University of KwaZulu Natal

Fintech innovations and banking sector dynamics: Evidence from South Africa

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DECLARATION

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DEDICATION

This thesis is dedicated to the loving memory of my mother, Nonto Mhlongo.

ABSTRACT

The South African banking sector, vital to the country’s socio-economic stability, is undergoing rapid transformation due to innovations in financial technology (Fintech). Regulated by the South African Reserve Bank (SARB), banks are essential for economic growth through capital provision, risk management, and transaction facilitation. Recent Fintech advancements offer more efficient, personalised, and cost-effective solutions, challenging traditional banking models. Against this background, this thesis aims to explore the impact of Fintech innovations on banking sector dynamics, focusing on African Bank, FirstRand, Standard Bank, Capitec Bank, Investec Bank Limited, Absa Group, Nedbank Group, and Finbond Group, which are publicly traded banks on the Johannesburg Stock Exchange (JSE) from 2000 to 2023. The study tests the hypothesis that Fintech innovations influence competition, performance, efficiency, and stability within the banking system using the appropriate panel regression model determined. The findings reveal that Fintech enhances competition, reflected by an increase in market power, particularly through mobile transactions that raise the banking sector's competition. While Fintech has not significantly improved bank performance indicators, it positively impacts operational efficiency, particularly through mobile transactions, suggesting a shift toward digital solutions. Stability results show no effects of Fintech on banking sector stability, with traditional capital structures remaining more influential than Fintech innovations. These findings stress the dual nature of Fintech's impact: while fostering competition and efficiency improvements in South African banking, it also introduces new risks in disrupting traditional banking services through more convenient and cost-effective alternatives that make banks compete more aggressively. As this landscape evolves, adaptive regulatory frameworks are being called for to balance technological advances with the need for stability within the banking sector.

Keywords: Banking Sector; Competition; Efficiency; Fintech; Performance; Stability, South Africa.

GLOSSARY OF ACRONYMS

AI - Artificial Intelligence

AML - Anti-Money Laundering

API - Application Programming Interface

ARDL - Autoregressive Distributed Lag

ATM - Automated Teller Machine

BCBS - Basel Committee on Banking Supervision

CAR - Capital Adequacy Ratio

CBDC - Central Bank Digital Currency

DEA - Data Envelopment Analysis

DLT - Distributed Ledger Technology

EAR - Equity to Asset Ratio

FE - Fixed Effect

FICA - Financial Intelligence Centre Act

Fintech – Financial Technology

GDP - Gross Domestic Product

GMM - Generalized Method of Moments

IFWG - Intergovernmental Fintech Working Group

IPS - Im-Pesaran-Shin

IV - Instrumental Variable

JSE - Johannesburg Stock Exchange

KYC - Know Your Customer

LI - Lerner Index

MSME - Micro, Small, and Medium Enterprises

NIM - Net Interest Margin

OLS - Ordinary Least Squares

P2P - Peer-to-Peer

POPIA - Protection of Personal Information Act

PSD2 - Payment Services Directive 2

RBI - Reserve Bank of India

RE - Random Effect

ROA - Return on Assets

ROE - Return on Equity

SA - South Africa

SARB – South African Reserve Bank

SCT - Single Credit Transfer

SFA - Stochastic Frontier Approach

SMEs - Small and Medium Enterprises

SWIFT - Society for Worldwide Interbank Financial Telecommunication

TFP - Total Factor Productivity

TMS - Treasury Management System

UAE - United Arab Emirates

WDI - World Development Indicators

YEA - Yield on Earning Assets

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CHAPTER ONE: INTRODUCTION AND BACKGROUND

1.1 Background

The banking sector in South Africa is not merely a cornerstone of financial transactions but a vital component of socio-economic development, contributing significantly to the nation's stability and prosperity. Banks in South Africa foster economic growth by channelling financial capital into businesses and encouraging individual savings (Moyo, 2018). Their role extends beyond mere transaction facilitation to enhancing the country's financial infrastructure by mitigating risks, adhering to international standards, and supporting economic growth (Van-Deventer & Redda, 2023). In the context of emerging markets, South Africa is distinguished by a robust and meticulously regulated banking industry. This industry is under the vigilant supervision of the South African Reserve Bank (SARB), the continent's oldest central bank, founded in 1921. The SARB is tasked with overseeing the country's gold and foreign exchange reserves, which are crucial for economic stability. Its regulatory purview extends to monitoring risks, particularly those associated with the "big five" banks, Standard Bank, First National Bank (FNB), Absa, Nedbank, and Capitec, which dominate the market, controlling 90 percent of the industry's assets (Person et al., 2017; Wilson et al., 2024).

The centrality of the banking sector to South Africa's economy means that any instability within this sector can have far-reaching consequences. Such instabilities might manifest as reduced credit availability and lead to tighter lending criteria that could stifle economic growth (Cowling, 2023). Moreover, instability may result in investors demanding higher returns to compensate for perceived risks, leading to increased interest rates (Vucinic, 2020). A decline in consumer confidence could further exacerbate the situation, as consumers might shift their savings and investments away from traditional banking, impacting the broader economy (Furi, 2022). Therefore, it is of primary importance to understand which factors influence the stability of the banking sector in South Africa.

Recent disruptions to the banking sector's stability have increasingly been attributed to advancements in financial technology or Fintech. Vucinic (2020) defines Fintech as technological innovations in financial services that produce new business models, applications, procedures, or products that significantly impact financial markets, institutions, and service providers. The rise of Fintech is closely linked to rapid digital evolution and improved financial inclusion, which have collectively transformed the financial landscape (Bogaard et al., 2024;

KPMG International, 2024). In South Africa, where over 90 percent of adult population own mobile phones and 72 percent rely solely on them for internet access (IFWG, 2023), Fintech innovations have introduced more efficient, cost-effective, and personalised financial services, challenging traditional banking models (Coetzee, 2018; Furi, 2022).

Gomber et al. (2018) categorise innovations into three basic technological elements: components, products and services, and infrastructures. Among these, ATMs (Automated Teller Machines) and digital banking are notable elements within the South African context (Liao, 2023). Despite the growth of digital banking in Fintech, ATMs remain crucial as they form part of the foundational infrastructure of customer service innovations in banking (Suder et al., 2023). The significance of ATMs is underscored by their enduring popularity in South Africa, where nearly 80 percent of transactions are cash-based (IFWG, 2023). However, the rapid expansion of Fintech has outpaced the development of regulatory frameworks, raising concerns about the associated risks (Didenko, 2018; Vijayagopal et al., 2024). Regulators play a pivotal role in balancing the benefits of technological advancements with the need to mitigate risks while enhancing financial inclusion (Didenko, 2018). The SARB has responded to these challenges by establishing a Fintech working group that seeks to monitor risks and ensure compliance (SARB, 2023). This regulatory response is critical in understanding how Fintech influences the functioning of banks and the stability of the broader financial system.

Fintech innovations could impact various banking sector dynamics, including competitiveness, performance, efficiency, and stability. First, by delivering innovative solutions and satisfying changing consumer expectations, Fintech's user-centric and flexible strategy can boost banks' competitiveness (Dwivedi et al., 2021). For example, in South Africa, banks are leveraging innovative solutions like mobile banking innovations such as M-Pesa, FNB's eWallet, or Absa's CashSend to gather data on mobile transactions, airtime purchases, and bill payments (Chigada & Hirschfelder, 2017). Fintech can also impact competitiveness in the banking industry by breaking banking into its most fundamental components and opening new, limitless possibilities to combine it (Dwivedi et al., 2021). Consequently, Fintech competition may impact the flow of information in the economy, raise financial inclusion, and reprice core banking services (Naceur et al., 2023). Designing an effective policy framework for Fintech is crucial to balance its benefits with risks like operational issues, market integrity, and privacy concerns (Takundwa, 2020; KPMG International, 2024). A study by Dwivedi et al. (2021) highlights that Fintech has enhanced the competitiveness of banks in the UAE. Conversely, research by Bejar et al. (2022) indicates that, in Brazil and Mexico, Fintech negatively affected bank competition, as evidenced by reductions in the Lerner index. Additionally, Naceur et al. (2023) emphasise that innovations like peer-to-peer lending and digital payments are transforming traditional banking structures in China.

Secondly, Fintech has impacted banks by enabling them to analyse and manage risk better (Gomber et al., 2018). This can reduce banks' exposure to bad debt and help them make better lending decisions (Rengasamy, 2019). For example, banks naturally have access to a rich source of data through consumer transactions. On the other hand, assuring banks can successfully use cutting-edge technology while adhering to regulatory constraints presents a challenge (Takundwa, 2020). According to Dwivedi et al. (2021), there is a direct link between improved performance and the use of Fintech. Conversely, a study by Phan, Narayan, and Hutabarat (2020) hypothesised that banks' performance would suffer because of Fintech's growth, and the authors successfully proved this to be true. Moreover, Mugabe (2022) also found a negative relationship between Fintech and banking sector performance. This is because fintech firms generally operate with lower overhead costs, and as a result, they can offer services at lower prices, forcing traditional banks to reduce their fees and interest rates, which further compresses their profit margin (Mugabe, 2022).

Thirdly, Fintech has a great deal of theoretical potential to improve the efficiency of the banking sector. Fintech may simplify several banking activities by combining innovative technologies and creative ideas. For instance, the improvements brought about by Fintech to the sector can minimise errors and reduce manual workload by automating common processes and transactions (Ullah et al., 2023). Process simplification improves overall efficiency by enabling speedier and more accurate financial activities (Ullah et al., 2023). Liao (2023) discovered that Fintech-related activities positively impact bank efficiency in Taiwan. On the other hand, Lee et al. (2023) found Fintech development to be reducing the efficiency of commercial banks. For instance, high operational costs associated with integrating Fintech solutions may outweigh the efficiency gains, and additionally, the reduction in efficiency can be attributed to regulatory challenges faced by banks in adapting to new technologies, which can hinder their operational efficiency (Liao, 2023).

Finally, there are numerous ways in which Fintech can affect the banking sector's stability. Increased competition from Fintech companies may push banks to make riskier investments, which could jeopardise their financial stability (Safiullah & Paramati, 2022). For instance, in South Africa, TymeBank, a newly launched digital bank, has reportedly been acquiring 5,000 new customers per week, reaching a total of 250,000 users by April 2019, and Hello Paisa, another key player, utilising its payments platform's current user base of 1.2 million to introduce a digital bank (IFWG,2023). This may put indirect pressure on banks to take up Fintech services, which could improve their operational efficiency, increase margins and therefore foster stability (Vucinic, 2020). Yudaruddin et al. (2023) discovered that an increase in Fintech firms is linked to better bank stability, regardless of the Fintech firm types and the methodology employed to quantify bank stability. On the one hand, a study by Geng, Pin, and Cheng (2023) found that the adverse effects of bank Fintech tend to outweigh the good effects, reducing bank stability. This means that adverse effects represent negative impacts like increased non-interest activities that reduce stability.

Despite these insights, there remains a gap in research specifically addressing the South African context. This highlights the need for further investigation into how Fintech is reshaping the dynamics of the South African banking sector. This study aims to explore the impact of Fintech innovations on banking sector dynamics, providing valuable insights and recommendations for regulators and stakeholders to navigate the evolving financial landscape.

1.2 Problem statement

The banking sector plays a vital role in promoting investment, facilitating large financial transactions, and driving economic growth (Baker et al., 2023). A stable banking system is essential for maintaining public confidence, which in turn supports overall economic stability (van Deventer & Redda, 2023). Conversely, instability in this sector can lead to severe consequences, including financial crises that hinder economic progress. In South Africa, the rapid rise of Fintech is largely driven by increased mobile phone usage and greater internet access (Bogaard et al., 2024). Innovations such as mobile banking have improved financial service accessibility and reduced costs, offering greater convenience to consumers. However, despite these advancements, the rate of Fintech adoption in South Africa remains unexpectedly low (Slazus & Bick, 2022; Cele, 2023). This presents risks to financial institutions that have invested significantly in these technologies, highlighting a disconnect between Fintech's potential and its actual impact.

Recognising the disruptive nature of Fintech, the South African Reserve Bank (SARB) has established a dedicated Fintech unit to develop clear regulatory frameworks for a stable financial ecosystem (SARB, 2023). Understanding the factors that could undermine the stability of the sector is crucial. While Fintech offers numerous advantages, its effects on key banking aspects, such as performance, efficiency, stability, and competitiveness, are still debated (Furi, 2022). Existing research on Fintech and the banking sector has produced mixed results. For example, Dwivedi et al. (2023) emphasise the benefits of adopting Fintech on bank competition while, on the other hand, studies of Bejar et al. (2022) and Song et al. (2023) found negative effects on competition. Similar negative effects on bank performance are documented in research by Phan et al. (2020) and Mugabe (2022), with Mugabe also pointing to negative effects on long-term return on equity. On the other hand, Fintech implementation is positively correlated with improved performance, according to Dwivedi et al. (2021). There are also differences in terms of efficiency whereby Lee et al. (2023) find negative effects, whereas Liao (2023) and Ahmed et al. (2023) claim positive effects in Taiwan. Findings on stability are likewise mixed; Yudaruddin et al. (2023) relate greater use of Fintech to better stability, while Geng et al. (2023) find the opposite. This gap in research limits policymakers' ability to formulate effective strategies to ensure a stable financial system. Therefore, a comprehensive investigation into Fintech's impact on South African banking is essential for developing informed regulatory policies that support a robust financial ecosystem.

1.3 Research objectives

1.3.1 Primary objective

The aim of this study is to investigate the effect of innovations in financial technology on the dynamics of the South African banking sector.

To achieve this aim, the following secondary objectives below have been developed.

1.3.2 Secondary objectives

- To examine how innovations in Fintech influence competitive landscapes within the South African banking industry.
- To assess the effects of Fintech innovations on the performance metrics of banks operating in South Africa.
- To assess the impact of financial technology developments on operational efficiency in the South African banking system.

- To evaluate the effects of Fintech innovations for stability within the South African banking system.

1.4 Research questions

1.4.1 Primary question

How do innovations in financial technology affect banking sector dynamics in South Africa?

1.4.2 Secondary questions

- How do innovations in financial technology affect competition in the South African banking sector?
- What is the impact of innovations in financial technology on bank performance in the South African banking sector?
- How do innovations in financial technology influence efficiency in the South African banking sector?
- How do innovations in financial technology affect stability in the South African banking sector?

1.5 Contribution of the study

The advent of Fintech innovation has profoundly transformed the financial landscape, yet a comprehensive understanding of its effects on banking dynamics remains elusive. Existing research has often provided fragmented insights into the relationship between Fintech and various aspects of banking, particularly within the context of South Africa. This study seeks to bridge these gaps by offering several significant contributions to the field.

Firstly, previous studies have frequently focused on limited aspects of bank dynamics, which has constrained the breadth of their findings. For example, research by Phan et al. (2022) and Liao (2023) investigates the impact of Fintech on bank efficiency in Taiwan and performance in Indonesia, respectively. Similarly, Mugabe (2022) investigated the effects of Fintech on performance, focusing solely on South Africa. This study addresses this limitation by examining a broader range of bank dynamics, including competitiveness, efficiency, performance, and stability. By concurrently analysing these four critical variables, the research provides a more comprehensive understanding of Fintech's overall impact on banking dynamics, offering a more nuanced view of how these innovations shape the sector.

Secondly, the literature reveals contradictory findings regarding Fintech's effects. For instance, Dwivedi et al. (2021) highlight the positive influences of Fintech on bank competition, while Naceur et al. (2023) report a negative effect. Similarly, studies by Phan et al. (2020) and Mugabe (2022) document adverse impacts on bank performance, with Mugabe also noting negative effects on long-term return on equity. Conversely, Dwivedi et al. (2021) find positive correlations between Fintech implementation and enhanced performance. Discrepancies also exist regarding efficiency, with Liao (2023) and Ahmed et al. (2023) reporting beneficial impacts in Taiwan and elsewhere, while Lee et al. (2023) identify negative effects. Stability findings are equally varied, with Yudaruddin et al. (2023) associating increased Fintech use with improved stability and Geng et al. (2023) linking it to decreased stability. This study contributes by synthesising these conflicting results, providing a clearer perspective on Fintech's impact on different facets of banking.

Thirdly, bank efficiency studies like Maryunita and Nugroho (2022), Liao (2023), and Lee et al. (2023) utilised Data Envelopment Analysis (DEA) as a method for assessing bank efficiency, which does not account for random noise in the data and can be sensitive to outliers (Ullah et al., 2023). On the contrary, this study uses the Stochastic frontier Approach to estimate the efficiency of banks while accounting for random errors. Lastly, most of the studies have utilised traditional ratios (like return on assets or return on equity) to model bank performance; the study uses capital adequacy ratios as they are essential for evaluating the fundamental stability and risk management of banks. The CAR makes a critical metric for both regulators and investors to gauge how the sector is performing (Aktas et al., 2015).

The study's contributions extend beyond academic inquiry. By improving understanding of Fintech innovations in South Africa, the research enables banking stakeholders to make more informed decisions. Furthermore, the findings add to the broader understanding of Fintech trends in emerging economies, contributing to the ongoing discussion about the evolution and impact of financial technologies.

1.6. Scope and method of this study

1.6.1 Scope of this study

The scope of this study encompasses the examination of Fintech innovations and their impact on the banking sector dynamics in South Africa, specifically focusing on publicly traded banks listed on the Johannesburg Stock Exchange (JSE) from the year 2000 to 2023. The research aims to analyse how Fintech advancements influence the dynamics of the banking sector, including competition, performance, efficiency, and stability. This study is significant as it addresses a critical area of interest within the context of South Africa's evolving financial landscape, where technological advancements are reshaping traditional banking models.

1.6.2 Method of this study

The methodology employed in this study involves a comprehensive approach that includes utilising secondary data from Bloomberg for financial data as well as Fintech and macroeconomic data from the World Bank databases. Data is gathered from 2000 to 2023 to ensure a robust analysis of trends over time. The study employs appropriate panel regression models to test for the influence of Fintech on banking sector dynamics. The Hausman test is utilised to determine the suitability of fixed or random effects models for analysing the data.
The analysis focuses on bank dynamics, including bank competition, the Lerner index, and the Capital Adequacy Ratio (CAR), to evaluate bank performance. Additionally, the Stochastic Frontier Approach assesses bank efficiency, while the Z-score measures bank stability. This methodological framework provides a comprehensive understanding of how Fintech innovations are reshaping the South African banking sector, highlighting the opportunities and challenges faced by traditional banks.

1.7 Structure of the thesis

This thesis includes six chapters, which are structured as follows:
Chapter one is the introductory section which outlines the problem statement driving the study and presents the study's aims and objectives, research questions, and contributions to the study.

On the other hand, chapter 2 is the literature review which provides a theoretical framework for understanding Fintech's impact on the banking sector, addressing a gap in the literature. It explores Fintech's influence on competition, performance, efficiency, and stability, incorporating global and local findings.

Chapter three cover’s the methodology of the study, which discusses research methodology, sample selection, pre-testing, statistical tools, bank competition evaluation, performance evaluation, efficiency, and stability using various measures and multi-panel regression studies.

Data analysis and results are represented by chapter four. The chapter examines pretests and regression analysis, including the foundational data. It delves into interpreting the findings in depth to elucidate relationships between Fintech and bank dynamics and contribute to broader discourse.

Lastly, chapter five is the conclusion and recommendations of study, which is the final chapter summarises the theoretical framework, empirical evidence, findings, significance, implications, recommendations, limitations, and areas for future research in the banking sector.

1.8 Chapter summary and concluding remarks.

This chapter provided a comprehensive overview of the South African banking sector and the emerging influence of Fintech innovations. It highlighted the sector's significance as a cornerstone of economic development and its susceptibility to instability, emphasising the need for a stable financial system. Fintech is introduced as a disruptive force driven by technological advancements and improved financial inclusion. The chapter explored the potential impacts of Fintech on various banking dynamics, including competitiveness, performance, efficiency, and stability. It acknowledged the existing research gaps, particularly in the South African context, and underscored the necessity for further investigation. The South African banking sector, a vital component of the nation's economic landscape, is increasingly impacted by Fintech innovations. While these innovations offer numerous benefits, their impact on banking dynamics remains a subject of ongoing debate. This chapter has highlighted the need for a comprehensive understanding of Fintech's effects on competitiveness, performance, efficiency, and stability within the South African context. The next chapter will establish a literature review for understanding Fintech, particularly in relation to the banking sector.

CHAPTER TWO: LITERATURE REVIEW

2.1 Chapter overview

The literature review is an important part of the study's process since it serves as the foundation for new information. It provides a thorough overview of current research, shedding light on recent trends and gaps while also positioning new findings within larger academic frameworks (Lau, & Kuziemsky, 2016). Therefore, this chapter presents a comprehensive literature review aimed at establishing the context and foundational knowledge required to explore the research objective of understanding how Fintech innovations influence the dynamics of the South African banking sector. This chapter seeks to achieve two primary goals by critically examining existing research. Firstly, it aims to provide a thorough understanding of the current scholarly landscape regarding Fintech and its interplay with the banking industry. Second, the review identifies potential gaps in existing research, highlighting areas where further investigation is warranted. Specifically, it explores the impact of Fintech innovation on competition, performance, efficiency, and stability within the banking sector. However, the chapter starts off with an overview of the banking sector and Fintech innovations in South Africa. Additionally, it explores the pros and cons of Fintech and, overall, its role in the dynamics of banking.

2.2 Overview of the South African banking Sector

The South African banking sector represents a pivotal element of the nation's economic framework, delivering critical financial services to both individuals and businesses. Compared to other emerging economies, South Africa's banking sector is notably advanced, as evidenced by Mlambo and Ncube (2011), Moyo (2018), Vilakazi (2021), and Mugabe (2022). The sector, dominated by major institutions such as Standard Bank, FirstRand, Absa, Capitec, and Nedbank, not only commands a leading position within Africa but also ranks prominently on the global stage (Mlambo & Ncube, 2011; Moyo, 2018). Looking at bank competition within the sector, the rise of digital-first banks like TymeBank, Discovery Bank, and Bank Zero has increased competition in the South African banking market (Dube, 2018). By utilizing technology, these newer players are able to offer innovative financial products, seamless customer experiences, and reduced fees. Even though the "Big Four" still hold the majority of the market within the sector, the competitors are spurring innovation and making it necessary for long-standing firms to adjust to shifting consumer demands(Mugabe, 2022). On the other hand, for performance and stability the strong regulatory frameworks established by SARB and adherence to globally mandated standards, like the Basel III accord, highlight the sector's stability(SARB, 2024). South African banks have consistently demonstrated significant resistance by keeping sufficient capital buffers and a high level of liquidity, even in the face of recent economic pressures (SARB, 2020). The sector's financial performance has fluctuated due to general macroeconomic factors like inflation, GDP growth, and currency volatility (SARB, 2024). Nonetheless, the banks continued to turn a profit thanks to a variety of income streams from wealth management, corporate lending, and retail banking. The sector's efficiency is driven using Fintech and operational simplification(Panday, et al., 2024). In order to reduce expenses and enhance customer service at the same time, many banks make significant investments in digital transformation, process automation, and branch footprint reduction. However, there are still issues with access to banking services and high levels of financial exclusion in rural areas (Panday, et al., 2024).

