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The impact of traditional and digital financial inclusion on bank profitability: Evidence from Ethiopian commercial banks

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Abstract

While prior research emphasizes the socio-economic benefits of financial inclusion, its implications for bank profitability remain underexplored. This paper employs seven traditional and four digital indicators to create a financial inclusion index through principal component analysis (PCA). To capture potential nonlinearities, quadratic specifications are incorporated within a two-step system generalized method of moments (GMM) framework and validated using the Lind and Mehlum (2010) U-shape test, while Granger causality tests examine directional effects over the 2015–2023 period. Results indicate that traditional financial inclusion positively influences profitability, although the hypothesized inverted U-shaped effect is economically plausible but not statistically confirmed. Digital financial inclusion initially reduces profitability, but its squared term reveals a statistically significant U-shaped effect, indicating gains after reaching a critical threshold. Granger causality test indicates a bi-directional relationship for traditional inclusion and a uni-directional for digital inclusion. The results emphasize the need for banks to integrate cost-effective digital tools alongside traditional services. Policymakers recommended adopting supportive regulatory frameworks, enhancing financial literacy, and ensuring consumer protection to foster digital transformation without undermining profitability. An integrated and phased approach aligning financial inclusion with profitability strategies is essential for promoting a resilient and inclusive banking sector.

Keyword: Traditional financial inclusion; digital financial inclusion; principal component analysis; bank profitability; nonlinear GMM; Ethiopia

JEL Classification: G21; C38; C13; O55

1. Introduction

Banks serve as critical components of the financial system, acting as intermediaries that channel surplus capital into productive investments, thereby facilitating efficient resource allocation and serving as a key driver of economic growth (Jajah et al., 2022; Guo and He, 2019; Bayiley, 2013). Beyond their direct contributions to growth, banks influence financial markets, controlling significant portions of the money supply and shaping the production landscape through the regulation of money circulation (Al Karim and Alam, 2013; Brigham and Houston, 2011). Furthermore, banks serve as conduits for transmitting government economic policies, particularly monetary policy, into the broader economy (Musau et al., 2018). Consequently, a well-functioning banking sector is essential for sustained economic progress, while poorly functioning banks can impede development and exacerbate poverty (Joseph et al., 2012).

The full potential of the financial sector can be realized if it is inclusive (Jajah et al., 2022). Financial inclusion (FI), facilitated largely by financial institutions, plays an important role in providing vulnerable and underserved populations with access to affordable financial services (Kanungo and Gupta, 2021; Demirguc-Kunt et al., 2018). This access is instrumental in elevating both individual economic standing and societal welfare, particularly for low-income society (Demirguc-Kunt et al., 2018; Lal, 2018). FI is commonly examined through access, availability, and usage of banking products and services (Erlando et al., 2020). 'Access' pertains to the penetration of financial services into society, 'availability' to the infrastructure that supports these services, and 'usage' to the actual adoption and utilization of financial products (Sedera et al., 2022). While banks strive to maximize shareholder value (Pilloff, 1996; Kumar, 2016; Pennacchi and Santos, 2021), there is an increasing demand from underserved segments of society for affordable, innovative financial services with flexible terms (Shihadeh, 2021; Arner, 2020; Fernandez-Olit et al., 2019). Governments are instrumental in promoting FI through initiatives that enhance financial literacy and incentivize banks to extend their services, particularly in rural areas (Arebo et al., 2025b; Shihadeh, 2021).

Historically, commercial banks have centered their business models on urban, formally employed, and well-documented clients, leaving vast segments of the population excluded from formal finance (Perdana et al., 2025). Efforts to extend conventional services to these underserved groups have increased workforce requirements, operational burdens, and risk exposure. As banks allocate more resources to long-tail customers, their ability to maintain service quality for high-value clients may weaken, contributing to deteriorating overall performance (Zhao et al., 2024). For decades, these customers were considered unprofitable due to high transaction costs, regulatory barriers, and perceived risks (Perdana et al., 2025). Expanding outreach often elevates operational costs and capital expenditures (Mehrotra and Yetman, 2015; Shihadeh, 2020), and lending to individuals and SMEs involves heightened credit risks arising from inadequate collateral, competition, and volatile income (Shihadeh et al., 2019). However, emerging evidence points to a structural transformation. Advances in digital finance, data analytics, and alternative delivery channels are enabling banks to serve previously excluded populations in commercially viable ways. Digital transformation has reduced marginal service costs, strengthened risk assessment, and broadened access for millions of consumers (Perdana et al., 2025; Zhao et al., 2024). In parallel, incorporating unbanked individuals and firms into the formal system can expand customer bases, mobilize deposits, and create new lending opportunities, thereby enhancing profitability (Ahamed et al., 2021; Shihadeh, 2020). Accordingly, the relationship between FI and bank profitability remains multifaceted, context-dependent, and theoretically contested (Jajah et al., 2022), underscoring the need to balance outreach with prudent risk management (Shihadeh, 2020).

This study offers several significant contributions to broader literature. First, despite the growing recognition of FI's importance, research on its effect on bank profitability remains sparse, particularly in the emerging economies context (Yakubu and Musah, 2022; Vo and Nguyen, 2021). Several empirical studies in Ethiopia have examined bank profitability (e.g., Mengstie et al., 2024; Muhammed et al., 2024; Addisu et al., 2023; Bushashe, 2023; Mohammed, 2023; Tura, 2023; Yusuf and Shikur, 2023; Isayas, 2022; Tibebe and Gujral, 2022; Ayalew, 2021; Biru, 2021; Tibebe, 2020; Berhe, 2019; Shifa et al., 2019; Teshome et al., 2018; Merin, 2016). These studies predominantly focus on macroeconomic and bank-specific factors affecting profitability, yet they fail to link bank profitability with FI. Similarly, research on FI in Ethiopia is emerging, with studies focusing on various aspects of FI, such as access to banking services, usage, and inclusion in rural areas (e.g., Arebo et al., 2025a; Denegetu, 2024; Fielding and Regasa, 2024; Menza et al., 2024; Mudessir et al., 2024; Ruey, 2024; Adera and Abdisa, 2023; Giday, 2023; Hundie and Tulu, 2023; Hussen and Mohamed, 2023; Dagnachew and Mawugatie, 2022; Mossie, 2022; Abdu and Adem, 2021; Oshora et al., 2021; Lakew and Azadi, 2020; Teka et al., 2020; Timbula et al., 2019; Desalegn and Yemataw, 2017; Rao and Baza, 2017; Alemu, 2014). However, these studies, too, overlook the critical intersection between FI and bank profitability.

Moreover, existing international studies provide mixed evidence. Some find FI enhances performance (e.g., Ayele et al., 2025; Guo and Ma, 2025; Aziz et al., 2024; Zhao et al., 2024; Zheng et al., 2023; Al-Eitan et al., 2022; Erülgen et al., 2022; Jajah et al., 2022; Sedera et al., 2022; Pal and Bandyopadhyay, 2022; Shihadeh, 2021; Vo and Nguyen, 2021; Shihadeh et al., 2018), while others document profitability-reducing effects (e.g., Djani-Feuzeu et al., 2025; Nguyen et al., 2025; Yakubu and Musah, 2022). A major gap in this literature is the neglect of potential nonlinearities, limiting understanding of how FI affects profitability across different levels of development, scale and adoption stages. Most existing works (e.g., Ayele et al., 2025; Guo and Ma, 2025; Aziz et al., 2024; Zheng et al., 2023; Erülgen et al., 2022; Jajah et al., 2022; Khatib et al., 2022; Yakubu and Musah, 2022; Kumar et al., 2021; Vo and Nguyen, 2021) apply linear GMM methods to address endogeneity arising from simultaneity, dynamism and heteroscedasticity in panel data. To the best of the researcher's knowledge, this study is the first to examine the nonlinear FI–profitability relationship in Ethiopia using a nonlinear two-step system GMM framework, with the turning point validated through Lind and Mehlum's (2010) U-test.

Secondly, a significant challenge in FI studies lies in the limited and often inconsistent metrics used to construct FI indices (Zheng et al., 2023; Jajah et al., 2022). Cross-country analyses relying on various datasets such as FAS, GFDD, or Findex often suffer from inconsistent periodicity, heterogeneous measurement scales, and limited sectoral coverage than single-country banking data. As a result, most studies employ only a few traditional indicators (such as branches, ATMs, accounts, cards, loan, deposits) to construct FI indices (e.g., Ayele et al., 2025; Bhatter et al., 2025; Djani-Feuzeu and Nguena, 2025; Hassan et al., 2025; Nguyen et al., 2025; Saidi et al., 2025; Sha'ban et al., 2023; Al-Eitan et al., 2022; Khatib et al., 2022; Jajah et al., 2022; Yakubu and Musah, 2022; Kumar et al., 2021; Vo and Nguyen, 2021). Although recent studies (e.g., Guo and Ma, 2025; Aziz et al., 2024; Zhao et al., 2024; Zheng et al., 2023) have begun to recognize the growing importance of digitalized banking services incorporating metrics (such as mobile banking, internet banking, agent banking, or mobile money), the integration of these metrics often overlooks the foundational role of traditional banking infrastructure, which underpins and enables digital expansion. As a result, most FI measurement frameworks still fall short of capturing the full spectrum of traditional and digital inclusion. This study addresses these gaps by constructing a comprehensive, data-driven FI index for Ethiopian commercial banks using PCA, combining seven traditional and four digital indicators from 2015–2023. It develops separate indices for traditional FI (TFI) and digital FI (DFI) to capture their distinct asymmetric returns for the banking sector. Finally, this study tests the causality between FI and profitability to understand the directional relationship.

The remainder of the study is structured as: Section 2 presents literature reviews. Section 3 outlines the methodology aspects. Section 4 presents the empirical findings, and Section 5 concludes with policy implications.

2. Literature Review

2.1 Theoretical Literature Review

The discourse surrounding FI has increasingly aligned with core banking theories, offering varied perspectives on the linkage between FI and bank performance. Three predominant schools of thought elucidate the banking sector's role in fostering financial development and stimulating economic growth. The relationship between FI and bank performance is illuminated through three major theoretical frameworks.

First, financial intermediation theory posits that banks function as crucial intermediaries between savers and borrowers, optimizing capital allocation and minimizing transaction costs linked to asymmetric information (Scholtens and Wensveen, 2003). This perspective highlights the role of banks in improving savings mobilization and credit allocation efficiency, particularly in emerging economies where financial exclusion is rampant (Maity and Sahu, 2020; Collard, 2007). As Mester (1992) and Allen and Santomero (1997) note, intermediation theory has expanded alongside changes in banking practice. Recent scholarship distinguishes between traditional and digital intermediation channels (Arebo et al., 2025a; Wang et al., 2024; Mao et al., 2023; Ren et al., 2023), with traditional finance relying on physical delivery mechanisms (Wang et al., 2024; Jin et al., 2023) and digital finance supplementing these through technological innovation (Wang et al., 2024; Yu and Wang, 2021). Within this theoretical frame, TFI can enhance profitability by expanding deposits, strengthening credit allocation, and reducing information frictions, particularly at early or moderate levels of expansion. However, as Babilla (2023) argues, TFI also imposes rising costs once outreach becomes geographically stretched as branch proliferation increases monitoring burdens, aggravates agency problems, dilutes managerial efficiency, and generates diminishing marginal returns. Consistent with Hong et al. (2025), financialization may therefore follow a nonlinear pattern due to early-stage gains in resource mobilization to improve performance, but extensive expansion raises operating complexity, credit risk, and cost burdens, weakening profitability at higher inclusion levels. From a digital intermediation perspective, the concept of technology spillover suggests that digital innovation through data analytics, AI, mobile platforms, or blockchain, can enhance banks' efficiency and convenience through knowledge diffusion, competition, and collaborative learning. Yet in early-stage markets, digital expansion typically lowers profitability because financial institutions must commit substantial resources to technology, infrastructure, cybersecurity, system integration, and human capital development (Yuan et al., 2025; Song et al., 2023). Yin et al. (2024) argue that digital finance initially exerts negative effects because scale requirements exceed technological gains, while digital adoption remains uneven across customer segments. This generates "tool exclusion" and "evaluation exclusion" (Yin et al., 2024) or a general "digital divide" (Putra et al., 2024), wherein low-income, rural, or digitally illiterate customers cannot fully access digital services. In such settings, digital finance becomes dependent on traditional banking users, limiting its ability to generate new business and inflating short-term costs. The early-stage cost burden is further amplified in banking because digital finance requires robust infrastructure, interoperable payment systems, high supervisory capacity, and regulatory alignment (Yin et al., 2024). Under weak digital endowment, the digital divide deepens access inequality and restricts the effective use of digital financial services, especially in rural and vulnerable communities (Putra et al., 2024). These dynamics explain why DFI may exhibit a nonlinear relationship with profitability during its formative stages. As digital systems mature, however, the mechanisms predicted by financial intermediation theory reemerge in digital form (Yin et al., 2024). Digital platforms reduce information asymmetry, strengthen risk monitoring, enhance credit scoring, lower transaction costs, and expand the long-tail customer base, thereby improving the profitability of banks (Hassan et al., 2025; Yin et al., 2024; Zhao et al., 2024; Babilla, 2023). Digital channels relax temporal and spatial constraints, reduce marginal service costs, and unlock previously latent demand among underserved customers (Wang et al., 2024; Mao et al., 2023). Once learning effects accumulate and "break-in" periods dissipate, digital finance enhances operational efficiency, reduces resource wastage, and supports sustainable growth (Yin et al., 2024).

