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Financial Inclusion and Bank Performance: Evidence from the Banking Sector in Ethiopia

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Abstract

Evidence shows that financial inclusion plays a key role in driving economic growth and social development by strengthening the financial system and reducing poverty and income inequality. However, its impact on the financial performance of banks remains inconclusive. This paper explores the relationship between financial inclusion and the financial performance of commercial banks in Ethiopia, using a sample of 16 banks. We analyse 10 years of data (2013–2022) collected manually from the National Bank of Ethiopia (NBE) and the annual reports of commercial banks. A two-step system Generalized Method of Moments (GMM) is employed, alongside other linear panel data model estimators. The findings reveal that increased financial inclusion has a significant positive impact on the financial performance (ROA and ROE) of commercial banks in Ethiopia. The GMM estimation result also shows that bank performance indicators (ROA and ROE) are positively associated with their past realizations. Regarding bank-specific control variables, the cost-efficiency ratio has a significant negative impact on bank profitability. The study recommends that banks improve accessibility by expanding branch networks and ATMs and by offering innovative financial products to enhance profitability.

Keywords: financial inclusion, GMM, bank performance, Ethiopia

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Introduction

Financial inclusion is gaining momentum globally [1] and has attracted increasing attention from scholars, policymakers, and other stakeholders in the financial industry [2]. It is a relatively recent and emerging topic in the financial literature, particularly from the supply-side perspective, and has become an important policy agenda in developing countries [3].

While financial inclusion is straightforward to define and recognize [4], it remains a multidimensional concept [5]. It can be described as the process of integrating the financially excluded population into the formal financial system, enabling them to access essential financial services such as savings, payments, credit, and insurance [6]. Financial inclusion is also defined as providing affordable, convenient, and timely financial services to all members of society, especially the poor and vulnerable [7]. One common indicator of financial inclusion is the ownership of formal accounts [2]. However, having access to financial services is not the same as using financial services. Even though individuals and businesses may have access to these services, they might choose not to use them due to various socioeconomic, cultural, or opportunity cost factors.

The performance of firms is defined as an economic outcome that reflects the effectiveness of organizations. Banks can mobilize deposits by increasing the number of individuals and businesses that open and use formal bank accounts. They can also expand access to loans, allowing more people and businesses to borrow, while simultaneously boosting investments in sectors such as business, education, and healthcare. This can be accomplished by offering innovative financial products at affordable prices. As a result, banks' financial performance and efficiency improve as more people and businesses utilize their loans and other financial services. Ultimately, this contributes to the development of an inclusive financial system, enabling banks to provide affordable services to all segments of the economy, particularly to the underprivileged [8].

A vast body of literature exists worldwide on the correlation between commercial bank performance and financial inclusion. However, research specifically examining the relationship between financial inclusion and the profitability of banking firms in Ethiopia remains limited, apart from a few empirical studies on financial inclusion, its status, drivers, and barriers.

In the existing global literature, there are two competing perspectives on the relationship between financial inclusion and bank performance. Some scholars argue that financial inclusion positively impacts bank performance, while others contend that it poses risks that may erode profitability. Most studies on this topic focus on cross-country or regional analyses, with limited research at the micro (bank) level. Therefore, the primary objective of this study is to examine the impact of financial inclusion on the financial performance of Ethiopian commercial banks using 10 years of bank-level data.

Literature Review and Hypotheses

In most cases, financial inclusion is primarily associated with access to credit from formal financial institutions. However, it is a multidimensional concept that extends beyond credit availability for individuals and firms [4]. To develop evidence-based policies, it is crucial to obtain reliable and comprehensive data that capture the various dimensions of financial inclusion [9]. This may involve establishing standardized definitions for financial inclusion indicators that can guide policymaking, track progress, and assess the impact of policy reforms.

Broadly, financial inclusion can be categorized into four key dimensions: access, quality, usage, and impact [9]. Therefore, multiple indicators must be considered to accurately measure financial inclusion. Commonly used indicators include the proportion of account holders per 1,000 adults (bank penetration), the number of bank branches and ATMs per 100,000 adults (availability/access), and the volume of outstanding bank loans and deposits (usage). Relying on any single indicator may provide only a partial and potentially misleading picture of financial inclusiveness.

A comprehensive measure of financial inclusion that integrates these indicators is necessary to gain a full understanding of a financial system's inclusiveness. An effective financial inclusion measure should reflect its multidimensional nature, be simple to compute, and allow for cross-country comparisons [10; 11].

Financial performance indicators of a firm can be categorized into accounting-based and market-based measures. Accounting-based measures assess a firm's (in this case, a bank's) profitability using traditional financial metrics such as Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM), Gross Income, and Net Income [12].

Market-based performance metrics, on the other hand, reflect profitability from a shareholder perspective. Common indicators include the Market-to-Book Value Ratio (MTB), Price-to-Earnings Ratio (P/E), Earnings Per Share (EPS), Tobin's Q, and Market Return [13; 14].

There is an ongoing debate in management research regarding the relationship between accounting-based and market-based metrics. While both are widely recognized as valid measures of financial health, their correlation remains contested. Theoretically, market-based indicators are considered forward-looking, representing projections of a firm's future or long-term financial performance, whereas accounting-based measures are retrospective, reflecting past or short-term financial outcomes. However, the extent to which past financial success translates into future performance remains unsettled [13].

