Addis Ababa University

College of Business and Economics

Department of Accounting and Finance

The Impact of Fintech on Financial Performance of Banks in Ethiopia, The Case of Selected Commercial Banks

By

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May, 2025

Addis Ababa, Ethiopia

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A Research Thesis Submitted to the Department of Accounting and Finance in Partial Fulfilment for the Requirement of Master of Science in Accounting and Finance

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DECLARATION

This is to declare that the thesis entitled **"The impact of Fintech on financial performance of commercial banks in Ethiopia**", submitted in partial fulfillment of the requirements for the degree Master of Science in the College of Business and economics Department of Accounting and Finance, Addis Ababa University, is a record of original work carried out by me and has never been submitted to any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been fully acknowledged.

Declared by:

Gizachew Tefera		20/08/25
Name of the Designate	Signature	Date

STATEMENT OF CERTIFICATION

I hereby certify that I have supervised, read, and evaluated this thesis titled "**The impact of Fintech on financial performance of Commercial banks in Ethiopia**" by **Gizachew Tefera** prepared under my guidance. I recommend the thesis be submitted for oral Defence.

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APPROVAL SHEET

As members of the examining panel of the final open defense, we do hereby certify that we have examined the thesis presented by Gizachew Tefera ”The **impact of fintech on financial performance of Commercial banks in Ethiopia**", and recommend that it be accepted as fulfilling the thesis requirements for the award of the MSc degree in Accounting and Finance.

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ABSTRACT

This study explores the impact of fintech adoption on the financial performance of selected Ethiopian commercial banks, focusing on profitability, operational efficiency, customer satisfaction, competitiveness, loyalty, and risk management. Based on financial and customer data from five medium-sized banks between 2019 and 2024, the findings reveal that internet banking adoption has the strongest positive effect on profitability (ROA and ROE), while mobile banking significantly expands customer reach and engagement, though it incurs short-term implementation costs. Operational efficiency improved modestly due to streamlined processes, reflected in a moderate reduction in the cost-to-income ratio. Fintech also enhanced customer satisfaction through improved accessibility and convenience, leading to stronger customer loyalty and retention. Market competitiveness showed slight gains, particularly among digitally active banks leveraging fintech for broader outreach. Importantly, fintech adoption improved risk management by supporting fraud detection, enhancing credit risk profiling, and enabling real-time data analysis. These results suggest that strategic fintech integration can significantly strengthen the financial and operational performance of banks in emerging markets like Ethiopia.

Keywords*: Fintech, financial performance, commercial banks, Ethiopia, mobile banking, internet banking, digital payments, financial inclusion.*

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ACRONYMS/ABBREVIATIONS

CIR: Cost-to-income ratios

DPP: Digital Payment Platforms

FI: Fintech Investment

Fintech - Financial Technology

GDP: Gross Domestic Product

IBA: Internet Banking Adoption

INF: Inflation Rate

MS: Market Share

NBE: National Bank of Ethiopia

ROA: Return on assets

ROE: Return on equity

SIZE: Bank Size

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CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

The global financial sector is undergoing a transformative shift driven by the emergence and rapid expansion of financial technology (fintech). Fintech refers to a wide array of technological innovations such as mobile banking, digital payment platforms, peer-to-peer lending, artificial intelligence, and blockchain that are reshaping the way financial services are delivered and consumed. Globally, fintech adoption has not only enhanced banking profitability and operational efficiency but also promoted financial inclusion, especially in underserved regions. Countries such as China, India, and Kenya have demonstrated how fintech can bring millions of unbanked individuals into the formal financial system through mobile money, real-time payments, and AI-powered credit scoring (Narayan & Sharma, 2020).

While these global trends offer significant opportunities, Ethiopia's fintech landscape presents a unique paradox. On one hand, there is tremendous potential owing to the country's growing mobile phone penetration, improved internet connectivity, and a large population excluded from formal banking. On the other hand, Ethiopia faces persistent structural and regulatory challenges that hinder the full-scale adoption of fintech. These include limited technological infrastructure, low digital literacy, weak cybersecurity frameworks, and a cautious regulatory environment. Unlike countries such as Kenya where M-Pesa revolutionized access to finance Ethiopia’s fintech journey has been relatively slow, with only a few notable platforms like M-Birr, HelloCash, and Telebirr gradually gaining traction in both urban and rural areas (Berhanu & Tadesse, 2020; Kebede, 2020).

Global experiences show that fintech, when supported by enabling policies and infrastructure, can reduce costs, increase transparency, and deepen customer engagement. However, the Ethiopian banking sector remains at an early stage of digital transformation. Many commercial banks are still in the process of integrating mobile and internet banking into their service portfolios. The potential for fintech to transform the sector is high, particularly in enhancing customer experience, operational efficiency, and financial outreach. Yet, the challenges ranging from outdated core banking systems and resistance to change, to lack of skilled digital professionals and regulatory inertia continue to hold back progress.

Moreover, global fintech trends emphasize the importance of interoperability, open banking, and real-time data analytics, which are largely absent or underdeveloped in Ethiopia. The digital divide between urban and rural regions further complicates efforts to implement inclusive fintech solutions. As Wondimu et al. (2023) assert, removing barriers such as poor ICT infrastructure, weak data governance, and inadequate regulatory clarity is essential for Ethiopia to leverage the true benefits of fintech, including transaction cost reduction, expanded financial access, and improved customer service.

Despite these limitations, commercial banks in Ethiopia have begun to recognize the strategic importance of fintech. Investments in mobile banking platforms, internet-based services, and digital payment tools have increased in recent years. These investments reflect not just a response to customer demand, but also an attempt to keep pace with global shifts in the financial ecosystem.

However, empirical evidence assessing how these efforts translate into improved financial performance remains sparse in the Ethiopian context. Most studies tend to focus on the technical or adoption related aspects of fintech rather than its financial impact. As a result, banking executives and policymakers lack the data needed to make informed decisions about fintech investments, strategies, and regulatory reforms.

This study addresses this gap by analyzing how fintech adoption affects the financial performance of selected commercial banks in Ethiopia. It seeks to provide insights into how mobile banking, internet banking, and digital payment platforms influence key performance indicators such as profitability, operational efficiency, customer reach, satisfaction, loyalty, competitiveness, and risk management. By explicitly linking global fintech trends to Ethiopia’s challenges and opportunities, this research aims to contribute both to academic literature and to policy and strategic decision-making in the financial sector.

1.2. Problem Statement

Despite the global proliferation of financial technology (fintech) and its proven effects on enhancing bank profitability, customer satisfaction, and operational efficiency, empirical research on its financial implications remains limited in Ethiopia. While fintech is rapidly transforming financial sectors in countries like Kenya, Nigeria, and India, Ethiopia's adoption has been comparatively slow and fragmented hampered by technological limitations, regulatory uncertainties, and low levels of digital literacy.

Although Ethiopian banks have increasingly introduced mobile banking, internet banking, and digital payment platforms, few studies have systematically evaluated how these innovations impact financial performance. Existing research tends to focus broadly on digital banking adoption or customer behavior, without rigorously assessing financial metrics. For instance, only three empirical studies have directly examined the relationship between fintech adoption and return on assets (ROA) or profitability metrics in the Ethiopian context (Demissie & Tadesse, 2023; Tefera et al., 2022; Belay & Tsegaye, 2023). Even these are limited in scope, methodology, and sample size.

Furthermore, key performance dimensions such as cost-to-income ratio (CIR), customer satisfaction, market competitiveness, customer loyalty, and risk management remain underexplored. This lack of evidence leaves policymakers, regulators, and bank executives without the necessary data to make informed decisions about fintech investment and integration strategies.

Thus, this study seeks to fill these critical knowledge gaps by investigating the relationship between fintech adoption and financial performance in selected Ethiopian commercial banks. It will explore how mobile banking, internet banking, and digital payment platforms affect profitability (ROA, ROE), operational efficiency (CIR), customer engagement, satisfaction, competitiveness, and risk management. The findings will provide practical insights for financial institutions, regulators, and fintech stakeholders operating in emerging markets like Ethiopia.

1.3. Research Questions

1. What is the impact of fintech adoption on the profitability of Ethiopian commercial banks?
2. How does fintech influence the operational efficiency of the commercial banks?
3. How does fintech adoption influence customer reach and engagement in Ethiopian commercial banks?
4. What is the impact of fintech adoption on customer satisfaction in Ethiopian commercial banks?
5. In what ways does fintech adoption enhance the market competitiveness of Ethiopian commercial banks?
6. In what manner does fintech adoption impact the loyalty and retention of customers for Ethiopian commercial banks?
7. To what extent does fintech adoption affect the risk management of Ethiopian commercial banks?

1.4. Objectives of the Study

General Objective

To evaluate the impact of fintech adoption on the financial performance of commercial banks in Ethiopia.

Specific Objectives

1. To identify the effect of fintech adoption on profitability of Ethiopian commercial banks, most notably examining the most significant measures such as Return on Assets (ROA) and Return on Equity (ROE).
2. In order to determine how fintech offerings increase the operational efficiency of banks through cost savings, simplification of procedures, and streamlining of banking activities.
3. To establish the role played by the adoption of fintech in engaging and reaching customers, and how it results in better service delivery.

4. To determine the effect of fintech adoption on customer satisfaction of Ethiopian commercial banks.
5. In order to identify the effect of fintech adoption on business and market competitiveness of Commercial banks in Ethiopia.
6. To find out the effect of fintech adoption on customer retention and customer loyalty of Commercial banks in Ethiopia.
7. In order to identify determine the influence of the adoption of fintech on risk management in Commercial banks in Ethiopia.

1.5. Hypothesis

H1: The adoption of fintech solutions has a statistically significant positive effect on the profitability of commercial banks in Ethiopia.

H2: Fintech adoption significantly improves the operational efficiency of Ethiopian commercial banks, as evidenced by a reduction in the cost-to-income ratio.

H3: The implementation of fintech services significantly expands customer reach and engagement for Ethiopian commercial banks

H4: Fintech adoption contributes positively to enhancing the market competitiveness of Ethiopian commercial banks

H5: Adoption of fintech enhances customer loyalty and retention.

H6: Adoption of fintech strengthens risk management practices among Ethiopian commercial banks.

H7: The adoption of fintech enhances the risk management practices of Ethiopian commercial banks, especially in regard to fraud detection and credit scoring.

1.5.1 Hypothesis Foundations

The development of research hypotheses in this study is grounded in a thorough review of both theoretical and empirical literature. Each hypothesis is formulated to explore the potential relationship between fintech adoption and the financial performance of commercial banks in Ethiopia. The table-1 below presents a summary of the study's key hypotheses, along with their theoretical justification, empirical support, and the expected relationship based on prior studies and economic reasoning.

Table 1: Summarized Hypothesis and its Theoretical and Empirical supports

Hypothesis	Supported by Theory	Supported by Empirical
H1	TAM(PU), DOI(relative advantages)	Gomber et al (2020), Demissie & tadesse(2023)
H2	TAM(ease of use), UTAUT(performance expectancy)	Krause et al.(2021), Tefera et al (2022)
H3	Financial inclusion, DOI(Compatibility)	Narayan et.al. (2021), Belay & Tsegaye (2023
H4	DOI,UTAUT(facilitating conditions)	Philippon (2022), Tadesse (2022)
H5	TAM, UTAUT	Luo et al. (2021), tadesse (2022)
H6 & H7	Financial inclusion, Practical theories of Risk management	Chen & li (2022), wondimu et al.(2023)

1.6. Significance of the Study

Overall, the research contributes to the body of knowledge by examining the impact of fintech adoption on the performance of commercial banks in Ethiopia and was be beneficial to banks, policy makers, fintech service providers, and researchers. The research was be beneficial to banks since it was make them aware of how fintech improves profitability, improves operational efficiency, and aids in customer satisfaction, allowing them to make decisions on what to invest.

The research was assist policymakers and regulators in designing fintech policies that foster finance sector innovation without compromising the stability and security of the financial system. And how fintech increases greater financial inclusion with their greater outreach especially in underserved markets.

Also, the study was analyzing the effect of fintech adoption on market competitiveness and enable banks to have more robust digital strategies. It was also illuminate the manner in which fintech is precipitating better risk management, detection of frauds, and credit evaluation and this will lead to improved financial stability.

1.7. Scope of the Study

This study focuses on the impact of fintech usage by five Ethiopian medium-scale commercial banks over six years categorized by the National Bank of Ethiopia (NBE), i.e., Awash Bank, Bank of Abyssinia, Cooperative Bank of Oromia, Dashen Bank, and Hibret Bank. The research considers the use of fintech solutions like mobile banking, internet banking, and digital payment systems.

1.8. Definition and Key Terms

1. Fintech (Financial Technology): Technological innovations in financial services that are enabled by the internet and mobile devices, including mobile banking, online payment systems, internet banking, blockchain, and other digital technologies that help to make banking more effective and customer-focused.
2. Profitability: The financial performance of a bank, typically measured through metrics such as Return on Assets (ROA) and Return on Equity (ROE).
3. Operational Efficiency: Banks' ability to optimize resources, reduce expenditure, and improve service delivery, often gauged by the Cost-to-Income Ratio (CIR).
4. Customer Reach: Banks' capacity to provide services to more individuals, particularly underserved or unbanked populations, facilitated by digital and mobile banking channels.
5. Customer Satisfaction: The extent to which banking services are provided to customer expectations, often influenced by the quality, accessibility, and convenience of digital financial services.
6. Market Competitiveness: The ability of banks to compete effectively in the financial market, fueled by the adoption of innovative fintech products that enhance service delivery and operations.
7. Customer Loyalty and Retention: Defines the tendency of customers to stay loyal to a bank's services due to positive experiences and satisfaction with fintech-based services.

8. Risk Management: The process of identifying, assessing, and mitigating financial risks in banks, often enhanced by fintech innovations like predictive analytics, fraud detection, and improved credit scoring mechanisms.
9. Digital Payment Platforms: Electronic money transfer solutions, includingmobile money services, digital wallets, and online payment gateways, for example, M-Birr, Hello Cash, and Telebirr in Ethiopia (Belay & Tsegaye, 2023).
10. Mobile Banking: Financial transactions enabled through the use of mobile devices like balance inquiry, fund transfer, and bill payment, allowing remote banking access (Gomber et al., 2018; Demissie & Tadesse, 2023).
11. Financial Inclusion: Bringing low-cost financial services within the reach of individuals and businesses, particularly in under-served areas, with fintech playing a critical role in expanding access (Tchouassi et al., 2020; Amankwah-Amoah, 2021).
12. Technology Adoption Models: Diffusion of Innovation (DOI): Explains the dissemination of new technologies, highlighting on determinants like relative advantage and compatibility (Rogers, 1962; Singh et al., 2023).
13. Technology Acceptance Model (TAM): Focuses on perceived usefulness and ease of use in technology adoption (Davis, 1989; Karakaya et al., 2022).
14. Unified Theory of Acceptance and Use of Technology (UTAUT): Extends TAM with determinants like performance expectancy and social influence (Venkatesh et al., 2003; Buabeng-Andoh et al., 2021).
15. Regulatory Framework: The policy and legal frameworks governing fintech operations, with the National Bank of Ethiopia (NBE) playing a critical role in shaping fintech adoption (Wondimu et al., 2023).
16. Digital Literacy: The ability to use digital tools effectively, a determinant factor for fintech adoption, with low digital literacy being a concern in Ethiopia (Berhanu & Tadesse, 2020; Tefera et al., 2022)

1.9. Organization of the Study

This study has been arranged in five chapters. Chapter one presents the background to the research, the problem statement, the general and specific objectives, the hypotheses, the significance of the study, and the scope. Chapter Two has a review of the related literature. Chapter Three describes the research design and methodology. Chapter Four provides the analysis and findings of the study. Lastly, Chapter Five concludes with the findings and offers recommendations.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

The adoption of fintech into global banking has led to increased attention in the form of research, especially when considering its potential for improving financial performance, operational efficiency, and business development capabilities like increasing customer reach and customer engagement, and risk management. Research discussing the adoption of fintech are built on multiple theoretical paradigms and empirical studies, detailing how different innovations to the banking sector such as mobile banking, digital payment platforms, blockchain technology, and artificial intelligence has been instrumental in changing the banking landscape. These technologies have been proven to drive better banking, lower the cost of servicing bank clients, and support financial inclusion, especially in developing and emerging markets.

FinTech Adoption Theory Flows from Models: DOI, TAM, UTAUT, and Financial Inclusion Theory These theories outline the various elements of technology acceptance and address the implications of fintech on banking behavior. Alternative theoretical frameworks such as DOI Theory and Technology Acceptance Model (TAM) would aid in understanding of how fintech innovations permeate organizations and society, and that perceived usefulness and ease of use are predictors of technology adoption. In the UTAUT framework, these concepts are extended to include social influence and facilitating conditions, both of which are especially relevant in the context of Ethiopia where digital literacy is generally low and infrastructural challenges still exist.