Second, fractional reserve theory extends intermediation view by emphasizing the systemic ability of banks to generate money through multiple deposit expansion (Werner, 2016; Humphrey, 1986), which is enhanced by FI initiatives that enhance deposit growth and subsequently credit expansion. This systemic credit creation underpins economic activity and banks' financial performance (Sapriza and Temesvary, 2024). In contrast, credit creation theory asserts bank as active creators of credit, asserting that lending activities generate new deposits irrespective of prior reserves (Werner, 2014), which significantly impacts profitability (Nair and Von Pischke, 2007; Jakab and Kumhof, 2014). This theory suggests that FI initiatives can significantly boost bank profitability by facilitating new credit creation, although it also cautions against the risks of macroeconomic instability stemming from unchecked credit expansion, as evidenced by past financial crises (Schularick and Taylor, 2012; Sutherland and Hoeller, 2012). Collectively, based these theories, it can be argued that FI is not merely about expanding access but fundamentally transforms the mechanisms of money creation and credit allocation, thereby reshaping bank performance and economic development.

2.2 Empirical Literature Review

In the growing body of empirical research, FI has emerged as a key component of financial sector development (Collard, 2007), particularly in its intersection with bank profitability. The relationship between FI and profitability remains an intricate subject, as empirical studies across various contexts yield mixed results. A robust review of recent literature underscores this dynamism, highlighting variations across regions, methodologies, and specific indicators of FI. Recognizing this conceptual and empirical heterogeneity, the present review classifies prior evidence based on the specific indicators used to construct FI indices and the linear versus nonlinear mechanisms underlying FI–performance linkages.

2.2.1 Nexus between traditional FI and bank performance

Analyzing a developed market, Kumar et al. (2021), for instance, examined the profitability of 122 Japanese banks from 2004 to 2018, revealing that FI, when measured through branch contraction, negatively impacts profitability. However, other indicators like loan accounts and ATM penetration showed no significant effect. Their study challenges the broad assumption that FI uniformly enhances profitability, particularly in developed markets where the maturity of financial services may reduce the incremental benefits of expanding access. This highlights the importance of country-specific factors such as cost management and bank size, which play more dominant roles in established financial ecosystems. Consistently, Sha'ban et al. (2023), using OLS for 88 high- and 43 low-income countries (2005–2014), find a trade-off between bank performance and credit deepening in high-income nations, whereas in low-income counterparts, FI (captured by deposits to GDP, number of deposits, and borrower accounts) does not harm profitability. Saidi et al. (2025) further reveal that FI improves bank performance in GCC economies and raises ROA (but not ROE) in non-GCC countries, implying that the profitability effects of FI depend on countries' structural characteristics and financial maturity.

In the context of emerging markets, empirical evidence presents a mixed result. Vo and Nguyen (2021), studying 1507 Asian banks, employed PCA and GMM to demonstrate a positive relationship between FI and bank profitability. Their research underscores the importance of financial product penetration and utilization as key drivers of profitability. However, in Jordan, even though the overall FI index has a positive effect, Al-Eitan et al. (2022) reported a negative relationship between usage of financial services (measured through loan and deposit size) and profitability, with financial leverage and bank size emerging as the most important determinants. These regional differences suggest that FI alone may not always suffice to boost profitability, particularly in economies where banking structures are heavily deposit accumulation and credit driven. This is corroborated by Shihadeh et al. (2018), who explored the Jordanian banking sector and found that while certain dimensions of FI, such as SME credit and ATM proliferation, positively affected bank performance, results varied depending on the specific measure of FI employed. These findings underscore that FI's profitability effects are highly dimension-sensitive and depend on the cost–risk structure of local banking markets.

In an exploration of Sub-Saharan Africa (SSA), Yakubu and Musah (2022), analyzing the region from 2000 to 2017, applied PCA to construct an FI index and utilized GMM to address endogeneity concerns. Their findings reveal a negative relationship between FI and bank profitability, particularly in the post-global financial crisis era. This suggests that inclusive financial policies may impose cost pressures on banks, particularly in fragile financial ecosystems. In addition, Djani-Feuzeu and Nguena (2025), using Driscoll–Kraay and GMM for 46 SSA countries (2004–2021), likewise document a negative effect. In contrast, Jajah et al. (2022), studying a longer time frame (1990-2017) for SSA banks, found a positive relationship between FI and profitability using system GMM. This discrepancy can be attributed to the broader dataset and longer time horizon employed by Jajah et al. (2022), which captures a more stable period for SSA bank's post-financial crisis. These divergent results imply that SSA banks' ability to translate FI into profitability depends on macro-financial stability, institutional quality, and innovation banking strategies that lower the costs of servicing new, previously excluded segments of the population.

In smaller, niche markets, such as Northern Cyprus, Erülgen et al. (2022) used dynamic panel techniques (GMM, PMG, and CS-ARDL) to demonstrate a positive relationship between FI and profitability, emphasizing deposit ratios and bank size as crucial drivers. Their study illustrates that FI can significantly enhance banking sector performance in smaller economies by encouraging deposit growth. Their policy recommendations, which advocate for relaxing customer identification criteria to include marginalized populations, highlight the social equity dimension of FI in insular markets. Similarly, in Palestine, Shihadeh (2021) found that branch and ATM proliferation enhance bank performance, further supported by Khatib et al. (2022), whose findings from 2012 to 2020 employing GMM and linear regression techniques revealed that the accessibility and quality of financial services drive profitability.

Sedera et al. (2022) explore FI's effect on bank profitability in Indonesia from 2015 to 2020. Their panel data analysis with fixed effects reveals a positive relationship between FI and profitability across all dimensions. The study distinguishes itself by focusing on bank-level data, as opposed to national-level analyses common in existing literature. This bank-centric perspective enriches the understanding of FI's microeconomic impacts in emerging markets, particularly in the Indonesian context. It suggests that FI policies can directly enhance bank performance, offering strategic insights for policymakers and financial institutions alike. Employing linear mixed model, Obiedallah and Abdelaziz (2024) examined Egyptian banks, found that the capital adequacy ratio (CAR) moderates the relationship between FI and performance. The study indicates that high CAR strengthens the association but also suggests that FI's impact on profitability may be constrained by regulatory requirements.

Recent studies increasingly highlight the nonlinear dynamics between FI and bank performance. Bhatter et al. (2025) report a U-shaped nexus between FI and profitability in Indian banks, suggesting that initial FI expansion imposes cost and risk pressures before profitability improves beyond a critical inclusion threshold. Djani-Feuzeu and Nguena (2025), using quantile regression, find FI exerts a consistently negative effect across the profitability distribution in SSA, though the magnitude varies by quantile. Shihadeh (2020) shows that additional branches disproportionately benefit low-ROA and mid-ROE banks, implying diminishing marginal returns to FI for highly profitable institutions. Ahamed et al. (2021) report FI improves efficiency only for mid-tier banks, while Setianto et al. (2025) observe that banks with greater market power benefit more from FI expansion. Beyond bank performance, Fomum and Opperman (2023) show that FI significantly enhances MSME turnover and business progression in Eswatini, though insurance effects vary by enterprise size. Hong et al. (2025) document an inverted-U effect of financialization on performance in Chinese private firms, reinforcing broader evidence that inclusion-or financialization-related expansions often yield diminishing marginal returns after a threshold. Together, these nonlinear studies suggest that FI can be either beneficial or detrimental depending on a bank's efficiency tier, market power, and expansion stage. Ahamed et al. (2021) claims that broadening access across diverse customer groups requires banks to offer a wider product mix, which can increase agency problems, operating costs, and organizational complexity. Thus, the empirical literature indicates that TFI produces competing effects like enhancing deposits, outreach, and intermediation efficiency at moderate levels, but raising costs and risks as scale intensifies.

Hypothesis 1: There is an inverted U-shaped nexus between TFI and bank profitability.

2.2.2 Nexus between digital FI and bank performance

Digitalisation is widely associated with improved outreach efficiency as "volume increased, scale expanded, price reduced, and risk controlled" (Zhu and Guo, 2024), yet digitalization's profitability implications are not linear. Tong and Yang (2025) note both positive channels (product innovation, cost reduction, customer expansion) and negative channels (competition intensification, customer attrition).

The empirical evidence largely confirms these mixed effects. Zheng et al. (2023) analyzed 40 developing countries between 2011-2021, using fixed-effects, two-stage least squares (2SLS-IV), and two-step system GMM. Their study found that fintech-driven FI significantly boosts profitability, with traditional and larger banks benefiting more than smaller or Islamic banks. This highlights the transformative potential of technology in amplifying the profitability gains from FI, particularly in high-growth developing economies. The role of fintech was also explored by Aduba et al. (2023), who found that fintech significantly drives financial development and, consequently, profitability in emerging economies, where traditional banking systems are less efficient. In a broader context, Akhisar et al. (2015) demonstrated that electronic banking innovations significantly impact profitability across both developed and developing countries, though their effects vary based on levels of financial development. Similarly, studies (like Zhao et al., 2024; Guo and Ma, 2025; Aziz et al., 2024) also document strong positive associations between digital FI and profitability. Liu et al. (2024) find that FinTech improves performance by promoting better lending and liability structures, especially for national and rural banks. However, Wu and Ma (2025) find digital finance weakens profitability due to volatility, heightened competition, and regulatory uncertainty around off-balance-sheet activities. Bashiru et al. (2023) find financial development reduces profitability in SSA, while Wang et al. (2025) report fintech improves liquidity rather than immediate profitability, emphasizing lagged effects and high adjustment costs.

A recent growing branch of literature reveals nonlinearities. Hassan et al. (2025) show that FinTech disproportionately improves performance among lower-performing banks, consistent with technology-enabled inclusion effects. Yuan et al. (2025) identify a critical fintech threshold (4.169), below which fintech significantly suppresses profitability due to customer diversion and cost escalation, but the negative effect weakens once maturity is reached, reflecting reduced competitive displacement and stronger complementarities. Zhu and Guo (2024) further show that while inclusive lending may initially depress profits due to cost–benefit asymmetry "doing business at a loss", digital FI mitigates these losses by reducing information asymmetry and transaction costs. Wang et al. (2024), using a threshold panel model, find that digital finance improves efficiency only after achieving sufficient scale, with diminishing returns beyond a critical point. Yang and Masron (2023) further document profit-reducing effects of early-stage digital transformation in China due to high initial investment and operational lags. Overall, these studies converge on the view that digital FI exerts competing effects as enhancing efficiency and outreach once digital maturity or scale is achieved, but compressing margins during early-stage adoption due to technological investment, competition, and risk exposure.

Hypothesis 2: There is a U-shaped nexus between DFI and bank profitability.

Existing research on the relationship between FI and bank profitability shows varied outcomes contingent upon regional, institutional, and economic factors. In developing economies, FI can enhance profitability, especially with innovative banking practices and conducive macroeconomic conditions. However, the Ethiopian context has been largely overlooked, and many studies lack digital metrics in their analyses. This research aims to fill this gap by incorporating digital initiatives to better understand their asymmetric impact on bank profitability in Ethiopia. Additionally, much of the existing literature neglects potential endogeneity in panel datasets. To address this, this study employs the GMM approach.

3. Methodology

3.1 Sample Population

This paper employed a data set of 17 commercial banks in Ethiopia from 2015-2023, excluding recently established banks with insufficient data. The included banks represent approximately 91 percent of total assets, 98 percent of deposits, 94 percent of credit, and 76 percent of equity in the financial sector (NBE-FSR, 2024; Arebo et al., 2024). Data was sourced from the National Bank of Ethiopia (NBE), annual reports from commercial banks (CBs), and the World Bank (WB), based on data availability.

To measure traditional and digital FI, the study employed PCA to develop composite indices. For estimation, the two-step system GMM approach was adopted, as supported by Jajah et al. (2022) and Kumar et al. (2021), to address econometric problems such as endogeneity and unobserved bank-specific effects, common in panel data settings. A detailed description of the variables and their symbols is mentioned in Table 1.

Table 1: Description of variables

Variables	**Symbol**	**Unit of measurement**	**Source**
		Dependent Variable	
Profitability Index	PI	Developed employing PCA combining ROA, ROE and NIM	NB
		Main independent Variable	
Traditional availability dimension index	TFI	Developed employing PCA combining BRP, ATMP and PoSP	NB, WB
Traditional usage dimension index		Developed employing PCA combining DAP, CDCP, PLOAN and PDEP	NB, WB
Digital Accessibility dimension index	DFI	Developed employing PCA combining MBP, IBP, MMP and APP	NB, WB
		Control Variables	
Z-score	lnZS	Natural logarithm of return to asset + equity-to-assets ratio/ standard deviation of return on asset	NB
Scale efficiency	SE	Using DEA to calculate SE based on the result of VRS/CRS	NB
Loan to deposit ratio	LDR	Overall extended loans/total deposits	NB
Real deposit interest rate	RDIR	Deposit interest rate minus inflation rate	NB
Total asset	lnTA	Natural logarithm of total asset	NB
Broad money supply	BM	Money supply/GDP	NB

Source: Prepared by authors

3.2 Variable Description

3.2.1 Dependent Variable

In line with the extant literature on bank performance measurement, profitability is often captured using ROA (Zheng et al., 2023; Khatib et al., 2022; Yakubu and Musah, 2022; Kumar et al., 2021; Vo and Nguyen, 2021; Jajah et al., 2022; Shihadeh et al., 2018), ROE (Zheng et al., 2023; Yakubu and Musah, 2022; Kumar et al., 2021; Jajah et al., 2022), and NIM (Zheng et al., 2023; Khatib et al., 2022; Jajah et al., 2022). Specifically, ROA reflects how effectively a bank uses its assets to generate earnings, while ROE measures the profitability relative to shareholder equity (Zheng et al., 2023; Kumar et al., 2021). In addition, NIM, provides insights into the ability with which a bank's interest-earning assets are employed to generate interest income (Khatib et al., 2022).