Accounting-based metrics are influenced by management's accounting choices and reporting standards, making them backward-looking. In contrast, market-based metrics, often preferred by shareholders, anticipate the future. They assume market efficiency, where stock prices are believed to reflect the firm's intrinsic value. Unlike accounting measures, market-based indicators incorporate all pertinent information and provide a broader perspective on performance. In theory, market-based metrics offer a more realistic assessment of a company's financial success compared to accounting-based measures [14].

Overall, financial success is not a one-dimensional concept, as accounting profitability and market performance represent distinct dimensions with limited empirical overlap [13]. Due to this separation, developing a unified theory of financial performance that effectively explains variations in both accounting-based and market-based measures remains a challenge.

Instead, researchers should prioritize formulating separate hypotheses for each metric and explore why their variations are largely uncorrelated. While accounting earnings reflect a company's past financial performance, stock market value represents its future potential. Although the two may be related, their underlying logic and theoretical foundations are fundamentally different and should not be assumed to be interchangeable [13].

The existing literature presents two competing perspectives on the relationship between financial inclusion and the financial performance of commercial banks. On the one hand, some argue that financial inclusion enhances bank performance. On the other, financial inclusion is viewed as a risky endeavour that may reduce profitability. Despite these contrasting views, a substantial body of research supports the notion that financial inclusion positively influences bank performance worldwide.

The positive relationship between financial inclusion and bank performance is supported by several key findings. Greater financial sector access and outreach help reduce asymmetric information and agency problems between borrowers and lenders [15]. Additionally, financial inclusion enables banks to mobilize deposits from a diverse customer base, thereby lowering return volatility [16]. As a result, banks become less dependent on risky and costly money market funds, further stabilizing their returns [17]. By expanding access to financial services, financial inclusion also enhances banking efficiency. Numerous empirical studies, particularly in developing and emerging economies, reinforce the positive impact of financial inclusion on bank performance (see, for example, [2; 8; 18–25]).

The other strand of literature argues that financial inclusion can have a negative impact on the performance of commercial banks (see, for example, [26–29]) or that there is no significant relationship between financial inclusion and bank performance [30]. Critics highlight potential risks such as higher operational costs, increased exposure to non-creditworthy borrowers, and lower profit margins from small-scale financial services, which could undermine banks' overall profitability.

Therefore, empirical findings on the relationship between financial inclusion and bank performance remain inconclusive, even though a vast majority of studies support a positive correlation between the two. In light of the reviewed literature, the following study hypotheses and sub-hypotheses are developed to further investigate this linkage:

H1: Financial inclusion has a significant positive effect on the financial performance of commercial banks in Ethiopia.

H1a: Financial inclusion has a significant positive effect on the Return on Assets (ROA) of commercial banks in Ethiopia.

H1b: Financial inclusion has a significant positive effect on the Return on Equity (ROE) of commercial banks in Ethiopia.

Data and Research Methodology

Sample and Data

As of the first quarter of 2023, the total number of banks in Ethiopia reached 31, comprising 2 public and 29 privately owned banks. However, many of these banks are still in their infancy; for instance, 13 of them were established in 2021/22.

Given data availability and sufficiency, this study includes 16 commercial banks and analyses 10 years of data from 2013 to 2022. Data was manually collected from the National Bank of Ethiopia (NBE) – the country's central bank – as well as from the annual reports of each commercial bank.

Variables and Measurements

Dependent Variables

Consistent with previous research studies [8; 21–25; 29; 30], this study employs Return on Assets (ROA) and Return on Equity (ROE) as metrics for assessing the financial performance of banks.

ROA is the ratio of profit before tax to total assets, measuring management's ability to generate income from the bank's assets. In other words, it reflects the efficiency with which a firm utilizes its resources to generate revenue [31].

ROE is an accounting ratio that represents the profit a company earns relative to the equity capital invested by shareholders. It also indicates how effectively management utilizes shareholders' capital to generate returns.

Independent Variables

Given that the main objective of this paper is to examine how financial inclusion affects the financial performance of commercial banks in Ethiopia, financial inclusion serves as the independent variable.

Financial inclusion can be measured using various indicators categorized into three key dimensions: access/availability of banking services, bank penetration, and usage of banking services [10; 11]. Consistent with prior studies [8; 22–25; 29; 30; 32–34], this study employs six financial inclusion indicators:

- Access/availability dimension: number of commercial bank branches and ATMs.
- Penetration dimension: number of deposit and loan accounts.

- Usage dimension: amount of outstanding deposits and loans.

Consistent with previous studies [8; 23; 30; 34], this study constructs a financial inclusion index using the Principal Component Analysis (PCA) technique to capture the common components of the six individual financial inclusion indicators.

To apply the PCA technique and develop a composite financial inclusion index, the first step involves computing a dimension index for each financial inclusion indicator at the bank level using the following formula [10; 11]:

$$d_i = \frac{A_i - m_i}{M_i - m_i},$$

where d_i refers to the dimension index for the i^{th} indicator;

A_i – to the actual value of indicator i;

M_i – the maximum value of indicator i;

m_i – the minimum value of indicator i.

The formula ensures that the index for the i^{th} dimension (d_i) falls within the range of 0 to 1 ($0 \le d_i \le 1$). A higher value of d_i (closer to 1) indicates greater efforts by banks towards financial inclusion, while a lower value of d_i (closer to zero) suggests weaker financial inclusion.

Given that there are n financial inclusion dimensions, bank i is represented as point $D_i = (d_1, d_2, d_3, \dots d_n)$ in an n-dimensional Cartesian space. Point $O = (0, 0, 0, \dots, 0)$ represents the worst-case scenario of financial inclusiveness, whereas point $I = (1, 1, 1, \dots)$ represents the best-case scenario across all financial inclusion dimensions.