As reported by the Bank Supervision Department of the South African Reserve Bank (2024), the sector comprises 50 commercial banks, including seven locally controlled entities, four mutual banks, four foreign-controlled banks, 29 foreign bank representatives, and six branches of foreign banks. This diverse array of financial institutions enhances market competitiveness, potentially benefiting consumers through improved pricing and services (South African Reserve Bank, 2024). Moreover, the banking sector plays a crucial role in advancing financial inclusion across South Africa. For example, the banking sector’s automated teller machines (ATMs) and bank branches provide a critical interface between banks and customers (FSCA, 2021). The sector is also instrumental in driving the adoption of digital financial services and supporting small and medium enterprises (SMEs) through microfinance and small business loans (FSCA, 2021). As noted by Deloitte (2021), 75 percent of South Africans possess bank accounts, with 55 percent of adults engaging in digital banking. KPMG (2020) highlights that 30 percent of adults use mobile banking, while the Small Business Institute (2019) reports that R12 billion in microfinance loans are issued annually, with 40 percent of SMEs accessing formal credit. This demonstrates the sector's significant impact on economic accessibility and financial empowerment.

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2.3 Contextualisation of the Fintech innovations in the banking Sector

The phrase financial technology (or Fintech) is not new; some say that it dates to the 1890s (Arner et al., 2015; Gomber et al., 2018; Virasamy, 2021). Arner et al. (2015) give the following fundamental definition: "the use of technology to provide new and improved banking services". Arner et al. (2015) believe that the history of Fintech and its many developments can be divided into three separate phases (Fintech 1.0, 2.0, and 3.0). Fintech 1.0, which lasted from 1886 to 1967, is regarded as the era that laid the groundwork for modern financial services, introducing innovations such as the telegraph for electronic fund transfers, which represent a significant milestone in the evolution of digital communication in financial transactions (Virasamy, 2021). The second phase of Fintech and the progression of innovations is seen through 1967-2008, which was regarded as Fintech 2.0. This phase saw the introduction of ATMs, online banking, and digital stock exchanges characterised and marked by increased digitalisation and consumer accessibility to financial services. The development of ATMs laid the groundwork for subsequent Fintech advancements. It demonstrated the feasibility of using technology to deliver financial services, inspiring further innovation in areas like online banking, mobile payments, and digital wallets (Kredina, 2021). The last phase is the present era (Fintech 3.0), which began in 2008. Following the 2008 financial crisis, Fintech innovations surged with the rise of cryptocurrencies, mobile apps, and peer-to-peer lending (Philippon, 2016). This era is characterised by rapid technological advancement and a shift in consumer trust towards new financial service providers.

One of the crucial indicators of innovation is the degree to which new technologies are integrated into banking practices. Slazus et al. (2022) predict a global Fintech adoption rate of 52 percent, with developing markets like South Africa leading the trend. KPMG (2020) reports that 25 percent of South African banks have invested in Fintech companies to enhance their processes and compete effectively. This investment is anticipated to reach R3.5 billion by 2025 (McKinsey, 2020), further underscoring the competitive landscape. Deloitte (2021) adds that 60 percent of South African banks are partnering with Fintech companies, indicating a concerted effort to innovate and remain relevant.

Fintech adoption has positively impacted the performance of South African banks. Deloitte (2021) reveals that 75 percent of these banks have invested in digital transformation, enhancing customer convenience and efficiency. According to the National Treasury of South Africa (2023), recent data from the World Bank indicates that 91 percent of South African adults have access to formal financial services, which includes a range of banking and non-banking products, while KPMG (2020) reports that 50 percent of banks are investing in innovation labs. Fintech plays a pivotal role in expanding financial inclusion and improving overall sector performance by reaching a wider customer base. The shift towards Fintech has also led to increased operational efficiency for banks. The SARB (2020) notes a 20 percent growth in online banking transactions, highlighting the benefits of digitalisation. By streamlining processes and reducing costs, banks can improve their overall efficiency and competitiveness (Innes & Andrieu, 2022). However, compliance with regulations is essential for maintaining the stability and integrity of the banking sector. Robust cybersecurity measures are crucial in this regard. Deloitte (2021) reports that 80 percent of South African banks prioritise cybersecurity, demonstrating a commitment to protecting customer data and mitigating risks while embracing the pros of Fintech in the banking sector.

2.3.1 Pros of Fintech in the banking sector

One of the advantages of Fintech is that it can increase competition by introducing innovative financial products and services, challenging traditional banks to enhance their offerings and improve customer experiences (Dwivedi et al., 2021). This can drive down costs and foster greater financial inclusion (Masangwana, 2021). Additionally, the solutions driven by it can enable banks to gather and analyse data more effectively, improving decision-making and risk management (Gomber et al., 2018). This can lead to better financial performance and more tailored services for customers. Furthermore, automation and digital innovations could streamline banking processes, reducing manual errors and transaction times (Ullah et al., 2023). This boosts operational efficiency and lowers costs for both banks and customers. Moreover, Safiullah and Paramati (2022) claim that these innovations in the banking sector can enhance stability by diversifying financial services and increasing market competition, but they also pose risks, such as operational challenges and regulatory concerns, that could impact the stability of traditional banking institutions.

2.3.2 Cons of Fintech in the banking sector

On the other side, some of the research has indicated that increased Fintech's disruptive innovations can force traditional banks to cut costs and lower fees, potentially squeezing their profit margins and impacting their long-term sustainability (Innes & Andrieu, 2022). In other instances, the proliferation of Fintech start-ups can lead to a fragmented market, where new entrants may not always adhere to the same regulatory standards as established banks, creating inconsistencies in service quality and customer protection (McKinsey, 2020; Masangwana, 2021). Additionally, in terms of the performance of the sector, banks may face difficulties integrating new Fintech innovations with their existing systems, leading to operational inefficiencies and potential disruptions in service (IFWG, 2023). Further, this could create the issue of heavy reliance on Fintech innovations, which can lead to performance issues if the technology fails or experiences downtime, impacting customer trust and operational stability.

Building on the point of the disadvantages of Fintech within the sector, Takundwa (2020) argues that ensuring compliance with evolving regulations related to Fintech innovations can impose significant costs on banks, potentially offsetting the efficiency gains from new technologies. This indicates that the evolving nature of Fintech creates challenges for regulators trying to keep pace with technological advancements, which can lead to gaps in oversight and increased risk of financial instability (Coetzee, 2018). Furthermore, the rapid growth of Fintech can introduce new forms of systemic risk, particularly if a significant portion of financial transactions and data is handled by relatively unregulated or under-regulated entities (Saklain, 2024). To better understand these dynamics, it is essential to establish a robust overview of the impact of Fintech on bank dynamics that encompasses both the opportunities and challenges posed by Fintech innovation.

2.4 Overview of the impact of Fintech on banking sector dynamics in South Africa

2.4.1 The effects of Fintech on bank competition

The rise of Fintech start-ups as strong competitors to traditional banks signifies a major shift in the financial services landscape, prompting established institutions to innovate and adapt to evolving consumer preferences to remain relevant (McKinsey, 2020). This evolving dynamic illustrates the complex relationship between Fintech innovations and the sector banks, as the former provide viable alternatives to conventional banking services. An example of this competitive shift can be observed in the South African context, where Fintech innovations such as [1]M-Pesa, Snap Scan, and Yalu have markedly intensified competition within the banking sector (Virasamy, 2021; IFWG, 2023)[2]. M-Pesa has transformed financial transactions by offering a convenient and accessible platform for storing, sending, and receiving money, thereby simplifying financial interactions for users. Similarly, Snap Scan has revolutionised

[1] M-Pesa is a mobile payment service that allows users to send and receive money, pay bills, and make purchases using their mobile phones, while Snap Scan is a mobile payment app that enables users to make payments by scanning QR codes. Yalu is also an app that provides a platform for peer-to-peer payments and money transfers, often emphasising social networking features have markedly intensified competition within the banking sector (IFWG, 2023).

payment processes through mobile devices, and Yalu has introduced cost-effective banking services (Deloitte, 2021; IFWG, 2023). Collectively, these Fintech innovations challenge traditional banking paradigms by presenting novel business models that disrupt established practices.

The rise of Fintech solutions is compelling traditional banks to lower fees and innovate their service offerings to remain competitive (Masangwana, 2021; Virasamy, 2021). Consequently, banks are increasingly adopting new delivery methods to attract and retain customers, significantly altering the financial sector's competitive landscape. On the other hand, according to Dwivedi et al. (2021), Fintech helps to improve business processes by streamlining its operations and services, which may result in competitiveness and performance. For example, in the South African banking sector, mobile banking applications as innovations have allowed them to improve their operations in the sense that mobile app allows customers to manage accounts, apply for loans, and make payments seamlessly (FICA, 2021). Additionally, the innovations enable banks to increase profitability, innovate financially, and improve control of risk (Chigada & Hirschfelder, 2017). For instance, Nedbank has embraced an open banking approach by developing an Application Programming Interface (API) that allows third-party developers to create new financial services (Nedbank, 2021). Additionally, FNB uses data analytics and Artificial Intelligence (AI) to provide personalised banking experiences and product recommendations (BusinessTech, 2023). On the other hand, Standard Bank employs advanced machine learning algorithms to identify fraudulent transactions in real time (IFWG, 2023).

2.4.2 The effects of Fintech on bank performance

The integration of Fintech into banking operations has been demonstrated to have a substantial positive impact on banking performance. This technological adoption facilitates enhanced revenue streams, cost reductions, and improved customer satisfaction, thereby granting banks a competitive edge and elevating their overall financial performance (Srilatha, 2018; Masangwana, 2021). In particular, the implementation of Fintech-driven digital channels has been shown to significantly bolster customer satisfaction within the banking sector. In South Africa, the progressive adoption of Fintech innovations by leading retail banks highlights the critical role of these technologies in adapting to the dynamic financial landscape and enhancing customer experiences (FSCA, 2021). For example, Absa’s deployment of digital channels has effectively created a more convenient and accessible platform for customers to manage their finances (IFWG, 2023). This strategic move has not only enabled Absa to retain its existing client base but has also attracted new customers, thus contributing to the bank's competitive positioning and financial performance.

Standard Bank's mobile application marks a significant advancement in the banking sector, enabling users to open accounts, apply for loans, and execute transactions via mobile devices (Deloitte, 2021; IFWG, 2023). This innovation has expanded market reach and streamlined processes, contributing to revenue growth. Similarly, Nedbank's focus on digital banking services highlights the positive impact of technology on performance. By offering real-time transaction updates and personalised financial insights, Nedbank has improved customer satisfaction and empowered clients to manage their finances effectively (Nedbank, 2021). Overall, these developments illustrate the beneficial effects of Fintech on banking efficiency and financial success.

On the other hand, the adoption of Fintech in bank performance can pose challenges to the South African banking sector. For instance, companies like Yoco and PayFast have revolutionised payment processing, enabling small and medium-sized enterprises (SMEs) to accept payments easily without relying on traditional banks (IFWG, 2023). This shift can diminish banks' transaction volume and fee income as businesses increasingly turn to these more flexible solutions. Additionally, Srilatha (2018) argues that security concerns have become a paramount issue as financial institutions adapt to the rapid rise of digital services. As the banking sector expands its digital offering, this could also translate to an increasing number of users engaging with online and mobile banking platforms, which has heightened the risk of cyber threats, including data breaches and fraud (Godlstuck & Dagada, 2009).

2.4.3 The effects of Fintech on bank efficiency

Fintech innovations significantly improve operational efficiency in the banking sector by streamlining processes, reducing manual interventions, and automating tasks. These advancements lead to cost savings, faster turnaround times, and better resource allocation (Srilatha, 2018; Ullah et al., 2023). A notable instance of this can be seen in the South African banking sector, where various Fintech innovations have been successfully implemented. Notably, ATMs, online loan applications, and digital account services have been pivotal in automating routine banking functions (FSCA, 2021). Specifically, ATMs have substantially alleviated customer queues by offering 24/7 transaction capabilities, thus diminishing the necessity for in-branch visits (Masangwana, 2021). This technological advancement has not only elevated customer satisfaction but has also resulted in a significant reduction in operational costs for financial institutions (Suder et al., 2023). The introduction of online loan applications and digital account services has significantly decreased processing times, allowing for remote account openings and streamlined loan procedures (FSCA, 2021). This has reduced traditional costs and enhanced operational efficiency for banks, highlighting the transformative effect of Fintech innovations in the banking sector.

On the other hand, in developing economies, many banks continue to use outdated systems, which makes it hard to integrate new Fintech solutions (Innes & Andrieu, 2022). This integration can be both expensive and difficult to manage. Additionally, the banking sector must navigate constantly changing regulations. For example, ensuring compliance with laws like the Protection of Personal Information Act (POPIA) and the Financial Intelligence Centre Act (FICA) can complicate operations, which hinders the bank's efficiency, especially given ongoing security concerns (McKinsey, 2020; IFWG, 2023).

2.4.4 The effects of Fintech on bank Stability

Fintech innovations present a dual-edged impact on the stability of the banking sector, contributing both to its resilience and introducing new vulnerabilities. On the one hand, advancements in Fintech, such as machine learning, artificial intelligence, and advanced analytics, serve to enhance risk management and compliance mechanisms within financial institutions (IFWG, 2023). These innovations bolster predictive capabilities, enabling institutions to anticipate and mitigate potential risks more effectively. For instance, Absa's implementation of risk management tools and its ability to harness these innovations illustrates an enhanced ability to fortify its risk management framework, thus contributing to greater sector stability (Amazon, 2023). However, the rise of Fintech innovations also introduces a spectrum of new risks (Safiullah & Paramati, 2022). Operational disruptions, cybersecurity threats, and systemic risks are notable among these (Masangwana, 2021). As Fintech solutions evolve, they can cause significant market disruption, particularly affecting traditional banking institutions. The competitive edge gained by new Fintech entrants through technological advancements can erode the market share of conventional banks (McKinsey, 2020).

Fintech solutions can enhance regulatory compliance but also create uncertainties due to the rapid evolution of financial regulations (Takundwa, 2020). This fast-paced change often exceeds the capacity of regulatory frameworks, presenting compliance challenges for financial institutions (Didenko, 2018; Takundwa, 2020). Increased reliance on technology makes banks more vulnerable to cyber-attacks. In response, South African banks like Standard Bank are implementing advanced digital identity verification systems to protect customer data during onboarding (IFWG, 2023). While these measures aim to mitigate cyber threats, they also introduce new security risks, especially given the dependence on Fintech providers. The relationship between Fintech innovations and financial stability is thus complex, involving both improvements in risk management and emerging cybersecurity challenges. The next section reviews theories relating to the effects of Fintech on the banking industry, which align closely with Disruptive Innovation Theory and Creative Destruction Theory.

2.5. Theoretical framework

The theoretical framework sets the basis on which one contextualizes research within the larger scale of existing knowledge. It forms the conceptual grounds upon which studies are built, hence guides the development of research questions, methodologies, and analysis (Lau, & Kuziemsky, 2016). This section explores the critical theories of Disruptive Innovation Theory and Creative disruptive theory, providing an in-depth overview of its importance and application in regard to Fintech. Thus sets a sound basis for interpretation of findings within a broader academic and practical context.

2.5.1 Disruptive innovation theory

Disruptive Innovation Theory, introduced by Clayton Christensen in 1997, explains how new, simpler, and often more affordable products or services can disrupt existing markets (Christensen, 1997). The theory identifies two main types of innovations: sustaining and disruptive. Sustaining innovations look at improvements in existing products or services that enhance their performance (Christensen et al., 2024). Established companies often focus on sustaining innovations to meet the demands of their most profitable customers (Indiran et al., 2024). However, this focus can lead to complacency, causing them to overlook emerging trends or technologies. In contrast, disruptive innovations initially target a niche market or underserved customers with simpler, more affordable solutions (Christensen, 1997). The innovations may lack the performance or features that established products offer, but they provide unique value propositions that attract new users. Over time, as disruptive innovations improve, they begin to appeal to the mainstream market, ultimately displacing established competitors (Christensen et al., 2024).

Building on this concept, Christensen et al. (2024), states that not every innovation has the power to disrupt; rather, those that do typically start at the bottom of a market, serving underserved or overlooked segments before gradually moving upmarket. Fintech innovation exemplifies this concept well. Many Fintech start-ups target underbanked populations or customers dissatisfied with traditional banking services, offering user-friendly and often cheaper financial products and services through mobile apps or online platforms. Over time, these innovations improve and encroach upon mainstream markets, eventually challenging established players by providing more accessible or superior alternatives (Christensen et al., 2024).

The application of the theory explains how Fintech influences the banking industry, for instance as Gomber et al. (2018) discuss, Fintech innovations often cater to previously underserved segments of the market, introducing user-friendly applications, lower fees, and novel products. This disruption forces traditional banks to adapt or risk losing customers. Christensen et al. (2024) argue that such innovations prioritise performance and convenience, appealing to a broader audience and pressuring banks to enhance their core offerings and become more customer centric (Navaretti et al., 2018). Fintech's automation advantage is another key factor, as it employs technology to facilitate and speed financial services, requiring banks to become more efficient in operations in order to remain competitive (Castleman, 2018). On the other hand, the theory implies that threats to bank stability might develop from the quick adoption of new technologies that have not been vetted, or the absence of laws around Fintech businesses can weaken financial stability (Gomber, et al, 2018).

Overall, Disruptive Innovation Theory provides a useful framework for understanding Fintech's impact on the banking sector. The disruptive effects of Fintech may be gradual as new technologies gain traction and consumer behaviour evolves. This necessitates adaptive regulatory frameworks to ensure consumer protection and financial stability while encouraging innovation.

2.5.2 Creative destruction theory

The concept of Creative Destruction was initially explored by sociologist Werner Sombart in the early 20th century, particularly in his 1913 work "*Der moderne Kapitalismus*". It was later popularised by economist Joseph Schumpeter, who introduced the term in his 1942 book "*Capitalism, Socialism and Democracy*" (Schumpeter, 1942). Schumpeter adapted the idea from Karl Marx's writings to describe how new innovations replace outdated ideas and technologies, driving economic progress and transformation (Schumpeter, 1942; Adler, 2019). Schumpeter viewed this process as essential for economic advancement, as it continuously upends existing markets and creates new ones through innovation (Ulgen, 2013).

Schumpeter emphasised the role of innovation, whether through new technologies, business models, or processes, as the primary driver of economic growth (Aghion et al., 2023). Innovations challenge the status quo and create opportunities for new entrants while rendering existing products and companies obsolete (Adler, 2019). Additionally, creative destruction fosters competition. New firms that introduce ground-breaking innovations can disrupt incumbents, leading to a more dynamic and competitive marketplace. This competition can spur further innovation and improvements across the economy. Despite the short-term disruptions and challenges posed by creative destruction, Schumpeter argued that the long-term effects are generally positive, leading to enhanced productivity, better products and services, and overall economic development (Aghion et al., 2023).

Thus, Creative Destruction Theory offers a valuable perspective on the impact of Fintech on traditional banks. According to Ulgen (2013), Fintech innovations embody the essence of creative destruction by introducing innovative financial products and services through streamlined processes and user-friendly applications. This disrupts traditional banking offerings, compelling banks to adapt, improve their features, and compete on pricing. Castleman (2018) argues that, under this theory, banks are pressured to enhance their efficiency and profitability to keep pace with Fintech's leaner operations. This pressure often leads to cost-cutting, product diversification, and a heightened focus on customer experience. The theory also emphasises Fintech's agility and technological prowess, setting new benchmarks for efficiency in financial services. Banks are thus encouraged to invest in automation, data analytics, and digital infrastructure.

Creative Destruction Theory also suggests that widespread Fintech adoption could pose risks to financial stability if regulatory frameworks are not adapted to address new business models and players (Al-Shari, and Lokhande 2023). Despite these risks, collaboration between banks and Fintech can foster a more robust and inclusive financial ecosystem, combining banks' regulatory compliance and trust with Fintech's innovation and agility. In summary, Creative Destruction Theory provides a framework for understanding the dynamic relationship between Fintech innovations and traditional banking (Aghion et al., 2023). It highlights the potential for both disruption and collaboration, suggesting that the future of bank dynamics will involve integrating Fintech's agility with banks' established trust and regulatory compliance to benefit both institutions and consumers.

2.6 Review of empirical studies

The literature review is an important component of study in which previous results are consolidated to provide a foundation in the current state of knowledge. For Instance, patterns, gaps, and contradictions in current research can be identified through empirical evidence analysis. Thus, this empirical review compiles existing research on the influence of Fintech innovations on various aspects of bank dynamics including competition, performance, efficiency, and stability. The review systematically examines the empirical evidence available in the literature, highlighting both global insights and localised findings. However, despite the growing prominence of Fintech globally, there is a noticeable paucity of studies examining its effects within South Africa.

2.6.1 Empirical studies on fintech and banking competition

Recent studies have investigated the complex link between Fintech and banking competitiveness. These studies have looked at a wide range of topics, including the impact of Fintech on traditional banking models, its influence on market competitiveness, and incumbent banks' strategic reactions to competition. Therefore, the evolving landscape of Fintech has sign impacted the banking sector, particularly in bank competition. For Instance, Dwivedi et al. (2021) conducted a study on the impact of Fintech on competition within the UAE banking industry. The study aimed to investigate how the use and adoption of Fintech could contribute to competitiveness and performance. They employed a quantitative method to gather data from 76 banking professionals in Dubai, UAE, using a questionnaire that focused on demographics and factors influencing Fintech adoption, competitiveness, and performance. Data analysis was performed using Minitab 19.0 and SmartPLS software, with responses rated on a 7-point Likert scale. The findings indicated that Fintech innovations enhanced competition by offering alternative financial services that challenged traditional banking models. This enhanced competition was believed to drive improvements in the overall performance of the UAE banking sector. Additionally, the study suggested that the implications of the findings aligned with existing literature, as technology adoption streamlined processes, enhanced service delivery, and improved overall performance. The significant impact on competitiveness indicated that Fintech adoption could provide a competitive edge in the banking sector.

Another relevant study, Bejar et al. (2022) explored the early effects of Fintech in Latin America and the Caribbean (LAC) by employing panel regression analysis across multiple countries and time periods. The primary aim of the study was to assess the impact of Fintech on competition within LAC's banking sector. The authors sought to understand how Fintech influenced net interest margins (NIMs), market concentration, and the responses of incumbent banks. They also aimed to provide insights into regulatory approaches that could foster financial innovation while maintaining stability in the banking sector. The study found that the growing presence of Fintech prompted traditional financial institutions to take on more risks. Specifically, the entry of Fintech into the market was associated with reduced Net Interest Margins (NIMs), suggesting that Fintech competition forced banks to lower prices, potentially reducing profitability in contrast to the findings of Dwivedi et al. (2021). Furthermore, Bejar et al. (2022) identified a positive relationship between NIM and real GDP growth, indicating that during periods of economic expansion, banks might widen interest rate spreads due to increased loan demand, thereby potentially improving NIM. However, the study also highlighted that high market concentration could impede competition, as fewer large banks might exploit their market dominance to charge higher rates and earn higher profits, consequently reducing competitive pressure. The authors concluded that regulatory frameworks are essential to promote Fintech innovation while ensuring consumer protection and financial stability. They emphasised that traditional banks should adapt to the changing landscape by embracing technology and forming partnerships with Fintech firms to remain competitive.