Different methods and combinations of variables have been proposed in the literature to construct a comprehensive measure of bank profitability. For instance, Aduba et al. (2023) developed a non-parametric approach to create a composite profitability index using ROA, ROE, and NIM as key metrics. This approach acknowledges that bank profitability is multifaceted and cannot be fully captured by any single measure. Similarly, Popa et al. (2021) employed PCA to construct a composite indicator of financial performance, which integrated both traditional accounting metrics (such as Earnings per share, ROA, ROE, Solvency) and value-based indicators (such as Economic value-added, Market value-added, Cash flow return on investment, Cash value-added). The advantage of such an approach lies in its ability to capture the latent dimensions of profitability while reducing the dimensionality of the data, thereby minimizing potential multicollinearity among the original variables. Sha'ban et al. (2023) employed PCA to construct a banking sector performance index employing the CAMEL rating system, including banks' solvency, asset quality, efficiency, profitability and liquidity.

In this study, we employ PCA to construct a composite index for bank profitability, drawing on the metrics of ROA, ROE, and NIM. The rationale for adopting PCA is twofold. First, PCA extracts the most significant information from a set of correlated variables, ensuring that the composite index captures the underlying structure of bank profitability. This aligns with the objectives of PCA, as outlined by Abdi and Williams (2010), which aim to reduce the attribute space from a larger set of variables to a smaller number of components that retain the highest variance. By doing so, PCA minimizes redundancy and ensures that the resulting index is both parsimonious and robust. Second, the use of PCA in the context of financial performance measurement is supported by its application in various studies. For instance, Sha'ban et al. (2023), Popa et al. (2021) and Liu et al. (2020) used PCA to combine multiple financial performance indicators into a single composite score, allowing for a more holistic assessment of a firm's financial performance. This method allows for a more accurate reflection of bank performance by aggregating the individual metrics (ROA, ROE, and NIM) into a single profitability index, which can be interpreted as a comprehensive measure of bank financial success. By capturing the common variance among these profitability metrics, the PCA-derived index provides a reliable measure that mitigates the risks of over-reliance on any single indicator, thereby offering a more nuanced understanding of bank profitability.

3.2.2 Independent Variables

FI and financial exclusion (FE) are binary terms that reflect the accessibility of financial services (Koefer et al., 2024; Fernández-Olit et al., 2019). FI aims to bridge the gap of FE, particularly for disadvantaged populations, by enabling affordable access to basic financial services (Hannig and Jensen, 2010; Dabla-Norris et al., 2015). The measurement of FI, its barriers, and its relation to real sector outcomes is critical (Beck, 2016). Sarma (2016) further emphasizes that effective measurement is fundamental to comprehending the effects of FI and informing policy measures. Nguyen (2021) and Vo and Nguyen (2021) highlight comparable indices across time and space are essential for evaluating FI efforts.

In this research, FI is categorized into traditional financial inclusion (TFI) and digital financial inclusion (DFI), both of which are analyzed as separate variables. According to Ren et al. (2023) and Jain et al. (2021), TFI encompasses financial services offered by conventional financial institutions, which include traditional banking methods such as physical branches, ATMs, and point-of-sale (PoS) systems. In contrast, DFI pertains to services provided by innovative entities that leverage technological advancements, specifically through the internet, mobile networks, and digital wallets. This dual categorization aligns with the structural transition occurring in modern banking, where digital tools expand scale and convenience, but traditional channels remain critical for complex services and trust formation (Keil and Ongena, 2023; Madegowda, 2025). Recent evidence shows that technological diffusion is reshaping financial systems, shifting decision-making from humans to algorithms and creating new vulnerabilities such as cyberattacks and digital-infrastructure dependence (Trotta et al., 2025; Omarova, 2020). Likewise, accelerated de-branching has produced adverse effects on firm creation, particularly when older or large-bank branches close (Cardamone and Trivieri, 2024). These findings underscore why separating TFI and DFI provides a clearer analytical lens since each dimension carries distinct operational costs, risks, and channels of profitability transmission in the banking sector. This study employs these classifications to evaluate the respective impacts of TFI and DFI on bank profitability. TFI is composed of seven indicators across two dimensions: availability and usage. Availability dimension includes: Bank branches per 100,000 adults (BRP), ATMs per 100,000 adults (ATMP), PoS terminals per 100,000 adults (PoSP). For the usage dimension, indicators include: Depositor accounts per 1,000 adults (DAP), Debit card holders per 1,000 adults (CDCP), Loan-to-GDP ratio (PLOAN), and Deposit-to-GDP ratio (PDEP). Similarly, DFI is captured through four indicators in the digital accessibility dimension: Mobile banking users per 1,000 adults (MBP), Internet banking users per 1,000 adults (IBP), Mobile wallet users per 1,000 adults (MMP), and Agents per 1,000 adults (APP).

Given the multidimensional nature of FI, this study applies PCA to construct composite indices for TFI and DFI. PCA is widely used to reduce data dimensionality while preserving the maximum amount of information (Nguyen, 2021; Vo and Nguyen, 2021). The principal component typically explains the highest variance, exceeding 60%, making it the most representative factor in the dataset (Hair et al., 2019). However, before applying PCA, as Freudenberg, (2003) and Jacobs et al., (2004) claimed, normalization is required to account for the heterogeneity of measurement units and to mitigate outliers. In the broader context of data scaling, techniques such as Min–Max scaling, mean normalization, Z-score standardization, and Gaussian-based transformations are sensitive to extreme values. Although outliers can influence range-based transformations, Min–Max normalization remains appropriate when the goal is to place all indicators on a fixed, interpretable scale. As demonstrated by Kim et al. (2024), Swift et al. (2023), and Ali (2022), constraining variables to a bounded interval enhances interpretability and provides a stable range for prediction and comparative analysis. This is particularly suitable for FI measurement, where a 0–1 scale allows direct interpretation of inclusion intensity. For this reason, the study adopts the Min–Max approach (MMA), where 1 represents full financial inclusion (FI) and 0 denotes financial exclusion (FE). The Min–Max formula is expressed as:

$$MMA = \frac{Actual\ number - Minimum\ number}{Maximum\ number - Minimum\ number}$$

After normalization, PCA is applied to calculate the eigenvalues of the variance matrix for each indicator. All sub-indices should meet standard PCA assumptions, including sufficient sampling adequacy (KMO ≥ 0.5), significant Bartlett's test results ($p < 0.05$), and strong internal consistency (Cronbach's alpha ≥ 0.6), supporting the reliability and suitability of PCA for index construction. The composite indices for TFI and DFI are then constructed using the following formulas:

$$\mathrm{PCA_{TFI}} = \sum_{n=1}^{3} \mathrm{loading_n} * \mathrm{TA\ Indicators_n} + \sum_{n=1}^{4} \mathrm{loading_n} * \mathrm{TU\ Indicators_n} \tag{1}$$

$$\mathrm{PCA_{DFI}} = \sum_{n=1}^{3} \mathrm{loading_n} * \mathrm{DA\ Indicators_n} \tag{2}$$

Where, $\mathrm{PCA_{TFI}}$ and $\mathrm{PCA_{DFI}}$ denotes the number of selected components for TFI and DFI, as well, TA stands for the traditional availability indicators, TU indicates traditional usage indicators, and DA represents digital accessibility indicators. loading, stands for the factor loadings of the corresponding indicators.

3.2.3 Control Variables

This study incorporates both bank-specific and macroeconomic control variables to enhance the robustness of the analysis. Among the bank-specific variables, scale efficiency is employed to assess the efficiency ratio. Technical efficiency scores serve as a critical indicator for monitoring the operational dynamics and potential of individual banks (Ullah et al., 2023), reflecting their capacity to conduct activities in an efficient manner. To measure efficiency, this research applies the Data Envelopment Analysis (DEA) approach, utilizing scale efficiency (SE) based on an output-oriented method. Following the methodology proposed by Li et al. (2013), scale efficiency is calculated using the formula,

$$\mathrm{SE} = {}^{\mathrm{CRS}}/_{\mathrm{VRS}}$$

Where, SE represents the ratio of constant returns to scale (CRS) efficiency to variable returns to scale (VRS) efficiency. In alignment with the work of Arebo et al. (2024), the Data Envelopment Analysis (DEA) model identifies inputs as salary and benefits, provisions, general expenses, and deposits, whereas outputs are characterized by net interest income and non-interest income.

Beyond scale efficiency, the study examines factors influencing banking performance, including banking stability (ZS), which reflects a bank's response to risks through the variability of returns relative to total assets (Vo and Nguyen, 2021). Consistent with Yakubu and Musah (2022), stability is represented by the Z-score, indicating default likelihood, calculated as:

$$\mathbf{Z-score_{it}} = \frac{\mathbf{ROA_{it}\ + EQA_{it}}}{\mathbf{sd(ROA)_{it}}}$$

Where, ROA represents the return on assets, EQA denotes equity-to-assets ratio and sd stands with standard deviation.

Additionally, the loan-to-deposit ratio (LDR) assesses liquidity's effect on profitability (Kumar et al., 2021), as well, bank size (log of total asset) can be used to capture the effect of size (Vo and Nguyen, 2021). Macroeconomic control variables including the real deposit interest rate (RDIR), adjusted for inflation, which is crucial for understanding bank profitability (López-Penabad et al., 2022). Lastly, the broad money supply (BM) measures overall market liquidity's impact on profitability (Omankhanlen et al., 2021).

3.3. Model specification

Building on prior empirical studies (Yakubu and Musah, 2022; Vo and Nguyen, 2021; Zheng et al., 2023; Jajah et al., 2022; Kumar et al., 2021; Khatib et al., 2022), this study specifies its model as follows:

$$\mathbf{Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it}}$$

Where, i and t, denote the cross-sectional and time dimensions, respectively. Y, indicates the dependent variable and X, signifies the vector of explanatory variables. The term β, signifies coefficients of these variables, while α, is the constant term. The error term is denoted by ε.

To address endogeneity, heteroscedasticity, and serial-correlation biases, this study employs a two-step robust system GMM estimator, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998), with further insights from Baltagi (2008) and Roodman (2009). This estimator effectively mitigates dynamic endogeneity, simultaneity, and time-invariant unobserved heterogeneity, which are common in panel regressions involving banking data (Khatib et al., 2022; Kumar et al., 2021). The GMM approach is widely validated in the literature for its robustness in resolving endogeneity concerns in such contexts (Yakubu and Musah, 2022; Vo and Nguyen, 2021; Zheng et al., 2023; Jajah et al., 2022; Kumar et al., 2021; Khatib et al., 2022).

However, in contrast to earlier works that assume linearity, this study explicitly incorporates nonlinear dynamics to examine whether the effects of traditional and digital FI on bank profitability vary across different stages of FI development. Following emerging nonlinear evidence (Arebo et al., 2025b; Bhatter et al., 2025; Xie and Deng, 2025; Yuan et al., 2025; Song et al., 2023), a quadratic specification is introduced to capture possible U-shaped or inverted-U patterns.

Nonlinear modeling is theoretically justified because the impact of FI is unlikely to be constant across all intensities or market conditions. As noted by Shaddady (2023), banking environments, especially in developing economies often face abrupt structural changes, making nonlinear responses more realistic. Assuming linearity when threshold effects exist can lead to biased coefficients and misleading policy implications. Accordingly, the nonlinear dynamic model is specified as:

$$\mathbf{PI_{it} = \alpha_i + \gamma l.\,PI_{i,t-1} + \beta_1 TFI_{it} + \beta_2 TFI^2{}_{it} + \beta_3 DFI_{it} + \beta_4 DFI^2{}_{it} + \sum\nolimits_1^n \beta_{it} X_{it} + \varepsilon_{it}}$$

Where, $\mathbf{PI_{it}}$ denotes bank performance, $\mathbf{PI_{it-1}}$ is its lagged value, $\mathbf{TFI_{it}}$ and $\mathbf{DFI_{it}}$ represent traditional and digital FI scores, and their squared terms capture nonlinear effects, $\mathbf{X_{it}}$ is the vector of control variables, $\boldsymbol{\alpha_i}$ is the individual-specific effect, $\boldsymbol{\gamma}$ is the coefficient for the lagged dependent variable, $\boldsymbol{\beta_{it}}$ **,** are the coefficients for the explanatory variables $\boldsymbol{\varepsilon_{it}}$ the idiosyncratic error.

To validate whether the estimated relationship truly exhibits a U-shape (or inverted U-shape) rather than a monotonic but curved form, this study employs the U-test developed by Lind and Mehlum (2010). Traditional quadratic models may incorrectly suggest a U-shape even when the true relationship is convex yet monotonic (Arebo et al., 2025b; Law et al., 2017). Hence, the U-test is applied to test the composite null hypothesis that the slope is non-increasing at the lower bound and non-decreasing at the upper bound of the FI range. Formally, the conditions are:

$$\mathbf{(\beta_1 + \beta_2 TFI_{min}) \leq 0) \cup (\beta_1 + \beta_2 TFI_{max} \geq 0)}$$

$$\mathbf{(\beta_3 + \beta_4 DFI_{min}) \leq 0) \cup (\beta_3 + \beta_4 DFI_{max} \geq 0)}$$

The likelihood-ratio test of Lind and Mehlum (2010) is then applied to determine whether the null hypothesis of a monotonic relationship can be rejected. Rejecting the null confirms a statistically valid U-shaped or inverted U-shaped relationship, while failure to reject implies that the quadratic term does not represent a true turning point.

3.4 Index development

In this study, we evaluated sample adequacy for factor analysis using the Kaiser-Meyer-Olkin (KMO) statistic and Bartlett's test of sphericity. A significant Bartlett's test ($P < 0.05$) indicates that the correlation matrix is not an identity matrix (Watkins, 2018). The KMO statistic vary between 0 and 1, with a commonly accepted minimum value of 0.5 (Chan and Idris, 2017; Hair et al., 2019).