In the second step, a composite financial inclusion index is constructed using the Principal Component Analysis (PCA) technique. Since all six financial inclusion indicators in this study tend to move together, it is reasonable to assign equal weights to each individual indicator.

Applying PCA is particularly useful in this context as it helps address correlations among variables, ensuring that the composite index effectively captures the common components of the six financial inclusion indicators [34].

In the PCA technique, the first principal component is the one that captures the highest variation in the dataset, explaining most of the fluctuations in the financial inclusion indicators.

Subsequent components capture the remaining unexplained variation in the dataset, following an orthonormal trend [34].

Control Variables

To account for the effects of omitted variables, this study incorporates a set of bank-specific factors that are expected to have a significant influence on bank performance. These factors include leverage, bank size, bank age, liquidity, and cost efficiency ratios. The selection of these variables aligns with previous empirical research (see, for example [25; 30]).

Data Analysis Techniques

The study analysed the data using STATA 15 software, applying the xtabond2 command for dynamic panel data estimation. STATA's xtabond2 command implements the Arellano-Bond and Arellano-Bover/Blundell-Bond Generalized Method of Moments (GMM) estimators, which are widely used in econometrics to address heteroskedasticity, autocorrelation, and endogeneity issues in panel datasets [35; 36].

Table 1. Description of the Variables Used in the Study

Variable Name	Symbol	Measurement	Dimension	References
Dependent Variables				
Return on Assets	ROA	Profit Before Tax / Total Assets (%)		[2; 8; 15; 19–25; 29; 30; 34; 35]
Return on Equity	ROE	Profit Before Tax / Total Equities (%)		
Independent Variables				
Number of bank branches	NBRANCH-ES	Log of the number of bank branches	Availability/ Access	[8; 9; 10; 11; 20–25; 29; 30; 32–37]

Variable Name	Symbol	Measurement	Dimension	References
Number of ATMs	NATMs	Log of the number of ATMs	Availability/ Access	[8; 9; 10; 11; 20–25; 29; 30; 32–37]
Number of deposit accounts	NDEPOSITAC	Log of the number of deposit accounts	Bank Penetration	
Number of loan accounts	NLOANAC	Log of the number of loan accounts		
Total amount of deposits	AMTDEPOSITS	Log of total amount of deposits	Usage of banking services	
Amount of outstanding loans and advances	AMTLOANS	Log of the number of loans and advances by banks		
Financial Inclusion	FI	The composite index of financial inclusion constructed from the above six indicators with the help of the PCA technique		
Control Variables				
Leverage	LEV	Total Liabilities / Total Assets at the end of financial year t (%)		[20; 23–25; 30]
Bank size	SIZE	Natural logarithm of total assets at the end of year t		
Liquidity ratio	LIQR	Liquid Assets / Total assets		
Cost efficiency ratio	CER	Cost-to-Income ratio		
Age of bank	AGE	The number of years the bank is in operation		

Model Specification

To empirically test the relation between financial inclusion and the profitability of the banking industry in Ethiopia, the following regression models were used:

$$ROA_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 LEV_{it} + \beta_3 LIQR_{it} + \beta_4 CER_{it} + \\ + \beta_5 LNSIZE_{it} + \beta_6 AGE_{it} + \varepsilon_{it}, \quad (1)$$

$$ROE_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 LEV_{it} + \beta_3 LIQR_{it} + \beta_4 CIR_{it} + \\ + \beta_5 LNSIZE_{it} + \beta_6 AGE_{it} + \varepsilon_{it}, \quad (2)$$

where *ROA* and *ROE* are alternative proxies for the performance of commercial banks; β_0 is the constant term; *FI* is the composite financial inclusion index constructed from the six financial inclusion dimensions by using the PCA technique; *LEV*, *LIQR*, *CER*, *LNSIZE*, and *AGE* are bank specific control variables representing leverage, liquidity ratio, efficiency ratio (cost-to-income ratio), size of banks (taken as the log of assets of banks), and age of banks in Ethiopia, respectively; β_0 represents the constant term; β_1–β_6 represent beta coefficients of the predictors; and ε_{it} denotes the error term.

To estimate the regression models, Ordinary Least Squares (OLS) and Fixed Effects (FE) model estimators were used as baseline regression analyses.

Both the Lagrange Multiplier (LM) test – to determine the presence of significant random effects in the panel data model – and the Hausman (DWH) test – to choose between Random Effects (RE) and Fixed Effects (FE) panel estimators – were conducted.

The Breusch-Pagan LM test results indicated that significant random effects exist in the panel when *ROA* is used as the financial performance measure. However, panel-wise random effects were not significant when *ROE* was used as the performance metric.

Subsequently, the Hausman test confirmed that the Fixed Effects (FE) model is preferred over the Random Effects (RE) model, with a significant p-value of 0.019.

Before interpreting the OLS and FE estimation results, several diagnostic tests were conducted to detect the presence of multicollinearity, heteroskedasticity, and autocorrelation (serial correlation) issues.

The Breusch-Pagan / Cook-Weisberg test for heteroskedasticity in OLS and the modified Wald test for groupwise heteroskedasticity both indicated the existence of heteroskedasticity in the dataset. Additionally, the Wooldridge test for autocorrelation in panel data revealed the presence of first-order serial correlation (autocorrelation) in the dataset.

