework complements this by addressing behavioral and organizational dimensions, emphasizing that technologies perceived as easy to use and valuable are more readily embraced, enhancing efficiency and profitability. By integrating these three frameworks, the study provides a comprehensive view of how FinTech transforms banking operations, aligning with recent research by *Sunardi et al.* (2022) and Fianto *et al.* (2021) and offering actionable insights for banks and policymakers in emerging economies.

6.2. Limitations and Area for Further Studies

This study had some limitations that warrant consideration. First, the analysis focuses primarily on the influence of the Bank FinTech Index on efficiency. However, it does not extensively explore the impact of other technological advancements or external disruptions, such as changes in regulatory frameworks or global shocks. Additionally, the study mainly addresses banks in Tanzania, limiting the generalizability of the findings to other regions with different financial infrastructures. Future studies should evaluate the long-term impact of Fintech on bank efficiency by including regulatory changes and global shocks across different countries.

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Appendices A

Appendix 1. FinTech Variable Dimensions and Applications.

Dimension	FinTech Applications				
Payment	Mobile Payments	Third-Party Payments	QR Code Payments	Remittances	POS
Resource allocation	Internet Loans	Network Investments	Online Lending's	P2PLoans	
Risk management	Internet Insurance	Online Financing	Regtech and suptech	e-KYC	Digital ID
Network channel	Mobile Banking	Online Banking Service	Agency Banking	Internet Banking	
Big data	Bigdata	Data Mining	Bigdata analysis	Big Data Application	
Artificial intelligence	Intelligent Robot	Artificial Intelligence	Machine Learning		
Distributed technology	Cloud Computing	Block Chain Technology			

Internet Technology	Vehicle Interconnection	Wireless	Mobile Internet	Mobile Communication
Security Technology	Biometrics	Fingerprint Identification		

Note. As adopted from: (Wang *et al.*, 2023; Wu *et al.*, 2023; Lv *et al.*, 2022; Wang *et al.*, 2021; Gai *et al.*, 2018).

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