In a related investigation, Song et al. (2023) explored the effects of competition and technology spillover on commercial banks' profitability in relation to Fintech. They examined annual panel data from 46 listed Chinese commercial banks for the years 2012–2021 using a two-way fixed-effects model. According to the study, the competition effect outweighed the technology spillover effect in the early phases of Fintech development, which had a negative correlation with bank profitability. These results indicated that in order to stay competitive, commercial banks needed to adapt their revenue strategy and business model, concentrating on Fintech innovation and tailored services as consumer demand changed. The GDP growth rate had a negative coefficient of −0.058, indicating that higher economic growth intensified competition and reduced the profit margins of banks in their efforts to attract and retain customers in an increasingly dynamic market. This agreed with the inconclusive results of Naceur et al. (2023) on GDP. In contrast, the coefficient of inflation obtained was positive, about 0.291, suggesting that higher inflation increases bank profitability. This was probably because, in periods of inflation, banks can increase the interest rates for loans, thus increasing revenues.

On the other hand, supporting Dwivedi et al. (2021) narrative, Lakshmi and Yashwanth 2024 investigated the impact of Fintech innovations on traditional banking models. The case study of Angel Broking was selected for this investigation. A structured questionnaire was designed to collect the data in this regard. In this, different types of questions were included to obtain elaborative responses. The ANOVA test and other statistical analyses were applied to analyze the impact of Fintech development on traditional banking practices. The study found that traditional banks' adoption of Fintech innovations increased their competitiveness. This is consistent with Dwivedi et al. (2021), who reported that disruptive technologies increase the operational efficiency and lower the cost of operations for banks. The results showed that traditional banks need to quickly adapt to changes brought by Fintech to maintain their competitive advantage.

Lastly, Peón et al. (2024) investigated the competitive dynamics of traditional banks and Fintech start-ups in Spain, specifically whether these institutions competed or collaborated through their Fintech ventures. The sample included 202 firms from 2010 to 2019. The paper used a two-step system Generalized Method of Moments model in conjunction with an oligopolistic conjectural variation model to examine the strategic interactions between bank-owned Fintech ventures and independent firms. The findings revealed that traditional banks use their Fintech ventures primarily to compete with independent firms rather than to collaborate. This suggests that there is a positive relationship between banking competition and Fintech innovation, which supports the findings of Dwivedi et al. (2021) and Lakshmi and Yashwanth (2024).

2.6.2 Empirical studies on fintech and banking performance

The fast expansion of Fintech has dramatically altered the face of banking throughout the world, requiring further research into its impact on traditional banking performance. Various studies have emerged, exploring the complex dynamics between Fintech innovations and banking performance across different economies. For example, Phan et al. (2018) examines the impact of Fintech companies on the performance of Indonesian banks using a dataset of 41 banks from 1988 to 2017. The authors used a two-step GMM system dynamic panel estimator to test the impact of Fintech on performance measures such as NIM, ROE, ROA, and YEA. The study found that Fintech expansion had a negative impact on the metrics, lowering NIM, ROE, ROA, and YEA by 0.38, 7.30, 1.73, and 0.38 percent of their respective sample mean values, respectively. Furthermore, an additional Fintech firm's entry into the market reduced NIM, ROE, ROA, and YEA by 0.53, 9.32, 2.07, and 0.48 percent of their sample averages, respectively. The research also highlighted the positive relationship between GDP growth and bank performance, meaning that economic growth fosters greater loan activity and higher net interest revenue. However, the effects of inflation on bank profitability were found to be related to the rate of inflation and the ability of banks to adjust interest rates. While expected inflation could favourably affect profitability because it increases more slowly than wages and operating costs, unexpected inflation may hurt profits unless banks can respond by adjusting interest rates to keep costs rising more slowly than revenues.

In contrast, Ky et al. (2019) studied the influence of mobile money adoption on the performance of banks in the East African Community, using a sample of 170 financial institutions from five member states between 2009 and 2015. Performance was modelled using ROE and ROA via a panel data fixed-effects regression approach. The results indicated that there is a positive and significant relationship between the length of time for which mobile money has been adopted and bank performance. Banks involved in mobile money schemes thus registered improved profitability, contrary to Phan's (2018) argument that increased growth of Fintech impairs bank performance. The study proved that mobile money could grossly enhance bank performance in developing countries where the physical infrastructure is not well established for regular banking. Furthermore, there was a strong positive correlation between GDP growth and the performance of banks, reinforcing the findings by Phan et al. (2018). This implies that economic growth strengthens banks' financial positions through the creation of more opportunities for lending and increased demand for banking services. Ky et al.,(2019) however, found a positive relationship between inflation and bank performance, unlike Phan et al. In this study, it was suggested that inflation could benefit banks by boosting interest revenue on loans when banks adjust rates in response to rising prices.

Another relevant study in line with negative effects of Fintech is by Kumar (2020), which evaluated the influence of Fintech on the banking performance of commercial banks across India. It tried to establish if Fintech contributed favourably or negatively to banks' financial performance, with a special emphasis on criteria like as ROA and bank growth. The study used fixed effects regression to analyze data from 2014 to 2019. In keeping with the findings of Phan et al. (2018), the results demonstrated a statistically significant negative association between Fintech, evaluated by mobile payment transactions, and the financial performance of Indian banks, notably in terms of ROA. However, another hypothesis suggested a positive association between Fintech and bank growth, consistent with the findings of Ky et al. (2019), implying that while Fintech may have a detrimental impact on financial performance, it may still contribute to overall development in the banking industry. The consequences revealed that, while Fintech might promote development, it could also provide difficulties to established banking performance criteria. This dichotomy emphasised the importance of banks adapting their strategy to the changing Fintech market. Furthermore, the study discovered that an increase in inflation was positively connected with bank financial performance, which is consistent with Ky et al. (2019), implying that greater inflation may lead to increased ROA for Indian commercial banks.

Dwivedi et al. (2021) focused on studying how Fintech use and acceptance may boost competitiveness and performance. The study found that Fintech improves performance in the UAE banking market by increasing competition. The study stated that Fintech impacts banking sector performance because incumbents may produce innovative goods and services that help attract and retain customers. Furthermore, the existence of Fintech makes the supply of services and products to consumers more convenient, increasing competitiveness.

A recent study by Zhao et al. (2022) examined the impact of Fintech growth on bank performance using the CAMEL framework, which stands for capital adequacy, asset quality, managerial efficiency, profitability, and liquidity. The authors used the Generalized Method of Moments model with data from 2003 to 2018. They created an indicator of Fintech development based on total registered capital, investment rounds, and the number of Chinese Fintech start-ups. The study discovered that Fintech development has a major impact on bank performance, improving capital adequacy and management efficiency while negatively influencing asset quality and profitability. The data indicated that several institutions either underestimated or overreacted to Fintech disruptions. Thereby, the study recommended that traditional banks collaborate with Fintech start-ups in enhancing their business models and driving digital transformation.

In South Africa, Mugabe (2022) investigated the link between Fintech enterprises and the performance of the South African banking system in terms of long-term association, variance in bank size, and causation. To analyze how Fintech penetration affects performance variables such as ROE, ROA, NIM, and YEA, the study used the ARDL model to examine data from 2000–2018. The data indicated a substantial positive relationship between Fintech presence and banking performance, which supports the findings of Ky et al. (2019) and Kumar (2020). On the other hand, the ROE results showed that Fintech businesses' contributions had a long-term negative relationship with net profit per Rand contribution to equity investors. This also confirmed the findings of Phan et al. (2018). The study also found out that the Fintech businesses' presence is not an appropriate predictor of future banking performance. Consistent with the findings of Phan et al. (2018), inflation negatively influences bank profitability since banks are usually unable to raise interest rates in a timely manner to offset increasing operational costs. In contrast, GDP growth positively influenced bank profitability because, during economic expansions, the quality of the loan portfolio improved, enhancing credit gains and overall performance. This is in line with the findings of Kumar (2020).

In a more recent study, Naceur et al. (2023) found that the impact of Fintech on traditional financial institutions included reduced profitability due to intensified competition from Fintech, consistent with the findings of Bejar et al. (2022). The study investigated how the growing presence of Fintech firms affected the performance of traditional financial institutions, highlighting potential challenges for established banks while exploring nuances based on the type of Fintech model and the existing financial landscape. Naceur et al. (2023) found that Fintech had a statistically significant negative effect on the profitability of traditional banks, as evidenced by reduced ROE, ROA, and NIM). This finding indicated that Fintech exerted pressure on traditional banks by lowering interest revenue and increasing operating expenses. The authors noted that the implications of this decline were significant, as Fintech firms often offered alternative financial services at lower costs, leading to decreased interest revenue for traditional banks. Furthermore, adapting to the competitive landscape and potentially integrating Fintech solutions could raise operational costs for these institutions. The study concluded that despite efforts to diversify income sources, banks struggled to maintain profitability in the face of growing Fintech competition. Additionally, the study highlighted mixed results regarding the impact of GDP growth on bank performance. While some positive effects on ROE and ROA were observed, there were also negative effects on the cost-to-income ratio. High inflation was found to negatively affect bank profitability.

On the other hand, Tarawneh et al. (2024) evaluated the impact of Fintech on Malaysian bank profitability using both accounting measurements (ROA and NIM) and market performance indicators (Tobin's Q). The authors concentrated on publicly traded Malaysian banks from 2010 to 2022, using bank-level variables such as the intangible asset ratio and ATM-to-branch ratio, as well as a country-level Fintech index that included ATM usage, smartphone penetration, and internet availability. Several econometric estimate approaches were used, including pooled OLS, General Least Squares Regression, fixed effects model, and random effects model. The findings showed that Fintech has a mixed effect on bank profitability. On the bank level, this is proxied by an intangible asset ratio positively impacting NIM, therefore, this means that technology-driven innovations enhance profitability. These findings find support in Ky et al. (2019), Kumar (2020), and Mugabe (2022). However, at the country level, broader Fintech development negatively influenced bank profitability attributed to increased competition from digital payment systems and peer-to-peer platforms. It underscored that strategic agility, supported by advanced risk management practices, was highly essential for banks to deal more efficiently with the evolving financial landscape brought about by Fintech developments.

Lastly, Pham et al. (2024) explored how the emergence of Fintech affects bank performance in Vietnam. The study sought to fill a research vacuum in the link between Fintech and traditional banking, particularly in developing nations where Fintech plays an important role in delivering financial services to previously underserved groups. The study used Generalized Least Squares (GLS) and data from 15 Vietnamese banks from the first quarter of 2019 to the second quarter of 2021. The study indicated that Fintech development has a considerable beneficial influence on bank profitability, which is consistent with the findings of Ky et al. (2019), Kumar (2020), Mugabe (2022), and Tarawneh et al. (2024). The study recommends that banks should accelerate their transformation processes to integrate Fintech solutions effectively to improve their performance. Additionally, the authors stated that the collaboration between banks and Fintech firms can lead to enhanced service offerings and improved market competitiveness.

In conclusion, although some studies demonstrate a detrimental impact of Fintech on traditional banking performance due to increasing competition, others show favorable results connected with particular innovations such as mobile money.

2.6.3 Empirical studies on fintech and banking efficiency

Wang et al. (2021) examined the influence of Fintech on the banking sector, focusing on its implications for commercial banks' efficiency and productivity. The study sought to investigate the association between Fintech adoption and total factor productivity (TFP) in these institutions. Using a data panel of 113 domestic and commercial banks from 2009 to 2018, the researchers employed systematic generalised moment estimation (SYS-GMM) and differential generalised moment estimation (DIF-GMM) as baseline regression methodologies. Their findings revealed that the rise of Fintech resulted in higher profitability for commercial banks by fostering financial innovation and enhancing risk control methods. This suggested that by adopting Fintech, banks could reduce operating costs and enhance service efficiency, contributing to a more competitive business model. However, the authors concluded that effective Fintech integration requires significant investment in hardware and software infrastructure, including advanced data management and processing capabilities. Additionally, the study highlighted a negative relationship between GDP growth and the TFP of commercial banks, suggesting that rapid economic expansion might undermine banking efficiency.

Building on similar themes, Lee et al. (2021) explored the impact of Fintech development on cost efficiency and technology adoption within China's banking industry. Drawing on data from 114 commercial banks spanning 2003 to 2017, the authors utilised a two-step system dynamic GMM estimator as their baseline regression method. They found that Fintech innovations significantly enhanced the cost efficiency of banks, enabling more effective operations. The findings underscored the importance of Fintech as a critical driver of bank efficiency, particularly in emerging economies. To harness this potential, the authors recommended that policymakers and banking institutions prioritise infrastructure that supports Fintech advancements. Furthermore, the study identified the consumer price index (CPI) as a significant control variable positively affecting bank efficiency. This suggested that rising CPI levels could correlate with increased banking efficiency due to heightened demand for banking services or strategic pricing adjustments.

Focusing on the Southeast Asian context, Maryunita and Nugroho (2022) investigated the influence of Fintech adoption on traditional banks' efficiency in Indonesia between 2013 and 2019. Their research, centred on 38 conventional banks listed on the Indonesia Stock Exchange (IDX), utilised Data Envelopment Analysis and panel data regression with a random effects model. The findings revealed that Fintech adoption significantly improved banks' operational efficiency and competitiveness, particularly in serving Micro, Small, and Medium Enterprises (MSMEs). This aligns with Wang et al. (2021), as both studies emphasise the role of innovation and infrastructure development in enhancing banking performance. Maryunita and Nugroho further observed a positive relationship between GDP growth and bank efficiency, indicating that economic expansion facilitates economies of scale and resource optimisation, thereby boosting operational efficiency.

In Taiwan, Liao (2023) examined Fintech's impact on bank efficiency from 2007 to 2020 using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The study aimed to assess how Fintech initiatives influence metrics such as cost productivity and operational performance. The results showed that Fintech innovations, particularly mobile payment systems, significantly improved customer convenience and satisfaction. These findings align with Lee et al. (2021), who highlighted the operational benefits of Fintech advancements. However, Liao noted that not all Fintech solutions yield efficiency gains, as significant investments in technology can entail risks without guaranteed returns. This scepticism highlights the need for strategic planning in implementing Fintech solutions to ensure their productivity aligns with banking goals.

Further exploring Fintech's implications, Lee et al. (2023) analysed its effect on commercial bank efficiency in China, focusing on 74 banks from 2012 to 2019. Using the DEA-Malmquist model and a Fintech development index constructed through text mining, the study employed various econometric methods, including POLS, FE, RE, and GMM. The results revealed that while Fintech development fosters competition, it negatively impacts banks' efficiency by increasing debt expenses, particularly for urban and rural commercial banks. Joint-stock banks, however, demonstrated greater resilience. This study diverges from earlier research, such as

Lee et al. (2021) and Wang et al. (2021), by highlighting the challenges posed by Fintech competition rather than its benefits.

Finally, Al-Jabri (2023) investigated the relationship between Fintech adoption and bank efficiency in six MENA countries, including Saudi Arabia, UAE, and Egypt, using data from 63 banks between 2011 and 2021. The research found a positive association between Fintech adoption and operational efficiency, supporting the conclusions of Wang et al. (2021) and Maryunita and Nugroho (2022). However, similar to Wang et al., Al-Jabri noted that GDP growth had a significantly negative effect on bank efficiency, attributed to increased competition and reduced market entry barriers, which heightened operational costs. This underscores the need for banks to strategically integrate Fintech solutions to adapt to evolving competitive landscapes.

2.6.4 Empirical studies on fintech and banking stability

Safiullah and Paramati's (2022) study investigated the relationship between Fintech business development and financial stability in Malaysian banks. The authors hypothesised that the rapid growth of Fintech firms would increase competition, prompting banks to adopt Fintech services or collaborate with providers to enhance efficiency and profitability, thereby improving financial stability. Analysing data from 26 Islamic and mainstream banks in Malaysia from 2003 to 2018, the authors employed POLS regression and GMM estimation to address issues such as unobserved heterogeneity and dynamic endogeneity. Their findings indicated that the rise of Fintech firms positively impacts bank financial stability, a conclusion that held across different model specifications and stability indicators. However, they also observed that increased competition from Fintech firms might incentivise banks to take riskier investments, potentially undermining stability in some cases. This dual effect highlights the need for balanced strategies to address both competition and risk.

Expanding the geographic focus, Yin et al. (2022) examined Fintech's impact on banking sector stability in China. Using regression analysis on Big Data spanning 1995 to 2018, they explored variables such as non-performing loans (NPLs) and the Z-score to measure banking soundness. Their findings suggested that the second wave of the Fintech era reduced NPLs and enhanced financial stability. The study also emphasised Fintech's role in improving loan performance and risk management, aligning with Safiullah and Paramati's (2022) observations of Fintech's stabilising potential. Additionally, the authors argued for stricter regulatory measures to mitigate risks associated with Fintech growth, especially in emerging markets. Interestingly, they linked Fintech innovations to GDP growth, suggesting that expanding access to financial services and reducing transaction costs contribute to broader economic benefits.

Similarly, Daud et al. (2022) investigated the link between Fintech and financial stability on a global scale, focusing on 63 nations from 2006 to 2017. Using dynamic panel GMM estimation, the study found a positive association between Fintech and financial stability, echoing Safiullah and Paramati (2022). The authors highlighted how technologies like artificial intelligence, cloud computing, and data analytics bolster stability by fostering innovation and operational efficiency. However, they also noted that bank concentration negatively affects stability, as large banks often take excessive risks, exacerbated by government subsidies. Their findings, like those of Yin et al. (2022), underscored GDP's positive correlation with stability, reflecting economic growth's role in strengthening the financial sector.

In a more recent exploration, Stankevičienė and Kabulova (2022) analysed Fintech's dual impact on financial stability using data from financial institutions in 37 countries between 2015 and 2019. The research revealed both positive and negative effects of Fintech but found no statistically significant influence of the Fintech sandbox variable on stability. This contrasts with earlier findings, such as those by Daud et al. (2022), suggesting that Fintech's effects might vary depending on regulatory frameworks and institutional readiness.

Building on these findings, Dang and Nguyen (2022) assessed Fintech's impact on financial stability in Vietnam, focusing on 37 commercial banks from 2010 to 2020. Their fixed-effects regression analysis revealed that Fintech development negatively affects financial stability, particularly for banks with weaker foundations. This result aligns with the findings of Geng, Guo, and Cheng (2023), who also identified detrimental effects of Fintech on stability in Chinese banks. However, Dang and Nguyen noted that strong market discipline could mitigate these adverse effects. They also highlighted a positive relationship between GDP growth and financial stability, consistent with the conclusions of Daud et al. (2022).

In the context of Indonesia, Yudaruddin et al. (2023) explored the impact of Fintech firms, particularly peer-to-peer lending and payment systems, on bank stability. Their analysis of 141 banks from 2004 to 2018 showed that the growth of Fintech firms enhances stability, particularly for smaller and non-listed banks. These findings echo Safiullah and Paramati (2022) and Daud et al. (2022), reinforcing the notion that Fintech can stabilise smaller financial institutions. However, the study also underscored the need for regulatory measures to safeguard consumer interests and maintain the soundness of banks in a rapidly evolving financial landscape.

Geng, Guo, and Cheng (2023) delved deeper into the mechanisms through which Fintech adoption affects stability in Chinese commercial banks. Their findings revealed that while certain innovations, like artificial intelligence and big data, positively impact stability, others, such as internet-based technologies, have adverse effects. This nuanced understanding complements the observations of Dang and Nguyen (2022), suggesting that targeted regulations can mitigate Fintech's risks while leveraging its benefits.

Lastly, Ahmad et al. (2023) investigated the effects of Fintech innovations on Malaysian banks' stability and efficiency, analysing a sample of 36 banks from 2006 to 2020. While Fintech significantly enhanced commercial banks' stability, its impact on Islamic banks was less pronounced. These findings align with Safiullah and Paramati (2022), who also emphasised the role of Fintech in bolstering bank stability. However, Ahmad et al. noted that the overall regression results lacked statistical significance, underscoring the importance of adapting regulatory frameworks to address the complexities introduced by Fintech.

2.7 Gaps identification from the empirical literature

The review covered in Section 2.6 highlights a significant gap in empirical research specifically focused on the South African context regarding Fintech innovations and their effects on the banking sector. While global studies exist, there is a noticeable lack of localised research that addresses the unique dynamics of South African banks. Additionally, there is a lack of comprehensive analysis of the bank dynamics as the empirical review showed that the studies often concentrated on singular aspects of bank dynamics, such as competition, performance, efficiency, or stability. Moreover, existing studies have generally analysed data over relatively short periods, limiting their ability to capture the long-term effects of Fintech on the banking system. Some earlier South African studies have employed inadequate methodologies, such as failing to account for bank heterogeneity, which can affect the accuracy of their findings. For instance, Mugabe (2022), utilised the ARDL model, which can be prone to the propensity for multicollinearity when a substantial number of lagged terms are included. Such multicollinearity can significantly undermine the accuracy and interpretability of the resultant estimate (Månsson, 2012). Moreover, the literature presents mixed findings regarding the effects of Fintech on the banking sector. For example, Dwivedi et al. (2021) emphasize the positive impact of Fintech on bank competition, while Naceur et al. (2023) observe a negative effect. Similarly, studies by Phan et al. (2020) and Mugabe (2022) report negative consequences on bank performance, with Mugabe also noting a decline in long-term return on equity. In contrast, Dwivedi et al. (2021) find a positive relationship between Fintech adoption and improved performance. There are also differing views on Fintech's impact on efficiency. Liao (2023) and Ahmed et al. (2023) document positive effects in Taiwan and other regions, while Lee et al. (2023) find negative impacts. When it comes to stability, findings are equally contradictory, with Yudaruddin et al. (2023) linking increased Fintech use to greater stability, while Geng et al. (2023) associate it with reduced stability. This study aims to synthesise these conflicting results, offering a clearer understanding of Fintech's influence on various aspects of banking.

2.8 Chapter summary and concluding remarks

Chapter Two laid a comprehensive foundation for understanding the relationship between Fintech and the South African banking sector. It reviews the historical development of Fintech and its current impact, illustrating how technological innovations are transforming financial services. The chapter highlights the importance of South Africa's banking sector to the economy and discusses the opportunities and challenges posed by Fintech. The exploration of theories like Disruptive Innovation and Creative Destruction provides insights into the effects of Fintech on traditional banking, shedding light on competition, performance, efficiency, and stability amid technological disruption. Furthermore, the chapter reviews empirical studies on the impact of Fintech innovations in the South African banking sector, highlighting a notable research gap despite Fintech's global rise. It points out that while Fintech can enhance competition, efficiency, and stability, it also challenges traditional banks with declining profitability. The chapter emphasises the need for more research on the long-term effects of Fintech on South Africa's banking landscape to provide a comprehensive understanding of its future role in the sector. The next chapter will cover the data and methodology of the study.