Serial and cross-sectional correlations, along with heteroskedasticity in the error terms of a panel dataset, are serious issues [38]. Various studies suggest that the standard OLS or fixed/random effects approaches are inefficient estimators when heteroskedasticity and serial correlation are present, and alternative model estimators should be considered [34; 38–40].

In such cases, it is suggested that Feasible Generalized Least Squares (FGLS) and OLS with robust standard errors are more efficient estimators than standard OLS [38]. The Generalized Least Squares (GLS) technique can also be used to overcome serial correlation issues, particularly in a balanced panel dataset with large N and relatively small T [40]. Similarly, OLS with robust standard errors is effective in addressing both heteroskedasticity and autocorrelation issues [34].

Miller and Startz also recommend the FGLS regression as more efficient than standard OLS when heteroskedasticity is present in the error terms [39]. Therefore, in line with the above empirical evidence, FGLS, OLS, and FE estimation methods with robust standard errors are employed.

Finally, the results from these estimators are compared with those from the two-step system GMM, one of the most widely used dynamic panel data model estimators, to address the issue of endogeneity.

In panel data analysis, the issue of endogeneity – which primarily arises from factors such as unobserved heterogeneity, simultaneity, measurement errors, and dynamic endogeneity – has gained increasing attention in recent empirical studies. This issue is particularly concerning as it may lead to inconsistent estimates or coefficients with incorrect signs, potentially resulting in misleading inferences, false conclusions, and wrong interpretations of theoretical frameworks [25; 34; 41].

In theoretical terms, the fixed effects technique is used to control for unobserved heterogeneity in situations where firm-specific variables are time-invariant and correlated with the explanatory variables under the assumption of strict exogeneity. Strict exogeneity implies that explanatory variables (such as financial inclusion indicators in this case) are not influenced by the past or current performance of the firm (*ROA* or *ROE*) [41; 42].

However, in practice, the strict exogeneity assumption may not hold, as past and present performance of the firm can potentially affect the current and future values of the independent variable. Furthermore, according to Wooldridge [40], the fixed effects approach is a static model estimator for panel data analysis, which does not allow for the inclusion of past realizations of the dependent variable as a predictor in the model.

Unlike FE or RE estimation techniques, the OLS estimator cannot address the issue of unobserved heterogeneity, even though the fixed effects method is effective in dealing with endogeneity when firm-specific factors are time-invariant and correlated with the regressors [40].

Generally, the OLS, FE, and RE model estimators may yield inconsistent and biased estimates when endogeneity problems, arising from any source of endogeneity, are present in the data. To address the issue of endogeneity, various dynamic panel data model estimators can be applied, including the Instrumental Variable (IV) method, Two-Stage Least Squares (2SLS), Three-Stage Least Squares (3SLS), as well as Difference and System GMM methods.

Consistent with previous studies [25; 30; 34; 40–42], this paper employs the two-step system GMM, which is the most widely used dynamic panel data model estimator and a robust technique to address the problem of endogeneity. This is particularly useful in situations where the variables of the study are susceptible to sources of endogeneity, such as unobserved heterogeneity, simultaneity, dynamic endogeneity, and omitted variable bias.

GMM mitigates endogeneity problems by transforming the data internally and using lagged values of the outcome variable as an explanatory variable [41]. As a result, the inferences and conclusions drawn in this research are based on the outputs from the two-step system GMM.

To empirically examine the relationship between the financial performance of commercial banks – measured by *ROA* and *ROE* – and financial inclusion, using the financial inclusion index (FI) constructed from six indicators as a composite measure of financial inclusion, the following dynamic panel data regression models are employed:

$$ROA_{it} = \beta_0 + \beta_1 ROA_{i,t-1} \ \beta_2 FI_{it} + \beta_3 LEV_{it} + \beta_4 LIQR_{it} + \\ + \beta_5 CER_{it} + \beta_6 LNSIZE_{it} + \beta_7 AGE_{it} + \varepsilon_{it}, \quad (3)$$

$$ROE_{it} = \beta_0 + \beta_1 ROE_{i,t-1} \ \beta_2 FI_{it} + \beta_3 LEV_{it} + +\beta_4 LIQR_{it} + \\ + \beta_5 CER_{it} + \beta_6 LNSIZE_{it} + \beta_7 AGE_{it} + \varepsilon_{it}, \quad (4)$$

Empirical Results and Discussion

Descriptive Analysis

Table 2 summarizes the descriptive statistics of the study variables in three sections: performance variables, financial inclusion variables, and control variables during the study period. The descriptive statistics of the study variables are computed using their actual values. However, for the purpose of the regression analysis, the logarithmic values of all the financial inclusion indicators and the assets of banks were used.

Regarding the financial performance variables, the profitability indicators of commercial banks (*ROA* and *ROE*) over the last 10 years were, on average, 2.8 and 22%, respectively, with standard deviations of 1.16 and 13.4%. Given its higher standard deviation, ROE is a relatively volatile measure of the financial performance of commercial banks in Ethiopia, compared to *ROA*.

Concerning the indicators of financial inclusion, it is observed that the mean number of branch networks of commercial banks and ATMs over the past 10 years were only 282 and 216, respectively. This suggests that, for a nation with a population of over 100 million, there were remarkably few bank branches and ATMs. The mean number of deposit account holders and borrowers (loan accounts) was found to be 2,222,814 and 14,627, with standard deviations of 5,109,629 and 29,501, respectively.

Commercial banks, on average, have mobilized a total of 47,261.686 million Ethiopian Birr from three main types of deposits: savings, demand, and time deposits. On average, they have also disbursed total loans of 26,641.862 million Ethiopian Birr to different sectors of the economy. The standard deviations of the number of bank branch networks, ATMs, depositors and loan borrowers, and the amount of deposits and loans are extremely high, mainly due to the presence of outliers in the dataset.