Table 2: Principal component analysis result

Estimation of principal components and eigenvalues for TFI and DFI sub indices				
Component	**Eigenvalue**	**Difference**	**Explained variance (EV)**	**Cumulative**
TFI Index (Availability Dimension)				
Comp1	2.7368	2.5655	0.9123	0.9123
Comp2	0.1713	0.0795	0.0571	0.9694
Comp3	0.0919		0.0306	1.0000
TFI Index Usage Dimension)				
Comp1	3.4725	2.9920	0.8681	0.8681
Comp2	0.4804	0.4430	0.1201	0.9882
Comp3	0.0374	0.0278	0.0094	0.9976
Comp4	0.0096		0.0024	1.0000
DFI Index (Accessibility Dimension)				
Comp1	2.6249	2.3927	0.8750	0.8750
Comp2	0.2322	0.0893	0.0774	0.9524
Comp3	0.1429		0.0476	1.0000

Scoring coefficients from orthogonal varimax rotation and related test outcomes						
Dimensions	**Indicators**	**Weight (PC1)**	**EV**	**KMO**	**Sphericity test & Overall KMO**	**Cronbach alpha**
TFI Index (Availability-Dimension)	BRP	0.5847	0.0644	0.7047	χ2(3)=472.28 (**P=0.000**), Overall-KMO=**0.76**	0.95
	ATMP	0.5778	0.0862	0.7560		
	PoSP	0.5694	0.1126	0.8353		
TFI Index (Usage-Dimension)	CDCP	0.4691	0.2360	0.5593	χ2(6)=1111.108 (**P=0.000**), Overall-KMO=**0.62**	0.94
	DAP	0.5195	0.0627	0.6725		
	PLOAN	0.4978	0.1396	0.5795		
	PDEP	0.5121	0.0892	0.6540		
DFI Index (Accessibility-Dimension)	MBP	0.5832	0.1072	0.7236	χ2(3)=366.502 (**P=0.000**), Overall-KMO=**0.76**	0.92
	APP	0.5665	0.1576	0.8300		
	MMP	0.5822	0.1103	0.7289		

Source: Computed from Stata 18 result. *Note*: *internet banking indicator's KMO result was less than 0.5, thus excluded from our analysis.*

Table 2 presents the PCA results for the TFI and DFI, showing KMO values (≥ 0.5) and significant p-values that support the applicability of PCA. Internal consistency was examined using Cronbach's alpha, with a threshold of 0.6 considered acceptable (Bonett and Wright, 2015). Correspondingly, the results indicate strong reliability, with scores of 0.95 for traditional availability, 0.84 for traditional usage, and 0.92 for digital accessibility.

In the process, the study employed an eigenvalue threshold exceeding 1 as the basis for factor selection (Phanniphong et al., 2024; Nguyen, 2021). The eigenvalues derived from PCA estimate the latent variables: traditional availability, traditional usage, and digital accessibility, with components that retain significant variance. An explained variance (EV) of 60% or more was regarded as acceptable (Hair et al., 2019), with the first principal component (PC1) accounting for over 91% of the variance for traditional availability, 87% for usage, and 88% for digital accessibility dimensions. The composite indices for TFI (Eq-3) and DFI (Eq-4) were formulated as follows:

$$\mathbf{TFI_{it}} = (\mathbf{0.5847BRP_{it}} + \mathbf{0.5778ATMP_{it}} + \mathbf{0.5694PoSP_{it}}) + (\mathbf{0.4691CDCP_{it}} + \mathbf{0.5195DAP_{it}} + \mathbf{0.4978PLOAN_{it}} + \mathbf{0.5121PDEP_{it}})$$

$$\mathbf{DFI_{it}} = \mathbf{0.5832MBP_{it}} + \mathbf{0.5665APP_{it}} + \mathbf{0.5822MMP_{it}}$$

For TFI, branch availability (0.5847) has the highest weight, emphasizing the continued importance of physical branches in Ethiopia, consistent with Kebede et al. (2021) findings. Within the usage dimension, deposit accounts (0.5195) rank highest, reflecting the sector's focus on customer base expansion and savings. In DFI, mobile banking holds the highest weight (0.5832), highlighting its preference over agency banking, which remains in its early stages in Ethiopia.

4. Discussion of empirical results

4.1 Descptive analysis

Table 3 provides a descriptive analysis of both the dependent and independent variables, including standard deviation, average, minimum, and maximum points, based on 153 observations from 2015 to 2023 across 17 commercial banks. Profitability (PI) shows a mean value of 0.123, indicating that Ethiopian commercial banks, on average, generated modest returns during 2015–2023. The minimum value is slightly negative (–0.008), suggesting that some banks experienced marginal losses in certain periods, while the upper bound (0.474) reflects periods of high profitability for a few institutions. TFI and DFI mean values are 0.334 and 0.071, respectively, suggest that, compared with traditional services, the adoption of digital channels remains at an early stage. The broader range of TFI (0.008 to 2.971) indicates larger variation in traditional outreach across banks, while the narrower range of DFI (0 to 1.584) reflects more homogeneous but lower levels of digital usage. The Z-score, a proxy for bank stability, averages 3.349, implying relatively stable banking conditions during the period, though the variation (2.194 to 4.383) highlights differences in risk profiles among banks. Scale efficiency (SE) is high, with a mean of 0.974, indicating that most banks operate close to their optimal production frontier. However, the lower bound of 0.708 shows that some banks experience operational inefficiencies. Bank size displays substantial variation (7.042 to 14.082), reflecting the wide differences between large and small commercial banks in Ethiopia. The loan-to-deposit ratio (LDR) averages 0.963, suggesting that banks deploy a significant proportion of mobilized deposits for lending, although some banks appear more conservative (0.533). The real deposit interest rate (RDIR) has a negative mean (–0.115), consistent with Ethiopia's inflation-driven negative real returns on savings during the sample period. This may discourage deposit mobilization and influence banks' cost structures. Broad money averages 0.518, indicating moderate liquidity in the banking system relative to total output. Its variation (0.277 to 0.890) reflects changes in monetary conditions influenced by policy adjustments and macroeconomic shocks.

Table 3: Summary analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
PI	153	0.123	0.053	(0.008)	0.474
TFI	153	0.334	0.601	0.008	2.971
DFI	153	0.071	0.204	0.000	1.584
lnZS	153	3.349	0.529	2.194	4.383
SE	153	0.974	0.049	0.708	1.000
lnTA	153	10.155	1.32	7.042	14.082
LDR	153	0.963	0.089	0.533	1.159
RDIR	153	(0.115)	0.096	(0.293)	(0.022)
BM	153	0.518	0.198	0.277	0.890

Source: Computed based Stata 18 result

4.2 Pre-estimation tests

4.2.1 Correlation and multicollinearity analysis

Multicollinearity can impede accurate regression coefficient estimation, potentially undermining model reliability (Al-Eitan et al., 2022). It indicates the strength and direction of relationships among explanatory variables (Kumar et al., 2021). Pearson correlation analysis shows most variables are within acceptable ranges, except for a significant negative correlation of -0.96 between inflation-adjusted deposit interest rates and the money supply, as shown in Table 4. This inverse relationship aligns with established economic theory, particularly the liquidity effect described by Monnet and Weber (2001), where unanticipated money supply reductions lower interest rates. Cooley and Hansen (1995) also noted a negative association between these variables, suggesting monetary policy shocks. To this end, despite the high correlation, both real deposit interest rates and money supply were included in the model, as they represent distinct economic concepts. Real deposit interest rates embody the opportunity cost of holding money, influencing the demand for liquidity within the economy. Conversely, the money supply, reflects the overall availability of funds within the financial system. In addition, the average variance inflation factor (VIF) is 5.91, indicating weak correlation and minimal multicollinearity among independent variables.

Table 4: Correlation and multicollinearity test

Variables	VIF	PI	TFI	DFI	lnTA	SE	lnZS	LDR	RDIR
TFI	7.00	0.358							
DFI	3.32	0.117	0.759						
lnTA	4.84	0.289	0.783	0.645					
SE	1.80	0.005	−0.58	−0.61	0.204				
lnZS	1.22	−0.09	−0.375	−0.308	−0.239	0.273			
LDR	1.32	0.12	0.436	0.311	−0.02	−0.16	0.22		
RDIR	13.1	0.135	−0.13	−0.36	0.067	0.044	−0.12	−0.16	
BM	14.7	−0.16	0.14	0.356	−0.08	−0.06	0.11	0.189	−0.96
Mean VIF	5.91								

Source: Computed based on Stata 18 result

4.2.2 Authocorrelation and heteroskedasticity tests

Autocorrelation and heteroskedasticity pose a problem in regression analysis, potentially leading to biased results. Autocorrelation involves correlated residuals across observations, which can underestimate standard errors and inflate t-statistics (Akpan and Moffat, 2018; Gujarati et al., 2012). Heteroskedasticity occurs when error term variances differ, resulting in inefficient estimates and unreliable confidence intervals (Onifade and Olanrewaju, 2020). This study uses the Wooldridge test for autocorrelation and both the modified Wald test and Breusch-Pagan (BP) test for heteroskedasticity. As revealed in Table 4, both issues were present in the dataset. To address these, the research employs the GMM estimator as suggested by Vo and Nguyen (2021).

Table 4: Heteroskedasticity and autocorrelation test

Tests	Wooldridge test	Modified Wald test	BP test
Type	Serial correlation	Heteroskedasticity	Heteroskedasticity
Sig level	$F(1,16) = 52.38$ ($p = 0.0000$)	$\chi2(17) = 477.87$ ($p = 0.0000$)	$\chi2(1) = 118.19$ ($p =0.0000$)

Source: Computed based on Stata 18 result

4.2.3 Cross-sectional dependence and unitroot test

Cross-sectional dependence (CD), often referred to as common correlation, can lead to under-rejection of the null hypothesis in panel unit root tests, resulting in type II errors (Khalid and Shafiullah, 2021). Implementing CD tests is crucial for selecting appropriate unit root tests, as panel data often exhibit dependencies from shared economic influences (Chen et al., 2023; Yameogo et al., 2020; De Hoyos and Sarafidis, 2006). This CD typically arises when error terms share unobserved common factors or are affected by external shocks (Khalid and Shafiullah, 2021; Shafiullah et al., 2019; De Hoyos and Sarafidis, 2006). First-generation tests considers cross-sectional independence, whereas second-generation tests account for interdependencies (Tugcu, 2018; Barbieri, 2009). The Pesaran (2004), Frees (1995), and Friedman (1937) tests in Table 5 confirm cross-sectional independence. Furthermore, considering the heterogeneity among banks, this study employs first-generation unit root tests, including the Levin, Lin and Chu (LLC) test (2002), Harris and Tzavalis test (1999), and Augmented Dickey-Fuller (ADF) test, to avoid imposing uniform effects across different cross-sections. This approach aligns with the country-specific approach of Yameogo et al. (2020) and accommodates unit-specific characteristics. As indicated in Table 5, all variables are stationary at I(0) or I(1), confirming the model's reliability in the absence of cross-sectional dependence.

Table 5: Cross-sectional dependence and unitroot test

Variables	LLC I(0)	LLC I(1)	HT I(0)	HT I(1)	ADF I(0)	ADF I(1)
PI	−7.7799***	−6.5116***	0.3932***	−0.1551***	4.4453***	6.8781***
TFI	−3.1044***	−12.2265***	0.7814	0.2689***	1.9209*	3.8158***
DFI	13.0704	−5.2572***	1.1862	0.0628***	4.9985***	10.5007***
lnTA	−6.7186***	−5.2178***	0.9592	0.0677***	5.0190***	2.3367***
lnZS	−6.5670***	−8.8614***	0.5099***	−0.2704***	4.6292***	9.0794***
SE	−12.1552***	−39.3679***	0.3208***	−0.4831***	14.0325***	21.2525***
LDR	−3.7723***	−4.4916***	0.1663***	−0.2987***	3.7896***	7.834***
RDIR	−5.0827***	22.1295	0.0000***	−0.3577***	−4.0411	12.7806***
BM	−8.5431***	1.6763*	0.0000***	0.0000***	−3.5919	2.159*
Pesaran CD test	0.346 (P=0.1987)					
Frees CD test	0.630 (P=0.2828)					
Friedman CD test	15.843 (P= 0.464)					

Source: Computed based on Stata 18 result, Notes: H0 states that the model shows no cross-sectional dependence and should be rejected if the p-value is below 0.01

4.3 Regression Result

Table 6 presents the results of the two-step GMM estimation, showing the effects of TFI, DFI, stability, scale efficiency, bank size, loan-to-deposit ratio, real deposit interest rate, and money supply on bank profitability.

The empirical results indicate that TFI exerts a positive and statistically significant impact on bank profitability. This finding supports the findings of previous studies, including Yakubu and Musah (2022), Vo and Nguyen (2021), Jajah et al. (2022), and Kumar et al. (2021), who employed TFI indicators, all of which highlight the critical role of TFI in enhancing bank performance. Kumar et al. (2021) emphasize that the proliferation of bank branches leads to an increase in customer acquisition, thereby boosting deposit mobilization, loan portfolio expansion, and risk diversification. Similarly, Nguyen (2014) highlights that maintaining bank branches in underserved regions is critical for fostering compliance with know-your-customer (KYC) requirements. Such compliance mitigates credit risks and enhances loan quality, whereas the closure of bank branches, especially in regions where lending is relationship-driven and information-intensive, can adversely impact credit availability to vulnerable sectors. In line with Hong et al. (2025), the findings also suggest that at lower levels, traditional financial inclusion improves capital access, resource allocation, and operational efficiency, thereby enhancing profitability. However, when TFI expands excessively, it may divert managerial attention and financial resources, increase operational costs, and expose banks to higher risks, ultimately weakening performance. Although the coefficients of TFI and TFI^2 point to an inverted U-shaped pattern, where profitability initially rises with TFI but eventually diminishes, the Lind and Mehlum (2010) U-test does not statistically validate this turning point. This implies that while the economic intuition for diminishing returns is plausible, the nonlinearity is not statistically confirmed in the Ethiopian banking context.