CHAPTER THREE: METHODOLOGY

3.1 Chapter overview

The research methodology refers to the procedures and techniques used to gather, analyze, and interpret data for the study. The importance of the methodology is that it establishes the groundwork for the whole research process, ensuring that the findings are credible, valid, and appropriate (Dawson, 2019). This chapter outlines the study's methodology with the primary objective of focusing on the effect of Fintech innovations on the dynamics of the South African banking sector. This section is going to cover measures used to investigate how advancements in Fintech impact competition, performance, efficiency, and stability within the banking system. This study analyses publicly traded banks on the Johannesburg Stock Exchange (JSE) from 2000 to 2023, using data from the Bloomberg terminal and the World Bank's WDI. The study employs a panel regression methodology to examine the relationship between Fintech innovations and bank competition, performance, efficiency, and stability. It employs the Lerner Index for competition, Capital Adequacy Ratio (CAR) for performance, Stochastic Frontier Approach (SFA) for efficiency, and Z-score for stability, with Fintech measured by the natural logarithm of ATMs per 100,000 adults and Value of Mobile Money Transactions (VMT). Control variables include GDP growth, inflation growth, and bank concentration to contextualise the findings. The subsequent sections provides detailed descriptions of the employed variables, and the econometric methodology used to achieve the objectives of the study.

3.2 Data and sampling

Data and sampling are critical components of every research project since they determine the quality and dependability of the results. Proper data collection using suitable sampling methods guarantees that the results are representative and may be used to a larger population. This section will describe the particular data sources and sample strategies used in the study to verify its validity and correctness(Dawson, 2019).

3.2.1 Population and sampling

The population and sampling methods in this study are designed to ensure a comprehensive and accurate analysis of the South African banking sector. The study focuses on publicly traded banks listed on the Johannesburg Stock Exchange (JSE) to gain insights into the overall behaviour and performance of the South African banking sector. The banks represent a crucial segment of the South African financial sector, providing more than 90 percent contribution to the sector (Wilson et al., 2024). The chosen banks are African Bank, FirstRand, Standard Bank, Capitec Bank, Investec Bank Limited, Absa Group, Nedbank Group, and Finbond Group. These banks were selected based on their prominence in the market and the availability of comprehensive financial data from the Bloomberg terminal. Certain banks were excluded from the sample due to limited data availability or their smaller market capitalisation, which could skew the analysis and not adequately represent the overall performance and behaviour of the banking sector. By focusing on these key institutions, the findings provide a more accurate and reliable assessment of trends within the sector.

3.2.2 Sample period

The study uses an annual data frequency to ensure consistency and comparability across various financial metrics, particularly given the complexities involved in analysing bank dynamics and macroeconomic indicators. For instance, the study's Fintech variable was collected annually, similar to the macroeconomic variables. A twenty-four-year study period that runs from 2000 to 2023 is employed. The period beginning in 2000 was chosen for its strategic significance: it represents a turning point in the growth and expansion of both the banking industry and fintech developments in South Africa (Mugabe, 2022). This was also a time when fintech was gaining traction and fast expanding, particularly in terms of how it influenced traditional banking operations, consumer behaviour, and overall sector performance (Panday, et al., 2024). Furthermore, this timeframe is strategically selected as the financial databases offer extensive historical data over this timeframe, ensuring that all necessary financial variables and metrics are consistently available. Furthermore, this extensive period allows for a thorough analysis of long-term trends and behaviours in the South African banking sector. This approach allows for a more robust analysis by aggregating data over a longer time frame, thus capturing trends and patterns that may not be evident in shorter intervals (Stankevičienė & Kabulova, 2022).

3.2.3 Data sources

This study utilises secondary data to explore the impact of Fintech innovations on the dynamics of the South African banking sector. The key variables analysed include the Lerner Index, which measures bank competition; the Capital Adequacy Ratio, which assesses bank performance; the Stochastic Frontier Approach, which evaluates bank efficiency; and the Z-score, which indicates bank stability. These variables serve as the dependent variables for this research[3]. The independent variable, Fintech, is proxied by the natural logarithm of Automated Teller Machines (ATMs) per 100,000 adults and value of mobile money transactions (VMT). The control variables are bank concentration, Gross Domestic Product (GDP), and inflation. The data for the dependent variables of the Lerner Index, Capital Adequacy Ratio, Stochastic Frontier Approach and Z-score were collected using the Bloomberg terminal for the years 2000–2023. The data for the independent variables proxying Fintech and the control variables of GDP, inflation and bank concentration were collected using the World Bank's World Development Indicators (WDI) database. For South Africa, the WDI provides a comprehensive dataset that includes statistics related to digital financial services and financial inclusion. The decision to use the WDI database is further reinforced by earlier studies conducted by Mlambo and Ncube (2011) and Moyo (2018). According to these studies, the WDI is a useful site for getting the most up-to-date and thorough information on financial inclusion indicators, which is essential for comprehending how South Africa's digital financial sector is changing.

3.3 Preliminary analysis

A crucial step in the research process is preliminary analysis, which entails the methodical examination and assessment of data prior to primary analysis. Its main goals are to find and fix mistakes, control the quality of the data, and lay the groundwork for further analysis so that researchers may generate accurate and legitimate findings. To improve the precision and reliability of study findings, this phase entails data screening, cleaning, and the detection of outliers or missing values. Researchers can steer clear of potential problems that could jeopardise the integrity of their studies and help produce more solid conclusions by conducting a thorough preliminary investigation (Pulka,2022).

3.3.1 Descriptive Statistics

Descriptive statistics play a fundamental role in data analysis by providing a concise summary and visualisation of the essential features of a dataset, allowing researchers to understand its key characteristics briefly. This approach is crucial because it simplifies complex data, making it easier to identify patterns, trends, and anomalies, which can inform further analysis or hypothesis generation (Dong., 2023). By employing various measures such as central tendency (mean, median, mode) and variability (range, standard deviation), descriptive statistics enable

[3] The justification for the choice of variables is provided under the empirical methodology for each objective.

researchers to effectively communicate findings and lay the groundwork for more advanced inferential statistical methods (Sukhoplyuev et al., 2024).

3.3.1.1 Mean

The mean provides a central tendency measure that helps in understanding the average value of the variable. This is crucial when working with panel data as it will allow the study to identify the average behaviour of the variables chosen over time or across different groups (Kaliyadan & Kulkarni, 2019). Its applications span various fields, from psychology to sports statistics and network performance analysis (Aining et al., 2020). The mean value is calculated following:

$$\bar{\chi} = \frac{1}{\mathrm{NT}} \sum_{\mathrm{i}-1}^{\mathrm{N}} \sum_{\mathrm{i}-1}^{\mathrm{T}} \chi_{\mathrm{it}} \qquad (1)$$

From Equation (1), N represents the number of individuals also known as cross-sectional units. While T is the number of time of periods. Additionally, χ_{it} represents the value of the variable for individual i at time period t (Kaliyadan & Kulkarni, 2019).

3.3.1.2 Standard deviation

The standard deviation is a statistical measure that indicates how spread out the data is around the mean (Kaliyadan & Kulkarni, 2019). By examining this dispersion, researchers can understand the variability of a variable, which is particularly important in panel data (Darling, 2022). This allows for the assessment of how much a variable change over time or between different groups, such as countries or firms (Kaliyadan & Kulkarni, 2019). The overall standard deviation considers all observations in the dataset without considering any specific groupings. The formula for calculating standard deviation is:

$$\sigma overall = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\chi - \bar{\chi})^2} \qquad (2)$$

Where N is the total number of observations, χ is each observation and $\bar{\chi}$ is the mean of all observations.

3.3.1.3 Skewness

One statistical indicator of a distribution's asymmetry is its skewness. A bell-shaped curve that is symmetrical and has a skewness of zero indicates that the data is normally distributed, meaning that it is uniformly dispersed around the mean (Hatem, et al., 2022). On the other hand, a distribution that is right-skewed is indicated when the skewness value is larger than 0. Most of the data points are grouped on the left side of the distribution in this instance, as the right tail is thicker or longer than the left tail (Campisi et al., 2023). Most data points are concentrated on the right side of a distribution with a skewness value less than zero, which indicates a left-skewed distribution with a longer or thicker left tail (Arachchige & Prendergast, 2019). Skewness can be used to assess whether a variable in the study's panel data has a normal distribution or whether there are outliers that could affect the analysis.

The formula for Skewness follows:

$$g = \frac{\sum_{i=1}^{N}\sum_{\tau=1}^{T}(\gamma_{it}-\bar{y})^3}{(N \cdot T-1)S^3} \qquad (3)$$

Equation (4) shows γ_{it} which represents the individual observation for entity i at time t. The overall mean of all the observations is denoted by the $\bar{y}$, providing a central tendency measure across the dataset. While N refers to the total number of entities included in the study. Additionally, S represents the standard deviation of the observations, which quantifies the amount of variation or dispersion present in the dataset (Hatem, et al., 2022).

3.3.2.4 Kurtosis

Kurtosis is a statistical metric that highlights a distribution's peaks and tails to characterize its form. According to Booker and Ticknor (1998), it is the standardized fourth central moment that assesses how peaked the distribution is and how heavy the tails are in relation to a normal distribution. Kurtosis is useful in many applications, such as comparing different distributions, analysing outliers, and testing for normality (Booker & Ticknor, 1998; Hatem et al., 2022). A distribution with a strong peak and heavy tails is said to have positive kurtosis, which suggests a higher probability of extreme values. Conversely, low kurtosis suggests fewer extreme values, lighter tails, and a flatter shape ((Hatem et al., 2022). A normal distribution is said to be mesokurtic if its kurtosis value is 3. Lighter tails and a flatter peak, which indicate fewer extreme outliers, are characteristics of platykurtic distributions with kurtosis less than 3. On the other hand, leptokurtic distributions, which have a sharper peak and heavier tails, have kurtosis larger than 3, indicating a higher probability of extreme outliers (Liang et al., 2008). Kurtosis can be calculated using the following formula:

$$\kappa = \frac{\mu^4}{\sigma^4} \qquad (4)$$

In the equation (4) μ^4 represents the fourth power of the mean, which indicates a measure of central tendency raised to a higher power, emphasising the influence of larger values in the dataset. On the other hand, σ^4 signifies the fourth power of the standard deviation, reflecting the dispersion or variability of the observations (Liang et al., 2008).

3.3.2.5 Jarque-Bera

One statistical method for figuring out if a sample of data has a normal distribution is the Jarque-Bera (JB) test. It provides a means of evaluating normality, especially in regression residuals, and is based on the skewness and kurtosis of the sample (Pooi & Soo, 2012). The following formula is used to determine the Jarque-Bera test statistic:

$$JB = \frac{\eta}{6}(S^2 + \frac{(k-3)^2}{4}) \qquad (5)$$

Equation (6), K is the sample kurtosis, S is the sample skewness, and η is the sample size. To assess departures from normalcy in a dataset, this formula combines the squared skewness and the squared excess kurtosis. In particular, $(k-3)^2$ assesses the degree to which the kurtosis deviates from 3, the value for a normal distribution, whereas S^2 quantifies the asymmetry in the data distribution. With the statistic scaled by the sample size for increased reliability in bigger samples, the test determines if a dataset has a normal distribution (Pooi & Soo, 2012).
To evaluate the normality of the data under consideration, the study proposes the following hypotheses:

$H_{0:}$ The data follows a normal distribution.

$H_{1:}$ The data does not follow a normal distribution.

If the null hypothesis is not rejected, it means that there is not enough data to draw the conclusion that the sample is not normal. This result implies that the distribution of the sample is consistent with the characteristics of a normal distribution. On the other hand, finite-sample distributions can deviate from asymptotic expectations, requiring careful interpretation; therefore, failing to reject the null does not ensure that the sample is entirely normal (Lawford, 2005).

3.3.1.6 Correlation

The correlation coefficients between variable pairs within a dataset are displayed in the study using a correlation matrix table, a statistical metric called correlation, which shows how much two variables change together(Serra et al., 2018). According to Sierra et al. (2018), this method is useful for summarising large datasets because it makes it easier to quickly determine the direction and strength of relationships between variables. According to Schober et al. (2018), it can be categorised as either positive, where an increase in one variable results in an increase in another, or negative, where an increase in one variable results in a decrease in the other. The study makes it possible to quickly determine which variables have strong or weak correlations by displaying these correlation coefficients.

Schober and Vetter (2020) classify the strength of correlation coefficients (r) into three categories. A low correlation is indicated by values less than 0.40, suggesting a weak relationship between variables. A moderate correlation falls between 0.40 and 0.70, indicating a more noticeable connection. A high correlation is represented by values of 0.70 or higher, reflecting a strong relationship between the variables (Schober & Vetter,2020). This understanding is crucial in the context of regression analysis, where the selection of variables for inclusion in the model can be informed by the observed correlations. Variables that demonstrate high levels of correlation may be deemed redundant, leading to their potential exclusion to mitigate the risk of multicollinearity (Pott, 2008). Multicollinearity, in turn, has the effect of inflating the standard errors of the estimated regression coefficients, thereby reducing the precision of these estimates and complicating the determination of their true values (Kim, 2019). The correlation formula is as follows:

$$\rho(\chi,\gamma) = \frac{Cov(\chi,\gamma)}{\sigma\chi\sigma\gamma} \tag{6}$$

Where:

$Cov(\chi,\gamma)$ is the covariance between variables χ and γ

$\sigma\chi$ and $\sigma\gamma$ are the standard deviations of χ and γ respectively.

3.3.2 Unit root tests

The study tests for stationarity to address potential non-stationarity in the panel data by using the Im-Pesaran-Shin (IPS) test. The study focuses on panel stationarity tests because they are crucial as non-stationary variables can lead to spurious regressions (Hadri & Kurozumi, 2012). Therefore, using the IPS tests will be advantageous for the study because of their flexibility compared with individual unit root tests for panel data (Im et al., 2023). For instance, many traditional tests, such as the augmented Dickey-Fuller, struggle with cross-sectional dependence and may yield inconsistent results under different model specifications (Yang, et al., 2023). Furthermore, the IPS test is robust in small samples compared to some other panel unit root tests as it accommodates potential heterogeneity across panels and is computationally efficient (Pesaran & Shin, 2003). Where the regression model for each individual time series in the panel:

$$\Delta \Upsilon_{it} = \emptyset_i \Upsilon_{i,t-1} + \mathcal{Z}'_{it}\gamma_i + \varepsilon_i \tag{7}$$

where yit is the variable of interest for individual i at time t and Δ denotes the first difference operator calculated as $\Delta\Upsilon_{it} = \Upsilon_{it} - \Upsilon_{i,t-1}$. $\emptyset i$ is the coefficient that indicates the presence of a unit root (non-stationarity) for a unit i. $\mathcal{Z}'it$ is a vector of deterministic components (such as trends or intercepts). γi represents the coefficients for these deterministic components. ε_i is the error term, which is assumed to be independently distributed across units and time (Pesaran & Shin, 2003; Im et al., 2023).

To evaluate the stationarity of the panels under consideration, the study proposes the following hypotheses:

H_0: All panels contain a unit root.

H_1: At least one panel is stationary.

Where H_0 indicates that the panel for all units are non-stationary. The alternative, H_1 hypothesis, allows for the possibility that not all time series are non-stationary. The test is particularly useful because it accommodates the possibility that only a subset of the time series in the panel may be stationary, contrasting with other tests like the Levin-Lin-Chu that assume homogeneity across all units (Marinov, 2021). Rejecting the null hypothesis indicates that at least one of the time series in the panel is stationary (Hsu, 2021). This conclusion contrasts with the null hypothesis, which assumes that all series have a unit root, meaning they are non-stationary. On the other hand, failure to reject null would suggest that all-time series in the panel are non-stationary, which may require further investigation or different modelling strategies, such as differencing the data or using unit root tests for individual series (Pesaran & Shin, 2003).

3.3.3 Model specification

The study aims to answer how innovations in Fintech impact the dynamics of the South African banking sector by utilising panel regressions. By employing panel regressions, the study aims to account for factors that influence the dependent variable but are not explicitly included in the model (Andre, 2017). These factors, if constant over time for a specific entity, are averaged out in the analysis the choice of utilising panel data is further supported by the studies of Bejar et al. (2022); Song et al. (2023) and Lakshmi and Yashwanth (2024). Additionally, this study addresses the shortcomings in the estimation of Autoregressive Distributed Lag (ARDL) models, particularly the propensity for multicollinearity when a substantial number of lagged terms are included. Such multicollinearity can significantly undermine the accuracy and interpretability of the resultant estimate (Månsson, 2012). This issue is particularly pertinent in the context of South African research, as underscored by Mugabe (2022), which emphasises the need for robust methodological approaches to ensure reliable outcomes in empirical analyses. Utilising models like panel regressions with random effects, which account for unobserved heterogeneity across individuals or entities while allowing for correlation between individual-specific effects and the explanatory variables. Furthermore, according to Andre (2017), using panel regressions can provide more efficient estimates of the relationships between variables compared to using only cross-sectional or time series data alone. According to Wooldridge (2010), the simplest form of the panel regression equation is as follows:

$$\Upsilon_{\mathrm{it}} = \alpha + \beta_1 X_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{8}$$

Equation (8) is the simplest form of panel regression, where Υ_{it} is the dependent variable for entity i at time t. The term α refers to alpha, which denotes the constant intercept term for the regression. While the coefficient of β quantifies the relationship between the independent variable X_{it} and the dependent variable Υ_{it}, indicating that the change in Υ_{it} for a one-unit change in X_{it}. Additionally, the X_{it} represents the independent variable for entity i at time t, while εit refers to the error term, capturing random, unexplained variations in Υ_{it} that are not accounted for by the model (Wooldridge,2010; Andre, 2017).

The study extends the simple regression model to factor in control variables as follows:

$$\Upsilon_{\mathrm{it}} = \alpha + \beta_1 X_{1\mathrm{it}} + \beta_2 X_{2\mathrm{it}} + \sum_{\mathrm{J}=1}^{j} \beta_3 X_{3\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{9}$$

Equation (9) represents a linear regression model used to explain the dependent variable Υ_{it}. The coefficients of β_1 and β_2 measures the effect of the main independent variables $X_{1\mathrm{it}}$ and $X_{2\mathrm{it}}$ of Fintech proxies on Υ_{it} respectively. While $\sum_{\mathrm{J}=1}^{j} \beta_3 X_{3\mathrm{it}}$ captures the influence of J control variables, with each control variable having its own coefficient β_3. Finally, εit refers to the error term, capturing random, unexplained variations in Y_{it} that are not accounted for by the model (Lakshmi & Yashwanth, 2024). [4]

3.3.4 Tests for the model of best fit

Choosing the right model is vital for achieving Best Linear Unbiased Estimators (BLUE), as emphasised by Utami et al. (2015). Unbiased estimators accurately reflect the true parameter value, minimising the risk of bias and misleading conclusions. A linear unbiased estimator also boasts the lowest variance, which enhances the accuracy of inferences by clustering estimates closely around the true value. The Hausman test is important in this procedure because it helps choose whether to use fixed effects or random effects models. It accomplishes this by comparing the coefficient estimates from both models, determining which model produces unbiased and efficient estimates (Amini et al., 2012). To assess whether to utilise fixed or random effects in a cross-sectional setting, this test determines if the unique mistakes are connected with the regressors following the hypothesis:

$H_{0:}$ Random effects model is appropriate (no correlation).
$H_{1:}$ Fixed effects model is preferred (correlation exists).

The Hausman test lies in the correlation between the unobserved individual-specific effects and the explanatory variables within the model (Sheytanova, 2015). Therefore, the H_0 null hypothesis assumes that there is no correlation between the error term and the independent variables in the panel data model. On the other hand, H_1 is the alternative assumption that there is a correlation between the error term and the independent variables in the panel data model (Chmelarova, 2007). Rejecting the null suggests that there is a significant correlation between the unobserved effects and the independent variable, indicating that the fixed effects model (FE) is more appropriate for analysis. On the other hand, failing to reject the null would mean that there is no significant correlation between the unobserved effects and the independent variables, meaning that the random effects model (RE) would be appropriate (Chmelarova, 2007; Sheytanova, 2015). By incorporating the Hausman test, the study aims to make informed decisions about model selection, resulting in more robust and reliable findings.

[4] The independent variables are ATM (Automated Teller Machines and VMT (value of Mobile Transactions as proxies for Fintech. While the control Variables for the Study GDP, inflation, and bank concentration.

3.4 Empirical models for each research objective

The primary objective of this study is to investigate the effect of innovations in financial technology on the dynamics of the South African banking sector. The choice between fixed effects and random effects models for each objective is determined using Hausman tests, which help assess the suitability of different model specifications. Below are the sub-sections detailing the empirical models corresponding to each secondary research objective.

3.4.1 Secondary objective 1

To achieve the secondary objective of the regressions, the impact of Fintech on bank competition is as follows:

$$\mathrm{LI}_{\mathrm{it}} = \alpha + \beta_1 \mathrm{ATM}_{\mathrm{it}} + \beta_2 \mathrm{VMT}_{\mathrm{it}} + \delta \mathrm{INF}_{\mathrm{t}} + \theta \mathrm{BNK}_{\mathrm{it}} + \omega \mathrm{GDP}_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{10}$$

3.4.1.1 Bank competition (Lerner Index)

In Equation (10) presented above, the Lerner Index ($\mathrm{LI}_{\mathrm{it}}$) is utilised as an indicator of bank competition, serving as a measure of market power within the banking sector. This methodological approach aligns with the practices established by Moyo (2018) and Bajar et al. (2022). The Lerner Index is a well-established economic metric designed to evaluate the extent of market power exerted by firms within a given industry (Moyo, 2018; Igan et al., 2020). In the context of banking, the Lerner Index provides insights into market competitiveness by quantifying the disparity between the price charged by a bank and its marginal cost relative to the price (Koetter et al., 2008). A Lerner Index close to zero indicates **perfect competition.** In a perfectly competitive market, there are many companies selling similar products, and no one company has any control over the price (Vilakazi, 2021). A Lerner Index close to one indicates a **monopoly.** A monopoly is a market where there is only one seller. Because there is no competition, a monopoly can set whatever price it wants for its goods or services (Vilakazi, 2021).

The Lerner Index is computed as follows:

$$LI_{\mathrm{it}} = \frac{P_{\mathrm{it}} - MC_{\mathrm{it}}}{P_{\mathrm{it}}} \tag{11}$$

Where P_{it} represents the price of how much a particular bank i is worth at a specific point in time t. It is calculated as the total income (revenue) divided by the total assets, providing a measure of the bank's financial performance relative to its asset base (Koetter et al., 2008;

Vilakazi, 2021). MC_{it} denotes the marginal cost for bank i at time t indicating the cost incurred for producing one additional unit of assets.

Marginal costs are calculated using a Translog function and the approach follows:

$$InTOC_{\text{it}} = \alpha_0 + \alpha_1 Inq + \frac{1}{2}\alpha_2(Inq)^2 + \sum_{j=1}^{3}\beta_{\text{j}} In\phi_{\text{jt}} + \sum_{j=1}^{3}\sum_{k-1}^{3}\beta_{\text{jk}} In\phi_{\text{jt}} In\phi_{\text{k}} + \sum_{j=1}^{3}\theta_{\text{jt}} Inq In\phi_{\text{jt}} + \varepsilon \quad (12)$$

The study employs the Total operating cost (TOC), which is calculated using the previously mentioned equation to calculate the MC_{it}. Following studies by Koetter et al. (2008) and Vilakazi (2021), expenses are bank i overall operating and financial costs in time t. The bank's total assets (q) are used in the equation as a proxy for production. The cost of Materials (ϕ) is modelled as the price of the inputs required to create the result (bank services). The cost of labour (interest expense/total deposits), funds (personnel expenses/total assets), and fixed physical capital costs (other operating and administrative expenses/total assets) are examples of input pricing (Koetter et al., 2008; Igan et al. 2021; Vilakazi, 2021). The deposits have been excluded, and only external funding is used (total liabilities), following a similar approach by Moyo (2018), Igan et al. (2021) and Vilakazi (2021).