The relatively low number of depositors and the small amount of deposits mobilized by commercial banks in Ethiopia, along with other factors, is largely attributed to the low level of outreach of commercial banks, especially through their branch networks.

In relation to the control variables, the financial leverage of the banks, calculated as the percentage of total liabilities to total assets, is found to be around 78 percent. This indicates that commercial banks are much more dependent on equity financing than debt financing.

The value of assets owned by commercial banks in Ethiopia was found to be, on average, around Birr 61,281.018 million during the study period. The liquidity ratio, calculated as the ratio of total liquid assets to total assets, was shown to be around 21 percent, with an 8 percent standard deviation.

The average cost-to-income ratio (also known as the cost-efficiency ratio or CER) was found to be around 56 percent. A lower cost-to-income ratio is typically preferable, as it has an inverse relationship with bank performance. This means that as the cost-efficiency ratio (CER) increases, banks become more inefficient and less profitable.

Lastly, the mean age of banks in Ethiopia is 17 years, suggesting that the banking sector is still in its infancy stage.

Table 2. Descriptive Statistics of the Variables Used in the Study

Variable	Observations	Mean	Std. Dev.	Min	Max
Performance Variables					
ROA	160	2.76	1.158	-7.507	5.127
ROE	160	21.999	13.384	-25.243	95.364
Financial Inclusion Variables					
NBRANCHES	160	281.669	339.993	7	1975
NATMs	160	216.056	553.191	0	3952
NDEPOSITAC	160	2,222,814.4	5,109,629.8	5346	35900000
NLOANAC	160	14,627.034	29,501.531	92	154637
AMTDEPOSIT	160	47261.686	120564.62	158.366	889708.14
AMTLOANS	160	26641.862	56715.016	100.328	481234.93
Control Variables					
LEV	160	78.215	21.241	17.389	96.283
SIZE	160	61281.018	161320.15	380.562	1200000
LIQR	160	21.031	7.993	8.232	52.413
CIR	160	55.694	16.436	24.554	204.232
AGE	160	17.094	12.091	2	60

Table 3a. Correlation Matrix of the Study Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) ROA	1.000												
(2) ROE	0.503*	1.000											
(3) NBRANCHES	-0.114	0.460*	1.000										
(4) NATMs	-0.107	0.281*	0.909*	1.000									
(5) NDEPOSITAC	-0.099	0.407*	0.951*	0.933*	1.000								
(6) NLOANAC	-0.039	0.571*	0.928*	0.858*	0.923*	1.000							
(7) AMTDEPOSIT	-0.076	0.408*	0.937*	0.945*	0.986*	0.932*	1.000						
(8) AMTLOAN	-0.080	0.412*	0.929*	0.899*	0.968*	0.895*	0.976*	1.000					
(9) LEV	0.011	0.054	0.125	0.132	0.172*	0.168*	0.143	0.115	1.000				
(10) NLSIZE	-0.023	0.508*	0.851*	0.664*	0.717*	0.726*	0.687*	0.720*	0.018	1.000			
(11) LIQR	0.092	-0.221*	-0.538*	-0.350*	-0.379*	-0.400*	-0.355*	-0.389*	0.031	-0.702*	1.000		
(12) CIR	-0.853*	-0.555*	-0.020	0.007	-0.007	-0.097	-0.034	-0.032	0.114	-0.197*	0.008	1.000	
(13) AGE	-0.004	0.619*	0.714*	0.649*	0.679*	0.807*	0.699*	0.654*	-0.062	0.615*	-0.261*	-0.195*	1.000

Note: The table presents Pearson's pairwise correlation coefficients.
*, **, *** represent statistical significance at 10%, 5%, and 1%, respectively

Table 3b. Correlation Matrix and *VIF* of the Study Variables after Applying *PCA* to the Financial Inclusion Indicators

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) *ROA*	1.000							
(2) *ROE*	0.503*	1.000						
(3) *FI*	-0.088	0.435*	1.000					
(4) *LEV*	0.011	0.054	0.147	1.000				
(5) *NLSIZE*	-0.023	0.508*	0.749*	0.018	1.000			
(6) *LIQR*	0.092	-0.221*	-0.414*	0.031	-0.702*	1.000		
(7) *CIR*	-0.853*	-0.555*	-0.031	0.114	-0.197*	0.008	1.000	
(8) *AGE*	-0.004	0.619*	0.721*	-0.062	0.615*	-0.261*	-0.195*	1.000
Multicollinearity Diagnostics								
VIF			3.56	1.11	4.67	2.30	1.18	2.44
1/*VIF*			0.28	0.90	0.21	0.43	0.85	0.41
Mean *VIF*			2.54					

Note: *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively

Correlation Analysis

The pairwise correlations among all the study variables and the variance inflation factor (VIF) of the explanatory and bank-specific control variables are presented in Tables 3a and 3b. As shown in Table 3a, the profitability measures of commercial banks (*ROA* and *ROE*) are not highly correlated, with a correlation coefficient of 0.503, making it justifiable to use both *ROA* and *ROE* as alternative measures of bank performance.

As expected, all the financial inclusion indicators exhibit substantial correlations, with the coefficient of association exceeding 85%. The strong correlation among the financial inclusion variables raises concerns about multicollinearity. To address this issue, the *PCA* technique was applied, and the results of the pairwise correlation and the *VIF* after applying the *PCA* are presented in Table 3b below. A single financial inclusion index (*FI*) was constructed from six financial inclusion indicators using the *PCA* technique, thereby alleviating the concern of multicollinearity.