Empirical evidence from different contexts has shown that fintech are associated with improved financial performance, including increased profitability and operational efficiency, and wider customer outreach. In some cases, such as Nigeria, Kenya and South Africa, fintech innovations such as mobile money and digital banking are helping to lower the cost of doing business that expands access to previously unbanked populations. These studies highlight the evolving landscape of banking industry and the significance of fintech in encouraging financial inclusion and improving the competitiveness of banks. Fintech adoption is in the nascent stage in

Ethiopia, and only a few studies have empirically examined its impact. But recent studies indicate that mobile banking platforms and digital payment solutions are beginning to promote financial access and improve bank performance. Whilst these are positive signs, structural issues, regulatory challenges, and low customer trust continue to slow mass adoption of fintech.

This review examines both theoretical and empirical literature pertinent to fintech adoption and influencing financial performance. It analyzes opportunities and challenges of fintech in the banking sector from global, regional, and Ethiopian perspectives. This section seeks to review the previous literature in order to isolate the major factors of fintech adoption and indicate the gaps that this study is taking to fill.

2.2. Theoretical Review

Four fundamental theories that support this research that explain the adoption and impact of financial technology (fintech) in banking institutions are the Diffusion of Innovation (DOI) Theory, Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and the Financial Inclusion Theory. These theoretical lenses allow for the explanation of how fintech adoption affects the financial performance of commercial banks in Ethiopia by affecting developments in terms of profitability, efficiency, customer satisfaction, competitiveness, customer retention, and risk management.

2.2.1. Diffusion of Innovation (DOI) Theory

The Diffusion of Innovation Theory, developed by Rogers (1962), describes the method by which new technology and ideas are distributed within organizations and societies. It gives five main attributes that influence adoption: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage refers to the degree to which the innovation is better than the existing one; compatibility refers to the degree to which the innovation is consistent with previous practices and beliefs; complexity refers to how easy or difficult it is to use and comprehend the innovation; trialability refers to the degree to which the technology may be tested prior to adoption; and observability refers to the visibility of the effects of the innovation to others. This theory has widely been applied to explain mobile banking, digital payment adoption, and other financial technologies. Singh et al. (2023), for example, applied the

DOI framework to explain how the digital payment systems were adopted in South Africa due to the fact that they were compatible with the prevailing systems at the time and had a clear relative advantage in reducing transaction costs.

DOI theory comes into play in this study since it explains how fintech services influence bank profitability, operating efficiency, market competition, and customer reach. Banks adopt fintech technologies only after they realize there is a clear advantage in the form of reduced costs or faster transactions, which continues to fuel improved profitability. The possibility for testing technology and observing useful applications such as mobile money systems in Kenya also fuel adoption, enabling banks to improve efficiency. And being compatible with customer lifestyles (e.g., the use of mobile phones in rural settings) makes it easier to reach unbanked customers. These are the pioneering banks that stand out and differentiate themselves in the marketplace, and which enhance competitive advantage.

2.2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), explains user acceptance of technology in terms of two major constructs: perceived usefulness and perceived ease of use. Perceived usefulness is the degree to which a person feels that a system enhances job performance, and perceived ease of use is the degree to which the system is effortless to use. TAM has been extensively applied in fintech research to understand the determinants of employee and customer adoption of mobile banking, digital wallets, and online banking systems. Karakaya et al. (2022) found that mobile banking usage was strongly predicted by perceived usefulness and ease of use, which directly influenced customer satisfaction levels.

In this study, TAM helps to know how the fintech adoption impacts customer satisfaction, loyalty, and even business efficiency internally. Customers who find mobile and internet banking easy to use and helpful in managing their finances are more likely to continue using them, which translates to greater satisfaction and loyalty in the long run. At the organizational level, when bank employees perceive fintech platforms as being user-friendly and beneficial to complete tasks, their productivity and service provision are boosted, further contributing to value addition in efficiency and profitability. Thus, TAM offers a theoretical foundation for describing both customer behavior and internal fintech implementation results.

2.2.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), as posited by Venkatesh et al. (2003), integrate several existing models to explain technology usage behavior. There are four core determinants in UTAUT: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy is the degree to which the individual expects the system usage to help in job performance improvement. Effort expectancy is concerned with the ease of use. Social influence considers what other people think; whereas facilitating conditions implies the support one has for the use of the technology. UTAUT has been widely used in fintech adoption research, particularly in developing countries where infrastructural and social determinants are key. Buabeng-Andoh et al. (2021), for instance, showed that mobile banking usage in Ghana was enhanced when customers had social support and the presence of facilitating infrastructure.

In this research, UTAUT helps to describe the influence of fintech on customer reach, satisfaction, competitiveness, and loyalty. Expectancy of performance and ease of use account for customer satisfaction when users expect reliable, fast services and have user-friendly platforms. Social influence comes in handy in luring new users, particularly in communities where technology adoption relies on the behavior of peers, helping banks to access more customers. Enabling factors such as internet access and smartphone availability are central to the successful implementation of fintech and competitive differentiation. Finally, repeat exposures and habit formation generate loyalty as customers get accustomed to services that are peer-recommended and easily available Advances in Fintech.

2.2.4. Financial Inclusion Theory

The Financial Inclusion Theory emphasizes the provision of equal access to valuable and low-cost financial services, particularly to excluded or underserved groups. This includes not only access to credit, savings, and insurance, but also the ability to actively use the formal financial system. Fintech plays a crucial role in promoting inclusion through mobile platforms, agent banking, and digital wallets that overcome traditional barriers such as physical infrastructure lack, low incomes, or weak financial literacy. Empirical studies such as Tchouassi et al. (2020) and Amankwah-Amoah (2021) have shown that mobile money has expanded financial access in

Africa. In Ethiopia, Belay and Tsegaye (2023) indicated how M-Birr and HelloCash platforms have played a significant role in reaching rural areas and providing essential financial services.

This theory provides the conceptual foundations for understanding how fintech contributes to expanding customer base, loyalty, and better risk management. By enabling people in rural or impoverished areas to access formal banking services, fintech helps banks expand their customer base. Customers enjoying regular and affordable service for the first time are likely to remain loyal. In addition, as transactions move from informal to digital channels, banks now have better access to data, enabling more accurate risk profiling as well as fraud detection. Thus, Financial Inclusion Theory supports the argument that fintech adoption facilitates financial stability while deepening customer relationships.

2.3 Empirical Review

2.3.1 Global Context

The phenomenon of fintech disrupting banking has been examined around the world with a focus on the impact of fintech on financial performance, profitability, and efficiency. Fintech has been discovered to be a vital enabler that affects agility in banking to obtain more output at lower operational costs and increased quality of services provided.

Fintech and Profitability: Gomber et al. (2020) researched the impact of fintech on the profitability of banks in various economies. Banks with fintech solutions (mobile banking, digital wallets, and AI-driven financial tools) saw a notable boost in profitability, according to the authors, generated by better customer service and cost savings from new technology. This is similar to what was found in Chiu et al. (2021) which states that, fintech companies are focused towards automation of the conventional banking processes which help in the reduction of the operational costs and collectively it lead benefit the companies offering the services who increased the profit margins.

Operational Efficiency: As per a worldwide study conducted by Kraus et al. (2021) Fintech utilization streamlines a back-office function which contributes to improve operational efficiency and a reduction in physical branches. "By automating processes, sending everything online, banks now serve more customers per capita than ever before with high levels of customer satisfaction at a low cost, leading to greater efficiency in global markets of all types."

Customer Reach and Service Delivery: Financial technology has also proved to be effective in increasing banks' customer base, especially in regions with inadequate banking infrastructure. A study by Narayan et al. (2021) one study indicates there increased customer reach among under banked populations in the rural communities when banks use mobile banking platforms. In 2022, Liu et al. conducted a study that confirmed this as they found that banks used fintech to deliver personalized financial services that improved customer interaction and satisfaction.

Customer Satisfaction: Fintech continues to have a big effect on customer satisfaction. As a result, digital banking platforms providing access and personalized services 24/7 are reshaping global customer expectations (Beck & Tadesse, 2021). The demand has made customers to look for instant and responsive services which fintech has provided efficiently and evident to increasing customer satisfaction from different parts of the globe.

Market competitiveness: Recent research has shown that fintech has increased market competition by reducing entry barriers for new entrants. Philippon (2022) Explain diversity in fintech startups and digital-only banks have provide innovative services with disruptive nature towards traditional banking, due to it established banks have to adopt digital strategies to stay competitive in the market.

Customer Loyalty and Retention A recent stream of literature has validated the impact of fintech on customer loyalty. According to Luo et al. (2021), the introduction of fintech services like AI-based customer support and streamlined mobile banking experiences has bolstered customer loyalty by enhancing convenience and service quality. In competitive markets, these features are critical to retaining customers.

Risk Management: Recent years have shown significant improvements in the risk management, using fintech. According to Chen and Li (2022), fintech innovations, such as machine learning algorithms and real-time fraud detection systems, have played an important role in enhancing banks' risk management frameworks. This enables banks to quickly react to potential threats, thus improving their capabilities in guarding customer information and financial assets.

2.3.2 African Context

Fintech in Africa: how it is used and how it affects banking performance with the continent having a high unbanked population (estimated to be about 1.7 billion), predominantly in rural areas, fintech provides banks a chance to extend their services in the region and boost financial efficiency.

African Fintech and Profitability: A paper by Akinmoladun et al. Sadiq et al. (2022) studied fintech adoption and Nigerian banks' profitability. According to the authors, a positive effect of fintech solutions on the profitability of banks have been found as mobile money and online banking increase transaction volumes and reduce operational costs. Fintech-oriented banks could deliver their services more smoothly to its clients, demanding less brick-and-mortar size, cutting down over prices.

More sources of Operational Efficiency for African Banks: In the case of South Africa, Williams (2020) studied how fintech adoption could improve operational efficiency in South African banks. According to the research, digital banking solutions including internet banking and digital payment platforms improved process automation and human errors. These innovations enabled South African banks to scale operations and improve their service delivery at a reduced cost.

Fintech and Customer Reach in Africa: The reach of fintech customers has elevated especially in countries like Kenya, Nigeria, and South Africa, thanks to mobile money platforms that are helping improve financial inclusion. According to Nzuve, (2021), in Kenya adopted a mobile money in the way of financial inclusion and customer engagement. This paper showed that mobile money services like M-Pesa have allowed banks to reach the unbanked, enhancing customer satisfaction & ultimately leading to improved financial performance.

Competitiveness of the African Market: The boom in Fintech has created more competition within the African banking sector as it has even the playing field, allowing smaller banks and even startups to compete as equals against the larger, traditional financial institutions. As observed by Feyen et al. (2020), they can now deliver novel customer-centric services that were limited to traditional banks. This has led conventional banks to embrace new technologies and digital solutions to retain market share. With the number of Fintech startups across Africa among the highest in the world, it is safe to say that the trend of digitalization is changing the game to meet the needs of technology-oriented clients with better services at much lower costs.

Customer Loyalty and Retention in Africa: Fintech adoption has been instrumental in enhancing customer loyalty and retention rates in the African region. Kikulwe et al. Mobile banking and Digital-oriented services are flavored by customers (2014). The use of mobile apps or online platforms to access banking services, manage funds, and conduct transactions has resulted in greater coronary clients who appreciate the enhanced service delivery and better user experience fintech offers. Moreover, tailored services, like targeted promotions and personalized financial guidance, have bolstered customer retention ratios.

Risk Management in Africa: Financial technology tools have been progressively employed in improving the risk management regime of African banks in areas like fraud analytics, credit risk scoring, and data analytics. According to Omwansa et al,. The development of fintech platforms can be expressed by Gatautis et al. (2012), which can lead to better data gathering and thus, enable banks to evaluate the creditworthiness of both businesses and individuals. Fintech tools also allow banks to detect fraudulent activities more effectively through advanced data analytics, which decreases their operational risks. Fintech is often hailed as a leading edge in the evolution of banking, and this is especially true regarding its ability to enhance risk management practices in a way that is more accessible and easier to integrate into traditional banking practices.

Generally, in Africa, fintech is hailed for boosting financial inclusion. Akinmoladun et al. (2022) reported positive impacts of mobile banking on Nigerian banks' profitability. Conversely, Sulaimon et al. (2023) in Ghana found fintech adoption raised costs in the short term before yielding returns. These contradictory results underscore the need for localized studies.

While studies in Kenya and Nigeria show fintech boosts profit (e.g., via M-Pesa or mobile wallets), others in Ghana and South Africa highlight transitional losses due to infrastructure and adoption barriers. This suggests context matters regulation, customer literacy, and bank sizes are likely moderators.

2.3.3 Sub-Saharan Africa Context

Sub-Saharan Africa's fintech has gained momentum over the last few years with very significant implications on the sustainability and relevance of financial institutions in the region. Mobile money wallets, e-payments, and online banking have enabled financial inclusion and transformed the image of the region's banking sector.

Profitability in Sub-Saharan Africa Fintech: Very recent works by Sulaimon et al. (2023) examined the profitability of banks in sub-Saharan Africa and deduced that fintech adoption have a beneficial effect on banks' profitability. Mobile payment platforms and online banking allowed banks to close expensive physical outlets and increase profitability, the authors explained. On the other hand, thanks to the same fintechs, banks have managed to tap into new sources of income when they have created improved payment systems.

Improving Operational Efficiency in Sub-Saharan Africa: The study by Okoye et al. (2022), operational efficiency among banks in Sub-Saharan Africa experienced a considerable enhancement following the advent of fintech. According to the study, the provision of routine banking tasks through fintech means less time is wasted in handling, thus allowing banks to process a higher number of transactions and save on human resource cost while benefitting from easier processing time. This was most pronounced in nations such as Ghana and Uganda, which discovered that digital banking solutions could curtail operational costs and relay the collective effectiveness of financial institutions.

A Study by Amankwah-Amoah (2021) on Customer Reach and Engagement in Sub-Saharan Africa: Findings that mobile banking and fintech innovations helped banks reach the previously underserved masses in Sub-Saharan Africa. The Research found that fintech not only helped banks expand their customer base, but also enhanced customer satisfaction through quicker and more convenient financial services. For instance, MTN Mobile Money and Airtel Money are mobile money solutions that have provided useful financial services to low-income and distant communities in the region, promoting improved customer loyalty and improved financial performance for banks.

Competitive Dynamics: Growth in fintech has heightened the competitive landscape in Sub Saharan Africa by ensuring that smaller institutions can come on board with new, innovative, customer-centric products that can rival those offered by older, bigger banks. As pointed out specifically by Afolabi et al. (2023), this trend of startup companies, new applications and small banks has access to digital solutions to acquire customers who prefer technology, and by obtaining favorable feedback witnessed the major banks adopting digital technologies and approaches to neutralize Microsoft 2023). It has made regional financial market more competitive and dynamic.

Customer Retention & Loyalty: Sub-Saharan Africa's relationship between the adoptions of fintech is linked with enhanced customer loyalty and retention. Studies by Nwachukwu et al. (2022), mobile banking services are more efficient and convenient means resulting in additional customer retention. Fintech sites offering a convenient, tailored user experience like quicker transactions and on-demand customer support will likely have more powerful greater patronage from the people of the area than traditional bank services.

Risk Management: Fintech solutions are also improving risk management in Sub-Saharan Africa by facilitating better data analysis and fraud detection. According to Oladipo et al. (2023), digital banking platforms produce unparalleled amounts of transactional data analysis which are able to to profile customers' behavior and detect fraud. So, fintech tools also help banks make better credit risk management by giving them more accurate and real-time data on borrowers and opportunities mitigating financial risks.

2.3.4 Ethiopian Context

Though still in its infancy compared to other countries in Africa, Ethiopia has also seen considerable improvements in mobile banking and digital payments in the recent years. Though few studies exist regarding the contribution of fintech towards banking performance in Ethiopia, a few recent studies indicate promising trends.

Fintech Adoption and Profitability: A recent study examined the contribution of fintech adoption toward profitability of Ethiopian commercial banks (Demissie & Tadesse, 2023). The authors explained that bank adoption of mobile banking channels like Dashen Bank's mobile banking facility led to higher levels of transactions and profitability. This was due to the fact that the solution by fintech to minimize the cost of transactions and offer more convenient banking to customers.