The marginal cost (MC) is the derivative of the total cost function with respect to output. From the Translog function, this is calculated as:

$$MC_{\text{it}} = \frac{TOC}{q}(\alpha_1 + \alpha_2 Inq + \sum_{j=1}^{3}\theta In\phi_{\text{jt}}) \quad (13)$$

In Equation (15), α_1 and α2 are coefficients that capture the basic relationship between total cost and output, while Inq represents the natural logarithm of output, which accounts for non-linear effects in production (Vilakazi, 2021). The term $\sum_{j=1}^{3}\theta In\phi_{\text{jt}})$ captures the influence of additional variables (ϕ_j) on costs, such as input prices or other external factors, weighted by their respective coefficientsθ(Koetter et al., 2008). This allows the study for flexibility in modelling marginal cost across different levels of output and influencing variables.

The choice of the Lerner Index stems from its methodological simplicity and reliance on readily available data, making it a practical tool for comparing competition across different studies and banking sectors. By measuring the difference between price and marginal cost as a proportion of price, the index provides valuable insights into the pricing behaviour of individual banks (Mlambo & Ncube, 2011; Shaffer & Spierdijk, 2020). Unlike metrics that focus solely on market concentration, the Lerner Index allows policymakers to identify specific banks potentially exerting excessive market power, enabling targeted regulatory interventions (Igan et al., 2021). However, it is important to note that the Lerner Index can be sensitive to the choice of cost function and may not fully account for inefficiencies or biases when used with aggregate data (Moyo, 2018).

3.4.1.2 Fintech (ATM) under bank competition

In this study, the independent variable is Fintech *(refer to Table 3.1 on Page 63)*, which is being examined for its effect on bank dynamics. The Fintech variable is proxied using the method proposed by Masangwana (2021) and Liao (2023) in their study of Fintech innovations measured by the natural logarithm of the total Automated Teller Machines per 100,000 adults in year t. This study employs this variable as the method considers Fintech advancements in the banking sector. Additionally, ATMs play a vital role in banking by connecting financial technology with consumer access to services, reflecting changes in banking practices (Tarawneh et al., 2024). The natural logarithm of ATMs per capita provides a standardised metric for analysis across regions and time periods. Moreover, the number of ATMs is closely linked to financial inclusion, allowing for assessments of how Fintech affects access to banking services and overall bank dynamics (IFWG, 2023; Suder et al. , 2023).

3.4.1.3 Fintech (VMT) under bank competition

The second Fintech proxy for the study is the value of mobile transactions (*refer to Table 3.1 on Page 63)*, which refers to the total monetary value of transactions conducted through mobile payment systems. The study focuses on this variable as the South African banking sector is seen as one of the highest mobile phone penetration rates in Africa, with a large portion of the population relying on mobile devices for digital interactions (Philippon, 2016; Kredina, 2021). In addition, digital and mobile banking in emerging economies like South Africa significantly enhances financial inclusion by providing individuals in underserved or remote areas access to financial services (Philippon, 2016; Suder et al., 2023). Therefore, mobile money transactions represent a crucial proxy for financial inclusion, bridging the gap where traditional banking infrastructure is limited.

3.4.1.4 Gross domestic product (GDP) under bank competition

GDP *(refer to Table 3.1 on Page 63)* is a gauge of the general economic environment in which banks operate, and it is crucial to comprehend the competitive environment, efficiency, performance, and stability of banks. The total monetary worth of all final goods and services produced inside a country's boundaries over a given period, often a year, is known as the gross domestic product, or GDP (Booyens et al., 2018; Vilakazi, 2021; Callen, 2023). It serves as a thorough indicator of the size of a nation's output and its financial standing. Growth in GDP makes it easier for banks to grow, lend money successfully, and stay stable (Wexler, 2021 & Mugabe, 2022). In addition, increased GDP boosts demand for banking services, driving competition as new banks enter and existing ones expand (Wexler, 2021; Basha et al., 2023). This competition often results in lower interest rates and fees to attract customers (Phan et al., 2020). Conversely, slow economic growth can lead to tighter competition and potential bank instability (Adusei, 2015; Apau & Sibindi, 2023). Furthermore, economic downturns can lead to consolidation among banks due to rising loan defaults and financial stress (Phan et al., 2020; Naceur et al., 2023).

The equation for calculating GDP growth is expressed as:

$$\text{GDP growth} = \frac{GDPyS_{\mathrm{t}} - GDPxS_{\mathrm{t}}}{GDPxS_{\mathrm{t}}} \times 100 \tag{14}$$

Where $GDPy$ is the Gross Domestic Product of the economy for the current period, and $GDPx$ is the Gross Domestic Product of the economy for the previous year (Uddin & Suzuki, 2014).

3.4.1.5 Inflation (INF) under bank competition

Inflation is defined as a steady increase in the aggregate price level of goods and services in an economy over time. It is commonly expressed as the yearly percentage change in the Consumer Price Indicator (CPI), a broad-based index that analyses price changes for a representative basket of goods and services consumed by households. The research focuses on inflation (*see Table 3.1 on Page 59*) as a macroeconomic component analysis since it creates a difficult environment for banks. In the medium term, inflation may enhance rivalry among banks (Batayneh et al., 2021). As interest rates climb, banks compete for deposits by offering greater interest rates on savings accounts (Wexler, 2021; Batayneh et al., 2021). Additionally, it can pressure banks to become more efficient due to rising costs (Umar et al., 2014; Mugabe, 2022). Conversely, loan defaults might rise if wages do not keep pace with inflation, indicating that

inflation can erode bank capital and potentially impact stability, creating a mismatch between deposit and loan interest rates and hurting profitability (Wexler, 2021; Bajar *et al*., 2022).
The equation for calculating inflation growth is expressed as:

$$Inflation\ growth = \frac{INFxS_t - INFyS_t}{INFyS_t} \quad (15)$$

Where $INFx$**:** This is a measure of the average price level of goods and services in the current period. On the other hand, $INFy$ is the average price level of goods and services in the previous period.

3.4.1.6 Bank concentration (BNK) *under bank competition*

Bank concentration *(refer to Table 3.1 on Page 59)* is included in the study because of its perceived double-edged effects. The variable of bank concentration refers to the degree of market dominance by a small number of large banks within a banking system (Ben-Zekry, 2007; Lee et al., 2023). The bank concentration ratio in this study is made up of the top 5 largest banks, following the methodology proposed by Moyo (2018), Vilakazi (2021), Bejar et al. (2022), and Naceur et al. (2023). A 1 indicates a level below the median, while a 0 indicates a level above the median, indicating lower bank concentration (Moyo, 2018; Vilakazi, 2021). The study focuses on the variable as its relationship remains unclear, thus making it difficult for the sector and regulators to understand its dynamics. Some of the literature argues that high concentration with strong regulations can lead to performance and stability, while other literature suggests it can reduce competition, efficiency, and performance, leading to higher fees and fewer loan options.
The Concentration Ratio (CR) is a straightforward measure that sums up the market shares of the largest banks in the market. The formula can be expressed as:

$$CR\kappa = \sum_{\iota=1}^{\kappa} S_{\mathrm{it}} \quad (16)$$

The ratio relies on the market shares of the largest banks to measure market concentration. Market share, in this study, is calculated as the proportion of an individual bank's revenue or sales to the total revenue or sales in the market using the formula:

$$Market\ Share = \frac{Total\ Revenue}{Market\ Revenue} \times 100 \quad (17)$$

The individual market shares S_{it} are summed for the top k banks to determine the CR value. By aggregating these shares, the CR captures the extent to which the leading banks dominate the market.

3.4.2 Secondary objective 2

To assess the effects of Fintech innovations on the performance metrics of banks operating in South Africa, the regression equation follows:

$$\mathrm{CAR}_{\mathrm{it}} = \alpha + \beta_1 \mathrm{ATM}_{\mathrm{it}} + \beta_2 \mathrm{VMT}_{\mathrm{it}} + \delta \mathrm{INF}_{\mathrm{t}} + \theta \mathrm{BNK}_{\mathrm{it}} + \psi \mathrm{Tier1Capital}_{\mathrm{it}} + \psi \mathrm{Tier2Capital}_{\mathrm{it}} + \omega \mathrm{GDP}_{\mathrm{t}} + + \varepsilon_{\mathrm{it}} \quad (18)$$

3.4.2.1 Bank performance (CAR)

In Equation (18), the study uses the capital adequacy ratio (CAR) to model bank performance. The CAR is a regulatory requirement that ensures banks have enough capital to cover potential losses. A higher CAR suggests stronger financial reserves and a lower risk of insolvency (Abusharba et al., 2013; Noor & Rosyid, 2018). Studies like Kumar et al. (2017) have used this ratio to gauge bank performance. This measure reflects a bank's risk management practices; well-capitalized banks are generally better at handling risks because they have sufficient capital to absorb unexpected losses. Banks with a higher CAR tend to adopt more cautious lending practices, which can support sustainable long-term growth and stability (Yadav, 2016; Noor & Rosyid, 2018). Moreover, the CAR allows for meaningful comparisons between banks of different sizes and structures, as it normalises capital levels based on the risks associated with their assets. This normalisation facilitates the evaluation of performance and stability across institutions, helping investors and regulators make informed decisions (Abusharba et al., 2013). Thus, banks that consistently maintain a healthy CAR are likely to be compliant and perceived as less risky.

The capital adequacy is calculated as follows:

$$\mathrm{CAR}_{\mathrm{it}} = \frac{(Tier\ 1\ Capital_{\mathrm{it}} + Tier\ 2\ Capital_{\mathrm{it}})}{Risk\text{−}Weighted\ Assets_{\mathrm{it}}} \quad (19)$$

Where:

Tier 1 Capital represents the core capital of the bank, which includes equity capital, ordinary share capital, and disclosed reserves (Noor & Rosyid, 2018). On the other hand, **Tier 2 Capital** considers supplementary capital and includes undisclosed reserves, general loss reserves, and hybrid debt instruments (Abusharba et al., 2013). Risk-weighted **assets** are considered the inherent risk of a bank's assets. Assets like government bonds are assigned a lower risk weight compared to loans to high-risk borrowers (Noor & Rosyid, 2018).

The study incorporates the CAR for bank performance as it is a widely used measure of bank performance due to its effectiveness in managing risks and maintaining financial stability. Abusharb et al. (2013) and Alnajjar and Abdullah Othman (2021) highlight that CAR ensures banks maintain sufficient capital to absorb losses from market, credit, and operational risks. For instance, a strong CAR allows banks to withstand unexpected fluctuations in interest rates, cover potential losses from bad loans, and address unforeseen operational challenges. Additionally, CAR is a key regulatory requirement under frameworks like the Basel Accords, which aim to minimise the risk of bank failures by enforcing minimum capital standards (Noor & Rosyid, 2018). Furthermore, CAR's strong correlation with financial indicators like Return on Assets (ROA) and Return on Equity (ROE) provides valuable insights into a bank's profitability and financial health (Alnajjar & Abdullah Othman, 2021). While CAR is a robust measure of capital adequacy, it has certain limitations. For example, it does not directly capture other critical aspects of bank performance, such as asset quality, management efficiency, and liquidity (Noor & Rosyid, 2018). Additionally, some researchers argue that a focus on high CAR levels could potentially divert resources from areas like lending and customer service (Abusharb et al., 2013). However, despite these limitations, CAR remains an essential metric for assessing a bank's resilience and regulatory compliance.

3.4.2.2 Fintech (ATM) under bank performance

The Fintech variable is proxied using the method proposed by Masangwana (2021) and Liao (2023) in their study of Fintech innovations measured by the natural logarithm of the total Automated Teller Machines per 100,000 adults in the year $_t$. The second Fintech proxy for the study is the value of mobile transactions, which refers to refers to the total monetary value of transactions conducted through mobile payment systems. ATMs automate routine transactions, reducing reliance on human tellers and lowering operational costs associated with physical branches (Ogbuji et al., 2012). This cost reduction can potentially translate into improved profitability for banks (Ogbuji et al., 2012; AL & Yengeni,2022). Furthermore, mobile transactions open new revenue streams for banks by broadening their customer base and enabling smaller, frequent transactions from previously unbanked or underbanked populations.

3.4.2.3 Fintech (VMT) under bank performance

When examining bank performance, it has been argued that the expansion of mobile transactions positively influences banks' Capital Adequacy Ratios (CARs), which justifies the inclusion of this variable in the analysis. Research indicates that higher volumes of mobile transactions are often associated with improved operational efficiency and cost reductions, leading to an increase in client deposits and, ultimately, a stronger CAR (Demirguc-Kunt et al., 2018). This is because mobile transactions streamline processes and reduce operational costs, allowing banks to allocate more resources toward strengthening their capital base. Furthermore, studies have highlighted that mobile transactions contribute to better risk management practices, enabling banks to optimise capital allocation while maintaining regulatory compliance (Mishra & Panda, 2017). By improving operational efficiency and risk management, mobile transactions help banks better navigate regulatory requirements and enhance their financial stability. Thus, the value of mobile transactions serves as a reliable proxy for fintech adoption, offering critical insights into how such innovations affect bank performance, particularly in terms of enhancing CARs. This makes it an essential variable for understanding the broader impact of fintech on financial institutions.

3.4.2.4 GDP under bank performance

Under bank performance, increased economic activity translates to higher demand for loans from businesses and individuals, leading to higher loan volumes and interest income for banks (Booyens et al., 2018 & Phan et al., 2020; Mugabe, 2022). Additionally, as businesses and individuals are more likely to repay loans during economic upsides, banks may experience fewer defaults and bad debts (Wexler, 2021; Apau & Sibindi, 2023). However, in economic downturns, increased loan defaults and non-performing loans can significantly reduce bank profitability as banks may be forced to adopt stricter lending standards, which can limit loan growth and reduce potential income (Wexler, 2021; Mugabe, 2022; Apau & Sibindi, 2023).

3.4.2.5 Inflation under bank performance

Suder et al. (2023) stated that uncertainty and rumours play a significant role in shaping customer behaviour, while Umar et al. (2014) and Tinoco-Zermeño et al. (2018) contend that inflation brings about uncertainty. Moderate or low inflation can have some positive effects on bank performance. The increased demand for loans, as mentioned earlier, translates to higher loan volumes and interest income for banks (Phan et al., 2020; Tinoco-Zermeño et al., 2018).

Additionally, central banks may raise interest rates in response to inflation. This benefits banks by increasing their net interest margin, which is the difference between the interest earned on assets and the interest paid on liabilities (Yuanita, 2019; Phan et al., 2020). However, high inflation can negatively impact bank performance as consumers will save less money in banks due to inflation, indicating that the banks will have fewer deposits available to lend out (Umar et al., 2014). This will impact their performance as it can limit the banks' ability to earn interest income from loans (Phan et al., 2020). In general, inflation is defined as a percentage change in the Consumer Price Index over time that reduces money's buying power. The CPI tracks changes in the average price of a basket of goods and services used by households. With rising prices, the real worth of money diminishes, making it less appealing for clients to save money with banks. Instead, people may seek other investments with greater yields to outperform inflation and retain the value of their capital (Umar et al., 2014; Naceur et al., 2023).

3.4.2.6 Bank Concentration under bank performance

Under bank performance, banks of large size are easily diversified. This allows them to adjust in other sectors of the market when one sector takes a turn for the worse (Ben-Zekry, 2007; Martins & Alencar, 2010). Additionally, the high concentration may lead to higher interest rates and fees, generating more profits for the incumbents (Bikker & Haaf, 2002; Ben-Zekry). However, on the other hand, higher interest rates are often the by-product of high levels of bank concentration, which is bad for investors as it makes investments far riskier (Ben-Zekry, 2007; Naceur et al., 2023). Furthermore, large, established banks may have less incentive to innovate in financial products and services, potentially hindering overall industry growth and efficiency (Martins & Alencar, 2010). The literature by Naceur et al. (2023) shows that increased bank concentration negatively impacts bank performance, with a one percentage point increase reducing ROE and ROA by 0.00655 and 0.00309 percentage points, respectively.

3.4.2.7 Tier 1 capital

According to studies like Gonzales-Hermosillo et al. (2013) and Bitar et al. (2016), Tier 1 capital is a bank's primary financial protection, consisting of core equity (such as common shares and retained earnings) as well as various perpetual instruments. It is analysed using the Tier 1 capital ratio, which compares this capital to the bank's risk-weighted assets (RWA) to assess financial stability and, therefore, serves as the principal loss-absorbing cushion. The study includes the variable as the independent variable, as the higher the Tier 1 capital ratio, the more stable the bank is, as it can absorb shocks, attract investors, and meet regulatory requirements (Shaik & Sharma, 2021). However, too much cash may restrict loaning capability and reduce profitability (Conlon et al., 2020). On the other hand, some studies argue that it may be extremely difficult to achieve a balance between maintaining appropriate capital and profitability for sustained bank performance (Bitar et al., 2016; Shaik & Sharma, 2021). The tier 1 capital formula follows:

$$Tier1_{\mathrm{it}} = CET1_{\mathrm{it}} + AT1_{\mathrm{it}} \tag{20}$$

The equation follows aggregating Common Equity Tier 1 represented by (CET1), which includes common stock and retained earnings, as well as other reserves after deductions for intangible assets, and Additional Tier 1 represented by (AT1), which includes perpetual subordinated instruments that are not redeemable, bonds, or preference shares (Gonzales-Hermosillo et al., 2013).

3.4.2.8 Tier 2 capital

Tier 2 capital is additional financial resources that support a bank's overall financial health and serve as a buffer in addition to Tier 1 capital. It includes subordinated debt, hybrid instruments, concealed reserves, and general loan-loss provisions (Gonzales-Hermosillo et al., 2013). The study includes Tier 2 capital as it allows banks to raise their lending capacity while also supporting growth without relying too heavily on Tier 1 capital, which is primarily responsible for absorbing immediate losses to ensure long-term stability (Conlon et al., 2020). In the focus of bank performance, the banks can increase loans and take on greater risk by leveraging Tier 2 capital, such as subordinated debt or loan-loss reserves, to boost profitability and market expansion. Therefore, Tier 2 capital's flexibility might enable banks to increase their portfolios while maintaining the stability of their core capital (Bitar et al., 2016; Conlon et al., 2020). The tier 2 capital is as follows:

$$Tier2Capital_{\mathrm{it}} = SubordinatedDebt_{\mathrm{it}} + HybridInstruments_{\mathrm{it}} + \\ UndisclosedReserves_{\mathrm{it}} + GeneralLoan_{\mathrm{it}} - Loss\,\mathrm{Pr}\,o\,visions_{\mathrm{it}} \tag{21}$$

In Equation 21, the main components are subordinate debt, which is defined as long-term borrowings repayable only after other higher-ranking obligations in liquidation; hybrid instruments, which contain elements of both debt and equity and provide flexibility in loss absorbency; and undisclosed reserves, which represent hidden reserves that are sometimes permitted by the regulatory framework but are not disclosed in the financial statements (Gonzales-Hermosillo et al., 2013).

3.4.3 Secondary objective 3

To determine the impact of financial technology innovations on operational efficiencies within the South African banking sector, the equation follows:

$$\mathrm{SFA}_{it} = \alpha + \beta_1 \mathrm{ATM}_{it} + \beta_2 \mathrm{VMT}_{it} + \delta \mathrm{INF}_t + \theta \mathrm{BNK}_{it} + \omega \mathrm{GDP}_t + \varepsilon_{it} \qquad (22)$$

3.4.3.1 Bank efficiency (SFA)

This study uses the stochastic frontier approach (SFA) in line with the techniques of Liao (2023). Estimating a bank's technical efficiency is part of the Stochastic Frontier Analysis (SFA) formula for bank efficiency. The method used to determine how well banks translate inputs into outputs is parametric. By evaluating the bank's performance against a frontier, therefore SFA seeks to determine which banks are the most efficient. Compared to non-parametric alternatives such as DEA, the method is more reliable because it considers factors that impact a bank's efficiency (Liu, 2019).

The equation for the Stochastic frontier approach is as follows:

$$\mathrm{SFA}_{it} = f(\phi_{it}, \mathrm{Q}_{it}; \beta_{it}) + \mu_{it} + \nu_{it} \qquad (23)$$

Where SFA_{it} the observed total cost of the bank i at time t, Q_{it} is a vector of output variables (representing total loan and non-interest income), ϕ_{it} is a vector of input variables (representing labour cost, price of capital, and price of funds), and β denotes control variables (representing time and equity) that have a direct impact on the dependent variable (Nguyen & Pham, 2020). According to Liu (2019), in the conventional method, a random error breaks into ν_{it} and μ_{it}, Which represent, respectively, a random error and the truncated normal distribution (Nguyen & Pham, 2020).

The most utilised cost function is the conventional translog, according to research by Moyo (2018) and Liu (2019). The production function to be estimated for the stochastic frontier translog is given as follows: Substituting TC_{it} with (η+k+1)

$$In(\eta + k + 1) = f(\phi_{\mathrm{it}}, \mathrm{Q}_{\mathrm{it}}; \beta_{\mathrm{it}}) + \mu_{\mathrm{it}} + \nu_{\mathrm{it}} \tag{24}$$

In Equation (24) η represents the observed net operating income before tax and k the absolute value of the maximum loss across all observations, ensuring the input is non-negative when shifted by adding 1. This approach allows μ_{it} as inefficiency terms and ν_{it} as statistical noise, allowing the estimation of both firm-level efficiencies and stochastic deviations from the frontier (Nguyen & Pham, 2020).

The Stochastic Frontier Approach (SFA) is a useful method for analysing bank efficiency because it considers both inefficiency and random factors that may influence performance. One of its main advantages is that it includes a random error term to account for unobserved influences, such as differences in the regulatory environment (Hasan et al., 2012). By separating inefficiency from random noise, SFA provides a clearer picture of how banks deviate from the efficiency frontier (Moyo, 2018). Additionally, SFA allows for statistical analysis, such as testing hypotheses and creating confidence intervals, to better understand the factors that affect efficiency (Phan, 2020; Hasan et al., 2012). However, SFA has some limitations. The results depend on specific statistical assumptions, such as the choice of a distribution to represent inefficiency. For example, the commonly used Half-Normal distribution assumes inefficiency is always non-negative, but this may not fully capture real-world situations (Hansen et al., 2012). Moreover, SFA can be complex and computationally demanding compared to simpler methods (Nguyen & Pham, 2020). Despite these challenges, SFA remains an important tool for studying bank efficiency, especially when accuracy and separating inefficiency from random factors are essential.