Regression Results

Tables 4 and 5 present the results of applying OLS, FE, FGLS, and GMM model estimators to the relationship between financial inclusion and the performance of banking companies in Ethiopia. Table 4 presents the regression results using the FE, FGLS, and GMM estimation techniques, with ROA as the measure of banks' financial performance and the financial inclusion index (FI) as the independent variable. Similarly, Table 5 reports the regression results from the OLS, FGLS, and GMM estimation methods with ROE as an alternative proxy for the financial performance of commercial banks. Both regressions also include key bank-specific variables that have a significant impact on profitability, such as leverage, bank size, cost efficiency, liquidity ratio, and bank age, to control for omitted variable bias.

Table 4. Effects of Financial Inclusion on Bank Performance (*ROA*)

		ROA	
Variable	**FE**	**FGLS**	**GMM**
L.ROA			0.469**
			(0.012)
FI	0.0836**	0.0514**	0.108**
	(0.026)	(0.018)	(0.016)
LEV	0.0120***	0.00519**	0.00368
	(0.001)	(0.026)	(0.267)
NLSIZE	0.256	0.172***	0.222
	(0.508)	(0.000)	(0.169)
LIQR	-0.0172**	-0.0119**	-0.0113
	(0.048)	(0.014)	(0.421)
CIR	-0.0666***	-0.0633***	-0.0561***
	(0.000)	(0.000)	(0.000)
AGE	0.140	-0.0126***	-0.0165**
	(0.181)	(0.001)	(0.019)
Constant	0.991	8.005***	7.009***
	(0.862)	(0.000)	(0.005)
Observation	160	160	144
Number of groups			16
Number of instruments			10
R-Squared	0.818		
AR(1) (p-value)			0.111
AR(2) (p-value)			0.619
Sargan test (p-value)			0.471
Hansen test (p-value)			0.616

Note: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively; the values in parentheses indicate p-values.

To apply dynamic panel data model estimators, it is generally required to meet the Sargan test for instrument validity, the Hansen test for model over-identification, and the Arellano-Bond test for first- and second-order autocorrelation of error terms (AR(1) and AR(2)). However, in a two-step system GMM estimation using the xtabond2 command, the Hansen test and the Arellano-Bond test for second-order autocorrelation (AR(2)) are considered more critical. Both tests should not be significant at the conventional 5% significance level. For the Hansen test, p-values between 0.05 and 0.80 are recommended, with the optimal range lying between 0.1 and 0.25 [43; 44].

In our model, the Hansen test for over-identification and the Arellano-Bond test for second-order autocorrelation (AR(2)) are not significant, with p-values of 0.590 and 0.451 when *ROA* is the dependent variable and 0.220 and 0.441 when *ROE* is the dependent variable, respectively. In addition, the number of instruments in both regressions is fewer than the number of groups, confirming that our models do not suffer from instrument proliferation.

The regression results from the FE, FGLS, and GMM estimation methods indicate that the financial inclusion index (FI) – constructed from six financial inclusion indicators – has a positive and significant impact on the performance of Ethiopian commercial banks, as measured by ROA, at the 10%, 1%, and conventional 5% significance levels, respectively. However, financial inclusion does not have a significant effect on the performance of commercial banks when measured by *ROE* in both OLS and GLS estimators. Nonetheless, in the GMM estimation, financial inclusion has a positive and significant effect on ROE at the 1% significance level, with a p-value of 0.004.

Thus, the findings of this study confirm hypothesis H1 and its sub-hypotheses (H1a and H1b), indicating that financial inclusion (FI) has a positive and significant association with the performance (*ROA* and *ROE*) of Ethiopian commercial banks. These results align with numerous prior empirical studies [8; 20–23; 25; 34], but contradict the findings of [29; 30].

In the GMM model, the lagged values of the dependent variables were also included as explanatory variables to assess the relationship between the outcome variables and their past values. According to prior research [41; 42], a maximum of two lags is generally sufficient to capture the effects of past values on the dependent variable. Accordingly, one lag of the dependent variables (ROA and ROE) was included in this study, and both were found to have a statistically significant positive relationship with their past values at the 5 and 1% significance levels, with p-values of 0.012 and 0.000, respectively.

Table 5. Effects of Financial Inclusion on Bank Performance (ROE)

	ROE		
Variable	**OLS**	**FGLS**	**GMM**
L.ROE			0.604***
			(0.000)
FI	0.546	0.600	1.114***
	(0.435)	(0.545)	(0.004)
LEV	0.0924**	0.0999***	0.0233
	(0.023)	(0.002)	(0.381)
NLSIZE	1.700**	2.260***	1.465
	(0.035)	(0.000)	(0.156)
LIQR	-0.00883	-0.0344	-0.142*
	(0.947)	(0.465)	(0.091)
CER	-0.360***	-0.300***	-0.370***
	(0.000)	(0.000)	(0.000)
AGE	0.554***	0.442***	0.0178
	(0.005)	(0.000)	(0.841)
Constant	8.850	2.435	44.60***
	(0.432)	(0.758)	(0.005)
Observations	160	160	144
R-squared	0.613		

Variable	ROE OLS	FGLS	GMM
Number of groups	16	16	16
Number of instruments			10
AR(1) P-value			0.101
AR(2) P-value			0.220
Sargan test (P-value)			0.074
Hansen test (P-value)			0.441

Note: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively; the values in parenthesis indicate p-values.