The results show that DFI exhibits a statistically significant U-shaped nonlinear relationship with bank profitability, reflected in the negative coefficient of DFI and the positive coefficient of DFI^2. The Lind and Mehlum (2010) test in Table 7 confirms this pattern, with a significantly negative lower bound (–1.001708) and a significantly positive upper bound (0.8328111). Thus, Hypothesis 2 is supported, indicating that profitability begins to rise only after the inflection point at a DFI level of 0.865. This result aligns with recent evidence (Xie and Deng, 2025; Yuan et al., 2025; Yin et al., 2024; Song et al., 2023; Yang and Masron, 2023) showing that digitalization initially depresses profitability due to high fixed costs, technological investments, capability-building, and intensified competition. As Xie and Deng, (2025) claimed, in this early "investment phase," returns are limited while expenses accumulate. Once digital usage and scale increase through greater customer adoption, higher transaction volumes, and improved data capabilities, unit costs fall, operational efficiency improves, and technology spillovers dominate the competition effect, lifting profitability in the "return phase." In Ethiopia's context, the early-stage nature of digital finance amplifies the negative side. Digital transformation remains nascent, and banks face substantial upfront investment costs and operational risks. According to the NBE-FSR (2024), data privacy vulnerabilities and weak consumer protection further undermine trust. Moreover, digital channel expansion mainly targets existing customers and relies on regressive service pricing models, limiting outreach to underserved populations and reducing potential gains. Low digital literacy and rural infrastructure gaps (Arebo, 2025) slow digital adoption, delaying the transition toward the profitability-enhancing stage of digital FI.

Despite earlier studies such as Erülgen et al. (2023), Yakubu and Musah (2022), and Vo and Nguyen (2021) reporting a positive association between Z-score and bank profitability, this study finds a negative and statistically significant effect. This result aligns with the “risk–return tradeoff” documented by Bakó and Neszveda (2024), Wang et al. (2017), Bhootra and Hur (2015), and Harvey (2001), who argue that institutions with higher stability often earn lower returns because they adopt more conservative risk exposures. Bhootra and Hur (2015) note that the negative risk–return relationship is most evident among firms with unrealized losses, while Wang et al. (2017) show that the negative pattern is particularly pronounced where capital gains overhang is low, implying that entities avoiding risk generate lower short-term returns. Within Ethiopia’s context, this negative relationship is both economically intuitive and structurally driven. Ethiopian banks rely heavily on interest income, yet recent policy measures (the recent 18% credit cap) restrict loan expansion and limit access to high-yield credit markets. As a result, banks maintain higher liquidity buffers and allocate more resources toward low-risk assets, which improves stability but suppresses returns. Additionally, persistent high inflation and macroeconomic volatility have encouraged banks to shift toward short-term, low-risk lending to protect real returns and reduce exposure to long-term credit and interest-rate risks. While these strategies strengthen banks’ solvency positions, they simultaneously depress profitability by limiting engagement in higher-yield, longer-maturity financing.

The loan-to-deposit ratio finding demonstrates a positive impact on bank profitability, aligning with the findings of (Muhammed et al., 2024; Ozili and Ndah, 2024; Jajah et al., 2022), but contrasting with Zheng et al. (2023). This finding reinforces the fractional reserve theory, as claimed by Espinosa et al. (2023), whereby banks profit by lending a significant portion of deposits while maintaining minimal reserves. Heffernan (-2005) highlights that this practice generates profit through interest rate differentials, provided intermediation costs and loan risk are managed. Supporting this, Jajah et al. (2022), this positive relationship reflects the wide gap between low deposit rates and high lending rates prevalent in Sub-Saharan Africa, which can enhance profitability. From Ethiopian context, Muhammed et al. (2024) attributes the positive effect in Ethiopian banking sector to interest revenues from loans exceeding the interest paid to depositors, demonstrating effective use of deposits in credit allocation. Similarly, Soesetio et al. (2022) argues that a high LDR enables robust credit distribution, increasing profitability despite liquidity risks.

Table 6: Non-linear empirical findings

	Main test	Robustness test
Variables	**Two-step system GMM**	**Inclusion of ROE**
l.PI	−0.0273 (−0.18)	
l.ROE		−0.043 (−0.24)
TFI	0.842* (2.08)	1.121* (1.80)
TFI²	−.125* (−1.77)	−0.147 (−1.37)
DFI	−1.002* (−2.01)	−1.446* (−1.81)
DFI²	0.579* (2.11)	0.814* (1.83)
lnTA	−0.098 (−1.67)	−0.147* (−1.8)
SE	−0.087 (−0.4)	−0.015 (−0.05)
lnZS	−0.526*** (−3.51)	−0.749*** (−3.23)
LDR	0.601*** (3.17)	0.833** (2.87)
RDIR	−0.319** (−2.81)	−0.435** (−2.58)
BM	−0.109 (−0.58)	−0.067 (−0.24)
N	119	119
Groups	17	17
Instruments	14	14
AR(2) test	0.962 (0.05)	0.901 (0.12)
Hansen test	0.882 (0.66)	0.665 (1.58)

Source: Computed based on Stata 18 result, Notes *p < 0.1, **p < 0.05, ***p < 0.01

Real deposit interest rates negatively affect profitability, consistent with Ogunbiyi and Ihejirika (2014). Higher inflation-adjusted deposit interest rates reduce the interest spread, leading to lower profits (Ogunbiyi and Ihejirika, 2014). Banks incur higher funding costs to attract deposits while inflation diminishes the value of future income, compounding profitability challenges.

Table 7: Results of Lind and Mehlum (2010) U-test

	TFI		DFI	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**
Interval	0.0077457	2.971483	0.00	1.58376
Slope	0.8395606	0.0960843	–1.001708**	0.8328111**
Extreme point	3.35		0.865**	

Source: Computed based on Stata 18 result, Notes *p < 0.1, **p < 0.05, ***p < 0.01

4.4 Causality test

This study undertook a causality test to investigate the relationship between traditional and digital financial inclusion in the context of bank profitability. While the findings of Dumitrescu and Hurlin (2012) suggest a unidirectional influence of TFI on bank profitability, the test by Juodis et al. (2021) indicates a bidirectional relationship, where TFI affects profitability and vice versa. This bidirectional dynamic posits that TFI not only impacts profitability but is also influenced by it. Furthermore, the Dumitrescu and Hurlin (2012) test emphasizes that bank profitability drives innovation and expansion into digital channels, reinforcing the unidirectional view that profitability catalyzes digital financial inclusion advancement. Additionally, the directional relationships of other variables with bank profitability, as analyzed through both models, are summarized in Table 8.

Table 8: Causality test

Test(Ho)	Dumitrescu and Hurlin (2012)		Direction	Juodis et al. (2021)		Direction
Direction	→	←		→	←	
PI ≠ DFI	-	-	PI ≠ DFI	−1.0383***		PI → DFI
PI ≠ TFI	3.5361***	4.6299***	PI ↔ TFI	-	−0.1773**	PI ← TFI
PI ≠ lnZS	9.6162***	1.9227*	PI ↔ lnZS	-	0.4458**	PI ← lnZS
PI ≠ LDR	5.1433***	2.6134***	PI ↔ LDR	−0.1081**	0.1713*	PI ↔ LDR
PI ≠ RDIR	-	2.1438**	PI ← RDIR	-	0.8380***	PI ← RDIR

Source: Computed based on Stata 18 result, Notes *p < 0.1, **p < 0.05, ***p < 0.01

4.5 Robustness test

The robustness of the regression model is substantiated by a series of diagnostic tests, as highlighted in pertinent literature (Aziz et al., 2024; Jajah et al., 2022; Yakubu and Musah, 2022; Kumar et al., 2021; Vo and Nguyen, 2021). These tests include the Hansen test for instrument validity and the Arellano-Bond tests for autocorrelation, both of which confirm the absence of second-order serial correlation and validate the model's specification. The results from the AR (2) and Hansen tests indicate that the conditions for GMM estimation are met. Furthermore, two approaches were employed to analyze the model's robustness. Initially, given the sensitivity of ROE to fluctuations in financial leverage, ROE (Pennacchi and Santos, 2021) was employed interchangeably with PI to evaluate the consistency of the results. The findings presented in Table 6 demonstrate that the results for each variable align with those obtained from the primary analysis, thereby reinforcing the validity of our earlier conclusions.

5. Conclusion

While the societal and economic benefits of FI are widely acknowledged, its direct implications for bank performance have received limited attention in the academic literature (Yakubu and Musah, 2022; Vo and Nguyen, 2021), particularly in the Ethiopian context. Moreover, whether FI unequivocally enhances bank profitability remains an unresolved question (Kumar et al., 2021). To that end, the present study analyzed the nonlinear impact of TFI and DFI on the profitability of 17 fully operational Ethiopian commercial banks over the period 2015–2023. Using PCA, indices for TFI and DFI were constructed from seven traditional and four digital indicators, respectively, while bank profitability index was developed using ROA, ROE, and NIM. To ensure methodological rigor, the study employed a two-step system GMM estimator and Granger causality test to analyze the directional relationships between FI and bank profitability. Robustness checks incorporated alternative specifications, considering the inclusion of ROE as a profitability measure to account for the pandemic's disruptive effects.

The findings reveal a positive impact of TFI on bank profitability, underscoring the role of physical banking services in mobilizing deposits and generating sustainable revenue streams. However, the diminishing marginal gains observed beyond a certain expansion point suggest that excessive outreach to long-tail segments may strain operational resources and elevate risk. DFI, in contrast, follows a nonlinear trajectory as its initial phases impose financial and operational burdens, consistent with Yuan et al. (2025), who emphasize that early digital adoption is typically costly due to investment in infrastructure, cybersecurity, system integration, and talent. In Ethiopia, this adverse impact is exacerbated by regulatory constraints, limited financial literacy, and the underutilization of digital platforms for core services like lending. Yet, as digital platforms scale, interoperability improves, and banks accumulate learning effects, DFI transitions into a profitability-enhancing force. This turning point mirrors the digital transformation path documented by Yuan et al. (2025), where efficiency gains, cost compression, and data-driven lending gradually outweigh upfront expenses. In addition, Granger causality tests indicate unidirectional causality between DFI and profitability, while TFI maintains a bidirectional impact, emphasizing its foundational role in the banking sector's revenue generation strategy.

These results have several policy implications. Regulators should develop comprehensive strategies to strengthen both traditional and digital financial infrastructures. Regulators should pursue a phased digital support strategy, initially easing cost burdens through targeted incentives and regulatory sandboxes, then gradually tapering support as banks reach maturity in digital adoption. Strengthening digital literacy, expanding infrastructure in rural areas, and incentivizing banks to diversify digital offerings will be vital for accelerating digital uptake. Relaxing stringent digital ID requirements in underserved areas, as posited by Jajah et al. (2022) and De Sousa (2015), could accelerate the inclusion process while the infrastructure for digital identification matures. Additionally, a strategic emphasis on consumer protection, data privacy, and the mitigation of cybersecurity risks is critical for sustaining trust in digital financial services.

Despite banking sector dominance as the primary source of credit, 99.8% of loans and advances are concentrated in urban areas (NBE-FSR, 2024), leaving rural populations underserved. This urban-centric focus undermines the paradigm of FI, which seeks to provide equitable financial access. Banks should adopt innovative approaches such as agent banking, partnerships with fintech firms, and a more efficient deployment of digital tools to reach underserved populations.

Finally, echoing Jajah et al. (2022), relaxing borrowing constraints and enhancing operational efficiencies can promote FI and, by extension, enhance profitability. A concerted effort from policymakers, regulators, and financial institutions is essential to align the banking sector with the broader developmental goals of FI, ensuring a sustainable and inclusive financial ecosystem.

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- Andualem Goshu Mekonnen: supervision, writing - review & editing

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Reference

Abdi, H., Williams, L. J. (2010). Principal component analysis. *Wiley interdisciplinary reviews: computational statistics*, 2(4), 433-459. https://doi.org/10.1002/wics.101

Abdu, E., Adem, M. (2021). Determinants of financial inclusion in Afar Region: Evidence from selected woredas. *Cogent Economics & Finance*, 9(1), 1920149. https://doi.org/10.1080/23322039.2021.1920149

Addisu, B. M., Ijara, T. M., Ijara, T. M. (2023). Impact of working capital management on profitability of private commercial banks in Ethiopia. *Journal of Innovation and Enterpreneurship*. https://doi.org/10.21203/rs.3.rs-2340164/v1

Adera, A., Abdisa, L. T. (2023). Financial inclusion and women's economic empowerment: Evidence from Ethiopia. *Cogent Economics & Finance*, 11(2), 2244864.

Aduba, J, Asgari, B., Izawa, H. (2023). Does FinTech penetration drive financial development? Evidence from panel analysis of emerging and developing economies. *Borsa Istanbul Review*, 23(5), 1078-1097. https://doi.org/10.1016/j.bir.2023.06.001

Ahamed, M. M., Ho, S. J., Mallick, S. K., Matousek, R. (2021). Inclusive banking, financial regulation and bank performance: Cross-country evidence. *Journal of Banking & Finance*, 124, 106055. https://doi.org/10.1016/j.jbankfin.2021.106055

Akhisar, I., Tunay, K. B., Tunay, N. (2015). The effects of innovations on bank performance: The case of electronic banking services. *Procedia-Social and Behavioral Sciences*, 195, 369-375. https://doi.org/10.1016/j.sbspro.2015.06.336

Akpan, E. A., Moffat, I. U. (2018). Modeling the Autocorrelated Errors in Time Series Regression: A Generalized Least Squares Approach. *Journal of Advances in Mathematics and Computer Science*. 26. 1-15. http://dx.doi.org/10.9734/JAMCS/2018/39949

Al Karim, R., Alam, T. (2013). An evaluation of financial performance of private commercial banks in Bangladesh: Ratio analysis. *Journal of Business Studies Quarterly*, 5(2), 65.