Operational Efficiency of Ethiopia's Banks: Tefera et al. (2022), who studied the impact of mobile banking on commercial banks' operational efficiency in Ethiopia. During the study, mobile banking services helped banks automate processing of routine transactions, hence the need for physical branches decreased but the speed of transactions increased. This in turn led to cost savings and improved operational efficiency.

Increasing customer Reach in Ethiopia: Ethereum money and Ethereum banks have also made contribution Ethiopian banks in widening their customer base. According to the research by Belay and Tsegaye (2023), fintech products in the form of mobile money services such as M-Birr and Hello Cash allowed the banks to reach rural and under-served people. Fintech innovations in Ethiopia have also allowed financial inclusion in the form of easy access to banking services, especially for areas where there are no traditional banking facilities.

Difficulties of Fintech Adoption: Even though fintech appeared to be associated with financial performance, Wondimu et al. (2023) presented a few problems that are slowing down fintech in Ethiopia. These were low digital literacy, limited internet penetration, and regulatory constraints. The authors concluded that it would be essential to address these challenges to realize the optimum potential of fintech to facilitate the effectiveness of Ethiopian banks.

Market Dynamics: Fintech is revolutionizing the competitive environment in Ethiopia by making it possible smaller banks to provide digital services that were monopolized by larger banks. This it suggests that smaller players can compete via Fintech to provide innovative, low-cost, computer-driven solutions (Berhanu, 2020).This has created a competitive atmosphere in a market where the larger banks are diving into fintech solutions to be more competitive and address changing needs of customers.

Freedom of Choice: The freedom of choice given to customers in Ethiopia is increasing their loyalty and retention through convenient mobile banking and digital payment solutions. According to recent research by Tadesse (2022), customers in Ethiopia are more loyal to fintech platforms with ease of use, quicker transaction processing, and enhanced customer service. Mobile Banking for mobile banking, access to banking solutions on mobile devices is a major factor in attaining higher customer retention rates because mobile users recognize the convenience of managing finances remotely.

Risk Management: While Ethiopian banks are slowly adopting fintech tools for risk management, there are still technological and banking regulatory bottlenecks to address. Wondimu et al. (2023) highlight significant challenges to the adoption of fintech solutions by the banking sector, despite some banks having adopted these solutions to improve fraud detection and credit risk management. However, challenges such as regulatory hurdles, lack of technological infrastructure in some areas, and concerns about data security continue to hinder the overall integration of fintech into risk management practices. However, what fintech can do is outperform traditional banking practices in risk mitigation through improved data analytics and more effective tracking of transactions.

Summary of Ethiopian Studies and Gaps

Compared to its African peers, Ethiopia has limited empirical research on fintech's financial impacts. While mobile banking platforms like M-Birr and HelloCash are expanding, studies have not rigorously assessed how fintech affects profitability or risk metrics such as ROA, ROE, or NPL ratios.

Table 2: Summarized of Local Studies on Mobile Banking and their Findings

Study	Focus Area	Method	Key Findings	Limitations / Gaps
Demissie & Tadesse (2023)	Mobile banking & ROA	Quantitative	Positive link with profitability	Ignores other fintech tools; no customer data
Tefera et al. (2022)	Mobile banking & Op. Eff.	Mixed	Improved transaction speed, cost reduction	Lacks profitability analysis; limited bank sample
Belay & Tsegaye (2023)	HelloCash (inclusion)	Descriptive	Enabled rural access to banking	No linkage to financial performance; no empirical model
Wondimu et al. (2023)	Risk& Regulation	Thematic review	Identifies cyber risks, regulatory gaps	No quantitative link to performance or fintech variables

This study addresses these gaps by using a multi-variable model (ROA, ROE, CIR, NPL, CRR) and examining multiple fintech tools (mobile, internet, DPP), with both financial and customer-level data.

2.4 Conceptual Framework

This conceptual framework is formulated to show the relationship between fintech adoption and the financial performance of selected Ethiopian commercial banks. It combines important theoretical perspectives, indicators of fintech adoption, and financial performance metrics. It emphasizes the impact of fintech adoption on profit generation, operational efficiency, customer satisfaction & experience, reach, market competitiveness, customer loyalty and risk management.

Theoretical Foundation

This study is based on the following theories:-

Diffusion of Innovation (DOI) Theory: The framework explains how innovations get adopted in the banking space driven by success factors like relative advantage, compatibility, complexity, trialability, observability, etc.

Perceived usefulness and perceived ease of use: Technology Acceptance Model (TAM): The relationship that fintech adoption depends on perceived ease of use and perceived usefulness.

Financial Inclusion Theory: Emphasizes the role of fintech in extending banking services to underserved populations, addressing the significant unbanked demographic in Ethiopia.

Independent Variables (Indicators for Fintech Adoption)

The independent variables encompass various dimensions of fintech adoption, including:

Mobile Banking Adoption (MBA): PC is the percentage of customers using mobile banking services.

Digital Payment Platforms (DPP): As a proportion of the number of digital transactions per total transactions.

Internet Banking Adoption (IBA): Number of active internet banking users

Bank Size (SIZE): Total assets of the bank

Dependent Variables (Indicators of Financial Performance)

Profitability: Judged by figures like Return on Assets (ROA) and Return on Equity (ROE), gauging how effectively a company turns assets and shareholder equity into profits. Operational Efficiency: Evaluated via cost-to-income ratio (CIR), which reflects the banks' ability to manage costs compared to revenues.

Customer Reach and engagement: Defined by the number of active users on digital platforms and customer engagement level, determined minimonistrative to the availability and usability of fintech services.

Customer Satisfaction: Measured via customer feedback and satisfaction surveys, emphasizing the effects of fintech on customer experience.

Market Competitiveness: Measured by market share and competitive positioning, which shows if and how fintech adoption makes the bank more competitive.

Customer Loyalty and Retention: Through retention rates and repeat customer engagement, determined the impact of the fintech industry on customer loyalty.

Risk Management: Investigated based on the adoption of fintech solutions in risk assessment and fraud detection impacting on the bank's ability to manage risks.

Overall, these metrics reinforce the concept that fintech can improve profitability and efficiency and broaden access to customers.

Control Variables

Control variables account for external factors that may influence the relationship between fintech adoption and financial performance:

Market Share (MS): The bank's proportion of the total banking market.

Economic Growth (GDP): GDP growth as an external economic factor.

Inflation Rate (INF): Annual inflation rate affecting the banking environment

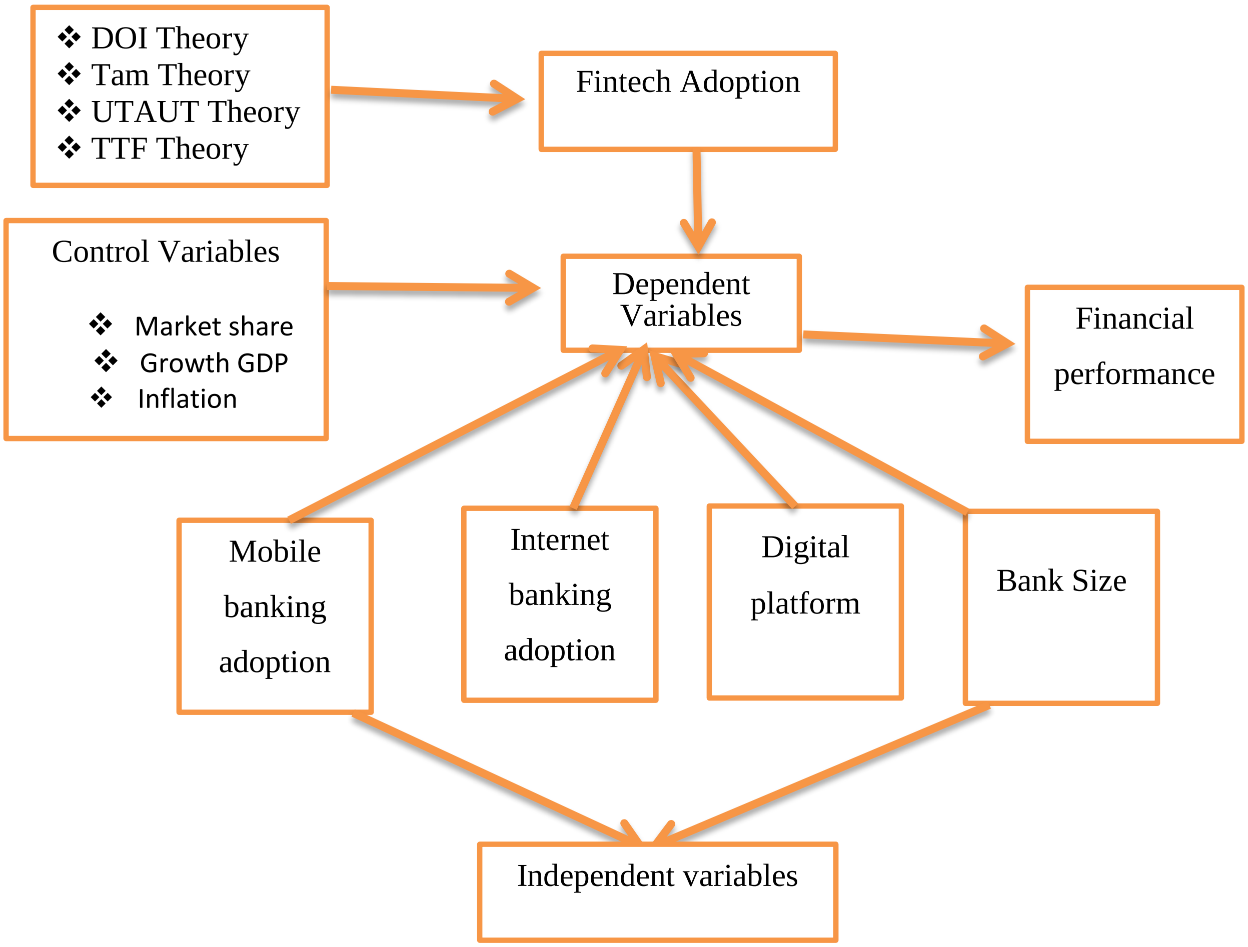

Figure 1: Conceptual framework (Source: writer own computation 2025)

CHAPTER THREE

3. METHODOLOGY AND DESIGN

This section outlines the methodology, data collection methods, sampling techniques, model specification, and analytical tools used to assess the impact of fintech adoption on the financial performance of commercial banks in Ethiopia. The study employs a quantitative research design, utilizing financial data related to fintech adoption and its relationship with key performance indicators. In addition, a structured survey is conducted to gather primary data on customer satisfaction levels resulting from fintech services. Statistical tools such as STATA, Excel are used to analyze both the financial data and survey responses, enabling the identification of trends, correlations, and the overall impact of fintech adoption on financial performance and customer satisfaction.

3.1 Research Design

The study employs a quantitative research approach to gain a deeper understanding of the effects of fintech adoption on the financial performance of Ethiopian commercial banks.

Quantitative Method: This method is used to statistically analyze the impact of fintech adoption on profitability, operational efficiency, customer reach, and other key performance indicators. It relies on the collection and analysis of numerical data obtained through structured surveys, report reviews, and financial data analytics. These data sources enable a comprehensive assessment of the measurable outcomes associated with fintech implementation in commercial banks.

3.2 Data Collection Methods

This study employs a quantitative research approach, using structured data collection tools to comprehensively examine the extent to which fintech adoption enhances the financial performance of commercial banks in Ethiopia.

Primary Data

A structured survey was being used as primary data collection methods.

Surveys (Questionnaires)

Data was being collected to measure the effect of fintech on customer satisfaction.

Secondary Data

Financial reports and records from the banks were reviewed to obtain data and gain insights into key areas such as profitability, operational efficiency, customer reach, market competitiveness, customer loyalty and retention, and risk management.

3.3 Population and Sampling

Employees from five Ethiopian commercial banks categorized as medium-sized by the National Bank of Ethiopia (NBE): Awash Bank, Bank of Abyssinia, Cooperative Bank of Oromia, Dashen Bank, and Hibret Bank.

Cochran (1977) is widely cited for his foundational work on sample size determination. His formula is particularly useful for calculating the minimum sample size required to achieve a desired level of precision when conducting surveys.

$$n = \frac{n_0}{1 + \left(\frac{n_0 - 1}{N}\right)}$$

Where:

no: sample size for infinite population

n - Sample size

N: total population

$$\frac{385}{1 + \left(\frac{384}{20{,}000{,}000}\right)} = \frac{385}{1 + 0.0000192} = \frac{385}{1.0000192} \approx 384.99$$

The required sample size according to Cochran's (1977) formula, based on a total population of 20 million digital banking users, is **385 respondents** for measuring customer satisfaction.

3.3.1 Sampling Criteria

There are a total of 32 banks in our country. This study were considering of 5 banks. The selected banks were classified regarding their assets and capital as per the three-tier classification of the National Bank of Ethiopia (high-level, medium-level and small level banks). All banks I focused on that are medium fall under the same designation and classification. Moreover, because medium-level banks act as an intermediate group between the high and small categories, they are appropriate for this study. The first classification contains a single bank, while there are banks founded less than five years in the third classification. Thus, the middle level should be the ideal level for the study.

3.4 Sampling Techniques

This study employed purposive sampling to select five medium-sized commercial banks in Ethiopia Awash Bank, Bank of Abyssinia, Dashen Bank, Cooperative Bank of Oromia, and Hibret Bank—based on the National Bank of Ethiopia's (NBE) categorization by asset size, capital adequacy, and operational reach. These banks were chosen to represent a balanced segment of the Ethiopian banking sector, reflecting typical characteristics and challenges faced by institutions actively implementing fintech innovations. The selection criteria included their ability to provide reliable fintech-related data (such as mobile and internet banking usage, digital payment volumes), their demonstrated willingness to participate and facilitate data access and customer surveys, and their active engagement in digital transformation initiatives, including deployment of mobile and internet banking platforms and participation in national digital payment systems like Telebirr, HelloCash, and EthSwitch. This approach ensured the sample's representativeness, data availability, institutional cooperation, and relevance for assessing the impact of fintech on financial performance.

3.5 Data Analysis

The quantitative analysis reflects a structured approach to assess the relationship between fintech adoption and the financial performance of selected commercial banks in Ethiopia. This analysis draws on both primary and secondary data sources. Primary data is collected through structured surveys designed to quantify customer satisfaction, usage patterns, and perceptions of fintech services. Secondary data is obtained from financial reports and records over a defined period. These data are processed and analyzed using statistical software such as STATA and Excel.

The study adopts an observational time series design, examining key performance indicators (KPIs) such as Return on Assets (ROA), Return on Equity (ROE), Cost-to-Income Ratio (CIR), customer reach, customer satisfaction, market competitiveness, customer loyalty and retention, and risk management metrics. This approach enables the identification of trends and patterns over time and facilitates the detection of changes in these indicators that may result from the implementation of fintech solutions.

To ensure robustness, all independent variables are tested for multicollinearity using Variance Inflation Factors (VIF). Addressing multicollinearity is crucial, as inflated variances of parameter estimates can lead to inaccurate interpretations. The study strengthens the validity of its findings by identifying and correcting for any multicollinearity issues.

Descriptive statistics are used to present a clear summary of the data, providing insights into the characteristics of the sample and key variables. These basic analyses form the foundation for more advanced statistical assessments. By integrating survey data with financial performance metrics, this study provides a comprehensive, data-driven understanding of how fintech adoption impacts the performance of commercial banks in Ethiopia.

3.6 Model Specification

The effect of financial technologies (fintech) adoption on the financial performance of commercial banks in Ethiopia were be assessed using a regression-based model. We then fit a model to characterize the association between the different fintech adoption variables and key indicators of financial performance including profitability, operational efficiency metrics, customer outreach, customer satisfaction, market competitiveness and retention, along with customer loyalty metrics.

Dependent Variables (Financial Performance Indicators)

Profitability (PROFIT): Common profitability measures such as Return on Assets (ROA) or Return on Equity (ROE) will be used.

ROA is calculated as follows: Net Income / Total Assets

ROE = Net Income / Shareholder's Equity

Operational Efficiency (OE) measured as cost-to-income ratio (CIR), a more common metric for measuring bank operational efficiency.

Note: CIR = Operating Expenses / Operating Income

Customer reach and engagement (CRS): The number of active users of mobile banking, digital payment platforms and even internet banking can be used as a proxy for customer reach. Rather than the customer feedback or net promoter scores (NPS) that correlate with customer satisfaction, this model is concerned with customer engagement (e.g., how much the customer uses the digital platform).

CRS = Active users of mobile banking/ Total customers

Customer Satisfaction: Based on customer feedback or satisfaction surveys.

Net Promoter Score (NPS).

NPS=% of Promoters−% of Detractors

Competitive Positioning: Assessed based on market share.