Regarding the impact of bank-specific control variables on the performance of commercial banks, the cost efficiency ratio (CER) significantly and negatively affects *ROA* and *ROE* across all models (OLS, FE, GLS, and GMM). This suggests that, as banks improve cost efficiency, their profitability increases.

The estimation results from the FE, OLS, and GLS models indicate that leverage (*LEV*) has a positive and significant effect on bank performance (*ROA* and *ROE*). However, in the GMM model, leverage remains positively associated with performance but is not statistically significant.

In the FE and GLS models, the liquidity ratio (LIQR) has a significant negative effect on *ROA*, while in the GMM model, although the coefficient remains negative, the impact is not statistically significant. Similarly, the liquidity ratio (*LIQR*) negatively correlates with *ROE* across all three models, with statistical significance at the 10% level only in the GMM estimation.

Unexpectedly, a negative and statistically significant relationship was found between bank age (*AGE*) and *ROA* in the GLS and GMM models, while the effect was positive but not significant in the FE model. However, regarding the link between AGE and ROE, it was positive and significant in the OLS and GLS models but not significant in the GMM model.

The inverse relationship between *AGE* and *ROA* aligns with the findings of [45–47]. This negative association may stem from increased organizational rigidities and the expansion of rent-seeking behaviour over time [47]. Additionally, the age-profitability relationship may follow a convex pattern, where profitability initially declines as firms age but improves again in later stages [45].

As evidenced by the GMM model, bank size (*LNSIZE*), proxied by the log of banks' assets, does not have a statistically significant relationship with performance (*ROA* and *ROE*), though the coefficients remain positive. However, results vary across different estimation models regarding the size-performance relationship.

Effects of Individual Financial Inclusion Variables on Bank Performance

In the preceding sub-sections, the relationship between financial inclusion and bank performance was discussed using a single financial inclusion index (FI), constructed from the first components of six financial inclusion indicators. In contrast, this sub-section presents the effects of individual financial inclusion indicators on bank performance. Tables 6 and 7 present the GMM estimation results for the association between each individual financial inclusion variable and bank performance, as measured by *ROA* and *ROE*, respectively.

As reported in the correlation analysis section, there are very high correlations (greater than 85%) among the individual financial inclusion indicators. This indicates the presence of multicollinearity, making it unjustifiable to use a single regression model to simultaneously estimate the effects of each individual financial inclusion variable on bank performance indicators. Therefore, in line with Bhatter & Chhatoi [24], a separate regression model was employed to assess the impact of each individual financial inclusion indicator on the performance of commercial banking institutions in Ethiopia.

As shown in Table 6 (Models 1–6), all individual financial inclusion indicators, except for the number of loan accounts (number of borrowers), have a positive and significant impact on the performance of Ethiopian banking companies when measured by *ROA*. Specifically, the number of bank branches (NBRANCHES), ATMs (NATMs), deposit accounts (*NDEPOSITAC*), total deposit amount (*AMTDEPOSIT*), and total loans and advances (*AMTLOANS*) are positively associated with *ROA*.

Similarly, as reported in Table 7, all financial inclusion indicators – except for the number of ATMs and the number of borrowers (loan accounts) – have a positive and significant effect on the profitability of Ethiopian banks when performance is measured by ROE. Additionally, the lagged values of the performance indicators (*L.ROA* and *L.ROE*) exhibit a positive and significant impact on commercial banks' performance across all models.

Thus, the effects of individual financial inclusion indicators on the performance of Ethiopian banking firms, as measured by *ROA* and *ROE*, align with the impact of the composite financial inclusion index (FI). This is evident from Model 7 in Tables 6 and 7.

Table 6. Effects of Individual Financial Inclusion Indicators on ROA

Variables	(Model 1) ROA	(Model 2) ROA	(Model 3) ROA	(Model 4) ROA	(Model 5) ROA	(Model 6) ROA	(Model 7) ROA
L.ROA	0.542***	0.457**	0.460**	0.421**	0.453**	0.455**	0.469**
	(0.007)	(0.013)	(0.013)	(0.018)	(0.013)	(0.012)	(0.012)
NLNBRANCHES	2.966**						
	(0.014)						
NLNATMs		1.237**					
		(0.041)					
NLNDEPOSITAC			1.740**				
			(0.027)				
NLNLOANAC				0.417			
				(0.439)			
NLAMTDEPOSIT					1.393**		
					(0.010)		
LNAMTLOAN						1.455*	
						(0.054)	
FI							0.108**
							(0.016)
LEV	0.003	0.004	0.003	0.005	0.004	0.005	0.004
	(0.406)	(0.173)	(0.305)	(0.168)	(0.226)	(0.186)	(0.267)
NLSIZE	-0.359*	-0.187	-0.227	-0.144	-0.189	-0.198	-0.222
	(0.077)	(0.160)	(0.186)	(0.325)	(0.195)	(0.211)	(0.169)
LIQR	-0.010	-0.012	-0.012	-0.010	-0.011	-0.011	-0.011
	(0.510)	(0.366)	(0.399)	(0.459)	(0.402)	(0.402)	(0.421)
CER	-0.057***	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	-0.022***	-0.0134*	-0.0153**	-0.0107*	-0.0142*	-0.0118*	-0.0165**
	(0.001)	(0.084)	(0.027)	(0.093)	(0.058)	(0.087)	(0.019)
Constant	7.935***	6.537***	7.007***	6.064***	6.568***	6.569***	7.009***
	(0.005)	(0.002)	(0.007)	(0.005)	(0.004)	(0.006)	(0.005)
AR(1) p-value	0.101	0.123	0.108	0.123	0.118	0.111	0.111
AR (2) p-value	0.625	0.628	0.614	0.609	0.618	0.612	0.619
Hansen p-value	0.592	0.662	0.644	0.628	0.618	0.594	0.616

Note: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively; the values in parenthesis indicate p-values.