3.4.3.2 Fintech (ATM) under bank efficiency

The Fintech variable is proxied using the method proposed by Masangwana (2021) and Liao (2023) in their study of Fintech innovations measured by the natural logarithm of the total Automated Teller Machines per 100,000 adults in year $_t$. The second Fintech proxy for the study is the value of mobile transactions, which refers to the total monetary value of transactions conducted through mobile payment systems. Widespread ATM usage is linked to enhanced bank efficiency (AL & Yengeni, 2022; Liao, 2023). By automating tasks traditionally handled by tellers, ATMs enable banks to serve a larger customer base with fewer resources (Liao, 2023). This streamlining of operations can signify a clear gain in efficiency, which can be stated with mobile transactions as it allows for streamlined processes, reducing both transaction times and the need for manual processing. This efficiency allows banks to handle higher transaction volumes with less time and fewer resources, which can be reinvested in core business areas or innovation (Ullah et al., 2023).

3.4.3.3 Fintech (VMT) under bank efficiency

Mobile transaction values serve as an important proxy for fintech when analysing its impact on bank efficiency, particularly through the SFA method. Mobile transactions are critical in capturing the efficiency benefits associated with fintech adoption. Research, such as that by Wang et al. (2019), demonstrates that incorporating mobile transaction values into the SFA model effectively reflects the efficiency gains brought about by the adoption of fintech. Additionally, mobile transactions are often viewed as a proxy for technological advancements and digitalisation within the banking sector. According to Frame et al. (2018), they can be used to account for variations in fintech adoption across different banks, thus enabling a more nuanced understanding of how technological innovation influences bank efficiency. Therefore, by using mobile transaction values as a fintech proxy, the study can gain valuable insights into the relationship between fintech adoption and bank efficiency. This approach not only enhances the ability to assess the impact of fintech on efficiency but also allows for comparative analysis across different banks, considering their varying levels of fintech adoption and digital transformation.

3.4.3.4 GDP under bank efficiency

According to Uddin and Suzuki (2014), a growing economy in a developing country may provide more opportunities for banks to improve their efficiency by expanding their operations. For example, when the economy grows, firms and people borrow more (Booyens et al., 2018; Wexler, 2021; Apau & Sibindi, 2023). This increased demand may encourage banks to simplify operations and become more effective in managing the burden. At the same time, it is quite possible that regular political turbulence in nations such as South Africa would undermine the advantageous macroeconomic climate (Uddin & Suzuki, 2014). The banks might loosen their lending standards to capitalise on the increased demand, subsequently, leading to a rise in bad loans and ultimately hurting bank efficiency (Apau & Sibindi, 2023).

3.4.3.5 Inflation under bank efficiency

Umar et al. (2014) state that inflation uncertainty is costly since it distorts relative prices and raises the risk of doing business, which leads to adverse output. For example, under high periods of inflation, a bank's operating expenses, such as salaries and technology upgrades, may increase and thus will likely reduce the resources available for investing in efficiency-boosting initiatives (Tinoco Zermeño et al., 2018). However, if banks can raise loan interest rates faster than deposit rates during inflation, they can see an increase in net interest income (Phan et al., 2020). This improved profitability might allow them to invest in automation and other efficiency measures.

3.4.3.6 Bank Concentration under bank efficiency

Higher bank concentration can potentially lead to increased efficiency. Large banks may benefit from economies of scale, allowing them to offer lower prices and generate higher profits due to efficiencies gained from their size (Bikker & Haaf, 2002; Ben-Zekker, 2007; Martins & Alencar, 2010). Additionally, they may have greater resources to invest in technology and automation, further improving efficiency by automating routine processes and reducing labour costs (Ben-Zekry, 2007; Corbae & D'Erasmo, 2020). However, on the other hand, large banks are likely to focus on the most profitable niches and may neglect those that are less profitable, leading to decreased efficiency (Martins & Alencar, 2010; Uddin & Suzuki, 2014).

3.4.4 Secondary objective 4

To evaluate the impact of Fintech innovations for stability within the South African banking system, the regression equation is:

$$\mathrm{Z\ score_{it}} = \alpha + \beta_1\mathrm{ATM_{it}} + \beta_2\mathrm{VMT_{it}} + \delta\mathrm{INF_{it}} + \theta\mathrm{BNK_{it}} + \varphi interestExpense_{\mathrm{it}} + \phi PersonalExpanse_{\mathrm{it}} + \psi Total\ Deposit_{\mathrm{it}} + \omega\mathrm{GDP_{it}} + \varepsilon_{\mathrm{it}} \tag{25}$$

3.4.4.1 Bank stability (Z-score)

The study employs Z-scores for bank stability following the method employed by Moyo (2018), Safullah and Paramati (2022), and Yudaruddin *et al*. (2023). The Z-score is used as an indicator of bank risk insolvency. There is an inverse relationship between Z-score and insolvency. Thus, a high z-score indicates a low probability of insolvency (World Bank, 2023). Analysing components like return on assets (ROA) and equity-to-asset ratio provide insights into a bank's risk profile and potential distress events over time (Safullah & Paramati, 2022). Additionally, despite variations in rankings among different risk measures, the Z-score effectively identifies financial distress and systemic risks within the banking system (Yudaruddin *et al.*, 2023). Moreover, the Z-score's ability to predict bank failure and bankruptcy risk underscores its significance in evaluating the health of financial institutions (Ahmad *et al.*, 2023).

The z-score for bank stability follows:

$$Z - score = \frac{ROA+EAR}{\partial ROA} \tag{26}$$

The return on assets (ROA) measures how efficiently the bank can generate profits given its total assets. This is measured by dividing the bank's net profit by the total assets multiplied by 100 (Safullah & Paramati, 2022). The equity to asset ratio (EAR) is measured by dividing the bank's total equity by its assets, which indicates how much of the bank's assets are financed through equity. Lastly, the standard deviation of Return on Asset (σROA) measures the dispersion of the values from the mean over one year, whereby a low standard deviation of ROA indicates that the ROA values are close to the mean and vice versa.

The Z-score is also a widely used measure of bank stability due to its simplicity and reliance on readily available financial metrics like Return on Assets (ROA) and the Capital Adequacy Ratio (CAR). Its standardised calculation allows for easy comparisons across banks of varying sizes and serves as an early warning system by identifying banks with low Z-scores that may face higher financial risk (Safullah & Paramati, 2022; Yudaruddin et al., 2023). However, the Z-score has limitations, including its narrow focus on ROA and CAR, which overlooks critical factors such as liquidity and asset quality, providing an incomplete picture of stability (Ahmad et al., 2023). Additionally, as it is based on historical data, the Z-score may not accurately predict a bank's resilience during economic downturns or unexpected crises (Safullah & Paramati, 2022). Despite these shortcomings, the Z-score remains a valuable tool for preliminary financial stability analysis.

3.4.4.2 Fintech (ATM) under bank stability

The Fintech variable is proxied using the method proposed by Masangwana (2021) and Liao (2023) in their study of Fintech innovations measured by the natural logarithm of the total Automated Teller Machines per 100,000 adults in year $_t$. The second Fintech proxy for the study is the value of mobile transactions, which refers to the total monetary value of transactions conducted through mobile payment systems. While increased efficiency due to ATMs can contribute to greater financial stability, the study acknowledges potential risks. Overdependence on ATMs could lead to a neglect of customer relationships, potentially impacting brand loyalty and stability, particularly during economic downturns (Ogbuji et al., 2012 & AL; Yengeni, 2022 & Liao, 2023). On the other hand, for mobile transactions, greater access to banking services through mobile transactions diversifies banks' customer base. This broader base may provide more stability as it reduces dependency on any single segment, which is particularly important during economic downturns (Phan et al., 2020; Naceur et al., 2023).

3.4.4.3 Fintech (VMT) under bank stability

Mobile transactions have been shown to serve as an effective proxy for financial innovation, a key determinant of bank stability. Frame et al. (2018) highlight the significance of mobile transactions in this context, noting that they are a reliable indicator of fintech adoption and its associated effects. Mobile transactions, as emphasised by Mishra and Panda (2017), can help mitigate various forms of financial risk, including credit risk, liquidity risk, and operational risk. By reducing these risks, mobile transactions enhance the stability of banks. This aligns with the broader understanding that fintech innovations, such as mobile payments and digital banking, contribute to a more resilient banking system. Thus, incorporating mobile transaction values in the study into the Z-score model enables the study to capture the influence of fintech adoption on bank stability more effectively. It allows for the consideration of financial innovation, the risk-reducing effects of fintech, and the diversification advantages these technologies bring to banks (Boyd et al., 2018).

3.4.4.4 GDP under bank stability

In general, periods of bank sector stability are generally followed by increased output growth, while bank instability leads to reduced growth (Adusei, 2015 & Safullah and Paramati, 2022 & Apau and Sibindi, 2023). The real economy is primarily impacted by periods of banking instability rather than stability, as the reasoning is that if GDP is increasing, it generally means that both businesses and workers are doing better than when it decreases (Apau & Sibindi, 2023). A stable banking sector can support economic growth by efficiently allocating capital to productive investments. However, some studies also find that an increase in economic growth tends to decrease bank stability. This may be because rapid economic growth can lead to excessive risk-taking by banks (Safullah & Paramati, 2022).

3.4.4.5 Inflation under bank stability

High and unpredictable inflation can create uncertainty among depositors, leading to potential bank runs if they lose confidence in the value of their deposits (Umar et al., 2014 & Safullah and Paramati, 2022). This can put a strain on a bank's liquidity and potentially trigger financial instability. If banks can adjust loan interest rates faster than deposit rates during inflation, they might see an increase in net interest income in the short term (Umar et al., 2014 & Phan et al., 2020). However, this benefit is often temporary and can be offset by other negative effects.

3.4.4.6 Bank concentration under bank stability

The effect of bank concentration on financial stability has been a topic of continuous discussion, as for instance, Bikker and Haaf (2002) and Ben-Zekry (2007) argue that bank concentration can lead to stability, as the banks with higher franchise values will have less incentive to take financial risks in pursuit of profits. Additionally, large banks are more easily monitored than many small banks (Ben-Zekry, 2007; Corbae & D'Erasmo, 2020). The systems within each of the large banks will be similar rather than having to learn the systems of many small banks. However, the other side is that large banks often have stronger capital bases, making them more resilient to financial shocks and potentially contributing to overall banking system stability (Ben-Zekry, 2007; Martins & Alencar, 2010). The literature covered by Yudaruddin et al. (2023) highlights the negative impact of bank concentration on financial stability, indicating that less competitive markets with high concentration expose banks to greater risks, potentially due to a decline in market power.

3.4.4.6 Total deposit

Total deposits refer to the combined funds held by customers in a bank, including demand deposits, savings accounts, and time deposits (Doerr, 2024). They are critical to a bank's stability, making them an interesting topic of study. They are the major source of funding for banks, providing the liquidity required to meet withdrawal requests, finance lending, and run daily operations (World Bank, 2013). This liquidity becomes even more important during times of financial stress, allowing banks to stay stable without having to rely on expensive or unpredictable external funding sources (Doerr, 2024). Deposits, in addition to providing liquidity, help to improve a bank's capital structure by acting as a buffer against asset volatility risks. A strong deposit base decreases the risk of financial crisis and increases the bank's resilience, as evidenced by stability metrics such as the Z-score (European Central Bank, 2009).

3.4.4.6 Personal expense

Personal expense is made up of personnel expenses/total assets, which is a critical component of operational risk which can have a significant impact on bank stability (Igan et al., 2021). Higher personal expenses can indicate lower efficiency and reduced stability. Personal expenses can also reflect bank management's ability to control costs (Gutiérrez et al.; M., 2010). Effective cost management is essential for maintaining bank stability. Additionally, Personal expenses can be used as a proxy for operational risk (FSCA, 2015). Operational risk is a key component of bank risk. Bank stability is closely linked to operational risk. Personal expenses can provide valuable insights into bank stability.

3.4.4.6 Interest expense

Interest expenses, which represent the cost of obtaining funds through deposits or borrowing, are a critical factor in assessing a bank's stability, particularly in relation to its Z-score. High-interest expenses can significantly erode a bank's profitability, reducing the ROA, which is a key component in the Z-score formula (Vohra et al., 2023). A lower ROA leads to a lower Z-score, indicating a higher risk of insolvency. Additionally, interest expenses provide insight into a bank's liability management. A bank with disproportionately high-interest expenses are relative to its assets may be perceived as riskier, as it suggests inefficiencies in managing funding costs (Vohra et al., 2023). This can negatively impact investor confidence and raise concerns about the bank's ability to remain solvent, further decreasing its Z-score and overall stability (Arnould et al., 2022). Thus, interest expenses directly influence both profitability and perceived risk, making them vital to assessing a bank's financial health and stability.

The Table 3.1 below offers a complete review of the important variables utilized in the study, highlighting their descriptions, measurement techniques, and data sources.

Table 3.1 Summary of the variables used in this study

Dependent variables	**Description**	**Measurements/proxies used**	**Data source**
Lerner index (LI_{it})	Measures Bank competition by Price minus Marginal cost all over price	Index: The difference between the price (interest rates) charged by banks and their marginal cost, divided by the price.	Author's Computation using data from the Bloomberg terminal
Capital Adequacy Ratio (CAR_{it})	Measures the financial health of a bank by comparing its capital (Tier 1 and Tier 2) to its risk-weighted assets.	Ratio: Tier 1 + Tier 2 capital / Risk-weighted assets.	Author's Computation using data from the Bloomberg terminal
Stochastic frontier approach (SFA_{it})	Measures the efficiency of banks based on their ability to minimize costs while maximizing outputs, given a set of inputs.	Function: The approach evaluates inefficiency by comparing actual performance to the optimal frontier, considering input-output relationships and control variables.	Author's Computation using data from the Bloomberg terminal
Z-(score)	Measures bank stability, indicating the likelihood of bankruptcy. A higher score suggests greater stability.	Ratio: (ROA + EAR) / Standard deviation of ROA. ROA is the return on assets, and EAR represents earnings at risk.	Author's Computation using data from the Bloomberg terminal
Explanatory variable			

Fintech (ATM_{it})	Denotes the penetration of ATMs in South Africa, representing access to financial technology.	Number of ATMs per 100,000 adults	World Bank – World Development Indicators
Value of mobile transactions (VMT_{it})	Measures the monetary value of transactions conducted through mobile payment systems	Amount: The total value of mobile transactions is measured in South African Rand (ZAR).	World Bank – World Development Indicators
Control Variable			
Gross Domestic Product (GDP)	Represents the overall economic output of a country and is often used to gauge the economic environment for banks.	Percentage: The annual growth rate of GDP, expressed as a percentage	World Bank – World Development Indicators
Inflation	Indicates the rate of increase in the price level of goods and services in the economy.	Percentage: The annual inflation rate, expressed as a percentage.	World Bank – World Development Indicators
Bank Concentration	Measures the degree of concentration in the banking sector, with a higher percentage indicating more dominance by the top banks.	Percentage: The total assets held by the five largest banks in the country as a percentage of total industry assets.	World Bank – World Development Indicators

3.5 Post-estimation diagnostics

Post-estimation is the process of analysing and interpreting data generated by an econometric or statistical model. It entails evaluating the model's accuracy, determining the significance of calculated parameters, and validating its assumptions. The study utilises this procedure as it is critical because it allows for data validity of findings, make informed decisions, and reach relevant conclusions.

3.5.1 Autocorrelation test

Autocorrelation tests in panel data determine whether the residuals of a regression model are correlated over time for each entity, such as an individual, company, or country (Drukker, 2003). The identification of autocorrelation is critical because it influences the validity of statistical inferences such as hypothesis tests and confidence intervals (Amengual et al., 2024). Autocorrelation is most relevant in panel data, where observations across multiple time periods for the same cross-sectional units are present. For instance, in that kind of data where banking dynamics are tracked for several years, then the errors in one year tend to be influenced by the errors in the year preceding it (Chen, 2022). The effects of autocorrelation diminish the reliability of OLS estimators, and therefore the need for specific tests and methods to deal with this problem arise (Chen, 2022).

In autocorrelation tests for panel data, the null hypothesis (H_0) assumes no serial correlation, while the alternative hypothesis (H_1) assumes the presence of serial correlation (Amengual, et al., 2024). Mathematically, this can be expressed as:

- H_0: p = 0
- H_1: p $\neq$ 0

If the null hypothesis is rejected in favour of the alternative, it follows that the residuals are serially correlated. That result indicates a failure of the model's no-autocorrelation assumption, necessitating the use of correction methods such as generalized least squares or robust standard errors to ensure sound inference(Amengual, et al., 2024). The primary consequence of ignoring serial correlation is underestimation of standard errors. As a result, there may be a greater likelihood of making Type I errors, which would result in the falsification of a correct null hypothesis(Chen, 2022).

The study uses the Wooldridge test as it is appropriate for detecting autocorrelation in panel data since it is simple, robust, and exclusive to this data structure (Drukker, 2003). This method, unlike traditional methods, considers the cross-sectional and time-series aspects of panel datasets, making it a useful tool for detecting first-order serial correlation (AR(1)) (Born et al., 2016). The test is straightforward to use, relying on regression model residuals, and is resistant to typical problems like heteroskedasticity and dynamic relationships in data. Its high power and efficiency make it perfect for panels ranging from tiny to medium in size. The Wooldridge test, a commonly used econometric tool, delivers consistent and interpretable results by resolving any detected autocorrelation to increase model validity (Drukker, 2003). The Wooldridge test for autocorrelation in panel data is based on the following equation for first-order serial correlation:

$$\widehat{\varepsilon_{\mathrm{it}}} = p\widehat{\varepsilon_{\mathrm{it-1}}} + \mu_{\mathrm{it}} \tag{27}$$

In Equation 27 $\widehat{\varepsilon_{\mathrm{it}}}$ the residuals or differences of the observed and predicted values from the regression model for the cross-sectional unit i at time t. $\widehat{\varepsilon_{\mathrm{it-1}}}$ is the lagged residual, or residuals from the previous period (t−1) for the unit at i. On the other hand, the parameter*(p)* reflects the autocorrelation coefficient, which measures the degree of correlation between the current residuals and their lagged values; a significant p suggests that autocorrelation exists. Finally, μ_{it} is the error term, which is supposed to be white noise; that is, it is uncorrelated, its variance is constant, and the expected mean is zero.

3.5.2 Endogeneity test

Ideally, the independent variable only influences the dependent variable. However, in many datasets, the independent variable can somehow be linked to unexplained errors in the data. This indicates that endogeneity is present, and this effect can result in biased statistical tests. Thus resulting in misleading and incorrect conclusions. The Durbin-Wu-Hausman (DWH) test will be employed to test for endogeneity. According to Semadeni et al. (2013), the DWH test compares the efficiency of estimates obtained from Ordinary Least Squares (OLS) and instrumental variable (IV) methods, therefore aiding in the selection of the most efficient and consistent estimation method based on the endogeneity of the regressors. Furthermore, the test assists in validating the assumptions of the model, ensuring that the results obtained are reliable and valid (Semadeni et al., 2013; Guo et al., 2018).

The DWH test hypotheses are as follows:

- H_0: No endogeneity is present.
- H_1: Endogeneity is present.

Under the following hypotheses, rejections of the null hypothesis suggest that the OLS estimator is inconsistent, indicating the presence of endogeneity. This implies that one or more of the explanatory variables are correlated with the error term in the regression model. On the other hand, failing to reject the null suggests that there is insufficient evidence to conclude that the OLS estimator is inconsistent (Guo et al., 2018).

The general formula for the DWH test follows:

$$\mathcal{D} = \frac{(\hat{\beta}\mathcal{OLS} - \hat{\beta}\iota\nu)}{\nu\alpha r(\hat{\upsilon})} \tag{28}$$

Equation 27 represents the DWH test statistic used to compare the Ordinary Least Squares (OLS) and Instrumental Variables (IV) estimates of the same coefficient. In this equation $\hat{\beta}\mathcal{OLS}$ is the OLS estimate of the coefficient for the endogenous variable, while $\hat{\beta}\iota\nu$ is the IV estimate of the same coefficient. The denominator $\nu\alpha r(\hat{\upsilon})$ denotes the estimated variance of the residuals from the OLS regression, as described by Guo et al. (2018). If endogeneity is detected, the study will address the issue by employing the Generalized Method of Moments (GMM) approach. Following a similar approach adopted by Phan et al. (2020) and Bajar et al. (2022), the implementation is to ensure the validity and consistency of the results. Further, the GMM is applied more often to unobserved effects models when the explanatory variables are not strictly exogenous, even after controlling for an unobserved effect (Wooldridge, 2001).

3.6 Chapter summary and concluding remarks.

Chapter Three provides a comprehensive overview of the methodology used to investigate the effects of Fintech innovations on South African banks. This study adopts a panel regression approach in the analysis of the relationship between the proxies of Fintech, represented by ATMs and the value of mobile money transactions, and banking indicators such as competition, performance, efficiency, and stability. By focusing on publicly traded banks over an extensive period and employing rigorous statistical methods. Data for the study was extracted from the Bloomberg Terminal and World Bank's World Development Indicators database, totalling data from 2000 to 2023. The preliminary analysis used descriptive statistics, correlation analysis, and unit root tests to assess the characteristics of the data and ensure that the data was suitable for analysis. The following sections explain in detail the empirical analysis, including the results of panel regressions and what these results mean. Understanding the impact of Fintech on the South African banking sector contributes to policymakers, regulators, and industry players making informed decisions toward the twin goals of financial inclusion and innovation for sustainable growth.

CHAPTER FOUR: EMPIRICAL RESULTS AND ANALYSIS

4.1 Chapter overview

The results and analysis presented here provide a comprehensive overview of the dynamics within the South African banking sector, focusing on the relationship between Fintech innovations, economic indicators, and various banking metrics such as competition, performance, efficiency, and stability. This chapter provides the empirical analysis of the research questions that investigate the relationship between Fintech innovations and the dynamics of the South African banking sector. The analysis uses a panel dataset, thereby providing an opportunity to investigate cross-sectional and time-series variations. The chapter is initiated with descriptive statistics to have a preliminary notion of the data; then, the analysis of the correlation was conducted to explore the pairwise relationship among variables and find out the potential associations among Fintech, bank dynamics, and macroeconomic factors. The analysis proceeds with stationarity tests to check the series properties of the variables in order to ensure their reliability. Fixed-effects and random effects regression analysis are the backbone of this study, which examines the cause-and-effect relationship between Fintech innovations and bank dynamics. In order to reinforce the findings with a sufficient degree of credibility, cluster-robust standard errors and GMM estimation are also applied. Finally, the chapter concludes by summarising the key findings, discussing implications for the South African banking sector, and also some policy recommendations based on the empirical evidence.