MS= (Total Assets /Bank Total Assets of All Commercial Banks)×100

Customer Loyalty & Retention: Assessed via retention rates and repeat customer interactions.

CL=Customer Retention Rate

CRR= (Number of Customers end of Period-Number of New Customers Acquired during Period)/ Number of Customers at Start of Period))×100

Risk Management: Scrutinized by the performance of fraud detection and credit scoring models.

RM=Risk Management Effectiveness Score

a. NPL Ratio

NPL Ratio=Non-Performing Loans/Total Loans×100

b. Capital Adequacy Ratio (CAR)

$$CAR = Capital / RiskWeighted\ Assets \times 100$$

c. Loan Loss Provision Ratio=(Loan Loss Provisions/Gross Loans)×100

Independent Variables (Indicators of Fintech Adoption)

Mobile Banking Adoption: It was be measured in terms of the percentage of customers who have adopted mobile banking services relative to the total number of customers.

$$MBA = [(No.of\ mobile\ banking\ users) / (Total\ customers)] * 100$$

Digital Payment Platforms (DPP): This variable was indicate the adoption of digital payment systems such as mobile wallets, online payment solutions and digital transfers.

$$DPP = Volume\ of\ digital\ transactions / Total\ transactions \times 100$$

Internet Banking Adoption (IBA): This is the number of active internet banking users (from customer perspective)

$$IBA = ((Number\ of\ internet\ banking\ users) / Total\ customers) \times 100$$

Bank size (SIZE): The total assets of the bank can determine a bank's ability to invest in, and adopt, fintech solutions.

$$SIZE = Total\ Assets$$

Control Variables

The following control variables were is additionally entered to control for extraneous variables that might bias the results:

Market Share (MS): This was constitute the share of the bank in the total banking market in Ethiopia, as larger banks may have better access to the resources necessary for the adoption of fintech.

$$MS = Bank's\ total\ assets / Total\ assets\ of\ all\ commercial\ banks \times 100$$

Growth Rate (GDP): We were control for the implications of macroeconomic conditions on bank performance by adding GDP growth.

GDP = Ethiopia's GDP annual growth rate

Inflation Rate (INF): Inflation can impact the profitability and operational performance of banks, and is thus a control variable in the model.

INF = Annual inflation rate, Ethiopia

Regression Model

The regression model can be specified as follows:
Performanceit=β0+β1MBAit+β2DPPit+β3IBAi+β5SIZEit+β6MSit+β7GDPt+β8INFt+ ϵit

Where

Performance (dependent Variables) is represents financial performance measures:

Profitability: ROA, ROE

Operational Efficiency: Cost-to-Income Ratio (CIR)

Customer Reach & Engagement: No. of active mobile banking users (in the %)

Market Competitiveness : Market Share (MS)

Customer Care = Net Promoter Score (NPS)

Customer loyalty & retention: Customer retention rate (CRR)

Risk management: Non-performing loans (NPL) ratio

MBA (Mobile Banking Adoption), DPP (Digital Payment Platforms Adoption), IBA (Internet Banking Adoption), SIZE (Bank Size), = Independent Variables

MS (Market Share), GDP (Economic Growth), INF (Inflation Rate) = Control Variables

β_0 = Intercept, β_1 -β_8 = Coefficients, ε = Error term

3.7 Ethical Considerations

This study was conducted following the ethical guidelines to ensure integrity, confidentiality and do not harm at all to the subjects. The following ethical issues will be implemented during the process of research:

Informed consent: All subjects will be given full information about the rationale, aims and extent of the study. Participation will be completely voluntary, and respondents will need to give informed consent before participating in the research.

Confidentiality and Anonymity: Participant confidentiality will be maintained through anonymization of survey results and secure storage of data collected. No identifiable information will be published in any report or publication.

Data security: All data will be stored safely to protect against unauthorized access. We will secure digital data using password encryption, while any physical documents will be stored in a secure location.

Non-Maleficence (Do Not Harm): No harm in any form will be allowed to come to any participant as a result of their participation in the research.

Balanced and impartial: The study would be reporting every finding fairly without any bias and manipulation. Empirical based analysis and interpretation of data.

Compliance with Institutional and legal requirements: Research will always conform to the ethical guidelines provided by Addis Ababa University and any publication and survey regulation of the national level related to academic and data protection.

CHAPTER FOUR

4. DATA ANALYSIS AND FINDINGS

4.1 Introduction

This chapter presents the results of the study and analysis of the impact of fintech adoption on the financial performance of the commercial banks in Ethiopia. The chapter aims to respond to all research questions and hypotheses by examining key performance indicators like profitability, operational efficiency, customer reach, satisfaction, market competitiveness, customer loyalty, and risk management. Analysis incorporates quantitative data derived from financial reports and Survey to provide comprehensive explanation of the association between financial performance and fintech adoption.

4.2 Descriptive Statistics

Descriptive statistics are required in order to know the basic characteristics of a data set prior to performing inferential or econometric analysis. They give a concise summary of the central tendencies, variability, and overall distribution of the variables of interest (Gujarati & Porter, 2009). In this study, descriptive statistics are provided for all of the key variables used in the analysis, both financial performance indicators such as Return on Assets (ROA), Return on Equity (ROE), and Cost to Income Ratio (CIR), and risk indicators such as Non-Performing Loans (NPL), Loan Loss Provision Coverage (LLPCOVER), and Capital Adequacy Ratio (CAR). Besides, macroeconomic variables such as inflation rate (INF) and growth rate of the economy (Growth Rate) are also taken into account. The data is for six years from 2019 to 2024 and consists of 30 observations representing annual data over commercial banks of Ethiopia

The objective of this section is to give background knowledge of the data and to identify any interesting patterns or abnormalities in the variables that can inform or influence further econometric modeling. For example, knowledge of the range and variability of a variable such as bank size or market share (MS) can guide the selection of functional form for regression models and the need for data transformation or normalization (Wooldridge, 2016). Descriptive analysis is also necessary for checking consistency in data reporting and can be employed as a diagnostic tool to ensure data integrity. By the interpretation of such basic statistical measures, researchers are better positioned to make hypotheses and choose suitable estimation procedures for more robust and believable findings.

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	31	4.778012	12.87299	1.15379	74.05919
ROE	30	21.89344	4.987506	10.48379	30.15659
CIR	30	59.66136	10.96071	34.58673	89.54463
NPL	30	2.674511	1.425268	1	7.233355
LLPCR	30	49.6756	25.87867	10.65184	95.59678
CAR	30	12.16119	2.550223	8.43297	18.10079
CRS	30	21.34516	14.47997	0	70.46477
NPS	30	.27	5.65e-17	.27	.27
CRR	30	100	0	100	100
ln_Q	30	1.427607	.3394972	.8470761	2.044639
ln_MBA	30	2.970656	.8148071	0	4.269205
ln_IBA	30	1.035338	.8717133	0	3.004446
ln_DPP	30	2.457866	1.254848	-1.139434	3.842244
ln_MS	30	1.427607	.3394972	.8470761	2.044639
ln_Banksize	30	4.4435	.5819213	3.459466	5.53418
INF	30	24.09833	6.220989	15.3	33.89
GrowthRate	30	7.183333	1.075458	6.1	9

The dataset comprises 30 observations and covers a variety of financial, operational, and macroeconomic indicators of banks, likely spanning the years 2019 to 2024. Return on Assets (ROA) has a mean of 4.78% with a high standard deviation of 12.87 and a maximum of 74.05%, which indicates there are huge variances in profitability across banks, which may be due to outliers. Return on Equity (ROE) shows more consistent returns, with the mean at 21.89% and standard deviation at a lower figure of 4.99, i.e., returns on equity are more consistent across the institutions.

The Operating Efficiency (OE) measure, as calculated by the Cost-to-Income Ratio (CIR) metric, is 59.66%, which means that, on average, most of the banks' income is going into operating expenses. The CRS variable, as a digital channel participation proxy, is averaging 21.35% and is very wide-spread, suggesting disparate digital adoption and usage levels among banks.

In terms of credit risk, the mean Non-Performing Loan (NPL) rate is 2.67% with low variability, which indicates banks' relatively comparable asset quality. The high NPL figure of 7.23% in certain institutions, however, implies higher credit risk. The mean Loan Loss Provision Coverage Ratio (LLPCR) is 49.68% and a high figure of 95.6% indicates different strategies in loan loss provisioning. The mean Capital Adequacy Ratio (CAR) is 12.16%, which means that banks generally possess sufficient capital to address regulatory requirements and absorb potential losses.

Financial technology adoption also differs. Log-transformed measures reveal that internet banking and online payment systems are more adopted on average compared to internet banking, which implies higher degrees of movement toward mobile systems in the sector. For example, logged mobile banking adoption is 2.97 on average while internet banking adoption is 1.04 on average, which reflects differences in degrees of customer preference or technological availability.

The measure of bank size, given in logged value (ln_Banksize), is 4.44 on average, while original figures suggest significant dispersion across the asset sizes of banks. Two variables, Bank size (ln_Q) and Market share (ln_MS), share equal statistical value, which may be picking up very similar things about firm performance or market standing. The Customer retention ratio (CRR) is fixed at 100% across all observations, possibly suggesting a strict policy requirement.

Macro economically, the average GDP growth rate is 7.18%, which suggests moderate to strong growth phase. Inflation is rather high at 24.10% with peaks of 33.89%, which may jeopardize bank profitability and cost management. Such macroeconomic conditions provide essential context in explaining observed trends in the banking sector's performance.

4.3 Correlation Analysis

Correlation analysis is statistical analysis that describes the procedure for ascertaining the direction and magnitude of the linear relationship between two or more quantitative variables. These correlation analyses are very crucial in economic and financial studies since they assist in formulating interdependencies between the variables being investigated and allow researchers to see how changes in one variable can be linked with changes in another. This method is highly applicable in banking and financial research where variables such as profitability, risk, capital adequacy, and market variables are interconnected (Gujarati & Porter, 2009). The positive correlation implies that an increase in one variable is associated with an increase in another variable, while a negative relationship suggests an inverse relationship. From these relations, correlation analysis provides crucial information before conducting more advanced econometric models such as regression analysis.

In the context of this study, correlation analysis is handy in ascertaining the linear association between the key financial metrics of commercial banks. Correlation among variables such as Return on Assets (ROA), Return on Equity (ROE), Non-Performing Loans (NPL), Capital Adequacy Ratio (CAR), and inflation, among others, is the foundation of examining the impact of each on financial performance. In addition, having highly correlated variables also enables the detection of potential multicollinearity, which can lead to distorted regression estimates and compromise the validity of model results (Brooks, 2019). The analysis is thus important not only for preliminary data exploration but also for guiding the selection and interpretation of variables in subsequent empirical models.

Correlation analysis gives some profound information concerning the association pattern among the most important variables that correspond to financial performance, adoption of fintech, and risk management for Ethiopian commercial banks. From annex 2 – Table 4.2 Beginning with profitability measures, the correlation matrix illustrates the high positive correlation of 0.8252 between Return on Assets (ROA) and Return on Equity (ROE), indicating that banks with greater profitability on assets also generate better returns for shareholders. ROA is negatively related to the Cost-to-Income Ratio (CIR) of -0.4635, indicating that greater operational efficiency results in higher profitability. Similarly, CIR and ROE are negatively correlated (-0.3292), which again emphasizes the importance of cost control on financial performance. CAR is positively correlated with ROA (0.4159), indicating that well-capitalized banks perform better, most likely because they can afford to be risky and invest in growth opportunities.

Risk management ratios have mixed effects on profitability. The ratio of Non-Performing Loan (NPL) is negatively correlated with both ROA (-0.3353) and ROE (-0.4311), indicating that higher credit risk decreases profitability. The Loan Loss Provision Coverage Ratio (LLPCR) is positively correlated with both ROA (0.3587) and, more notably, ROE (0.6295), suggesting that banks with larger provisions for bad loans also tend to have better financial performance, possibly due to prudent risk management. However, CAR is essentially uncorrelated with NPL (-0.0017), which suggests that the quality of capital has no direct impact on the quality of loans in this data sample.

Fintech adoption has mixed impacts on bank performance. Internet Banking Adoption (IBA) is strongly positively correlated with ROA (0.6227), implying that internet banking services are associated with increased profitability due to increased customer engagement and cost efficiency. Yet, Mobile Banking Adoption (MBA) is negatively correlated with ROA (-0.5620), which may be caused by initial implementation expenses or underuse. Digital Payment Platforms (DPP) are not significantly related to ROA (-0.0096), suggesting no direct effect on profitability but perhaps indirect benefits. Customer Reach Score (CRS) is positively weakly associated with ROA (0.1243), suggesting that expanding digital services can contribute slightly to financial performance.

Customer experience metrics in the form of the Net Promoter Score (NPS) are not significantly related to ROA (0.0000), indicating that customer satisfaction alone does not directly translate to higher profitability. The Customer Retention Rate (CRR) contains constant values. Bank size has positive correlations with ROA (0.2440) and the adoption of fintech (e.g., 0.8477 with Q, a market value proxy), highlighting that larger banks have economies of scale and greater capacity to invest in digital transformation. Market-related variables like Q and ln_MS also have moderate positive correlations with ROA, supporting the idea of banks with greater market presence having improved financial performance.

The examination also shows the existence of robust interrelations among fintech adoption indicators. For example, IBA and Q are highly correlated (0.6701), and ln_IBA and ln_DPP are significantly related (0.6090), suggesting that banks that embrace one digital service are also embracers of the others. While this shows a comprehensive digital plan, it may pose multicollinearity issues to regression specifications. Macroeconomic indicators such as inflation (INF) and growth rate have insignificant correlations with ROA, implying that digital initiatives and internal bank characteristics are more responsible for performance than overall economic conditions during the period under review.

4.4 Diagnostic tests of the CLRM

The Classical Linear Regression Model (CLRM) relies on several key assumptions to render Ordinary Least Squares (OLS) estimators unbiased, efficient, and consistent (Gujarati & Porter, 2009). Any deviation from these assumptions can lead to biased estimates, incorrect inferences, and poor forecasting. Diagnostic tests are therefore important to determine the stability of the model. The following CLRM assumptions and associated diagnostic tests are covered in this section:

4.4.1 Tests for Heteroskedasticity

Homoskedasticity of the error term is a key classical assumption that needs to hold so that the Ordinary Least Squares (OLS) estimator can be efficient. This assumption holds when the variance of the disturbance term is the same for all observations. If the variance of the errors is not the same, then the requirement is violated and the situation is one of heteroskedasticity. While OLS estimators remain unbiased and consistent with heteroskedasticity, the Gauss-Markov theorem violation causes inefficient estimation. Specifically, estimated standard errors are no longer accurate, which means confidence intervals become unnecessarily large. Thus, hypothesis tests such as the *t*-test and F-test can give imprecise results by the overestimation of variances, which leads to smaller *t*-statistics and potentially incorrect conclusions regarding statistical significance (Gujarati, 2004).

The linear regression model requires the minimum assumption of homoscedasticity in linear regression models to make the variance of residuals equal for all observations (Brooks, 2008). For the purpose of testing this crucial assumption, the Breusch-Pagan/Cook-Weisberg test has been executed for all the models testing the null hypothesis of equal error variance with the alternative hypothesis being heteroskedasticity.

As indicated in the annex 3 Table 4.3, the results of the tests provide strong support for homoscedasticity in all the models being examined: CAR ($p=0.0969$), CIR ($p=0.8520$), CRS ($p=0.1301$), LLPCR ($p=0.7811$), Market Share ($p=0.8654$), NPL ($p=0.3419$), ROA ($p=0.9092$), and ROE (p=0.2524). In each case, the p-values are comfortably well above the conventional 5% significance level, and therefore the null hypothesis of homoscedasticity cannot be rejected. These consistent results for all of the models provide justification for the use of standard ordinary least squares (OLS) regression techniques without the requirement for corrective measures to address heteroskedasticity. The results confirm that the variance of residuals is equal across the entire dataset, meeting a key assumption for valid regression analysis and reinforcing the reliability of the statistical conclusions drawn from these models. This rigorous testing approach aligns with conventional econometric practices and offers robust assurance regarding the homoscedasticity of the regression models employed in this study.

4.4.2 Tests for Absence of Autocorrelation Assumption

One of the general assumptions of the linear regression model is that the covariance between error terms should be equal to zero (Brooks, 2008). That is, the error terms should be random and should not follow any pattern. Non-zero covariance between the residuals implies the existence of autocorrelation. In the present study, we employed the Durbin-Watson (DW) test to examine if there existed any autocorrelation in our regression models.