Al-Eitan, G. N., Bassam Al-Own, Tareq Bani-Khalid (2022). Financial Inclusion Indicators Affect Profitability of Jordanian Commercial Banks: Panel Data Analysis. *Economies* 10: 38. https://doi.org/10.3390/economies10020038

Alemu, G. (2014). Financial inclusion, regulation and inclusive growth in Ethiopia. *Achieving Financial Stability and Growth in Africa*, 1-54. https://media.odi.org/documents/9278.pdf

Ali, P. J. M. (2022). Investigating the Impact of Min-Max Data Normalization on the Regression Performance of K-Nearest Neighbor with Different Similarity Measurements. *ARO-The Scientific Journal of Koya University*, 10(1), 85–91. https://doi.org/10.14500/aro.10955

Allen, F., Santomero, A. M. (1997). The theory of financial intermediation. *Journal of banking & finance*, 21(11-12), 1461-1485. https://doi.org/10.1016/S0378-4266(97)00032-0

Almeshari, A., Bin Dato Haji Yahya, M. H., Bin Kamarudin, F., Abd Hamid, S. A. (2023). Liquidity creation and economic growth: are they monotonically related? Evidence from MENA countries. *Economies*, 11(1), 24. https://doi.org/10.3390/economies11010024

Arebo M, Hando F and Mekonnen A. (2025b). Financial inclusion and stability in Ethiopia using bank-level data: A two-step system GMM estimation. *F1000Research*, 13 (1369), 3-40. https://doi.org/10.12688/f1000research.158461.2

Arebo, M. J. (2025c). Asymmetric analysis of the financial inclusion – growth nexus: A NARDL approach. *Research in Globalization*, 11, 100316. https://doi.org/10.1016/j.resglo.2025.100316

Arebo, M. J., Hando, F. H., Mekonnen, A. G. (2025a). A Multidimensional Financial Inclusion Index for Ethiopia. *Prague Economic Papers*, 34(1), 98-136. https://doi.org/10.18267/j.pep.886

Arebo, M., Hando, F., Mekonnen, A. (2024). Financial inclusion and stability in Ethiopia using bank-level data: A two-step system GMM estimation. *F1000Research*, 13, 1369. https://doi.org/10.12688/f1000research.158461.1

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

Arner, D.W., Buckley, R.P., Zetzsche, D.A. (2020).Sustainability, FinTech and Financial Inclusion. *Eur Bus Org Law Rev*, 21, 7–35. https://doi.org/10.1007/s40804-020-00183-y

Ayalew, Z. A. (2021). Capital structure and profitability: Panel data evidence of private banks in Ethiopia. *Cogent Economics & Finance*, 9(1), 1953736. https://doi.org/10.1080/23322039.2021.1953736

Ayele, A. B., Malhotra, K., Sharma, M. (2025). Financial Inclusion and Bank Performance: Evidence from the Banking Sector in Ethiopia. *Journal of Corporate Finance Research*, 19(1), 54-69. https://doi.org/10.17323/j.jcfr.2073-0438.19.1.2025.54-69

Aziz, S. A., Razak, L. A., Slesman, L. Y., Abduh, M. (2024). The Impact of Digital Financial Inclusion on Bank Profitability: Evidence from Developing Countries. *Journal of Theory and Applied Management*, 17(2), 203–215. https://doi.org/10.20473/jmtt.v17i2.57508

Babilla, T. U. K. (2023). Digital innovation and financial access for small and medium-sized enterprises in a currency union. *Economic Modelling*, 120, 106182. https://doi.org/10.1016/j.econmod.2022.106182

Bakó, B., Neszveda, G. (2024). An aspirational perspective on the negative risk-return relationship. *Finance Research Letters*, 61, 104977. https://doi.org/10.1016/j.frl.2024.104977

Baltagi, B. H. (2008). Econometric analysis of panel data (4th ed.). Chichester, England: John Wiley.

Barbieri, L. (2009). Panel unit root tests under cross-sectional dependence: An overview. *Journal of Statistics: Advances in Theory and Applications*, 1(2), 117-158. https://www.researchgate.net/publication/267090484_Panel_Unit_Root_Tests_under_Cross-sectional_Dependence_An_Overview

Bartlett, M.S. and Kendall, D.G. (1946). The Statistical Analysis of Variance Heterogeneity and the Logarithmic Transformation. *Supplement to the Journal of the Royal Statistical Society*, 8, 128-138. https://doi.org/10.2307/2983618

Bashiru, S., Bunyaminu, A., Yakubu, I. N., Al-Faryan, M. A. S., Carthy, J. M., Nyamekye,K. A.(2023). Quantifying the Link between Financial Development and Bank Profitability. *Theoretical Economics Letters*, 13, 284-296. https://doi.org/10.4236/tel.2023.132018

Bayiley, Y. T. (2013). A Dynamic and Multivariate Analysis of treasury bill behavior in a Bank Asset Portfolio. *European Journal of Scientific Research*, 9(7):275- 287.

Beck, T. (2016). Financial Inclusion–Measuring progress and progress in measuring.

Berhe, A. G. (2019). Investigating the determinants of commercial banks profitability in Ethiopia. *European Journal of Business and Management*, 11, 37–46. https://doi.10.7176/EJBM/11-1-05

Bhatter, H. K., Gupta, J., Chhatoi, B. P. (2025). Unveiling the curvilinear dynamics: financial inclusion and bank performance in India. *Managerial Finance*, 51(11), 1742–1757. https://doi.org/10.1108/mf-12-2024-0925

Bhootra, A., Hur, J. (2015). High idiosyncratic volatility and low returns: A prospect theory explanation. *Financial Management*, 44(2), 295-322. https://doi.org/10.1111/fima.12057

Biru, A. M. (2021). Determinants of financial performance of private commercial banks in Ethiopia. *Academy of Accounting and Financial Studies Journal*, 25(S4), 1-17.

Blundell, R., S. Bond. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115–143

Bonett, D. G., Wright, T. A. (2015). Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of organizational behavior*, 36(1), 3-15. https://doi.org/10.1002/job.1960

Brigham, E. F., Houston, J. F. (2011). Fundamentals of Financial Management.(10th Ed.).Ohio, USA: Thomson South Western.

Bushashe, M. A. (2023). Determinants of private banks performance in Ethiopia: A partial least square structural equation model analysis (PLS-SEM). *Cogent Business & Management*, 10(1), 2174246. https://doi.org/10.1080/23311975.2023.2174246

Cardamone, P., Trivieri, F. (2024). Out of sight, out of mind! Bank branch closures and new firm creation in Italy. Regional Studies, Regional Science, 11(1), 122–152. https://doi.org/10.1080/21681376.2024.2315187

Chan, L. L., Idris, N. (2017). Validity and reliability of the instrument using exploratory factor analysis and Cronbach's alpha. *International Journal of Academic Research in Business and Social Sciences*, 7(10), 400-410. https://doi.org/10.6007/IJARBSS/v7-i10/3387

Chen, Y. S., Chen, Z., Ali, S., Ullah, M. I., Anser, M. K. (2023). Dynamic common correlated effects of financial inclusion on foreign direct investment: Evidence from East-Asia and Pacific countries. *Borsa Istanbul Review*, 23(3), 541-549. https://doi.org/10.1016/j.bir.2022.12.002

Collard, S. (2007). Toward financial inclusion in the UK: Progress and challenges. Public Money and Management, 27(1), 13-20. https://doi.org/10.1111/j.1467-9302.2007.00550.x

Cooley, T. Hansen, G. (1995). 7 Money and the Business Cycle. In T. Cooley (Ed.), Frontiers of Business Cycle Research, 175-216. Princeton: Princeton University Press. https://doi.org/10.1515/9780691218052-011

Dabla-Norris, M. E., Ji, Y., Townsend, R., Unsal, M. F. (2015). Identifying constraints to financial inclusion and their impact on GDP and inequality: A structural framework for policy. International Monetary Fund. https://doi.org/10.5089/9781498381598.001

Dagnachew, T. G., Mawugatie, T. W. (2022). The analysis of financial inclusion and its determinants in the rural area of south Wollo zone, Amhara Region, Ethiopia. *Cogent Economics & Finance*, 10(1), 2146298. https://doi.org/10.1080/23322039.2022.2146298

De Hoyos, R. E., Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *The stata journal*, 6(4), 482-496. https://doi.org/10.1177/1536867X0600600403

Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S., Hess, J., (2018). The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. World Bank Publications. https://doi.org/10.1093/wber/lhz013

Denegetu, D. H. (2024). Financial Inclusion of Refugees in Ethiopia. Available at SSRN 4756354. https://doi.org/10.2139/ssrn.4756354

Desalegn, G., Yemataw, G. (2017). Financial inclusion in Ethiopia: Using LSMS (Ethiopia socioeconomic survey) data. *Ethiopian Journal of Economics*, 26(2), 31-58. https://ethiopianjournalofeconomics.org/index.php/EJE/article/view/187

Djani-Feuzeu, H.D., Nguena, L.C. (2025). Does financial inclusion fuel bank profitability in Africa? Empirical evidence on panel data. *Finance Research Open*, 1(4). https://doi.org/10.1016/j.finr.2025.100062

Dumitrescu, E.-I., Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, 29(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

Erlando, A., Riyanto, F. D., Masakazu, S. (2020). Financial inclusion, economic growth, and poverty alleviation: evidence from eastern Indonesia. *Heliyon*, 6(10), e05235. https://doi.org/10.1016/j.heliyon.2020.e05235

Erülgen, A., Rjoub, H., Adalier, A., Abualrub, A. (2022). Financial inclusion and bank profitability: Evidence from island banking sector. *Advances in Decision Sciences*, 26(4), 78-97. https://doi.org/10.47654/v26y2022i4p78-97

Espinosa, V. I., Alonso-Neira, M. A., Huerta de Soto, J. (2023). The Ethics of Fractional-Reserve Banking System: A Private Property Rights Approach. *Economies*, 11(9), 221. https://doi.org/10.3390/economies11090221

Fernández-Olit, B., Martín, J. M., Porras González, E. (2019). Systematized literature review on financial inclusion and exclusion in developed countries. *International Journal of Bank Marketing*, 38(3), 600-626, http://dx.doi.org/10.1108/IJBM-06-2019-0203

Fielding, D., Regasa, D. (2024).Banking competition and financial inclusion: Evidence from Ethiopia. *World Development*, 183, 106733.https://doi.org/10.1016/j.worlddev.2024.106733

Fomum, A.T., Opperman, P. (2023). Financial inclusion and performance of MSMEs in Eswatini. *International Journal of Social Economics*, 50(11), 1551-1567. https://doi.org/10.1108/IJSE-10-2020-0689

Frees, E. W. (1995). Assessing cross-sectional correlation in panel data. *Journal of econometrics*, 69(2), 393-414. https://doi.org/10.1016/0304-4076(94)01658-M

Freudenberg, M. (2003). Composite indicators of country performance: a critical assessment. STI Working Paper 16, https://doi.org/10.1787/18151965

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American statistical association*, 32(200), 675-701. https://doi.org/10.1080/01621459.1937.10503522

Giday, H. G. (2023). Financial inclusion and its demand-side determinants: Evidence from Ethiopia. *Cogent Economics & Finance*, 11(1), 2186031. https://doi.org/10.1080/23322039.2023.2186031

Gujarati, D. N., Porter, D. C., Gunasekar, S. (2012). Basic econometrics. Tata McGraw-hill education.

Guo, F., He, S. (2019). The finance-growth nexus in China: a meta-analysis. *Applied Economics Letters*, 27(13), 1071–1075. https://doi.org/10.1080/13504851.2019.1659926

Guo, R., Ma, B. (2025). Does digital inclusive finance enhance the profitability of commercial banks? — Evidence from China. *Applied Economics Letters*, 1–7. https://doi.org/10.1080/13504851.2025.2510576

Hair, J.F., Black, W.C., Babin, B.J. Anderson, R.E. (2019).Multivariate Data Analysis, 8th Edition, Cengage Learning EMEA. https://www.cengage.uk/c/multivariate-data-analysis-8e-hair-babin-anderson-black/9781473756540/?searchIsbn=9781473756540

Hannig, A., Jansen, S. (2010). Financial inclusion and financial stability: Current policy issues. https://dx.doi.org/10.2139/ssrn.1729122

Harris, R. D., Tzavalis, E. (1999). Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of econometrics*, 91(2), 201-226. https://doi.org/10.1016/S0304-4076(98)00076-1

Harvey, C. R. (2001). The specification of conditional expectations. *Journal of Empirical Finance*, 8(5), 573-637. https://doi.org/10.1016/S0927-5398(01)00036-6

Hassan, M. I. U., Wu, M., Lu, J., Sohu, J. M., Ali, S., Anjum, H. N., Bilal, M. (2025). Financial technology and banking performance in developing countries: evidence from an advanced quantile regression approach. *Humanities and Social Sciences Communications*, 12(1). https://doi.org/10.1057/s41599-025-05571-8

Heffernan, Shelagh (-2005). Modern Banking. Chichester: John Wiley and Sons. https://www.wiley.com/en-us/Modern+Banking-p-9780470020043

Hong, H., Bao, S., Kang, X. (2025). Inverted U-shaped impact of financialization on private enterprise business performance: Capital structure threshold effect. *International Review of Economics & Finance*, 104418. https://doi.org/10.1016/j.iref.2025.104418

Humphrey, T. M. (1986). The theory of multiple expansion of deposits: what it is and whence it came. https://fraser.stlouisfed.org/title/960/item/477341

Hundie, S. K., Tulu, D. T. (2023). Determinants of financial inclusion gender gap in Ethiopia: Evidence from decomposition analysis. *Cogent Business & Management*, 10(2), 2238124. https://doi.org/10.21203/rs.3.rs-746583/v1