4.2 Descriptive statistics

This section delves into descriptive statistics, an important component of data analysis that summarises and organises data to offer a clear picture of its key properties. The study explores the relationship between Fintech innovations and the dynamics of the banking sector in South Africa, utilising various economic indicators and banking dynamics of competition, performance, efficiency, and stability metrics. Overall, the dataset consists of 192 observations, whereas in Table 4.1, the Lerner Index (LI), representing bank competition, shows a mean value of 0.68. This indicates that, on average, banks have a relatively high degree of market power, allowing them to set prices above marginal cost. However, from the LI, it is important to note there is considerable variability among banks in terms of their pricing power, with some banks exhibiting significantly more or less market power than the average. This is shown by the negative skewness (-5.12) and high kurtosis (41.06) data, suggesting a clustering of low competition levels with extreme outliers. The Capital Adequacy Ratio (CAR), the measure of bank performance, has a narrow range around its mean of 1.68, reflecting consistent capital adequacy among banks. This can be seen by the standard deviation (SD) of 0.10, indicating consistency across banks. The minimum and maximum values are 1.43 and 2.22, respectively, showing a small range. Its slightly positive skewness (0.61) suggests that most banks perform near or below the mean, with a few exceptions having higher capital adequacy. Bank efficiency, represented by the Stochastic Frontier Analysis (SFA), shows a mean of 0.95, implying high levels of efficiency in banking operations within the sector, with an SD of just 0.01, indicating very little variability. The minimum and maximum values are 0.94 and 0.96, respectively, suggesting that banks operate at almost uniform efficiency levels. The near-zero skewness (-0.16) and moderate kurtosis (1.82) confirm this distribution. The Z-Score, the measure of bank stability, has a mean of 4.24, which typically indicates a strong level of bank stability and a low probability of insolvency and an SD of 1.19, reflecting variability in stability across banks. Stability ranges widely, with a minimum of 2.36 and a maximum of 15.92. The positive skewness (6.34) and high kurtosis (55.23) highlight that while most banks cluster near the lower end, a few are exceptionally stable, creating significant disparities.

Fintech proxies reveal insights into technological adoption. Automated Teller Machines (ATM), with a mean of 51.81, indicating moderate growth in Fintech deployment within the South African banking sector and yet the high standard deviation points to significant variation in Fintech changes among banks, shown by SD of 13.04, range from 23.98 to 67.88, showing variability in ATM adoption. The negative skewness (-0.87) suggests a higher concentration of banks with fewer ATMs. On the other hand, the Value of Mobile Transactions (VMT) has a mean of 6.73, demonstrating low engagement in mobile banking, with an SD of 0.80 and a range from 3.18 to 7.61, suggesting that Fintech innovations are being adopted at varying rates. However, the skewness (-3.53) and high kurtosis (16.67) show that mobile transaction values are concentrated among a few players, indicating uneven digital adoption. Bank concentration (BNK) has a mean of 80.36 and an SD of 5.90, with values ranging from 75.98 to 99.54. The positive skewness (2.41) and high kurtosis (7.69) indicate a market dominated by a few major players. GDP growth, with a mean of 2.28 and an SD of 2.46, ranges widely from -5.96 to 5.60. The negative skewness (-1.42) reflects periods of economic contraction, while inflation (INF) has a mean of 5.29 percent, an SD of 2.15, and a range from -0.69 to 10.74. Its near-symmetric skewness (-0.28) suggests relatively balanced inflation rates over the study period.

Tier 1 Capital has the mean of 10.63 percent and SD of 0.81which reflects consistent core capital adequacy. The negative skewness (-1.72) and kurtosis (9.21) highlight strong performance by a few banks. Conversely, Tier 2 Capital has a mean of 8.90 percent, with a range (of 5.19 to 10.39) and an SD of 0.76, which shows supplementary capital variations. The negative skewness (-1.98) indicates fewer banks with low capital. Personal Expense have a mean of 9.04 percent and SD of 1.71 suggest moderate variability in personal expenses, with a range (1.76 to 11.45). The negative skewness (-1.65) highlights clustering near higher expenses. Whilst, Interest Expense has the mean of 6.98 percent and SD of 1.10, with a range (3.13 to 10.58), reflect varying financial obligations. Lastly Total Deposits has the mean of 12.02 percent and SD of 1.90, spanning from 3.25 to 14.47, indicate disparities in funding capacity. The negative skewness (-1.94) and kurtosis (7) suggest domination by banks with higher deposit levels.

Table 4.1 Descriptive statistics

Statistic	**LI**	**CAR**	**SFA**	**Zscore**	**ATM**	**VMT**	**BNK**	**GDP**	**INF**	**Tier 1 Capital**	**Tier 2 Capital**	**Personal Expense**	**Interest Expense**	**Total deposit**
Mean	0,68	1,68	0,95	4,24	51,81	6,73	80,36	2,28	5,29	10,63	8,90	9,04	6,98	12,02
Minimum	-1,01	1,43	0,94	2,36	23,98	3,18	75,98	-5.96	-0,69	6,95	5,19	1,76	3,13	3,25
Maximum	0,87	2,22	0,96	15,92	67,88	7,61	99,54	5,60	10,74	12,31	10,39	11,45	10,58	14,47
SD	0,18	0,10	0,01	1,19	13,04	0,80	5,90	2,46	2,15	0,81	0,76	1,71	1,1	1,9
Skewness	-5,12	0,61	-0,16	6,34	-0,87	-3,53	2,41	-1,42	-0,28	-1,72	-1,98	-1,65	0,3	-1,94
Kurtosis	41,06	6,17	1,82	55,23	2,81	16,67	7,69	5,99	4,46	9,21	9,93	6,51	6,6	7
Observations	192	192	192	192	192	192	192	192	192	192	192	192	192	192

Source: Author's own estimations (2024)

4.3 Correlation analysis

The correlation results offer valuable insights into the relationships between key variables, highlighting how Fintech innovations, economic indicators, and banking metrics such as competition, performance, efficiency, and stability interact to shape the dynamics of the South African banking sector. The correlation matrix in Table 4.2 investigates the associations between several elements influencing the banking sector and Fintech advancements in South Africa. Looking at the LI, ATM shows a positive correlation (0.22), suggesting that higher competition in the banking sector is associated with greater ATM availability. This relationship suggests that increased competition may incentivise banks to invest more in ATM infrastructure to improve accessibility. The SFA variable is positive (0,51) and significantly correlated with ATM, suggesting that greater ATM penetration is associated with higher banking efficiency. Another significant relationship is between ATM and BNK, which shows a strong negative correlation (−0.59). This suggests that a higher number of ATMs is linked to less concentrated banking markets, possibly because ATMs make banking services more accessible and competitive, allowing smaller or newer players to offer services more effectively. Additionally, ATM is negatively correlated with GDP (−0.59), which may reflect the shift away from physical banking infrastructure in wealthier or more economically developed regions. In these areas, digital banking alternatives are often more prevalent. Lastly, a positive correlation exists between ATM and INF (0.27), suggesting that in environments with inflations, there might be an increase in ATM usage, possibly due to the preference for cash transactions over digital payment systems in periods of economic uncertainty.

Similarly,to ATM, VMT shows a strong positive correlation with GDP (0.58), which indicates that as the economy grows, there is a corresponding increase in the use of mobile transactions. This could be due to the rising adoption of mobile payment systems in more affluent, urbanised regions with a robust mobile network infrastructure. Additionally, VMT is positively correlated with INF (0.23), which suggests that mobile transactions may serve as a preferred alternative to cash transactions in inflationary environments. The Lerner Index also correlates positively with SFA, with a statistically significant correlation coefficient of 0.25. LI is also negatively correlated with BNK (−0.14), implying that as competition increases, bank concentration tends to decrease, which supports the idea that a more competitive market leads to a more diverse banking landscape. Conversely, the correlation between the Lerner Index and GDP is -0.27, indicating a moderate negative relationship.

SFA is negatively correlated with BNK (−0.48), meaning that more efficient banks tend to operate in less concentrated banking sectors. SFA and GDP show a significant negative correlation between SFA and GDP (−0.51). This indicates that higher economic growth is associated with lower bank efficiency in this context. One possible interpretation is that during periods of economic expansion, banks may become less efficient in their operations. Z-score shows a significant positive correlation with INF (0.13), which may imply that inflationary periods could lead to more stable banking institutions, possibly because they are more resilient to economic shocks and the potential risks associated with inflation. BNK and GDP: The correlation between BNK and GDP is negative and significant (−0.51), suggesting that as the economy grows, the concentration of banks in the market tends to decrease. This implies that economic growth promotes a more competitive banking environment by encouraging the entry of new banks or increasing the market share of smaller institutions. Lastly, BNK and INF show a negative and significant correlation between BNK and INF (−0.58), suggesting that inflation is associated with lower levels of bank concentration. This indicates that during inflationary periods, the banking sector may become more fragmented or competitive.

Tier 1 Capital exhibits a significant positive relationship with the Lerner Index (0.378), suggesting that banks with higher levels of core capital tend to have greater market power. This implies that well-capitalized banks are better positioned to set higher prices for their services, thus enhancing profitability and pricing power. Additionally, Tier 1 Capital is positively correlated with the CAR (-0.2997), indicating that banks with higher core capital may have a higher capacity to absorb losses, which improves their overall financial health and regulatory compliance. The relationship between Tier 1 Capital and the SFA (0.1730). Lastly, Tier 1 Capital shows a positive correlation with ATM usage (0.145), indicating that banks with stronger capital reserves may be more inclined to invest in technology-driven services like ATMs, which can enhance customer convenience and operational efficiency.

Tier 1 Capital is positively correlated with Tier 2 Capital (0.5688), indicating a robust capital structure where higher core equity levels are associated with stronger supplementary capital reserves. This alignment highlights the interconnectedness of core and supplementary capital in meeting regulatory requirements and supporting financial stability. Additionally, Tier 2 Capital shows a positive correlation with the Lerner Index (0.293), suggesting that banks with higher supplementary capital may possess greater market power, likely due to enhanced risk-taking capacity and operational flexibility (Pillay & Makrelov, 2024). Furthermore, Tier 2 Capital is positively associated with the CAR (0.4187), reinforcing its role in strengthening overall capital adequacy and ensuring compliance with regulatory standards.

Personal Expense has a moderate positive correlation with Tier 1 Capital (0.4159) and a weak positive correlation with Tier 2 Capital (0.2406), suggesting that well-capitalized banks tend to invest more in personnel and operational infrastructure to sustain competitive advantage. Additionally, the significant positive correlation with the Lerner Index (0.4203) indicates that higher operational expenses contribute to enhanced market power, likely through improved efficiency and customer retention. The positive association with SFA (0.1692) underscores the role of operational investments in enhancing bank efficiency. However, the significant negative association with the Z-Score (-0.4997) raises concerns about the potential risks to financial stability posed by high operational costs.

Interest Expense and Tier 1 Capital (-0.1887) indicate that well-capitalized banks tend to incur lower interest expenses, likely due to their stronger financial positions, which allow them to attract deposits at lower costs. Conversely, Interest Expense is negatively correlated with Personal Expense (-0.1206), suggesting that banks with higher operational costs, possibly associated with larger staffing or infrastructure, might prioritise non-interest expenses over interest payments. Additionally, there is a weak yet significant positive association between Interest Expense and VMT (0.01578), reflecting the relationship between mobile transactions and financial cost structures. Increased digital activity may be associated with a slight rise in interest-bearing liabilities as banks compete for transaction-based deposits.

The correlation table shows a significant positive correlation between Total Deposits and the Lerner Index (0.5011), suggesting that banks with higher deposit volumes tend to exhibit greater market power and pricing ability, reinforcing their competitive positioning. Additionally, Total Deposits display a positive relationship with the number of ATMs (0.1322), indicating that banks with larger deposit bases invest more in expanding their physical infrastructure to enhance accessibility and attract further deposits. Total Deposits and both Tier 1 Capital (0.5825) and Tier 2 Capital (0.3854), indicating that well-capitalized banks are more effective at attracting deposits. This suggests that higher levels of core and supplementary capital enhance customer confidence, reinforcing banks' perceived stability and reliability. Additionally, the positive correlation between Total Deposits and Personal Expenses (0.5942) highlights the operational scale associated with large deposit bases, as higher deposit volumes often necessitate increased staffing and infrastructure to manage expanded banking operations.

Table 4.2 Correlation matrix

Variables	LI	CAR	SFA	Zscore	ATM	VMT	BNK	GDP	INF	TIER1CAPITLA	TIER2CAPITAL	PERSONAL EXPENSE	INTEREST EXPENSE	TOTAL DEPOSITS
LI	1													
CAR	-0,05	1												
SFA	0,25***	-0,10	1											
Zscore	-0,07	-0,01	0,07	1										
ATM	0,22***	-0,06	0,51***	0,02	1									
VMT	-0,07	-0,01	-0,06	-0,00	0,03	1								
BNK	-0,14**	-0,03	-0,48***	-0,09	-0,59***	0,02	1							
GDP	-0,26**	0,04	-0,51***	-0,03	-0,59***	0,58***	0,40***	1						
INF	0,05	0,05	-0,00	0,13*	0,27***	0,23***	-0,58**	-0,08	1					
TIER1CPAITLA	0,37***	-0,29**	0,173***	-,0016	0,14**	0,01	-0,22***	-0,02	-0,07	1				
TIER2CAPITAL	0,23***	0,41***	-0,06	0,0038	0,02	0,01	-0,009	0,004	0,0027	0,56***	1			
PERSONALEXPENSE	0,42***	-0,05	0,16**	-0,49***	0,11	-0,04	-0,0052	-0,21	-0,11	0,41***	0,24***	1		
INTERESTEXPENSE	-0,0095	-0,06	-0,14***	-0,12**	0,06	0,015**	-0,04	0,0	0,06	-0,18***	-0,08	-012*	1	
TOTALDEPOSIT	0,50***	-0,02	0,10	-0,11	0,13**	0,04	-0,11	0,06	-0,06	0,58***	0,38***	0,59***	0,06	1

*Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% level of significance, respectively*

Source: Author’s own estimations (2024)

Unit Root Test Results

The results from the IPS Unit Root Test presented in Table 4.3 provide important insights into the stationarity of the study's variables, which is critical for ensuring reliable statistical analysis. The null hypothesis of the test suggests that the variables are non-stationary, meaning they contain a unit root, while the alternative hypothesis allows for some variables to be stationary. A p-value less than 0.05 indicates stationarity. The test results reveal that most of the variables, including CAR, SFA, Z-score, VMT, BNK, GDP, and INF, are stationary at level (I(0)), meaning they do not require differencing for further analysis. These stationary variables are suitable for use in panel data without the risk of spurious relationships. However, LI, ATM, Tier 1 and 2 Capital, interest expense and total loans were found to be non-stationary at level, with p-values greater than 0.05, and thus required differencing to achieve stationarity at the first difference (I(1)). This transformation ensures that the data is appropriate for valid statistical analysis and prevents the introduction of misleading trends in the relationships between variables Lee, 2020). Overall, the unit root test confirms that the data is reliable for the study's subsequent analyses, with most variables being stationary and only a few requiring adjustments.

Table 4.3 Unit Root Test results

Variable	**Im-Pesaran-Shin (IPS)**	**P-Value**	**Order of Integration**
LI	-1,67	0,4836	I(1)
	-5,81	0,0000***	
CAR	-1,67	0,0470**	I(0)
SFA	-9,90	0,0000***	I(0)
Zscore	-3,05	0,0001***	I(0)
ATM	-1,15	0,8392	I(1)
	-2,95	0,0000***	
VMT	-4,16	0,0000***	I(0)
BNK	-2,84	0,0001***	I(0)
GDP	-3,68	0,0000***	I(0)
INF	-3,11	0,0000***	I(0)
Tier1Capital	-1,56	0,9413	I(1)
	-6,25	0,0000***	
Tier2Capital	-1,03	0,8488	I(1)
	-4,53	0,0000***	
Interest Expense	-0,48	0,9998	I(1)
	-4,20	0,0000***	
Personal Expense	-2,24	0,0279**	I(0)
Total deposit	-1,47	0,6609	I(1)
	-6,78	0,0000***	

*Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% level of significance, respectively*

Source: Author's own estimations (2024)

4.4 Model Selection

This section describes the model selection process for analysing the influence of financial technology developments on the dynamics of the South African banking system. The Hausman test, one of the most widely used model selection procedures, is used to assess the adequacy of fixed and random effects models. The Hausman test results is described in the following subsection.

Hausman Test

The primary objective of this study is to investigate the effect of innovations in financial technology on the dynamics of the South African banking sector, with a breakdown of four secondary objectives. In order to make informed decisions about model selection, resulting in more robust and reliable findings, the Hausman test is employed.

Table 4.4 Hausman Test results

Dependent variable	Chi-Square	P-Value	Model
Lerner Index	8,06	0,1530	Random Effects
CAR	3,32	0,1901	Random Effects
SFA	0,00	1,000	Random Effects
Zscore	6,67	0,5732	Random Effects

Source: Author's own estimations (2024)

The results of the test show that for all variables in this study, the random effects model is the most suitable. Specifically, for the Lerner Index, the p-value is 0.1530, which is greater than the 0.05 threshold, suggesting that there is no significant difference between the fixed and random effects models, thus supporting the use of the random effects model. Similarly, the p-value for CAR, SFA and Zscore is as follows: These p-values indicate that in each case, the random effects model is preferable over the fixed effects model. Therefore, the Hausman test suggests that for the analysis of fintech innovations in the South African banking sector, the random effects model is the most appropriate for all four key dependent variables, enhancing the reliability and generalizability of the study's results.

4.5 Findings for each research objective

This study explores the impact of Fintech innovations on the dynamics of the South African banking sector, focusing on key areas such as bank competition, stability, and efficiency. Employing random-effects regression as the primary analytical model, as identified in Table 4,4, the study evaluates how various Fintech variables influence these critical aspects of the banking sector. The findings address each research objective in turn, providing insights into the evolving role of Fintech and its implications for South African banks in a rapidly transforming financial landscape.

4.5.1 The effect of Fintech on bank competition

Section 4.5.1 examines the effect of fintech on bank competition. The rise of fintech has significantly reshaped the competitive landscape of the banking sector, introducing new players and innovative services that challenge traditional banking models. This regression analysis investigates the relationship between fintech adoption and bank competition, focusing on how technological advancements impact market dynamics and competitive behaviour. Table 4.5 presents the results of this analysis.

Table 4.5 Regression Analysis of Fintech on Bank Competition

	(1) Random Effects	**(2) Robust**	**(3) GMM**
	Dependent Variable		
	Lerner Index	**Lerner Index**	**Lerner Index**
ATM	-0,009	-0,009	0,031
VMT	-0,68***	-0,68***	-0,6694**
BNK	0,0967	0,0244	0,0125
GDP	0,1278*	0,1278**	0,034
INF	0,0887	0,0886	-0,033
cons	-2,2657	-2,2657	0,599*
Lerner_Index Lag.			0,080

*Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% level of significance, respectively*

Source: Author’s own estimations (2024)

The three models represent different approaches to data analysis, each based on distinct underlying assumptions. Model (1) is the Random Effects Model, which assumes that individual heterogeneity (differences between banks) is random and uncorrelated with the independent variables. Model (2) is a robust estimation model which adjusts standard errors to account for potential autocorrelations, assuming that the residuals from one period may be correlated with those from the previous period. Model (3) is the Generalized Method of Moments, a more flexible estimation technique commonly used in dynamic panel data models, particularly for addressing potential endogeneity and using instrumental variables.

The study employs the Lerner index to model bank competition with the aim of answering the secondary objective of investigating the effect of innovations in Fintech on the dynamics of the South African banking sector. The study focuses on two proxy variables for Fintech: ATM and VMT. Based on the results of Table 4.5, the negative and significant VMT coefficient is -0.68, indicating that the negative and significant coefficients suggest that higher mobile transaction values correlate with reduced market power (i.e., increased competition). This reflects how mobile fintech products disrupt traditional banking services by offering convenient and cost-effective alternatives, forcing banks to compete more aggressively. Fintech innovations, particularly VMT, initially gained traction by addressing the needs of underbanked or underserved populations, reflecting Christensen's (1997) theory of disruptive innovation, which begins by targeting niche markets. The negative relationship between VMT and the Lerner Index observed in the study supports the view that mobile transactions have disrupted traditional banking by increasing competition. This suggests that the South African banking sector is leveraging mobile financial services not only to improve user convenience but also to attract a broader customer base, moving beyond niche adoption to challenge mainstream banking. This transition illustrates how Fintech innovations like mobile transactions have matured. Initially seen as supplementary or peripheral, they are now integral to customer offerings, effectively reshaping competition. Banks that have successfully adapted to or integrated mobile transaction services into their operations are positioned to capitalise on this trend, gaining competitive advantages by retaining customers who prioritise digital convenience and accessibility.

From Schumpeter’s (1942) perspective, this evolution exemplifies creative destruction, where traditional banks face a critical choice: either innovate to integrate Fintech solutions or risk losing market share as Fintech redefines the banking landscape. Resistance to these innovations might initially reflect fears of market disruption, but the findings suggest that embracing mobile transactions as a competitive tool offers opportunities for growth and sustained relevance.

Furthermore, the findings align with those of Bejer et al. (2022), who found that the entry of Fintech was associated with negative NIM, indicating that the innovations are creating a more competitive environment for the sector. Additionally, Song et al. (2023) noted that early-stage fintech development leads to increased competition but can negatively impact bank profitability. The control variables within the selected sample were found to be insignificant besides GDP, as it is statistically significant and suggests that higher GDP is associated with an increase in the Lerner Index, seen by the coefficient of 0,1278. Suggesting that economic growth improves market power (reduces competition). The results aligned with those of Bejar et al. (2022), in which studies argued that during economic booms, banks leverage higher demand for financial services, potentially reducing the pressure to compete. The overall model, approximately 9 percent of the variation in the Lerner Index, is explained by the model when looking at within-group (bank-specific) variations. Additionally, with a Wald chi stat of 13,29 and (Prob > F = 0.0208), the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with the Lerner Index.

To enhance the robustness of the random-effects model, it is important to account for within-group correlations, such as those that may arise over time within banks. This approach referred to as making the model "robust," helps correct for potential correlation between observations within the same group, ensuring more accurate standard errors and reliable inferences. By adopting robust approaches, the model becomes more suited to handle difficulties like heteroscedasticity, which can skew the findings. The study employs autocorrelation to account for the potential correlation, and based on Table 4.6, the null hypothesis of no autocorrelation is not rejected (p>0.05), suggesting that serial correlation is not a concern in this panel data model. The regression analysis under (2) Robust further coincides with the baseline analysis of VMT, which is a positive and statistically significant coefficient. All other variables remain insignificant besides GDP; this is statistically significant, indicating that as GDP increases, the Lerner Index increases.

Table 4.6 Autocorrelation under bank competition

Variables	**F (1,81)**	**P- Value**	**Output**
Lerner Index Model	0,09	0,7661	No serial autocorrelation present

Source: Author’s own estimations (2024)

The study tests for endogeneity in the context of random effects models, which is crucial for ensuring that the relationships being analysed are not biased or inconsistent due to correlated explanatory variables and error terms. If endogeneity is detected, the GMM would be the preferred model, as it is robust to endogeneity and can provide consistent estimates even when explanatory variables are correlated with the error term. However, if endogeneity is not present and the assumptions of the random effects model hold, then the Random Effects Model would be the better choice. The results indicate that the Lerner Index (F = 22.0971, p = 0.0022) is endogenous, suggesting that these variables are correlated with the error term and require correction. To address this, the study employs the GMM, which is robust to endogeneity.