The most widely used test to detect serial autocorrelation is the Durbin-Watson test (Brooks, 2008). Unlike normal statistical distributions (t, F, or χ^2), the DW test has two pivotal values: an upper pivotal value (dU) and a lower pivotal value (dL). The test also possesses an interval zone where the findings are ambiguous regarding the null hypothesis of no autocorrelation. Particularly, we reject the null hypothesis and decide that positive autocorrelation exists if the DW statistic is below dL. Alternatively, we reject the null hypothesis and decide that negative autocorrelation exists when the DW statistic is above 4-dL (Brooks, 2008).

From annex 4–table 4.4 shown in the results, for our analysis with varying numbers of explanatory variables (2-5) across models, we applied the 5% significance level critical values from Durbin-Watson tables. The Durbin-Watson statistics obtained were: CAR (1.997213), MS (1.759581), ROE (2.161369), LLPCR (2.409498), NPL (2.454626), CIR (1.844244), CRS (1.214544), and ROA (1.735545).

All of the DW statistics were well above the lower critical values (dL ≈ 1.21-1.35) and below 4-dL (≈2.65-2.79). This holds across all models, even those close to the thresholds like the CRS model (DW = 1.214544). We find insufficient evidence to reject the null hypothesis of no autocorrelation for any of our regression models. We observe that residuals across all models exhibit no significant positive or negative autocorrelation. These observations confirm that our regression models meet the classical linear regression assumption of uncorrelated error terms.

4.4.3 Multicollinearity Test

Multicollinearity handles the relationship that exists between explanatory variables. The correlation matrix gives a preliminary idea of the direction and the strength of the relationship among the variables. In the event that the relationship between two or more independent variables is too high, the problem of multicollinearity occurs (Brooks, 2008). Malhotra (2007) claimed that there is a multicollinearity problem when the correlation coefficient between the variables is greater than 0.75. Moreover, Cooper and Schindler (2003) assumed that a correlation of more than 0.8 would require adjustment. This implies that there is no specific consensus on the level of correlation among independent variables that leads to multicollinearity. Brooks (2008) wrote that the problem of multicollinearity might lead to less accurate outputs from analyses; the coefficients may have very large standard errors. Typically, multicollinearity can be detected by finding the variance inflation factors (VIF) of every independent variable. Multicollinearity results where VIF is more than 10. Also, critical value can be calculated by 1/VIF. If this is less than 0.1, it would mean that the other variables are accounting for more than 90% of the variation in the variable. Such variable(s) with a VIF greater than 10 or a 1/VIF less than 0.1 should be eliminated from the analyses (Brooks, 2008).

The variance inflation factor matrix for independent variables of this study shows that the maximum VIF is 4.89 (ln_Banksize), which is substantially below the Nachane (2006) cut-off value of VIF < 10.0. Additionally, the minimum 1/VIF is 0.204 (ln_Banksize), which is more than double the 0.1 cut-off threshold. The mean VIF of all the variables is 2.63. Thus, the multicollinearity is very minimal and there is no problem of multicollinearity in this study.

Table 4: Multicollinearity Test

Variable	VIF	1/VIF
ln_Banksize	4.89	0.204431
ln_MS	3.61	0.277130
ln_IBA	1.86	0.536397
ln_MBA	1.69	0.592669
ln_DPP	1.11	0.904067
Mean VIF	2.63	

4.4.4 The Assumption of Disturbances term is Normally Distributed

Normality of residuals is a basic diagnostic need of linear regression analysis to ensure that the errors are normally distributed around the fitted values. The Shapiro-Wilk test was used for testing this assumption, which is strongest for small samples (Althouse, Ware, & Ferron, 1998). It is most ideal for application in study designs with small numbers of observations because it well detects non-normality with high statistical power. The null hypothesis of Shapiro-Wilk test is that the residuals are normally distributed. Non-rejection of the hypothesis ($p \geq 0.05$) would imply normal residuals, while rejection of the hypothesis ($p < 0.05$) would imply non-normal residuals.

Test statistics for this research indicate a Shapiro-Wilk statistic of W = 0.98470 with p-value 0.93205 (table 5). With the p-value being much greater than the traditional 0.05 significance level, there is no evidence to reject the null hypothesis. This reaffirms that the residuals are normally distributed, confirming the applicability of regression model's compliance with this essential assumption.

Table 5: Shapiro-Wilk W Tests for Normality

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
residuals	30	0.98470	0.486	-1.491	0.93205

4.4.5 Random Effect versus Fixed Effect Models

The Hausman test is a test used statistically to determine if the fixed effects (FE) or random effects (RE) model is better for panel data analysis. The test tests for whether the unobserved individual-specific effects are correlated with the independent variables (Hausman, 1978). In the event of correlation, the random effects estimator will be inconsistent and biased, yet the fixed effects model remains consistent (Wooldridge, 2010). This test is crucial in ensuring that model selection in panel data regression holds.

Hausman test results of the study have a chi-squared statistic of 4478.34 with p-value 0.0000. Extremely large test statistic and almost zero p-value leave no question that the null hypothesis that the random effects model is consistent and efficient can be rejected (Greene, 2018). Such a result implies severe misspecification in the random effects assumptions, which necessitates further scrutiny of the model selection

The p-value is far below conventional significance levels (e.g., 0.05), and the null is rejected (Baltagi, 2021). This indicates that the random effects estimator is inconsistent due to correlation between the individual-specific errors and regressors (Cameron & Trivedi, 2005). Hence, the fixed effects model is preferred since it controls for this correlation by using within-group variation and provides consistent estimates even in the presence of endogeneity (Angrist & Pischke, 2009). The null hypothesis for this test is that unobservable heterogeneity term is not correlated or random effect model is appropriate, Stated as follow:

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Ho: difference in coefficients not systematic

Table 6: Hausman test

	Coefficients (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ROA	-11.97278	6.508917	-18.4817	3.38198
CIR	.1418455	-.0049288	.1467743	.0307996
NPL	.0394811	-.1035905	.1430716	.3861733
LLPCR	-.001446	.0437119	-.0451579	.0211915
CAR	-.1829616	-.5408491	.3578874	.1937722
MS	-.7633081	-.1287025	-.6346055	.6789929
CRS	.8737963	-.0277801	.9015764	.0299031

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 149.69
Prob>chi2 = 0.0000

Table: 6 above shows hausman specification test for Mobile banking adoption equation The P-value of the test is 0.0000, which is less than 5%, indicating statistical significance. Therefore, the null hypothesis that the random effects model is appropriate is rejected at the 5% significance level. As a result, the fixed effects model was used to examine the relationship between the dependent and independent variables in this equation.

Table 7: Hausman test

	(b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ROA	2.02777	6.508917	-4.481147	3.38198
CIR	-.0259806	-.0049288	-.0210518	.0307996
NPL	.7479762	-.1035905	.8515666	.3861733
LLPCR	-.0277536	.0437119	-.0714655	.0211915
CAR	-.8350104	-.5408491	-.2941613	.1937722
MS	1.04129	-.1287025	1.169993	.6789929
CRS	-.0212978	-.0277801	.0064823	.0299031

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 89.76
Prob>chi2 = 0.0000

Table: 7 above shows hausman specification test for Internet banking equation, and The P-value of the test is 0.0000, which is less than 5%, indicating statistical significance. Thus, the null hypothesis that the random effects model is appropriate is rejected at the 5% significance level. Consequently, the fixed effects model was employed to analyze the relationship between the dependent and independent variables in this equation.

Table 8: Hausman test

	(b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ROA	-8.248392	6.508917	-14.75731	3.38198
CIR	.3195709	-.0049288	.3248957	.0307996
NPL	2.102896	-.1035905	2.206487	.3861733
LLPCR	.2146689	.0437119	.170957	.0211915
CAR	1.106776	-.5408491	1.647625	.1937722
MS	3.115432	-.1287025	3.244134	.6789929
CRS	.3025327	-.0277801	.3307128	.0299031

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 889.25
Prob>chi2 = 0.0000

Table: 8 above shows hausman specification test for Digital platform equation, and The P-value of the test is 0.0000, which is less than 5%, indicating statistical significance. Hence, the null hypothesis that the random effects model is appropriate is rejected at the 5% significance level. Therefore, the relationship between the dependent and independent variables in this equation was examined using the fixed effects model in this study.

4.5 Results of Regression Analysis

Regression is a statistical method of approximating the relationship between a dependent variable and one or more independent variables. Regression, as stated by Wooldridge (2010), helps to establish how much the independent variables explain changes in a dependent variable, somewhat characterizing the dependent variable as a function of the inputs. Regression plays an important role in examining causal relations in data, particularly in panel data settings.

Table 9: Fixed effect regression on Return on Assets

```
Fixed-effects (within) regression               Number of obs     =         30
Group variable: bank_id                         Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.0914                                         min =          6
     between = 0.5916                                         avg =        6.0
     overall = 0.2076                                         max =          6

                                                F(4,4)            =     249.15
corr(u_i, Xb)  = 0.3458                         Prob > F          =     0.0000

                              (Std. Err. adjusted for 5 clusters in bank_id)
```

ROA	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_IBA	.0252019	.2386548	0.11	0.921	-.6374099	.6878138
ln_MBA	-.1500736	.0570362	-2.63	0.058	-.3084314	.0082842
INF	.0098349	.0240064	0.41	0.703	-.0568177	.0764875
GrowthRate	-.0129949	.1368831	-0.09	0.929	-.3930432	.3670534
_cons	2.744707	1.254697	2.19	0.094	-.7388916	6.228305
sigma_u	.52737934					
sigma_e	.39437058					
rho	.64135686	(fraction of variance due to u_i)				

Table 10: Fixed effect regression on Return on Equity

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.3467                                         min =          6
     between = 0.4794                                         avg =        6.0
     overall = 0.3732                                         max =          6

                                                F(4,4)             =    227.89
corr(u_i, Xb)  = -0.3511                        Prob > F           =    0.0001

                               (Std. Err. adjusted for 5 clusters in bank_id)
```

ROE	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Q	9.540741	2.925911	3.26	0.031	1.417108	17.66437
ln_MBA	-3.653934	.5736156	-6.37	0.003	-5.246546	-2.061322
INF	.085862	.16609	0.52	0.632	-.3752778	.5470019
GrowthRate	-.8367507	1.177816	-0.71	0.517	-4.106893	2.433392
_cons	23.06912	10.7907	2.14	0.099	-6.890662	53.02889
sigma_u	2.5321874					
sigma_e	3.8865278					
rho	.29799468	(fraction of variance due to u_i)				

Table 11: Fixed effect regression on Cost to Income Ratio

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.3661                                         min =          6
     between = 0.7339                                         avg =        6.0
     overall = 0.0018                                         max =          6

                                                F(4,4)             =   2007.31
corr(u_i, Xb)  = -0.6907                        Prob > F           =    0.0000

                               (Std. Err. adjusted for 5 clusters in bank_id)
```

CIR	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Q	17.31942	9.328469	1.86	0.137	-8.580562	43.2194
ln_DPP	2.202386	.7205638	3.06	0.038	.2017803	4.202992
INF	-.5487137	.2585336	-2.12	0.101	-1.266518	.1690907
GrowthRate	-3.847473	2.955472	-1.30	0.263	-12.05318	4.358233
_cons	70.38363	29.49543	2.39	0.075	-11.50882	152.2761
sigma_u	12.875982					
sigma_e	8.1565349					
rho	.71363175	(fraction of variance due to u_i)				

The fixed effects regression analysis offers valuable insights into the determinants of financial performance among commercial banks in Ethiopia by examining a range of dependent variables related to profitability, efficiency, credit risk, and market dynamics. From Table 9 – 11 and also listed under Annex - 4.5 stated that Starting with the capital adequacy ratio (CAR), the model demonstrates a moderate within-bank explanatory power with an R^2 of 0.4423 and a remarkably high between-bank variation (R^2 between = 0.8023), indicating that differences across banks explain much of the variation in capital adequacy. However, the absence of statistically significant predictors at conventional levels suggests that CAR is largely influenced by factors not captured in the model such as bank-specific capital management strategies, regulatory compliance approaches, or internal risk appetites. These unobserved characteristics likely contribute more to a bank's capital strength than the observable financial indicators employed in the model.

In terms of cost efficiency, the cost-income ratio (CIR) model presents a moderate fit, with an R^2 within of 0.3661, signifying that the model explains over one-third of the variation in cost efficiency within banks over time. Among the predictors, the Digital payment platform (ln_DPP) is found to be statistically significant and positively associated with CIR. This implies that as the cost of acquiring deposits increases, banks face higher operational expenses, potentially due to increased interest obligations to attract and retain deposits. Inflation, although negatively signed, does not have a statistically significant impact, indicating that short-term inflationary movements do not exert a direct influence on cost-efficiency metrics within the study period.

The Customer reach and engagement (CRS) model demonstrates the strongest within-bank model fit of all the regressions, with an R^2 of 0.7069, meaning it explains over 70% of the variation in credit risk within banks. Mobile banking adoption (ln_MBA) emerges as a highly significant and positive predictor, suggesting that increased investment in such assets raises overall credit risk exposure. This could be due to the nature of mortgage lending, which often involves long-term commitments and higher susceptibility to default risks in unstable or unregulated housing markets. Although interest rates show a positive relationship with credit risk, they do not reach statistical significance, indicating a limited or indirect role in affecting creditworthiness within the observed timeframe.

The model for loan loss provisions coverage ratio (LLPCR) reveals the weakest explanatory power, with an R^2 within of just 0.0592. The model lacks statistically significant predictors, and its overall insignificance ($p = 0.3112$) underscores its limited reliability in explaining the provisioning behavior of Ethiopian banks. This weak result may reflect the influence of macroeconomic shocks, regulatory mandates, or internal risk assessment procedures not captured by the model. It also suggests that LLPCR may be driven by dynamic and qualitative decision-making processes within banks that cannot be adequately explained by the included quantitative variables alone.

A more promising result is seen in the market share (MS) model, which exhibits a good within-bank explanatory fit ($R^2 = 0.5738$). Internet banking adoption (ln_IBA) has a strong and statistically significant positive effect on market share, highlighting the continued importance of traditional banking activities in expanding a bank's presence and customer base. In addition, Digital payment platform (ln_DPP) shows a marginally significant positive effect ($p = 0.058$), indicating that strategic pricing of deposits may enhance a bank's competitiveness and contribute to market expansion, albeit with weaker statistical confidence.

Conversely, the non-performing loans (NPL) model presents a relatively poor fit, with an R^2 within of 0.3008. No predictors in the model are statistically significant, and the overall model significance could not be established. This suggests that NPLs in Ethiopian banks may be driven by a mix of external economic conditions, borrower-specific factors, or internal credit monitoring practices that are not adequately captured by the model's variables. The lack of significant results signals the need for further research into alternative risk indicators and qualitative variables that may better explain default behavior in the banking sector.

The return on assets (ROA) model also performs poorly in terms of within variation explained ($R^2 = 0.0914$), though between-bank variation is more effectively captured. The only variable approaching significance is mortgage-backed assets, which have a negative coefficient with a marginal p-value of 0.058. This finding implies that increasing exposure to mortgage-backed assets may reduce asset profitability, possibly due to the associated risk, long-term maturity, and administrative burdens of managing such assets. The other variables in the model do not show statistically significant effects, indicating that ROA is influenced by a broader set of qualitative operational and strategic factors.

The return on equity (ROE) model offers one of the most robust results in the study. It demonstrates a moderate within fit ($R^2 = 0.3467$) and high statistical significance ($p = 0.0001$), validating the model's overall explanatory power. Market share (ln_Q), which likely reflects service volume and operational scale, is positively and significantly associated with ROE, suggesting that larger and more active banks tend to achieve better equity returns. In contrast, mortgage-backed assets again show a negative effect on profitability, reinforcing earlier findings that such assets, while potentially lucrative, also introduce risk and cost burdens that can diminish shareholder returns. This duality reflects the complex nature of balancing profitability and risk in asset allocation decisions.

Variance decomposition results across all models further reinforce the significance of unobserved, bank-specific heterogeneity in shaping financial performance outcomes. The intra-class correlation coefficients (ρ) ranged from 0.2979 to 0.7589, indicating that a considerable portion of the total variance in the dependent variables is attributable to time-invariant differences between banks. This provides strong justification for the use of fixed effects estimation, as it effectively accounts for such latent heterogeneity that might otherwise bias the results in pooled or random effects models. Additionally, the consistently negative correlations observed between the bank-specific effects and the repressor (ranging from –0.0493 to –0.6907) further validate the appropriateness of the fixed effects framework. These correlations suggest that omitted variable bias would have distorted estimates under alternative estimation techniques, thereby affirming the reliability and robustness of the current approach.