Hussen, M. S., Mohamed, M. A. (2023).Impact of financial inclusion on household welfare in Ethiopia. *Future Business Journal*, 9(1), 67. https://doi.org/10.1186/s43093-023-00243-y

Isayas, Y. N. (2022). Determinants of banks' profitability: Empirical evidence from banks in Ethiopia. *Cogent economics & finance*, 10(1), 2031433. https://doi.org/10.1080/23322039.2022.2031433

Jacobs, R., Smith, P., Goddard, M. (2004). Measuring performance: an examination of composite performance indicators. CHE Technical Paper Series 29. https://www.york.ac.uk/che/pdf/tp29.pdf

Jain, P., Upadhyay, D., Purswani, G. (2021). Digital financial inclusion: Strategic issues and imperatives. Financial Inclusion in Emerging Markets: A Road Map for Sustainable Growth, 297-309. https://doi.org/10.1007/978-981-16-2652-4_15

Jajah I.Y., Anarfo EB, Aveh FK (2022). Financial inclusion and bank profitability in Sub-Saharan Africa. *Int J Fin Econ*, 27, 32–44. https://doi.org/10.1002/ijfe.2135

Jakab, Z., Kumhof, M. (2014). Models of banking: loanable funds or loans that create funds?. Available at SSRN 2474759. https://dx.doi.org/10.2139/ssrn.2474759

Jima, M. D., Makoni, P. L. (2023). Determinants of Sustainable Financial Inclusion in Sub-Saharan Africa: A System GMM Approach. *Prague Economic Papers*, 32(6). https://doi.org/10.18267/j.pep.845

Jin, L., Dai, J., Jiang, W., Cao, K. (2023). Digital finance and misallocation of resources among firms: Evidence from China. *The North American Journal of Economics and Finance*, 66, 101911. https://doi.org/10.1016/j.najef.2023.101911

Joseph, M. T., Edson, G., Manuere, F., Clifford, M., Michael, K., Kamoyo, M. (2012). Non performing loans in commercial banks: a case of CBZ Bank Limited in Zimbabwe. *Interdisciplinary Journal of Contemporary Research in Business*, 4(7), 467-488. https://www.semanticscholar.org/paper/Interdisciplinary-Journal-of-Contemporary-Research-Tendai-Joseph/b69613a430cdbdbb5f3f51e042827cb10dc64781

Juodis, A., Karavias, Y. Sarafidis, V. (2021). A homogeneous approach to testing for Granger noncausality in heterogeneous panels. *Empir Econ*, 60, 93–112. https://doi.org/10.1007/s00181-020-01970-9

Kanungo, R. P., Gupta, S. (2021). Financial inclusion through digitalisation of services for well-being. *Technological Forecasting and Social Change*, 167, 120721. https://doi.org/10.1016/j.techfore.2021.120721

Kebede, J., Naranpanawa, A., Selvanathan, S. (2021). Financial inclusion: Measures and applications to Africa. *Economic Analysis and Policy*, 70, 365-379. https://doi.org/10.1016/j.eap.2021.03.008

Keil, J., Ongena, S. (2023). The demise of branch banking – Technology, consolidation, bank fragility. *Journal of Banking & Finance*, 158, 107038. https://doi.org/10.1016/j.jbankfin.2023.107038

Khalid, U., Shafiullah, M. (2021). Financial development and governance: A panel data analysis incorporating cross-sectional dependence. *Economic Systems*, 45(2), 100855. https://doi.org/10.1016/j.ecosys.2021.100855

Khatib, S. F., Hendrawaty, E., Bazhair, A. H., Rahma, I. A. A., Al Amosh, H. (2022). Financial inclusion and the performance of banking sector in Palestine. *Economies*, 10(10), 247. https://doi.org/10.3390/economies10100247

Kim, Y., Kim, M. K., Fu, N., Liu, J., Wang, J., Srebric, J. (2024). Investigating the impact of data normalization methods on predicting electricity consumption in a building using different artificial neural network models. *Sustainable Cities and Society*, 118, 105570. https://doi.org/10.1016/j.scs.2024.105570

Kline, R.B. (2015) Principles and Practice of Structural Equation Modeling. 4th Edition, Guilford Press, New York. https://www.guilford.com/books/Principles-and-Practice-of-Structural-Equation-Modeling/Rex-Kline/9781462523344

Koefer, F., Bokkens, A., Preziuso, M., Ehrenhard, M. (2024). Addressing financial and digital literacy challenges for inclusive finance: Insights from microfinance institutions and fintech organisations (No. 2024/97). EIF Working Paper.

Kumar, R., (2016). Perspectives on value and valuation. https://doi.org/10.1016/B978-0-12-802303-7.00001-2

Kumar, V., Thrikawala, S., Acharya, S. (2021). Financial inclusion and bank profitability: Evidence from a developed market. *Global Finance Journal*, 53, 100609. https://doi.org/10.1016/j.gfj.2021.100609

Lakew, B. T., Azadi, H. (2020). Financial inclusion in Ethiopia: is it on the right track? *International journal of financial studies*, 8(2), 28. https://doi.org/10.3390/ijfs8020028

Lal, T. (2018). Impact of financial inclusion on poverty alleviation through cooperative banks. *International Journal of Social Economics*, 45(5), 808–828. https://doi.org/10.1108/IJSE-05-2017-0194

Law, S. H., Lee, W. C., Singh, N. (2018). Revisiting the finance-innovation nexus: Evidence from a non-linear approach. *Journal of Innovation & Knowledge*, 3(3), 143-153. https://doi.org/10.1016/j.jik.2017.02.001

Levin, A., Lin, C. F., Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of econometrics*, 108(1), 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Li, L., Li, M., Wu, C. (2013). Production efficiency evaluation of energy companies based on the improved super-efficiency data envelopment analysis considering undesirable outputs. *Mathematical and Computer Modelling*, 58(5-6), 1057-1067. https://doi.org/10.1016/j.mcm.2012.07.001

Lind, J. T., Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. *Oxford bulletin of economics and statistics*, 72(1), 109-118. https://doi.org/10.1111/j.1468-0084.2009.00569.x

Liu, Y. D., Wu, Q. L., Yuan, F. (2020). Financial Performance Evaluation of Listed Companies in Anhui Province Based on Principal Component Analysis. *Open Journal of Social Sciences*, 8, 293-303. https://doi.org/10.4236/jss.2020.85021

Liu, Z., Li, X., Li, Z. (2024). Inclusive FinTech, open banking, and bank performance: evidence from China. *Financial Innovation*, 10(1), 149. https://doi.org/10.1186/s40854-024-00679-3

López-Penabad, M. C., Iglesias-Casal, A., Neto, J. F. S. (2022). Effects of a negative interest rate policy in bank profitability and risk taking: Evidence from European banks. *Research in International Business and Finance*, 60, 101597. https://doi.org/10.1016/j.ribaf.2021.101597

Madegowda, J. (2025). The Enduring Role of Branch Banking in the Digital Era: A Perception Study. *Prajnan: Journal of Banking and Financial Management*, 54(1), 22-38. https://doi.org/10.1177/09708448251370431

Maity, S., Sahu, T. N. (2020). Role of public sector banks towards fi nancial inclusion during pre and post introduction of PMJDY : A study on effiiciency review. *Rajagiri Management Journal*, 14(2), 95–105. https://doi.org/10.1108/RAMJ-03-2020-0009

Mao, F., Wang, Y., Zhu, M. (2023). Digital financial inclusion, traditional finance system and household entrepreneurship. *Pacific-Basin Finance Journal*, 80, 102076. https://doi.org/10.1016/j.pacfin.2023.102076

Mehrotra, A. N., Yetman, J. (2015). Financial inclusion-issues for central banks. *BIS Quarterly Review*, 83-96. https://www.bis.org/publ/qtrpdf/r_qt1503h.pdf

Mengstie, B., Mosisa, T., Mosisa, T. (2024).Impact of working capital management on profitability of private commercial banks in Ethiopia. *Journal of Innovation and Entrepreneurship*, 13(1), 23.https://doi.org/10.1186/s13731-024-00379-3

Menza, M., Jerene, W., Oumer, M. (2024).The effect of financial technology on financial inclusion in Ethiopia during the digital economy era. *Cogent Social Sciences*, 10(1), 2309000. https://doi.org/10.1080/23311886.2024.2309000

Merin, M. A. (2016). Determinants of bank profitability in Ethiopia: A case study of private commercial banks. *Research Journal of Finance and Accounting*, 7(9), 28-43. https://iiste.org/Journals/index.php/RJFA/article/view/30304

Mester, L. J. (1992). Traditional and nontraditional banking: an information-theoretic approach. *Journal of Banking & Finance*, 16(3), 545-566. https://doi.org/10.1016/0378-4266(92)90044-Z

Mohammed, H. (2023). Modeling Determinants of Private Banks Profitability in Ethiopia. University Library of Munich, Germany. https://mpra.ub.uni-muenchen.de/116817/

Monnet, C., & Weber, W. E. (2001). Money and interest rates. *Federal Reserve Bank of Minneapolis Quarterly Review*, 25(4), 2-13. https://www.researchgate.net/profile/Cyril-Monnet/publication/5049132_Money_and_Interest_Rates/links/53fc6a4c0cf2dca8ffff1bef/Money-and-Interest-Rates.pdf

Mossie, W. A. (2022). Understanding financial inclusion in Ethiopia. *Cogent Economics & Finance*, 10(1), 2071385. https://doi.org/10.1080/23322039.2022.2071385

Mudessir, A. H., Kedir, A. M., Kassie, A. (2024). The Influence of Digital and Financial Literacy on Interest-Free Banking Financial Inclusions: Insight from Ethiopia's Country-Specific Socioeconomic Survey 2018–19. *Ethiopian Journal of Business and Economics* , 14(1), 94-140. https://dx.doi.org/10.4314/ejbe/v12i1.1

Muhammed, S., Desalegn, G., Emese, P. (2024). Effect of Capital Structure on the Financial Performance of Ethiopian Commercial Banks. *Risks*, 12(4), 69. https://doi.org/10.3390/risks12040069

Musau, S., Muathe, S., Mwangi, L. (2018). Financial inclusion, bank competitiveness and credit risk of commercial banks in Kenya. *International Journal of Financial Research*, 9(1), 203-218. https://doi.org/10.5430/ijfr.v9n1p203

Nair, A., Von Pischke, J. D. (2007). Commercial banks and financial access. Building Inclusive Financial Systems: A Framework for Financial Access. Washington: Brookings, 89-116. https://www.brookings.edu/books/building-inclusive-financial-systems/

National Bank of Ethiopia's (NBE-FSR) (2024). Second Financial Stability Report. https://nbe.gov.et/fsr/

Nguyen, A.H.T., Pham, V.Q. Phan, H.T. (2025). Applying Bayesian methods to measure the impact of financial inclusion on banking performance: An empirical analysis for selected countries in Asia. *J Econ Finan*, 49, 493–510. https://doi.org/10.1007/s12197-025-09713-1

Nguyen, H. L. Q. (2014). Do bank branches still matter? The effect of closings on local economic outcomes. Massachusetts Institute of Technology, Working Paper. https://reinvestmentpartners.org/file_download/inline/b3a90d2a-c243-4c1d-a81c-63996ae9875c#:~:text=First%2C%20closings%20are%20associated%20with,competitive%20effects%20of%20the%20merger.

Nguyen, T. T. H. (2021). Measuring financial inclusion: a composite FI index for the developing countries. *Journal of Economics and Development*, 23(1), 77-99. https://doi.org/10.1108/JED-03-2020-0027

Obiedallah, Y. R., Abdelaziz, A. H. (2024). Financial inclusion and Financial Performance: The interplay role of capital adequacy requirements in Egyptian Banks. *Future Business Journal*, 10(1), 96. https://doi.org/10.1186/s43093-024-00383-9

Ogunbiyi, S. S., Ihejirika, P. O. (2014). Interest rates and deposit money banks' profitability nexus: The Nigerian experience. *Arabian Journal of Business and Management Review*, 3(11), 133-140. https://doi.org/10.12816/0016525

Omankhanlen, A. E., Ilori, N., Isibor, A., Okoye, L. U. (2021). Monetary policies and the achievement of bank profit objective. *Journal of Central Banking Theory and Practice*, 10(2), 201-220. https://doi.org/10.2478/jcbtp-2021-0020%0A

Omarova, S. T. (2020). Technology v Technocracy: Fintech as a Regulatory Challenge. *Journal of Financial Regulation*, 6(1), 75–124. https://doi.org/10.1093/jfr/fjaa004

Onifade, O. C., Olanrewaju, S. O. (2020) Investigating Performances of Some Statistical Tests for Heteroscedasticity Assumption in Generalized Linear Model: A Monte Carlo Simulations Study. *Open Journal of Statistics*, 10, 453-493. https://doi.org/10.4236/ojs.2020.103029

Oshora, B., Desalegn, G., Gorgenyi-Hegyes, E., Fekete-Farkas, M., Zeman, Z. (2021). Determinants of financial inclusion in small and medium enterprises: Evidence from Ethiopia. *Journal of Risk and Financial Management*, 14(7), 286. https://doi.org/10.3390/jrfm14070286

Ozili, P. K., Ndah, H. (2024). Impact of financial development on bank profitability. Journal of Economic and Administrative Sciences, 40(2), 238-262. https://doi.org/10.1108/JEAS-07-2021-0140

Pal, S., Bandyopadhyay, I. (2022). Impact of financial inclusion on economic growth, financial development, financial efficiency, financial stability, and profitability: an international evidence. *SN Business & Economics*, 2(9), 139. https://doi.org/10.1007/s43546-022-00313-3

Pennacchi, G. G., Santos, J. A. (2021). Why do banks target ROE? *Journal of Financial Stability*, 54, 100856. https://doi.org/10.1016/j.jfs.2021.100856

Perdana, A., Deppeler, A., Bharathi S, V., Karim, R., Wijesooriya, C. (2025). Digital financial inclusion: Profitable models from Africa, Asia, and the Pacific. *Journal of Information Technology Teaching Cases*, 0(0), 1-16. https://doi.org/10.1177/20438869251395749

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics, no. 0435.

Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross Section Dependence. *Journal of Applied Econometrics*, 22, 265–312. https://doi.org/10.1002/jae.951

Phanniphong, K., Niangchaem, L., Na-Nan, K., Arunyaphum, A. (2024). Unraveling the complexity of cyberbullying: Development and validation of a comprehensive questionnaire. *Transnational Corporations Review*, 16(3). https://doi.org/10.1016/j.tncr.2024.200073

Pilloff, S. J. (1996). Performance changes and shareholder wealth creation associated with mergers of publicly traded banking institutions. *Journal of Money, Credit and Banking*, 28(3), 294-310. https://doi.org/10.2307/2077976

Popa, D. C. S., Popa, D. N., Bogdan, V., Simut, R. (2021). Composite financial performance index prediction–a neural networks approach. *Journal of Business Economics and Management*, 22(2), 277-296. https://doi.org/10.3846/jbem.2021.14000

Putra, F. H., Suhardjanto, D., Trinugroho, I., Arifin, T. (2024). Overcoming barriers to inclusion: The role of financial literacy and digital divide in expanding financial access in Indonesia. *Journal of Ecohumanism,* 3(8). https://doi.org/10.62754/joe.v3i8.5608

Rao, K. S., Baza, A. U. (2017). Barriers to access to and usage of financial services in Ethiopia. *Business and Economic Research*, 7(1), 139-149. https://doi.org/10.5296/ber.v7i1.11034

Ren, K., Wang, Y., Liu, L. (2023). Impact of traditional and digital financial inclusion on enterprise innovation: Evidence from China. *Sage Open*, 13(1). https://doi.org/10.1177/21582440221148097

Roodman, D. (2009). How to do Xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal*, 9(1), 86-136. https://doi.org/10.1177/1536867X0900900106

Ruey, C. J. (2024). Factors That Affect Rural Financial Inclusion: A Case of Gambella Town, Gambell Peoples National Regional State, Ethiopia. *KnE Social Sciences*, 760-786. https://doi.org/10.18502/kss.v9i14.16143

Sapriza, H., Temesvary, J. (2024). Economic activity and the bank credit channel. *Journal of Banking & Finance*, 164, 107216. https://doi.org/10.1016/j.jbankfin.2024.107216

Sarma, M. (2016). Measuring Financial Inclusion for Asian Economies. In: Gopalan, S., Kikuchi, T. (eds) Financial Inclusion in Asia. *Palgrave Studies in Impact Finance. Palgrave Macmillan*, 3-34. https://doi.org/10.1057/978-1-137-58337-6_1

Scholtens, B., Van Wensveen, D. (2003). The theory of financial intermediation: an essay on what it does (not) explain (No. 2003/1). SUERF Studies. https://hdl.handle.net/10419/163455

Schularick, M., Taylor, A.M., (2012). Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review,* 102 (2), 1029–1061. https://doi.org/10.1257/aer.102.2.1029

Sedera, R. M. H., Risfandy, T., Futri, I. N. (2022). Financial inclusion and bank profitability: Evidence from Indonesia. *Journal of Accounting and Investment*, 23(3), 398-412. https://doi.org/10.18196/jai.v23i3.14721

Setianto, R. H., Azman-Saini, W. N. W., Law, S. H., Ahmad, A. H., Daud, S. N. M. (2025). Does financial inclusion affect bank market power? International evidence. *Finance Research Letters*, 108302. https://doi.org/10.1016/j.frl.2025.108302

Sha'ban, M., Girardone, C., Sarkisyan, A., Arun, T. (2023). On the relationship between financial inclusion and bank performance. *Economic Notes*, 52(3), e12225. https://doi.org/10.1111/ecno.12225

Shaddady, A. (2023). Unveiling the dynamics of financial institutions and markets in shaping economic prosperity in MENA. *International Journal of Financial Studies*, 11(4), 148. https://doi.org/10.3390/ijfs11040148

Shafiullah, M., Okafor, L. E., Khalid, U. (2019). Determinants of international tourism demand: Evidence from Australian states and territories. *Tourism Economics*, 25(2), 274-296. https://doi.org/10.1177/1354816618800642

Shifa, M. A., Debela, K. L., Tarfa, E. G. (2019). Determinants of the profitability of commercial banks in Ethiopia. *Copernican Journal of Finance & Accounting*, 8(4), 185-201. https://doi.org/10.12775/CJFA.2019.024

Shihadeh, F. (2020). The influence of financial inclusion on banks' performance and risk: new evidence from MENAP. *Banks and Bank Systems*, 15(1), 59-71. https://doi:10.21511/bbs.15(1).2020.07

Shihadeh, F. (2021). Financial inclusion and banks' performance: Evidence from Palestine. *Investment Management and Financial Innovations*, 18(1), 126- 138. http://dx.doi.org/10.21511/imfi.18(1).2021.11

Shihadeh, F. H., Hannon, A., Guan, J., Haq, I. U., Wang, X. (2018). Does financial inclusion improve the banks' performance? Evidence from Jordan. In Global tensions in financial markets. *Emerald Publishing Limited*, 117-138. https://doi.org/10.1108/S0196-382120170000034005

Shihadeh, F., Gamage, S. K. N., Hannon, A. (2019). The Causal Relationship Between SME Sustainability and Banks' Risk. *Economic Research-Ekonomskalstraživanja*, 32(1), 2743-2760. https://doi.org/10.1080/1331677X.2019.1655465

Soesetio, Y., Waffiudin, W., Rudiningtyas, D. A., Siswanto, E. (2022). Determinants of Profitability on Indonesian's Small Commercial Banking. *Jurnal Dinamika Akuntansi*, 14(1), 1-16. https://dx.doi.org/10.15294/jda.v14i1.33532

Song, X., Yu, H., He, Z. (2023). Heterogeneous Impact of Fintech on the Profitability of Commercial Banks: Competition and Spillover Effects. *Journal of Risk and Financial Management*, 16(11), 471. https://doi.org/10.3390/jrfm16110471

Sutherland, D., Hoeller, P., (2012). Debt and Macroeconomic Stability: an Overview of the Literature and Some Empirics. OECD Economics Department Working. Paper No. 1006, https://doi.org/10.2139/ssrn.2188941

Swift, D., Cresswell, K., Johnson, R., Stilianoudakis, S., Wei, X. (2022). A review of normalization and differential abundance methods for microbiome counts data. *Wiley Interdisciplinary Reviews Computational Statistics*, 15(1). https://doi.org/10.1002/wics.1586

Teka, B., Nahusenay, S., Asmare, T. (2020).Determinants of financial inclusion in East Gojjam, Ethiopia. *Journal of Applied Finance & Banking*, 10(4), 69-88.

Teshome, E., Debela, K., Sultan, M. (2018). Determinant of financial performance of commercial banks in Ethiopia: Special emphasis on private commercial banks. *African Journal of Business Management*, 12(1), 1-10. https://doi.org/10.5897/AJBM2017.8470

Tibebe, A. N. (2020). Determinants of financial performance of private commercial banks in ethiopia: Camel approach. *International Journal of Research in Business Studies and Management*, 7(4), 25-34.

Tibebe, A. N., Gujral, T. M. S. (2022). Determinants of profitability of commercial banks in Ethiopia: A study on internal factors. *Journal of positive school Psychology*, 6(8), 1219-1238.

Timbula, M. A., Mengesha, T., Mekonnen, Y., Kebede, M. (2019). Financial Inclusion and its Determinants among Households in Jimma Zone of Oromia Regional State, Ethiopia. *International journal of Commerce and Finance*, 5(2), 106-119.

Tong, X., Yang, W. (2025). Empirical analysis of the impact of financial technology on the profitability of listed banks. *International Review of Economics & Finance*, 98, 103788. https://doi.org/10.1016/j.iref.2024.103788

Trotta, A., Gallucci, C., Rania, F., Strano, E., Tipaldi, R. (2025). The "black box" of digital finance: An umbrella review of the challenges and drawbacks in advancing financial inclusion. *Research in International Business and Finance*, 81, 103188. https://doi.org/10.1016/j.ribaf.2025.103188

Tugcu, C. T. (2018). Panel data analysis in the energy-growth nexus (EGN). In The economics and econometrics of the energy-growth nexus (pp. 255-271). *Academic Press*. http://dx.doi.org/10.1016/B978-0-12-812746-9.00008-0

Tura, B. D. (2023). Banking sector performance evaluation in Ethiopia for the period of growth and transformation plan (GTP-II): private vs public commercial banks. *Journal of Banking Regulation*, 24(4), 484-494. https://doi.org/10.1057/s41261-022-00209-0

Ullah, S., Majeed, A., Popp, J. (2023). Determinants of bank's efficiency in an emerging economy: A data envelopment analysis approach. *Plos one*, 18(3), e0281663. https://doi.org/10.1371/journal.pone.0281663

Vo, D. H., Nguyen, N. T. (2021). Does financial inclusion improve bank performance in the Asian region? *Asian-Pacific Economic Literature*, 35(2), 123-135. https://doi:10.1111/apel.12330

Wang, H., Yan, J., Yu, J. (2017). Reference-dependent preferences and the risk–return trade-off. *Journal of Financial Economics*, 123(2), 395-414. https://doi.org/10.1016/j.jfineco.2016.09.010

Wang, W., Xiong, D., Li, Y. (2025). The Impact of FinTech on Financial Institution Performance and Risk: An Empirical Analysis from China. *SAGE Open*, 15(2). https://doi.org/10.1177/21582440251344376

Wang, Y., Jiang, A., Zhang, S., Chen, W. (2024). Traditional finance, digital finance, and financial efficiency: An empirical analysis based on 19 urban agglomerations in China. *International Review of Financial Analysis*, 96, 103603. https://doi.org/10.1016/j.irfa.2024.103603

Watkins, M. W. (2018). Exploratory Factor Analysis: A Guide to Best Practice. *Journal of Black Psychology*, 44(3), 219-246. https://doi.org/10.1177/0095798418771807

Werner, R. A. (2014). Can banks individually create money out of nothing? —The theories and the empirical evidence. *International Review of Financial Analysis*, 36, 1-19. https://doi.org/10.1016/j.irfa.2014.07.015

Werner, R. A. (2016). A lost century in economics: Three theories of banking and the conclusive evidence. *International Review of Financial Analysis*, 46, 361-379. https://doi.org/10.1016/j.irfa.2015.08.014

Wu, S., Ma, X. (2025). Research on the Regional Impact of Digital Inclusive Finance Development on the Profitability of Commercial Banks. In 2025 3rd International Academic Conference on Management Innovation and Economic Development, 820-831. *Atlantis Press*. https://doi.org/10.2991/978-94-6463-835-6_86

Xie, M., Deng, H. (2025). FinTech and Traditional Banking Performance in China. *Sage Open*, 15(4). https://doi.org/10.1177/21582440251387934

Yakubu, I. N., Musah, A. (2022). The nexus between financial inclusion and bank profitability: A dynamic panel approach. *Journal of Sustainable Finance & Investment*, 14(2), 430-443. https://doi.org/10.1080/20430795.2022.2105792

Yameogo, C. E., Omojolaibi, J. A., Dauda, R. O. (2020). Economic globalisation, institutions and environmental quality in Sub-Saharan Africa. *Research in Globalization*, 3, 100035. https://doi.org/10.1016/j.resglo.2020.100035

Yang, F., Masron, T. A. (2023). Does financial inclusion moderate the effect of digital transformation on banks' performance in China? *Cogent Economics & Finance*, 11(2), 2267270. https://doi.org/10.1080/23322039.2023.2267270

Yin, Q., Su, N., Ding, C. (2024). The Nonlinear Effects of Digital Finance on Corporate ESG Performance: Evidence from China. *Sustainability*, 16(18), 8274. https://doi.org/10.3390/su16188274

Yu, N., Wang, Y. (2021). Can digital inclusive finance narrow the Chinese urban–rural income gap? The perspective of the regional urban–rural income structure. Sustainability, 13(11), 6427. https://doi.org/10.3390/su13116427

Yuan, X., Puah, C.-H., Marikan, D. A. b. A. (2025). Financial Technology and Chinese Commercial Banks' Overall Profitability: A "U-Shaped" Relationship. *FinTech*, 4(3), 41. https://doi.org/10.3390/fintech4030041

Yuan, X., Puah, C.-H., Marikan, D. A. b. A. (2025a). An Empirical Study on the Impact of Financial Technology on the Profitability of China's Listed Commercial Banks. *Journal of Risk and Financial Management*, 18(8), 440. https://doi.org/10.3390/jrfm18080440

Yusuf, J. M., Shikur, A. A. (2023). Bank Regulations and Firm Performance: In the Case of Ethiopian Commercial Banks. *International Journal of Finance and Banking Research*, 9(4), 58-67. https://doi:10.11648/j.ijfbr.20230904.11

Zhao J, Wang C, Ibrahim H, Chen Y (2024). The impact of digital financial inclusion on bank performance: An exploration of mechanisms of action and heterogeneity. *PLoS ONE*, 19(8): e0309099. https://doi.org/10.1371/journal. pone.0309099

Zheng, C., Rahman, M. A., Hossain, S., Moudud-Ul-Huq, S. (2023). Does Fintech-Driven Inclusive Finance Induce Bank Profitability? Empirical Evidence from Developing Countries. *Journal of Risk and Financial Management*, 16(10), 457. https://doi.org/10.3390/jrfm16100457

Zhu, K., Guo, L. (2024). Financial technology, inclusive finance and bank performance. *Finance Research Letters*, 60, 104872. https://doi.org/10.1016/j.frl.2023.104872