Table 7. Effects of Individual Financial Inclusion Indicators on ROE

Variables	(Model 1) ROE	(Model 2) ROE	(Model 3) ROE	(Model 4) ROE	(Model 5) ROE	(Model 6) ROE	(Model 7) ROE
L.ROE	0.657***	0.553***	0.608***	0.537***	0.589***	0.602***	0.604***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NLNBRANCHES	28.59***						
	(0.001)						
NLNATMs		3.916					
		(0.565)					
NLNDEPOSITAC			19.43***				
			(0.001)				
NLNLOANAC				6.219			
				(0.434)			
NLAMTDEPOSIT					15.61***		
					(0.005)		
NLAMTLOAN						21.42***	
						(0.002)	
FI							1.114***
							(0.004)
LEV	0.012	0.043	0.019	0.033	0.030	0.028	0.023
	(0.639)	(0.153)	(0.453)	(0.249)	(0.316)	(0.335)	(0.381)
NLSIZE	-2.920**	-0.682	-1.417	-0.757	-1.076	-1.438	-1.465
	(0.017)	(0.515)	(0.135)	(0.431)	(0.289)	(0.184)	(0.156)
LIQR	-0.139*	-0.135	-0.143*	-0.124	-0.138*	-0.143*	-0.142*
	(0.099)	(0.110)	(0.086)	(0.123)	(0.100)	(0.091)	(0.091)
CER	-0.379***	-0.374***	-0.371***	-0.372***	-0.368***	-0.368***	-0.370***
	(0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	-0.045	0.120	0.017	0.080	0.040	0.042	0.018
	(0.528)	(0.320)	(0.830)	(0.548)	(0.674)	(0.651)	(0.841)
Constant	56.10***	34.67***	43.28***	36.44***	39.34***	42.37***	44.60***
	(0.000)	(0.008)	(0.001)	(0.005)	(0.003)	(0.003)	(0.002)
AR (1) p-value	0.0801	0.117	0.0970	0.0909	0.111	0.120	0.101
AR (2) p-value	0.211	0.229	0.222	0.222	0.224	0.226	0.220
Hansen p-value	0.311	0.575	0.435	0.560	0.495	0.432	0.441

Note: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively; the values in parenthesis indicate p-value.

Conclusion and Recommendations

This study used a two-step system GMM technique on a sample of sixteen commercial banks to examine the impact of financial inclusion on the financial performance of Ethiopia's banking industry. The GMM estimation results were compared with other linear panel data analysis techniques, including OLS, FE, and Feasible Generalized Least Squares (FGLS).

The study utilized ten years of data (2013–2022), manually collected from the country's central bank, officially known as the National Bank of Ethiopia (NBE), and the annual reports of each commercial bank included in the sample. Since bank performance was measured using two alternative indicators – *ROA* and *ROE* – two separate econometric models were specified to estimate the relationship between financial inclusion and these performance metrics.

Initially, six financial inclusion indicators were considered: the number of branch networks and ATMs (measuring banking service availability/access), the number of depositors and borrowers (reflecting banking penetration), and the amounts of outstanding deposits and loans (capturing financial service usage). In the next step, a composite financial inclusion index (FI) was constructed by applying the PCA technique to extract the first principal component from these six indicators.

To account for omitted variable bias, the study also included several bank-specific control variables known to significantly influence financial performance, such as leverage, liquidity ratio, cost efficiency ratio, bank size, and bank age.

The study found that the composite financial inclusion index (FI) has a significant positive impact on the performance of Ethiopia's banking sector, as measured by both *ROA* and *ROE*. The GMM model estimation also revealed that the lagged values of performance measures (*L.ROA* and *L.ROE*) have a positive and significant effect on the current and future financial performance of commercial banks.

Regarding the control variables, the cost efficiency ratio is the only variable that significantly affects both *ROA* and *ROE*, with negative coefficients. No statistically significant relationship was found between the liquidity ratio and *ROA*, whereas its association with *ROE* is negative and significant at the 10% significance level. Leverage does not have a significant effect on either *ROA* or *ROE*. Bank age negatively and significantly affects ROA, while its effect on ROE is positive but not statistically significant. Additionally, bank size shows no significant relationship with either performance measure.

The findings of this research will contribute to a broader global understanding of the relationship between financial inclusion and the performance of commercial banks.

Firstly, this study provides empirical evidence that increased financial inclusion activities positively influence the profitability of commercial banks. It also highlights key bank-specific variables that determine their financial performance.

Secondly, the findings will be valuable to financial institutions in shaping their strategic initiatives to enhance financial inclusion efforts.

Thirdly, the study offers insights for government agencies and financial sector regulators responsible for promoting financial inclusion in the country. Given that Ethiopia is the second most populous country in Africa, with a large unbanked population, banks have a significant opportunity to expand their outreach. This can be achieved by increasing branch networks and ATMs, offering accessible and tailored financial services, and promoting financial literacy among the population.

Statement of availability of data

This study used data collected manually from the National Bank of Ethiopia (NBE) and annual reports of each commercial bank in the sample.

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