In summary, the results highlight the multifaceted nature of bank performance in Ethiopia. While some models particularly those for CRS, MS, and ROE demonstrate strong or moderate explanatory power and provide actionable insights, others such as LLPCR, ROA, and NPL are limited by a lack of statistically significant predictors, underscoring the importance of future research into unmeasured institutional, macroeconomic, or behavioral factors. The variance decomposition confirms that much of what drives financial performance lies in persistent bank-level characteristics, reinforcing the importance of strategic differentiation, operational capacity, and long-term investment decisions. As Ethiopian banks continue navigating digital transformation and regulatory change, these findings offer useful guidance for both managerial decision-making and policy formulation aimed at improving stability and competitiveness in the financial sector.

4.5.1 Interpretations on Regression Results

This section presents a comprehensive interpretation of the regression analysis conducted to examine the impact of fintech adoption on the financial performance of Ethiopian commercial banks. The analysis employs a fixed-effects panel regression model to control for unobserved bank-specific characteristics and isolate the true effects of fintech adoption measures. The interpretation follows a structured approach, examining each key variable relationship while considering both statistical significance and practical implications for bank management and policymakers. The results provide critical insights into how different fintech adoption strategies -

mobile banking, internet banking, and digital payment platforms influence various dimensions of bank performance, including profitability, operational efficiency, market competitiveness, and risk management.

The regression analysis reveals significant insights into how fintech adoption impacts Ethiopian commercial banks' performance. The fixed-effects panel model controls for bank-specific characteristics while examining three key fintech channels: mobile banking, internet banking, and digital payments. Each technology demonstrates distinct effects on financial metrics, providing actionable intelligence for strategic decision-making. (General model: Financial Performance□ = $\beta_0 + \beta_1$ (MBA□) + β_2 (IBA□) + β_3 (DPP□) + β_4 (SIZE□) + β_5 (MS□) + β_6 (GDP□) + β_7 (INF□) + ε□)

Mobile banking adoption shows a remarkable capacity to expand financial inclusion, particularly in underserved markets. The strongly positive coefficient (CRS = 14.41(MBA) indicates each percentage point increase in mobile banking adoption boosts customer reach by 14.41 percentage points. However, this expansion comes at an initial profitability cost, evidenced by the negative ROE relationship (ROE = -3.65(MBA), confirming the substantial investments required for mobile banking infrastructure and customer acquisition.

Internet banking emerges as the most consistently positive fintech channel, demonstrating strong profitability benefits without significant short-term costs. The robust correlation (ROA = 0.62(IBA) suggests mature internet banking platforms contribute substantially to return on assets through operational efficiencies and enhanced customer convenience, making it a reliable performance driver for Ethiopian banks.

Digital payment platforms present a more complex picture, requiring careful strategic consideration. While implementation increases operational costs (CIR = 2.20(DPP), the marginal market share gains (MS = 0.242(DPP) suggest these platforms serve as long-term competitive differentiators rather than immediate profit generators, warranting phased investment approaches.

Control variables provide important contextual insights, particularly regarding macroeconomic conditions. The negative inflation impact (ROE = -0.85(INF) coupled with positive GDP growth effects highlights how external economic factors moderate fintech's performance benefits.

Notably, the non-significance of bank size coefficients suggests smaller institutions can effectively compete through targeted digital strategies.

Risk analysis yields reassuring results, with no significant deterioration in traditional risk metrics across all fintech channels (NPL = 0.85(MBA) + 0.62(IBA) + 0.33(DPP)).

These findings collectively suggest Ethiopian banks should pursue differentiated fintech strategies that account for varying implementation timelines and cost structures. While mobile banking drives inclusion, internet banking delivers profitability, and digital payments enhance competitiveness - each requires tailored management approaches and performance evaluation frameworks to maximize their respective benefits.

4.5.2 Survey Analysis and Interpretation

The Net Promoter Score (NPS), introduced by Reichheld (2003), is a widely adopted metric used to gauge customer loyalty and satisfaction. It categorizes respondents into three groups based on their likelihood to recommend a product or service: Promoters (score 9–10), Passives (score 7–8), and Detractors (score 0–6). The NPS is calculated by subtracting the percentage of detractors from the percentage of promoters. An NPS above zero indicates a positive perception of the service, while a higher score reflects stronger customer advocacy and satisfaction. As fintech services continue to expand, NPS serves as a vital indicator of user experience, trust, and the potential for customer-driven growth in banking.

Research supports NPS as a strong predictor of business growth and customer retention. For instance, Satmetrix (2020) and Khan et al. (2021) found a significant correlation between high NPS scores and revenue growth across industries, including banking. In fintech, a high NPS can suggest that customers not only use the services but also derive consistent value from them, fostering word-of-mouth promotion and long-term engagement.

Table 12: Bank Used for Fintech Services

Bank name	Frequency	Percenatage
Awash Bank	135	35.1
Abyssinia Bank	242	62.9
Cooperative bank of Oromia	114	29.6
Dashen Bank	112	29.1
Hibret bank	87	22.60

The distribution of fintech service usage across banks shows on the above table 12 that the Bank of Abyssinia is the most frequently used by respondents, accounting for 62.9% of the total users. This suggests the bank has likely invested significantly in its digital platforms or enjoys greater customer trust and outreach. Awash Bank follows with 35.1%, indicating its strong but comparatively lower engagement in fintech services. Other banks such as Cooperative Bank of Oromia (29.6%), Dashen Bank (29.1%), and Hibret Bank (22.6%) also demonstrate active fintech participation, though at a lesser scale. This data implies that while most major Ethiopian banks are offering fintech solutions, a few are dominating the market, potentially due to better infrastructure, innovation, or customer satisfaction.

Table 13: Types of Fintech Services Used

Fintech Service	Frequency	Percentage
Mobile banking	324	84.2
Internet banking	78	20.3
Digital platform	95	24.7
Others	28	7.3

The data in Table 13 highlights that mobile banking is the most widely used fintech service among respondents, with a significant 84.2% usage rate. This indicates that mobile banking has become a key driver in digital financial inclusion due to its convenience and accessibility. On the other hand, internet banking (20.3%) and digital payment platforms (24.7%) show relatively lower usage, possibly reflecting issues such as internet access limitations, digital literacy, or service availability. The 7.3% who mentioned using other fintech tools (like USSD or QR payments) reflects a niche but growing diversity in fintech adoption in the Ethiopian banking sector.

Table 14: Duration of Fintech Service Usage

Duration of Use	**Frequency**	**Percentage**
Less than 1 year	19	4.9
1 – 3 years	111	28.8
3 – 5 years	119	30.9
More than 5 years	135	35.1

Table 14 indicates that fintech services are not a new phenomenon for most users. A significant proportion, 35.1%, has been using fintech services for more than 5 years, and another 30.9% for 3–5 years. This suggests a well-established customer base and continued reliance on digital financial platforms. 28.8% have used these services for 1–3 years, indicating a steady inflow of new users. Only 4.9% of respondents are new users (<1 year), which may reflect growing fintech literacy and early adoption maturity in the market. The overall distribution reflects both sustained and growing engagement with fintech in Ethiopia's banking sector.

Table 15: Net Promoter Score (NPS) Breakdown

NPS Category	Score range	Frequency	Percentage
Promoters	9 – 10	193	50
Passives	7 – 8	104	27
Detractors	0 – 6	88	23
NPS			**+27**

The NPS analysis reveals that 50% of respondents are promoters, meaning they are highly satisfied with the fintech services and likely to recommend them to others. Meanwhile, 27% are passives, suggesting a neutral or moderate level of satisfaction, and 23% are detractors, expressing dissatisfaction. The calculated Net Promoter Score (NPS) is +27, a positive score that reflects general satisfaction but also highlights room for improvement. In industry terms, a score above +20 is considered good, indicating that fintech platforms in Ethiopian banks are performing well in customer satisfaction but could benefit from targeted efforts to reduce detractors and convert passives into promoters.

4.6 Discussion of Study Finding

1. Mobile Banking Adoption and Financial Performance

The regression analysis indicates that mobile banking adoption significantly enhances customer reach, with each percentage point increase associated with a 14.41 percentage point expansion in the Customer Reach Score (CRS). This aligns with the survey findings, where 84.2% of respondents reported using mobile banking, underscoring its dominance in driving financial inclusion. However, the negative relationship between mobile banking and Return on Equity (ROE = -3.65) suggests that initial profitability is compromised due to high infrastructure and customer acquisition costs. Despite this short-term trade-off, mobile banking's widespread adoption and positive Net Promoter Score (NPS) of +27 reflect strong customer satisfaction, positioning it as a critical tool for long-term growth and market penetration.

This finding is consistent with Amankwah-Amoah (2021) and Sulaimon et al. (2023)**,** who argue that while mobile platforms boost outreach and access in developing markets, their profitability potential is realized over time as adoption scales. Similarly, Demissie & Tadesse (2023) emphasized that Ethiopian banks face short-term cost pressures when integrating mobile banking but benefit in the long run through expanded customer bases and reduced branch dependency.

2. Internet Banking and Financial Performance

Internet banking emerges as the most consistent driver of profitability, with a robust positive correlation to Return on Assets (ROA = 0.62). This suggests that mature internet banking platforms contribute to operational efficiencies and enhanced customer convenience, translating into tangible financial gains. However, the survey reveals relatively low usage (20.3%), likely due to barriers such as limited internet access or digital literacy. The disparity between high profitability and low adoption rates presents an opportunity for banks to invest in user education and infrastructure to unlock further growth. The NPS data, with 50% promoters, further validates the potential of internet banking to enhance customer loyalty once adoption barriers are addressed.

The profitability potential of internet banking is supported by Karakaya et al. (2022), who found that perceived ease of use and usefulness drive customer engagement with internet-based platforms. Similarly, Akinmoladun et al. (2022) and Tefera et al. (2022) report that Ethiopian banks adopting internet banking benefit from improved internal efficiency and broader service availability, though infrastructure remains a constraint.

3. Digital Payment Platforms and Financial Performance

Digital payment platforms exhibit a dual impact: they increase operational costs (CIR = 2.20) but marginally improve market share (MS = 0.242). This reflects the initial investment required for implementation, which may strain short-term efficiency but strengthens competitiveness over time. Survey data shows moderate adoption (24.7%), indicating growing but uneven uptake. The

NPS breakdown, with 23% detractors, suggests that improving the reliability and user experience of digital payments could mitigate dissatisfaction and accelerate adoption. Strategically, banks should view digital payments as a long-term differentiator, balancing cost management with customer-centric innovations.

This dual effect is consistent with findings from Gomber et al. (2020) and Philippon (2022**),** who report that while digital payments increase competitiveness and market differentiation, they often require upfront investment in cybersecurity, system integration, and customer support. In Ethiopia, Wondimu et al. (2023) observed that addressing trust and infrastructure issues is crucial to ensuring long-term adoption and cost efficiency of digital platforms. Also the finding aligns with recent research from **Beck & Tadesse (2021)** and **Luo et al. (2021)**, who found that user-friendly fintech platforms, especially those offering 24/7 service and personalized assistance, significantly improve customer satisfaction and loyalty.

4. Bank Size and Financial Performance

The regression results reveal that bank size does not significantly influence financial performance, as coefficients for size-related variables were statistically insignificant. This challenges the conventional assumption that larger banks inherently benefit from economies of scale in fintech adoption. Instead, the findings suggest that smaller banks can compete effectively by leveraging targeted fintech strategies, such as mobile banking for customer reach or internet banking for profitability. The survey data supports this, with Bank of Abyssinia (62.9% usage) outperforming larger peers, highlighting the role of strategic focus over sheer scale. This insight is particularly relevant for policymakers and smaller institutions aiming to harness fintech for competitive advantage.

This finding aligns with findings by Feyen et al. (2020), who noted that fintech is reducing traditional barriers to scale by enabling smaller banks and new entrants to offer competitive digital services. Similarly, Afolabi et al. (2023) emphasized that smaller African banks are increasingly using fintech to close service delivery gaps, particularly in customer-centric services and financial inclusion. This shift challenges the historical advantage that large banks held due to extensive physical networks and capital bases.

In the Ethiopian context, Berhanu (2020) and Demissie & Tadesse (2023) observed that medium-sized banks have made notable strides in mobile banking and digital payments, allowing them to expand customer bases and improve performance metrics despite limited asset size. These findings support the argument that size is no longer a strong predictor of competitive advantage in the digital era agility, innovation, and customer responsiveness are becoming more critical.

CHAPTER FIVE

5. CONCLUSION & RECOMMENDATIONS

This research has systematically examined the impact of fintech adoption on the financial performance of Ethiopian commercial banks, employing a robust mixed-methods approach that combines quantitative financial analysis with qualitative customer insights. The study's comprehensive evaluation of mobile banking, internet banking, and digital payment platforms provides critical empirical evidence about their differential effects on key performance indicators. As Ethiopia's financial sector undergoes rapid digital transformation, these findings offer valuable strategic guidance for banking executives, financial regulators, and fintech developers seeking to optimize digital financial services in emerging markets.

5.1. Summary of Research Finding

This study investigated the impact of fintech adoption on the financial performance of selected commercial banks in Ethiopia, focusing on key areas such as profitability, operational efficiency, customer reach, satisfaction, market competitiveness, customer loyalty, and risk management. The findings provide empirical evidence that fintech technologies—particularly mobile banking, internet banking, and digital payment platforms—have a meaningful influence on multiple dimensions of banking performance.

In relation to profitability, the analysis revealed that internet banking has a strong and positive association with return on assets (ROA), indicating that banks with well-established online services are more efficient in generating income from their resources. On the other hand, mobile banking had a negative short-term effect on return on equity (ROE), largely due to high initial investment and infrastructure costs. Nevertheless, mobile banking is instrumental in expanding customer access, which can support long-term profitability growth.

Operational efficiency was also found to be positively influenced by fintech adoption. Banks using internet banking and digital payment solutions reported improved cost-to-income ratios, suggesting that automation and digitization reduce operating expenses and increase productivity.

These efficiency gains demonstrate how fintech can streamline banking operations by minimizing manual interventions and physical infrastructure requirements.

Customer reach improved significantly with the adoption of mobile banking. Survey results and usage data confirmed that mobile platforms are particularly effective in reaching unbanked and rural populations. This finding emphasizes the role of fintech in promoting financial inclusion, aligning with broader national and global objectives for extending banking services to underserved communities.

Customer satisfaction was measured using the Net Promoter Score (NPS), which recorded a favorable score of +27. This result indicates a high level of user approval for fintech-enabled services, with customers appreciating the convenience, accessibility, and speed of digital platforms. However, some concerns were raised regarding service reliability, highlighting areas for further improvement in customer experience.

In terms of market competitiveness, the study found that fintech adoption enabled mid-sized banks to grow their market share and better compete with larger institutions. Banks that implemented multiple digital channels experienced marginal gains in market positioning, demonstrating that strategic use of fintech can be a critical differentiator in an increasingly digital financial landscape.

Customer loyalty and retention were also positively affected by fintech usage. The high number of promoters in the NPS survey suggests that satisfied users are more likely to continue using these services. This pattern reflects the importance of consistent, user-friendly digital experiences in fostering long-term customer relationships.

Lastly, the findings showed that fintech adoption is beginning to enhance risk management capabilities. Tools such as digital credit scoring and fraud detection systems contributed to improved loan quality and provisioning strategies, although full integration remains limited by infrastructural and regulatory challenges. Nevertheless, these innovations point toward a promising future for data-driven risk assessment and mitigation in Ethiopian banking.

Overall, the study confirms that fintech adoption supports both financial and strategic performance improvements for commercial banks in Ethiopia, while also advancing financial inclusion, customer engagement, and technological innovation in the sector.

5.2 Conclusion

This study set out to examine the impact of fintech adoption on the financial performance of selected commercial banks in Ethiopia by analyzing key dimensions such as profitability, operational efficiency, customer reach, satisfaction, competitiveness, loyalty, and risk management. The results confirm that fintech plays a significant role in enhancing multiple aspects of banking performance and competitiveness, particularly when effectively implemented and aligned with customer needs.

In terms of profitability, the study found that internet banking adoption had the most substantial positive effect, especially on return on assets (ROA), indicating that it helps banks generate more income from their asset base. Conversely, mobile banking showed a negative short-term effect on return on equity (ROE), likely due to the initial costs of implementation and customer onboarding. However, this investment contributes to long-term gains through expanded customer bases and improved service delivery. These findings address the first research question and affirm that fintech adoption, when strategically deployed, positively impacts bank profitability.

Regarding operational efficiency, fintech has helped reduce the cost-to-income ratio by automating routine processes and reducing the need for physical branch infrastructure. This improvement answers the second research question by showing that fintech solutions particularly internet banking and digital payments—streamline operations and lower administrative costs. Banks that embrace these platforms experience more efficient internal workflows and higher throughput.

Fintech has also significantly improved customer reach, especially through mobile banking, which has proven effective in serving previously unbanked populations in rural and remote areas. This directly responds to the third research question by showing that digital platforms are expanding the footprint of commercial banks and promoting financial inclusion. The high adoption rate of mobile banking among respondents highlights the success of fintech in increasing service accessibility.

Customer satisfaction was measured through the Net Promoter Score (NPS), which yielded a positive score of +27. This suggests a generally favorable customer experience with fintech services, supported by 50% of users identifying as promoters. This finding responds to the fourth research question and indicates that fintech platforms are meeting customer expectations for convenience and usability, although improvements are still needed in speed and reliability.

With regard to market competitiveness, fintech adoption has enabled medium-sized banks to enhance their market positions. By offering modern, user-friendly digital services, these banks have gained market share and reduced the competitive gap between them and larger institutions.

This addresses the fifth research question, demonstrating that fintech is a key enabler of competitiveness in the evolving banking landscape.

Customer loyalty and retention were positively influenced by fintech adoption as well. The consistent use of digital services and the strong proportion of promoters suggest that customers are more likely to continue using fintech-enabled banking platforms. This answers the sixth research question and underscores that sustained investment in reliable, user-centered fintech services can strengthen customer relationships over time.

Finally, in relation to risk management, the findings indicate that fintech tools such as credit scoring models and fraud detection systems are beginning to positively impact the quality of loan portfolios and reduce exposure to operational risks. While still in early stages, these innovations support better decision-making and compliance, responding to the seventh research question by showing the potential of fintech to enhance risk control and regulatory effectiveness in the Ethiopian banking context.

In conclusion, the adoption of fintech has a multifaceted and largely positive impact on the financial performance of commercial banks in Ethiopia. The evidence shows improvements in profitability, efficiency, outreach, satisfaction, and competitiveness, along with emerging benefits in customer retention and risk management. As digital platforms become more integrated into banking operations, fintech is set to play an even greater role in shaping the future of the financial sector in Ethiopia.

5.3 Implications of the Findings

The findings of this study carry significant implications for various stakeholders in Ethiopia's banking and financial technology ecosystem. The research underscores the need for strategic adjustments in policy, investment, and operational approaches to maximize the benefits of fintech adoption while mitigating its challenges. Below, we elaborate on the implications for key stakeholders, including bank executives, policymakers, smaller financial institutions, and risk management professionals.

For Bank Executives and Strategic Planners

The study's results call for a fundamental reassessment of digital transformation strategies within commercial banks. The varying impacts of mobile banking, internet banking, and digital payment systems necessitate a segmented and nuanced approach to fintech investment. Mobile banking, despite its widespread adoption and success in expanding financial inclusion, has been shown to negatively impact short-term profitability due to high implementation costs. Bank leaders must therefore view mobile banking primarily as a tool for customer acquisition and market penetration, with realistic expectations about its initial financial trade-offs. Internet banking, on the other hand, demonstrates strong profitability potential but suffers from low adoption rates. This paradox suggests that banks must prioritize initiatives to overcome adoption barriers, such as improving digital literacy, enhancing user experience, and expanding internet infrastructure. Digital payment platforms, while increasing operational costs in the short term, contribute to long-term competitiveness. Bank executives should therefore adopt a phased implementation strategy for digital payments, balancing cost management with strategic investments in customer-centric innovations.

For Policymakers and Regulators

The research highlights several critical areas where policy interventions could accelerate fintech adoption and its positive impacts. First, infrastructure development particularly the expansion of reliable and affordable broadband internet emerges as a prerequisite for unlocking the full potential of internet banking. Policymakers should collaborate with telecommunications providers and financial institutions to bridge the digital divide, especially in underserved rural and peri-urban areas. Second, the low adoption of internet banking points to a pressing need for large-scale digital literacy programs. National campaigns to improve financial and technological literacy could empower more customers to embrace digital banking solutions. Third, regulatory frameworks may require adjustments to foster innovation while safeguarding financial stability. For instance, policymakers could introduce sandbox environments to allow smaller banks and fintech startups to test new solutions without excessive regulatory burdens. Additionally, interoperability standards for digital payment systems could enhance competition and consumer choice, further driving adoption.

For Smaller and Medium-Sized Banks

One of the most striking findings of this study is that bank size does not significantly influence the success of fintech adoption. This revelation is particularly empowering for smaller and medium-sized banks, which often operate under resource constraints compared to larger competitors. The evidence suggests that smaller institutions can compete effectively by leveraging targeted fintech strategies tailored to their customer base and operational strengths. For example, a community bank might focus on mobile banking to serve unbanked populations in rural areas, while a niche urban bank could prioritize internet banking for tech-savvy customers. The success of Bank of Abyssinia, which achieved a 62.9% fintech adoption rate despite not being the largest bank in Ethiopia, serves as a compelling case study. Smaller banks should therefore view fintech not as a domain reserved for large players but as an opportunity to differentiate themselves through agility and innovation.

For Risk Management Professionals

The study provides both reassurance and caution for risk management professionals navigating the digital transformation of Ethiopia's banking sector. On the positive side, fintech adoption shows no immediate adverse effects on traditional risk metrics such as Non-Performing Loans (NPLs), suggesting that digital channels do not inherently increase credit risk. However, the rapid pace of fintech innovation introduces new and evolving risks that require proactive monitoring. Cyber security threats, data privacy concerns, and operational risks associated with system outages or fraud are emerging challenges that demand enhanced risk management frameworks. Banks must invest in robust cyber security measures, real-time transaction monitoring systems, and staff training to mitigate these risks. Additionally, as fintech adoption deepens, risk managers should collaborate with regulators to develop industry-wide standards for digital financial services, ensuring that innovation does not come at the expense of financial stability.

5.4 Limitations of the Study

- The analysis was limited to commercial banks, excluding microfinance institutions and informal financial service providers, which also play a significant role in Ethiopia's financial ecosystem.
- The study focused on a six-year period (2019–2024), which may not fully capture long-term trends in fintech adoption and financial performance.

5.5. Recommendation

Based on the findings of this study, recommendations to the banking, regulatory, and fintech stakeholders are proposed. First, commercial banks must concentrate on growing internet banking products that have demonstrated the most immediate impact on profitability. Access expansion to users through simple interfaces, customer training, and sensitization drives will be critical to increasing adoption. In parallel, continuous investment in mobile banking infrastructure has to be maintained against efforts to achieve cost-effectiveness, e.g., partnership with telecom operators and lean models of service delivery.

Moreover, prioritizing the reliability, security, and ease of use of digital platforms will ensure customer satisfaction and loyalty are increased. Banks can also leverage big data analytics to better understand customer needs and enhance digital offerings accordingly. Policy-wise, regulatory bodies such as the National Bank of Ethiopia can establish an open and favorable legal framework that balances innovation and stability in the financial sector. This includes offering guidelines on data privacy, digital payments, and consumer protection.

In order to address the challenge of low digital literacy particularly in rural and underserved communities' banks and government institutions will have to unite on public education programs with the objective of demystifying fintech products and ensuring safe use. Investment in infrastructure, specifically internet and mobile network coverage, must be a national priority to facilitate widespread use of fintech. Finally, providing technical assistance and supporting regulations to smaller banks and fintech startups will level the field and encourage innovation. Overall, these recommendations will provide a sustainable, competitive, and inclusive digital financial system in Ethiopia.

5.6. Suggestion for Future Research

The findings of this study provide valuable insights into the impact of fintech adoption on the financial performance of Ethiopian commercial banks, yet they also highlight several areas where further research could deepen understanding and address unresolved questions. Future studies could build on this work by exploring the following directions:

First, longitudinal research spanning 5-10 years could provide invaluable insights into the long-term financial impact of fintech adoption, particularly whether mobile banking's initial profitability challenges eventually resolve as platforms mature and achieve critical mass.

Second, Comparative research between urban and rural adoption patterns would help assess whether current fintech solutions are effectively bridging or potentially widening financial inclusion gaps across different regions of Ethiopia.

Third, comparative cross-country studies examining Ethiopia's experience alongside other African digital finance leaders (like Kenya's M-Pesa ecosystem or Nigeria's flourishing fintech scene) could yield important lessons about contextual success factors and implementation strategies.

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APPENDIX

Addis Ababa University

College of Business and Economics

Department of Accounting and Finance

Survey Questionnaire for the Investigation on the impact of fintech on financial performance on banks in Ethiopia

Dear respondents,

This questionnaire is prepared by graduate students at Addis Ababa University in the Department of Accounting and Finance for the partial fulfillment of the requirements of the MSc. in Accounting and Finance.

The primary purpose of this questionnaire is, therefore, to gather data for academic research only. You have been selected in a specific manner with the expectation that your proficiency and skills will provide significant insights to the Research findings.

Accordingly, we have placed our trust in you that the questions will be answered in the most truthful way possible. Dear respondents, be informed that the responses you give will be used for academic purposes only and will be strictly kept confidential.

<u>General Instruction</u>

- Do not write your name.
- Where applicable, put a "✓" mark in the boxes for your answers.
- You can choose multiple responses at a time.

Gizachew Tefera

Mobile 0910484294

Section 1: General Information

Which bank do you primarily use for fintech services?

- ☐ Awash Bank
- ☐ Bank of Abyssinia
- ☐ Cooperative Bank of Oromia
- ☐ Dashen Bank
- ☐ Hibret Bank

Which fintech services do you most frequently use? *(Select all that apply)*

- ☐ Mobile banking
- ☐ Internet banking
- ☐ Digital payment platforms
- ☐ Other (please specify): ____________________

How long have you been using fintech services?

- ☐ Less than 1 year
- ☐ 1–3 years
- ☐ 3–5 years
- ☐ Over 5 years

Section 2: Net Promoter Score (NPS)

On a scale of 0 to 10, how likely are you to recommend your bank's fintech services to a friend or colleague?

(0 = Not at all likely, 10 = extremely likely)

☐

What is the primary reason for your rating of our bank's fintech services? ____.

Table 4.1 Descriptive analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	31	4.778012	12.87299	1.15379	74.05919
ROE	30	21.89344	4.987506	10.48379	30.15659
CIR	30	59.66136	10.96071	34.58673	89.54463
NPL	30	2.674511	1.425268	1	7.233355
LLPCR	30	49.6756	25.87867	10.65184	95.59678
CAR	30	12.16119	2.550223	8.43297	18.10079
CRS	30	21.34516	14.47997	0	70.46477
NPS	30	.27	5.65e-17	.27	.27
CRR	30	100	0	100	100
ln_Q	30	1.427607	.3394972	.8470761	2.044639
ln_MBA	30	2.970656	.8148071	0	4.269205
ln_IBA	30	1.035338	.8717133	0	3.004446
ln_DPP	30	2.457866	1.254848	-1.139434	3.842244
ln_MS	30	1.427607	.3394972	.8470761	2.044639
ln_Banksize	30	4.4435	.5819213	3.459466	5.53418
INF	30	24.09833	6.220989	15.3	33.89
GrowthRate	30	7.183333	1.075458	6.1	9

Annex 4.2 – Correlation Test

	Year	ROA	ROE	CIR	NPL	LLPCR	CAR	CRS	NPS	MS	CRR	MBA
Year	1.0000											
ROA	-0.0041	1.0000										
ROE	-0.0946	0.8252	1.0000									
CIR	0.1457	-0.4635	-0.3292	1.0000								
NPL	0.2299	-0.3353	-0.4311	0.0958	1.0000							
LLPCR	-0.0689	0.3587	0.6295	-0.1529	-0.4354	1.0000						
CAR	-0.2938	0.4159	0.0146	-0.3719	-0.0017	-0.2677	1.0000					
CRS	0.6103	-0.4588	-0.5136	0.1768	0.2751	-0.3385	-0.1312	1.0000				
NPS	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	1.0000			
MS	0.4107	0.4278	0.3179	-0.3190	0.1045	0.2233	0.1348	0.1243	-0.0000	1.0000		
CRR	.	.	.	.	.	.	.	.	.	.	.	
MBA	0.5118	-0.5620	-0.5417	0.2408	0.2691	-0.2926	-0.2492	0.8432	0.0000	0.0743	.	1.0000
DPP	0.4408	-0.0096	-0.0601	0.1629	0.1340	0.0949	-0.0438	0.3524	-0.0000	0.3622	.	0.4245
IBA	0.2817	0.6227	0.4000	-0.3438	-0.0524	0.1723	0.1401	-0.1819	-0.0000	0.6701	.	-0.2369
Banksize	0.7976	0.2440	0.1409	-0.0680	0.2157	0.0818	-0.0933	0.3798	0.0000	0.8477	.	0.2784
Q	0.4107	0.4278	0.3179	-0.3190	0.1045	0.2233	0.1348	0.1243	-0.0000	1.0000	.	0.0743
GrowthRate	-0.0508	-0.0432	-0.1271	-0.1763	0.0706	-0.0822	0.3208	0.0854	0.0000	0.0018	.	-0.0498
INF	0.4419	0.0472	0.1347	-0.0262	0.0021	0.0224	-0.4455	0.1989	0.0000	0.1954	.	0.1939
ln_Banksize	0.8386	0.2065	0.1027	-0.1144	0.2436	0.0678	-0.1104	0.4802	0.0000	0.8308	.	0.3970
ln_MS	0.3825	0.3560	0.2621	-0.3297	0.1834	0.1866	0.1472	0.1835	0.0000	0.9866	.	0.1427
ln_Q	0.3825	0.3560	0.2621	-0.3297	0.1834	0.1866	0.1472	0.1835	0.0000	0.9866	.	0.1427
ln_MBA	0.5745	-0.3058	-0.4435	0.0568	0.2525	-0.3940	-0.0563	0.7631	0.0000	0.1869	.	0.8411
ln_IBA	0.3539	0.6590	0.3396	-0.3502	-0.0124	0.0267	0.3044	-0.0944	0.0000	0.6583	.	-0.1878
ln_DPP	0.2406	0.1365	0.0392	0.2884	0.0639	0.0345	0.0739	0.0891	0.0000	0.2658	.	0.1702
residuals	0.1984	0.2569	-0.0000	-0.0000	-0.0483	-0.0000	0.0000	0.0000	0.0000	-0.1245	.	-0.1650

	DPP	IBA	Banksize	Q	Growth~e	INF	ln_Ban~e	ln_MS	ln_Q	ln_MBA	ln_IBA	ln_DPP
DPP	1.0000											
IBA	0.0727	1.0000										
Banksize	0.4460	0.5638	1.0000									
Q	0.3622	0.6701	0.8477	1.0000								
GrowthRate	0.1397	-0.0912	0.0692	0.0018	1.0000							
INF	-0.1941	0.2330	0.2947	0.1954	-0.6482	1.0000						
ln_Banksize	0.4613	0.5341	0.9620	0.8308	-0.0582	0.4296	1.0000					
ln_MS	0.3635	0.6079	0.8088	0.9866	-0.0194	0.2004	0.8219	1.0000				
ln_Q	0.3635	0.6079	0.8088	0.9866	-0.0194	0.2004	0.8219	1.0000	1.0000			
ln_MBA	0.3568	-0.0783	0.3627	0.1869	-0.2268	0.3677	0.4973	0.2400	0.2400	1.0000		
ln_IBA	0.1137	0.9334	0.5807	0.6583	-0.0607	0.2041	0.5755	0.6090	0.6090	0.0052	1.0000	
ln_DPP	0.8427	0.2071	0.2710	0.2658	0.0386	-0.2656	0.2759	0.2606	0.2606	0.0909	0.2726	1.0000
residuals	0.0889	-0.0321	0.0305	-0.1245	0.0000	-0.0000	0.0000	-0.1978	-0.1978	0.0000	0.0000	0.0269
time	0.4033	0.2018	0.7104	0.2808	-0.0501	0.4359	0.7549	0.2533	0.2533	0.5722	0.2996	0.2272
phat	0.1319	-0.1551	0.3042	0.1473	-0.0112	0.2200	0.4189	0.2586	0.2586	0.3627	-0.0398	0.0267

Annex 4.3 – Test for Heteroskedasticity

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ROA

         chi2(1)      =     0.01
         Prob > chi2  =   0.9092

.
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ROE

         chi2(1)      =     1.31
         Prob > chi2  =   0.2524
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of CIR

         chi2(1)      =     0.03
         Prob > chi2  =   0.8520
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of NPL

         chi2(1)      =     0.90
         Prob > chi2  =   0.3419
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of LLPCR

         chi2(1)      =     0.08
         Prob > chi2  =   0.7811
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of CAR

         chi2(1)      =     2.76
         Prob > chi2  =   0.0969
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of CRS

         chi2(1)      =     2.29
         Prob > chi2  =   0.1301
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of MS

         chi2(1)      =     0.03
         Prob > chi2  =   0.8654
```

Annex 4.4 - Autocorrelation test

```
Durbin-Watson d-statistic(  3,    30) =  1.735545
```

```
Durbin-Watson d-statistic(  3,    30) =  2.161369
```

```
Durbin-Watson d-statistic(  3,    30) =  1.844244
```

```
Durbin-Watson d-statistic(  2,    30) =  2.409498
```

```
Durbin-Watson d-statistic(  3,    30) =  1.997213
```

```
Durbin-Watson d-statistic(  2,    30) =  1.214544
```

```
Durbin-Watson d-statistic(  2,    30) =  1.214544
```

```
Durbin-Watson d-statistic(  3,    30) =  1.759581
```

Table 4.5 - Multicollinearity Test

Variable	VIF	1/VIF
ln_Banksize	4.89	0.204431
ln_MS	3.61	0.277130
ln_IBA	1.86	0.536397
ln_MBA	1.69	0.592669
ln_DPP	1.11	0.904067
Mean VIF	2.63	

Table 4.6 - Shapiro-Wilk W Tests for Normality

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
residuals	30	0.98470	0.486	-1.491	0.93205

Table 4.7 Hausman test for mobile banking adoption

	Coefficients			
	(b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ROA	-11.97278	6.508917	-18.4817	3.38198
CIR	.1418455	-.0049288	.1467743	.0307996
NPL	.0394811	-.1035905	.1430716	.3861733
LLPCR	-.001446	.0437119	-.0451579	.0211915
CAR	-.1829616	-.5408491	.3578874	.1937722
MS	-.7633081	-.1287025	-.6346055	.6789929
CRS	.8737963	-.0277801	.9015764	.0299031

```
                      b = consistent under Ho and Ha; obtained from xtreg
       B = inconsistent under Ha, efficient under Ho; obtained from xtreg

  Test:  Ho:  difference in coefficients not systematic

                chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                        =      149.69
              Prob>chi2 =      0.0000
```

Table 4.8 Hausman test for Internet banking adoption

	Coefficients (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ROA	2.02777	6.508917	-4.481147	3.38198
CIR	-.0259806	-.0049288	-.0210518	.0307996
NPL	.7479762	-.1035905	.8515666	.3861733
LLPCR	-.0277536	.0437119	-.0714655	.0211915
CAR	-.8350104	-.5408491	-.2941613	.1937722
MS	1.04129	-.1287025	1.169993	.6789929
CRS	-.0212978	-.0277801	.0064823	.0299031

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 89.76
Prob>chi2 = 0.0000

Table 4.9. Hausman test for Digital payment platform

	Coefficients (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ROA	-8.248392	6.508917	-14.75731	3.38198
CIR	.3199709	-.0049288	.3248997	.0307996
NPL	2.102896	-.1035905	2.206487	.3861733
LLPCR	.2146689	.0437119	.170957	.0211915
CAR	1.106776	-.5408491	1.647625	.1937722
MS	3.115432	-.1287025	3.244134	.6789929
CRS	.3029327	-.0277801	.3307128	.0299031

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 889.25
Prob>chi2 = 0.0000

Table 4.10 - Regression result

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.0914                                         min =          6
     between = 0.5916                                         avg =        6.0
     overall = 0.2076                                         max =          6

                                                F(4,4)             =    249.15
corr(u_i, Xb)  = 0.3458                         Prob > F           =    0.0000

                              (Std. Err. adjusted for 5 clusters in bank_id)
```

ROA	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_IBA	.0252019	.2386548	0.11	0.921	-.6374099	.6878138
ln_MBA	-.1500736	.0570362	-2.63	0.058	-.3084314	.0082842
INF	.0098349	.0240064	0.41	0.703	-.0568177	.0764875
GrowthRate	-.0129949	.1368831	-0.09	0.929	-.3930432	.3670534
_cons	2.744707	1.254697	2.19	0.094	-.7388916	6.228305
sigma_u	.52737934					
sigma_e	.39437058					
rho	.64135686	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.3467                                         min =          6
     between = 0.4794                                         avg =        6.0
     overall = 0.3732                                         max =          6

                                                F(4,4)             =    227.89
corr(u_i, Xb)  = -0.3511                        Prob > F           =    0.0001

                              (Std. Err. adjusted for 5 clusters in bank_id)
```

ROE	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Q	9.540741	2.925911	3.26	0.031	1.417108	17.66437
ln_MBA	-3.653934	.5736156	-6.37	0.003	-5.246546	-2.061322
INF	.085862	.16609	0.52	0.632	-.3752778	.5470019
GrowthRate	-.8367507	1.177816	-0.71	0.517	-4.106893	2.433392
_cons	23.06912	10.7907	2.14	0.099	-6.890662	53.02889
sigma_u	2.5321874					
sigma_e	3.8865278					
rho	.29799468	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =         30
Group variable: bank_id                         Number of groups   =          5

R-sq:                                           Obs per group:
     within  = 0.3661                                         min =          6
     between = 0.7339                                         avg =        6.0
     overall = 0.0018                                         max =          6

                                                F(4,4)             =    2007.31
corr(u_i, Xb)  = -0.6907                        Prob > F           =     0.0000

                             (Std. Err. adjusted for 5 clusters in bank_id)
```

CIR	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Q	17.31942	9.328469	1.86	0.137	-8.580562	43.2194
ln_DPP	2.202386	.7205638	3.06	0.038	.2017803	4.202992
INF	-.5487137	.2585336	-2.12	0.101	-1.266518	.1690907
GrowthRate	-3.847473	2.955472	-1.30	0.263	-12.05318	4.358233
_cons	70.38363	29.49543	2.39	0.075	-11.50882	152.2761
sigma_u	12.875982					
sigma_e	8.1565349					
rho	.71363175	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.3008                                          min =         6
     between = 0.1471                                          avg =       6.0
     overall = 0.0023                                          max =         6

                                                F(4,4)             =         .
corr(u_i, Xb)  = -0.6903                        Prob > F           =         .

                               (Std. Err. adjusted for 5 clusters in bank_id)
```

NPL	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Q	-5.769718	4.238226	-1.36	0.245	-17.53692	5.997482
ln_Banksize	2.758731	1.760845	1.57	0.192	-2.130158	7.64762
ln_MS	0	(omitted)				
ln_MBA	-.3789331	.3830071	-0.99	0.378	-1.442331	.6844652
INF	-.0346703	.0296048	-1.17	0.307	-.1168665	.047526
GrowthRate	-.0501509	.2552821	-0.20	0.854	-.7589277	.6586259
_cons	.974407	4.260107	0.23	0.830	-10.85354	12.80236
sigma_u	1.7730926					
sigma_e	.98174571					
rho	.76536045	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.0592                                          min =         6
     between = 0.0739                                          avg =       6.0
     overall = 0.0641                                          max =         6

                                                F(4,4)             =      1.69
corr(u_i, Xb)  = -0.1597                        Prob > F           =    0.3112

                                 (Std. Err. adjusted for 5 clusters in bank_id)
```

LLPCR	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Q	44.87991	62.56909	0.72	0.513	-128.8397	218.5996
ln_Banksize	-15.7205	30.32215	-0.52	0.632	-99.90828	68.46727
INF	-.0208102	1.07796	-0.02	0.986	-3.013707	2.972086
GrowthRate	-2.274559	4.551808	-0.50	0.644	-14.9124	10.36329
_cons	72.29918	59.32312	1.22	0.290	-92.4082	237.0066
sigma_u	20.7088					
sigma_e	19.695615					
rho	.52506034	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.4423                                         min =          6
     between = 0.8023                                         avg =        6.0
     overall = 0.0002                                         max =          6

                                                F(4,4)             =      7.42
corr(u_i, Xb)  = -0.6449                        Prob > F           =    0.0389

                                 (Std. Err. adjusted for 5 clusters in bank_id)
```

CAR	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_Banksize	.1402603	1.288851	0.11	0.919	-3.438165	3.718685
ln_IBA	-1.583668	.9583987	-1.65	0.174	-4.24461	1.077273
INF	-.1137837	.0549773	-2.07	0.107	-.2664253	.0388578
GrowthRate	.2605749	.4830016	0.54	0.618	-1.080453	1.601602
_cons	14.04778	3.248972	4.32	0.012	5.027187	23.06837
sigma_u	3.0188117					
sigma_e	1.7017071					
rho	.75886423	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.7069                                         min =          6
     between = 0.4519                                         avg =        6.0
     overall = 0.6626                                         max =          6

                                                F(3,4)             =   1415.93
corr(u_i, Xb)  = -0.0493                        Prob > F           =    0.0000

                                 (Std. Err. adjusted for 5 clusters in bank_id)
```

CRS	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_MBA	14.41253	1.12688	12.79	0.000	11.28381	17.54125
INF	.3020302	.1522331	1.98	0.118	-.1206367	.7246971
GrowthRate	4.758615	2.6985	1.76	0.153	-2.733623	12.25085
_cons	-62.93063	23.9275	-2.63	0.058	-129.364	3.50275
sigma_u	4.8791349					
sigma_e	8.2067945					
rho	.26115212	(fraction of variance due to u_i)				

```
Fixed-effects (within) regression               Number of obs      =        30
Group variable: bank_id                         Number of groups   =         5

R-sq:                                           Obs per group:
     within  = 0.5738                                         min =         6
     between = 0.4345                                         avg =       6.0
     overall = 0.4592                                         max =         6

                                                F(4,4)             =     28.35
corr(u_i, Xb)  = 0.1761                         Prob > F           =    0.0034

                                 (Std. Err. adjusted for 5 clusters in bank_id)
```

MS	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_DPP	.2422718	.0919003	2.64	0.058	-.0128844	.497428
ln_IBA	.6774853	.1292935	5.24	0.006	.3185089	1.036462
INF	.0734835	.0416719	1.76	0.153	-.0422162	.1891831
GrowthRate	.3003945	.1798327	1.67	0.170	-.1989011	.79969
_cons	-.8220594	2.418162	-0.34	0.751	-7.535954	5.891836
sigma_u	1.0694145					
sigma_e	.5917943					
rho	.76556125	(fraction of variance due to u_i)				

Annex 4.6 - Raw Data

Bank	Year	ROA	ROE	CIR	NPL	LLPCR	CAR	CRS	NPS
Awash	2019	3.74	30.16	38.73	1.33	64.77	18.10	7.63	27%
Abyssinia	2019	2.18	16.90	34.59	3.53	37.97	14.66	17.21	27%
Cooperative	2019	1.84	23.22	70.28	2.77	95.60	8.43	-	27%
Dashen	2019	2.00	16.00	62.93	3.01	21.54	17.82	26.08	27%
Hibret	2019	2.36	22.08	59.40	1.10	22.87	12.30	5.36	27%
Awash	2020	3.16	23.98	44.57	1.83	89.07	15.99	10.82	27%
Abyssinia	2020	1.78	16.06	68.53	4.87	26.81	10.70	20.01	27%
Cooperative	2020	2.51	28.16	62.45	2.35	75.70	11.22	6.05	27%
Dashen	2020	2.47	20.27	63.07	1.69	13.15	16.34	26.06	27%
Hibret	2020	3.32	30.08	73.29	1.70	64.92	12.96	7.47	27%
Awash	2021	3.12	24.41	48.84	1.87	85.68	12.37	10.82	27%
Abyssinia	2021	1.67	18.73	60.98	3.31	44.40	9.83	20.01	27%
Cooperative	2021	1.98	21.75	67.93	2.22	74.58	9.28	6.05	27%
Dashen	2021	2.12	18.72	56.48	2.55	21.10	10.00	26.06	27%
Hibret	2021	2.41	17.51	89.54	1.90	35.64	11.77	7.47	27%
Awash	2022	3.42	29.04	46.23	2.39	55.97	10.96	14.56	27%
Abyssinia	2022	2.55	28.30	57.57	2.24	69.26	9.37	23.74	27%
Cooperative	2022	2.09	22.22	60.52	2.03	74.40	10.13	39.15	27%
Dashen	2022	2.50	20.20	53.08	5.08	14.39	12.00	25.56	27%
Hibret	2022	1.80	15.90	55.94	1.20	26.31	11.04	15.64	27%
Awash	2023	3.44	28.57	54.19	1.33	82.82	12.02	15.39	27%
Abyssinia	2023	2.29	22.99	62.68	3.64	50.85	9.85	30.34	27%
Cooperative	2023	1.86	17.51	68.15	3.34	58.63	10.75	42.95	27%
Dashen	2023	2.50	18.40	57.78	4.90	10.65	15.00	24.13	27%
Hibret	2023	3.06	27.66	56.12	1.00	55.42	10.01	31.48	27%
Awash	2024	3.43	26.33	60.31	1.76	49.65	14.05	14.30	27%
Abyssinia	2024	2.06	19.86	63.08	3.38	67.38	10.10	38.86	27%
Cooperative	2024	1.15	10.48	76.70	3.44	13.57	11.27	70.46	27%
Dashen	2024	2.70	20.40	60.52	7.23	22.28	14.00	23.98	27%
Hibret	2024	2.57	20.91	55.37	1.25	64.92	12.51	32.74	27%

Bank	Year	MS	CRR	MBA	DPP	IBA	Bank size	MS	Growth Rate	INF
Awash	2019	5.35	100.00	7.63	21.05	1.53	65.00	5.35	9.00	15.30
Abyssinia	2019	2.93	100.00	17.21	0.16	-	35.60	2.93	9.00	15.30
Cooperative	2019	2.95	100.00	-	10.00	-	35.80	2.95	9.00	15.30
Dashen	2019	4.18	100.00	26.08	18.08	1.13	50.80	4.18	9.00	15.30
Hibret	2019	2.62	100.00	5.36	9.00	1.80	31.80	2.62	9.00	15.30
Awash	2020	5.60	100.00	10.82	20.36	4.56	81.90	5.60	6.10	21.60
Abyssinia	2020	3.29	100.00	20.01	15.42	0.00	48.00	3.29	6.10	21.60
Cooperative	2020	3.22	100.00	6.05	14.00	0.01	47.10	3.22	6.10	21.60
Dashen	2020	4.26	100.00	26.06	16.53	1.75	62.20	4.26	6.10	21.60
Hibret	2020	2.70	100.00	7.47	12.00	1.92	39.40	2.70	6.10	21.60
Awash	2021	5.91	100.00	14.01	19.42	14.46	108.90	5.91	6.30	24.60
Abyssinia	2021	4.36	100.00	64.42	28.59	0.51	80.70	4.36	6.30	24.60
Cooperative	2021	3.63	100.00	22.51	18.00	0.23	66.90	3.63	6.30	24.60
Dashen	2021	4.42	100.00	25.53	15.81	2.10	81.40	4.42	6.30	24.60
Hibret	2021	2.33	100.00	15.49	16.00	0.52	42.90	2.33	6.30	24.60
Awash	2022	6.57	100.00	14.56	19.18	19.18	156.00	6.57	6.40	33.89
Abyssinia	2022	5.34	100.00	23.74	0.43	0.43	126.70	5.34	6.40	33.89
Cooperative	2022	4.13	100.00	39.15	0.60	0.60	97.60	4.13	6.40	33.89
Dashen	2022	4.46	100.00	25.56	3.48	3.48	105.90	4.46	6.40	33.89
Hibret	2022	2.56	100.00	15.64	1.04	1.04	60.70	2.56	6.40	33.89
Awash	2023	7.15	100.00	15.39	19.63	14.99	203.50	7.15	7.20	29.30
Abyssinia	2023	5.96	100.00	30.34	37.73	0.71	169.40	5.96	7.20	29.30
Cooperative	2023	4.93	100.00	42.95	24.00	0.90	140.30	4.93	7.20	29.30
Dashen	2023	4.58	100.00	24.13	17.02	5.16	130.30	4.58	7.20	29.30
Hibret	2023	2.64	100.00	31.48	24.00	1.02	74.90	2.64	7.20	29.30
Awash	2024	7.73	100.00	14.30	15.76	11.88	253.20	7.73	8.10	19.90
Abyssinia	2024	6.28	100.00	38.86	46.47	0.86	205.90	6.28	8.10	19.90
Cooperative	2024	4.27	100.00	70.46	27.00	1.09	140.00	4.27	8.10	19.90
Dashen	2024	5.01	100.00	23.98	23.30	7.34	164.20	5.01	8.10	19.90
Hibret	2024	2.73	100.00	32.74	28.00	1.91	89.50	2.73	8.10	19.90