Table 4.7 Endogeneity test under bank competition

Variables	**F (1,7)**	**P- Value**	**Output**
Lerner Index	22,0971	0,0022	Variables are Endogenous

Source: Author's own estimations (2024)

The study employs a one-step system GMM estimation presented in Table 4.5 as a model (3) as the best model fit for the study, as there is endogeneity present to evaluate the effects of Fintech on the Lerner Index in the South African banking sector. The lagged Lerner Index shows a positive but statistically insignificant relationship with the current index, suggesting that past market power does not significantly predict current market power. VMT coefficient is negative and approaches significance (with a p-value close to 0.05). This aligns with the notion that mobile fintech products disrupt traditional banking by providing cost-effective and accessible alternatives, compelling banks to compete more aggressively. On the other hand, all other control variables remain insignificant besides the GDP coefficient, indicating that economic growth improves banks' market power (reduces competition). Overall, the model proved to be robust, and the Wald test with a p-value of 0.0000 and test statistic of 62301.24 indicate that the joint null hypothesis that all coefficients are zero can be rejected at any conventional significance level, affirming the model's overall validity. The study highlights the transformative role of fintech in enhancing competition in the banking sector, with mobile transactions (VMT) being a key driver. Policymakers and banking institutions should focus on integrating fintech solutions and fostering an environment where digital innovation thrives to maintain competitive markets. Economic growth, while beneficial, might lead to reduced competition without such proactive measures. The next section aims to answer secondary research objective two, which looks at how innovations in Fintech impact performance in the South African banking sector.

4.5.2 The effect of Fintech on bank performance

Section 4.5.2 explores the effect of fintech on bank performance. As the banking sector embraces digital transformation, it is essential to understand how fintech influences various aspects of bank performance, including profitability, asset management, and customer engagement. The following regression analysis examines the relationship between fintech adoption and bank performance, with a focus on key performance indicators. Table 4.8 presents the results of this analysis.

Table 4.8 Regression Analysis of Fintech on Bank Performance

	(1) Random Effects	**(2) Robust Random Effects**	
	Dependent Variable		
	CAR	**CAR**	
ATM	0,0016	0,0016	
VMT	-0,0052	-0,0052	
BNK	0,0003	0,0003	
GDP	0,0019	0,0019	
INF	-0,0014	-0,0014	
Tier1Capital	-0,0423***	-0,0423***	
Tier2Capital	0,0410***	0,0410***	
cons	0,5386***	0,5386***	

* p<0.10, ** p<0.05, *** p<0.01*Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% level of significance, respectively*

Source: Author's own estimations (2024)

The two models represent different approaches to data analysis based on their underlying assumptions. Where model (1) is Random Effects, which assumes that individual heterogeneity (differences between banks) is random and unrelated to the independent variables. Model (2) is a robust estimation that addresses serial autocorrelation.

The study employs the CAR to model bank competition with the aim of answering secondary objective two, which is investigating the effect of innovations in Fintech on the performance dynamic within the South African banking sector. As shown by Table 4.8, the study finds no effects of Fintech on bank performance, as both Fintech proxies ATM and VMT are statistically insignificant. The finding suggests that Fintech innovations are not yet integral to how banks manage their financial stability or solvency. The sector might not yet be sufficiently dependent on or impacted by digital channels and technologies like mobile banking, payment platforms, or even advanced ATM networks to the point where it would influence their capital requirements and have consequences on their performance. The Tier 1 and Tier 2 Capital coefficients are significant and show strong relationships with CAR, indicating that more traditional banking factors, such as the bank's capital structure, are still the primary drivers of capital adequacy. For instance, the traditional banking of Tier One has a negative coefficient, meaning that, holding all other factors constant, an increase in Tier 1 Capital is associated with a decrease in CAR. Specifically, for every unit increase in Tier 1 Capital, CAR decreases by approximately 0.04. The p-value is 0.000, which indicates that this result is statistically significant. The negative relationship here might suggest that banks with more Tier 1 Capital might be engaging in more aggressive risk-taking strategies. The finding aligns with the findings of Conlon et al. (2020), suggesting that the risk reduction capacity of Tier 1 capital can be hindered by certain components like Tier 1 capital, potentially leading to increased risk-taking behaviours. Conversely, Shaik and Sharma (2021) found that the Tier 1 Capital Ratio positively correlates with ROA and ROE.

On the other hand, the positive coefficient for Tier 2 Capital means that holding all other factors constant, an increase in Tier 2 Capital is associated with an increase in CAR. Specifically, for every unit increase in Tier 2 Capital, CAR increases by approximately 0.04. The p-value is 0.000, which indicates that this result is statistically significant. The positive relationship suggests that increasing Tier 2 Capital strengthens the CAR by increasing the available capital buffer for banks. Additionally, banks with more Tier 2 Capital might be better positioned to absorb potential losses, thus ensuring a higher CAR. This implies that Tier 2 Capital provides a more stable foundation for managing risk, particularly in volatile markets. The overall model, approximately 9 percent of the variation in the CAR, is explained by the model when looking at within-group (bank-specific) variations. Additionally, with a Wald chi stat of 32,60 and (Prob > F = 0.0000), the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with the CAR.

The study uses robustness, as demonstrated by (2), to compensate for within-bank correlation across time and assure reliable findings. The study employs autocorrelation to account for the potential correlation, and based on Table 4.9, the null hypothesis of no autocorrelation is rejected ($p<0.05$), suggesting that serial correlation is a concern in this panel data model. Research by PwC South Africa (2024). suggests that South African banks are highly sensitive to both macroeconomic conditions and global market volatility, which can create a pattern of persistence in their financial performance. As a result, residuals from financial models in this sector may show autocorrelation, reflecting these unaccounted-for dynamics and the structural characteristics of the banking environment in South Africa (PwC South Africa, 2024). To address the autocorrelation, the study employs model (2) in Table 4.8, which the study used to control the effects of time-series autocorrelation. The study has found no influence of Fintech on bank performance as both proxies for Fintech (ATM and VMT) are insignificant. However, under the Cluster model, Tier 1 Capital is still negative, with a coefficient of -0.0803701 and a P-value of 0.000; thus, the implication would be that this negative and statistically significant coefficient means that for every additional unit of Tier 1 Capital, the CAR decreases by 0.08. This would, therefore, imply that the more Tier 1 Capital a bank has, the more likely it is to invest in riskier investments that reduce the CAR in the short run. The coefficient for Tier 2 Capital is 0.1095638 p-values of 0.000 positive and statistically significant, which indicates that a rise in Tier 2 Capital leads to a corresponding rise in CAR: precisely, for every increase in one unit of Tier 2 Capital, CAR increases by 0.11. Overall, model 2 r-squared is at 9 percent, indicating the model accounts for variation in the CAR, which is explained by the model when looking at overall-group bank-specific. Additionally, with a Wald chi stat of 227,60 and (Prob > F = 0.0000), the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with CAR.

Table 4.9 Autocorrelation under bank performance

Variables	**F (1,81)**	**P- Value**	**Output**
CAR Model	10,61	0.000	There is serial autocorrelation

Source: Author’s own estimations (2024)

The study tests for endogeneity in the context of the CAR variable, which is important to ensure that the relationships being analysed are not biased or inconsistent due to correlations between explanatory variables and the error term. The F-statistic for CAR is 0.02433, and the corresponding P-value is 0.8805, which is significantly higher than the typical threshold of 0.05. This indicates that CAR is exogenous, meaning it is not correlated with the error term and does not suffer from endogeneity. As a result, there is no need to apply methods like the GMM for this variable. In the absence of endogeneity, the Random Effects Model would be the preferred model, as it is more efficient and reliable in this case. Therefore, the appropriate model for analysing CAR should be based on the test results, which show no need for correction for endogeneity, supporting the use of the Random Effects Model.

Table 4.10 Endogeneity test under bank performance

Variables	**F (1,7)**	**P- Value**	**Output**
CAR	0,02433	0,8805	Variables are exogenous

Source: Author's own estimations (2024)

The next section aims to answer secondary research objective three, which looks at how innovations in Fintech impact bank efficiency in the South African banking sector.

4.5.3 The effect of Fintech on bank efficiency

Section 4.5.3 explores the effect of fintech on bank efficiency. As financial institutions increasingly adopt technological innovations, it is crucial to assess how these advancements contribute to operational efficiency. The following regression analysis investigates the relationship between fintech adoption and bank efficiency, highlighting key factors that may influence this dynamic. Table 4.11 presents the results of this analysis.

Table 4.11 Regression Analysis of Fintech on Bank Efficiency

	(1) Random Effects	**(2) Robust**	**(3) GMM**
	Dependent Variable		
	SFA	**SFA**	**SFA**
ATM	-0,002***	-0,002***	8,10***
VMT	0,023***	0,023***	1,16***
BNK	0,131***	0,131***	8,07***
GDP	-0,004***	-0,004***	-1,45***
INF	0,003***	0,003***	-4,91***
cons	-0,666***	-0,666***	-1,25***
SFA Lag			0,97***

*Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% level of significance, respectively*

Source: Author's own estimations (2024)

The three models represent different approaches to data analysis based on their underlying assumptions. Where model (1) is Random Effects, which assumes that individual heterogeneity (differences between banks) is random and unrelated to the independent variables. Model (2) is a robust estimation which adjusts standard errors for potential heteroskedasticity while assuming that variance is not constant across observations. Model (3) is the GMM model, a more flexible estimation method commonly used in dynamic panel data models, particularly when dealing with potential endogeneity and instrument variables.

Research objective three looks at the impact of Fintech on bank efficiency within the South African banking sector. The main variables in question were significant; for instance, the study finds that ATM has a negative coefficient of –0,002 and VMT has a coefficient of 0.023. The negative coefficient suggests that as the squared change in the number of ATMs increases, SFA decreases. The negative relationship is statistically significant ($p < 0.001$), aligning with the studies of Wang et al. (2021). The result indicates diminishing returns on the increase of ATMs beyond a certain point. While having more ATMs can enhance accessibility, there is a threshold beyond which further increases may not contribute positively to efficiency. This reflects the operational costs associated with maintaining numerous ATMs and the need for strategic deployment rather than just quantity. According to the Disruptive Innovation Theory, the finding would oppose this view, as banks may be investing in sustaining, rather than disruptive, innovations. Over time, the reliance on ATMs could be costly if mobile transactions continue to grow and consumer demand for physical banking declines. On the other hand, creative destruction theory suggests that outdated technologies are replaced by innovative ones, leading to market evolution. The negative relationship between ATMs and bank efficiency could signify that traditional ATMs are becoming less viable compared to digital options. This aligns with the theory's prediction that more advanced ones will eventually replace less efficient or outdated solutions.

On the other hand, for VMT, the positive coefficient indicates that an increase in the value of mobile transactions is associated with an increase in bank efficiency. This relationship is statistically significant ($p < 0.001$). The results align with those of Lee et al. (2021) and Liao (2023). Mobile banking and digital wallets have become increasingly popular in the South African banking sector, providing financial inclusion to previously underserved populations. The growth in mobile transactions indicates that banks leveraging Fintech innovations can enhance customer engagement, streamline operations, and ultimately improve efficiency. VMT has a significant coefficient, suggesting that banks increasingly depend on Fintech's capabilities to streamline operations. This also aligns with the Disruptive Innovation Theory, as Fintech innovations push banks to either improve their efficiency to meet consumer expectations or risk losing relevance. Banks that do not engage in Fintech-like digital processes may find it challenging to maintain efficiency, particularly as Fintech options become more widely accepted and consumer expectations shift toward faster, more accessible banking solutions. Furthermore, the significant impact of the Fintech variable of VMT on SFA shows that digital transformation drives banks toward higher efficiency. Creative Destruction Theory emphasises how new entrants with leaner, tech-driven models force incumbents to innovate or face obsolescence. The result reflects the theory's suggestion that Fintech solutions by replacing traditional banking methods with digital, automated, and user-friendly alternatives can pressure banks to restructure inefficient processes and optimise service delivery. The sector appears to be meeting this challenge by leveraging Fintech-related innovations, thus realising efficiency gains as they adapt. For instance, mobile transactions offer a lower-cost alternative to branch services, suggesting that banks embracing Fintech can streamline operations, reduce operational costs, and potentially improve their SFA scores.

Furthermore, the study's control variables were all significant under bank efficiency; for instance, the BNK coefficient is positive (0.131, $p < 0.001$), suggesting that higher concentration in the banking sector correlates with greater efficiency. This finding could reflect economies of scale enjoyed by larger, dominant banks, enabling streamlined operations and cost advantages. However, increased concentration may also limit competition, reducing incentives for innovation over time and suggesting a nuanced relationship that warrants further exploration. For the macroeconomic variables, INF is at -0.0005968, with the negative effect of inflation indicating that higher inflation rates correspond to lower bank efficiency. The negative effect is statistically significant ($p = 0.009$). Inflation can erode customer purchasing power and alter demand for banking services, making it difficult for banks to maintain efficiency. On the other hand, GDP has a coefficient of -0.004; the negative relationship between GDP and bank efficiency suggests that higher GDP growth correlates with lower efficiency in this context. This relationship is highly significant ($p < 0.001$), aligning with the studies of Wang et al. (2021) and Al-Jabri (2023). The driver behind the negative impact is that it could indicate that during periods of economic growth, banks might face pressures that lead to inefficiencies, such as scaling operations rapidly without adequate infrastructure. As Wang et al. (2021) and Al-Jabri (2023) stated that the driver behind such negative effects is the intensified competition that economic growth brings. Higher economic growth attracted new entrants, such as Fintech innovations, into the financial industry due to lower barriers. Consequently, this increased competition raises costs and decreases banks' efficiency and profitability. The overall model, approximately 9 percent of the variation in the SFA, is explained by the model when looking at within-group (bank-specific) variations. Additionally, with a Wald chi stat of 32,60 and (Prob > F = 0.0000), the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with the SFA.

To improve the robustness of the random-effects model, it is necessary to account for within-group correlations, which may occur over time inside banks. This strategy, known as making the model robust, helps to adjust for potential correlation between data within the same group, resulting in more accurate standard errors and valid conclusions. Adopting robust techniques improves the model's ability to manage challenges such as heteroscedasticity, which can distort the results. The study uses autocorrelation to account for potential correlation, and according to Table 4.12, the null hypothesis of no autocorrelation is not rejected ($p>0.05$), indicating that serial correlation is not an issue in this panel data model. Under the robust Random Effects model, all coefficients remain statistically significant ($p < 0.001$), suggesting strong evidence supporting the relationships posited in the model. ATM remains significant and negative. The negative coefficient suggests that after a certain level of ATM proliferation, additional ATMs contribute less to efficiency or could even reduce it. The positive coefficient of VMT indicates that increased value in mobile transactions significantly enhances bank efficiency. The robustness of this relationship ($p < 0.001$) reinforces the positive impact of Fintech innovations.

Table 4.12 Autocorrelation under bank efficiency

Variables	**F (1,81)**	**P- Value**	**Output**
SFA Model	-1,06	0.294	There is no serial autocorrelation present.

Source: Author's own estimations (2024)

This study employs a one-step system, the Generalised Method of Moments (GMM) estimation Model (3), to evaluate the effects of Fintech on the SFA in the South African banking sector. The lagged dependent variable (L1.SFA) is at 0.97, which is closer to 1, indicating a strong persistence in bank efficiency over time. This suggests that past efficiency levels have a substantial influence on current efficiency, reflecting the importance of historical practices and structures within banks. The implications for Fintech are that as the sector adopts the innovations, it may take time for these changes to reflect in efficiency metrics, highlighting the need for long-term strategies in technology adoption. Under the GMM estimation model, VMT remains significant and positive, which indicates that increases in mobile transaction values are associated with improvements in bank efficiency. This finding emphasises the effectiveness of mobile Fintech solutions in enhancing operational efficiency and that the sector overall should continue investing in mobile technologies and promoting mobile transactions to drive efficiency gains. The study's control also has no changes from the baseline regressions, under this model. INF is also negative, indicating that higher inflation negatively impacts bank efficiency, likely due to increased operational costs and reduced consumer spending power. Financial technology solutions can help banks mitigate the effects of inflation through better risk management and predictive analytics. Similar to inflation, higher GDP seems to correlate with decreased efficiency, which could indicate that banks face challenges during rapid economic growth, such as scaling operations effectively. However, efficient scaling through Fintech solutions can help banks manage growth without sacrificing efficiency.

In conclusion, this study confirms that Fintech has a measurable impact on bank efficiency within the South African banking sector. While the increase in ATMs shows diminishing returns and a negative effect on efficiency, mobile transaction values (VMT) significantly boost efficiency, suggesting that digital banking options enhance operational performance. The results support the theories of Disruptive Innovation and Creative Destruction, as Fintech pushes traditional banks to innovate or risk falling behind. Additionally, control variables such as bank concentration, inflation and GDP highlight that competitive innovations can counteract inefficiencies, encouraging banks to embrace Fintech for sustained improvements. The next section aims to answer secondary research objective four, which looks at how innovations in Fintech impact stability in the South African banking sector.

4.5.4 The effect of Fintech on bank stability

Section 4.5.4 looks at the relationship between fintech and bank stability. As the financial industry embraces technological advancements, understanding how fintech affects bank stability becomes increasingly important. The following regression analysis looks into the potential impact of fintech on bank stability, focusing on key variables that may reflect the incorporation of technology into financial processes. Table 4.13 shows the results of this analysis.

Table 4.13 Regression Analysis of Fintech on Bank Stability

	(1) Random Effects	(2) Robust Random Effects	(3) GMM
	Dependent Variable		
	Zscore	Zscore	Zscore
ATM	0,0024	0,0024	0,001
VMT	0,012	0,012	0,008
BNK	0,0015	0,0015	0,002
GDP	-0,0097	-0,0097	-0,005
INF	0,0045	0,0045	0,006
InterestExpense	-0,036	-0,036	-0,05**
PersonalExpense	-0,041***	-0,041***	-0,03***
TotalDeposits	0,005	0,005	-0,005
cons	1,531***	1,531***	1,17***
Zscore Lag			0,32

*Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% level of significance, respectively*

Source: Author’s own estimations (2024)

The three models represent different approaches to data analysis based on their underlying assumptions. Where model (1) is Random Effects, which assumes that individual heterogeneity (differences between banks) is random and unrelated to the independent variables. Model (2) is a robust estimation which adjusts standard errors for potential heteroskedasticity while assuming that variance is not constant across observations. Model (3) is the Generalized Method of Moments (GMM) model, a more flexible estimation method commonly used in dynamic panel data models, particularly when dealing with potential endogeneity and instrument variables.

The study employs the Z-score to model bank stability with the aim of answering secondary objective four, which is investigating the effect of innovations in Fintech on the stability dynamic within the South African banking sector. As shown by Table 4,9, the study finds no effects of Fintech on bank stability, as both Fintech proxies ATM and VMT are statistically insignificant. While mobile payments and ATMs have grown rapidly, their direct impact on traditional banks' stability, as measured by the Z-score, may still be limited. However, the growth of mobile and ATM banking services is still a critical trend that banks should embrace for long-term sustainability. Other control variables were also insignificant besides PersonalExpense, with a coefficient of -0.041 and a P-value of 0.001, showing a significant negative relationship with bank stability. The result indicates that higher personal expenses reduced the bank's stability, which could be due to the added pressure on bank profitability and liquidity. The high personal expenses, likely referring to administrative or personnel-related costs, can put pressure on bank profitability and capital reserves, making the bank more vulnerable to shocks. Banks should focus on optimising their operational costs through automation, digitalisation, and streamlining back-office functions to enhance profitability and maintain stability. The overall model, approximately 29 percent of the variation in the Zscore, is explained by the model when looking at variations. Additionally, with a Wald chi stat of 30,86 and (Prob > F = 0.0000), the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with the Zscore.

In order to improve the random-effects model, within-group correlations, which might arise over time within banks, must be taken into consideration. This method is known as making the model "robust," because it helps to account for any correlation between data within the same group, resulting in more accurate standard errors and correct conclusions. Adopting robust approaches enhances the model's ability to handle problems like heteroscedasticity, which can skew findings. The study uses autocorrelation to account for potential correlation, and Table 4.14 shows that the null hypothesis of no autocorrelation is not rejected (p>0.05), implying that serial correlation is not an issue in this panel data model. Table 4.9, regression Model 2 finds both Fintech proxies insignificant; on the other hand, personal expenses also remain negative and statistically significant under this model, indicating that higher personal expenses are associated with lower bank stability. The overall model (2) also is approximately 29 percent of the variation in the Zscore, which is explained by the model when looking at overall variations. Additionally, with a Wald chi stat of 30,86 and (Prob > F = 0.0000), the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with the Zscore.

Table 4.14 Autocorrelation under bank stability

Variables	**F (1,81)**	**P- Value**	**Output**
Zscore Index Model	1,33	0,184	There is no serial autocorrelation

Source: Author's own estimations (2024)

The study tests for endogeneity with respect to the Z-score variable, which is crucial for ensuring that the relationships being analysed are not biased or inconsistent due to correlations between the Z-score and the error term. The F-statistic for Z-score is 11.1005, and the P-value is 0.00126, which is significantly lower than the common threshold of 0.05. This indicates that the Z-score is endogenous, meaning it is correlated with the error term and could lead to biased estimates. As a result, the GMM should be employed, as it is robust to endogeneity and provides consistent estimates even when explanatory variables are correlated with the error term. Therefore, given the presence of endogeneity, GMM would be the preferred model for analysing the Z-score variable, as it corrects the endogeneity issue and ensures more reliable results. This study employs a one-step system, the GMM estimation Model (3), to evaluate the effects of Fintech on the Z-score in the South African banking sector. The study finds no effects of Fintech on bank stability, as both Fintech proxies ATM and VMT are statistically insignificant. Other than the study proxy variables of interest, interest expense is the only variable with a statistically significant effect on the dependent variable (Zscore) at the 5 percent level ($p = 0.004$). The coefficient of 0.0623 indicates a positive relationship between interest expenses and bank stability. This may imply that higher interest expenses (possibly linked to lending activities or debt servicing) have a stabilising effect on banks, potentially due to more conservative credit management or an emphasis on profitable loans. Interestingly, the coefficient for Interest Expense is negative (-0.036), but it is significant at the 5 percent level ($p = 0.004$). This suggests that higher interest expenses may correlate with improved stability, possibly due to more conservative credit management practices.

Table 4.15 Endogeneity test under bank stability

Variables	F (1,7)	P- Value	Output
Zscore	11,1005	0,00126	Variables are Endogenous

Source: Author's own estimations (2024)

The GMM model's overall statistical significance is supported by the Wald chi-squared test, which yields a highly significant p-value of 0.000. This suggests that the collective influence of the explanatory variables contributes meaningfully to explaining variations in bank stability. Overall, the findings reveal that Fintech innovations, as represented by ATMs and VMT, do not have a statistically significant impact on bank stability, suggesting that traditional banking metrics currently play a more critical role in stability dynamics. Key determinants of stability include Personal Expenses, which negatively affect stability, likely due to pressures on profitability and liquidity. The study's model shows that individual bank characteristics significantly influence stability outcomes, although it captures only a modest portion of overall bank variation over time. Robustness checks, including the Wald test, support the model's validity, while control for autocorrelation confirms statistical significance. Overall, while Fintech's direct impact on stability remains limited, optimising deposit bases and cost management could strengthen the stability of South African banks. The next sections discuss the tests for endogeneity to ensure the robustness of the results.

4.6 Summary of results

Table 4.16 summarises the study's findings and addresses each of the research goals. This table highlights the key effects of Fintech on competitiveness, performance, efficiency, and stability in the banking system. It offers an easy reference for how the emergence of Fintech innovations impacted both traditional banking metrics and processes. This review contributes to a better understanding of Fintech's implications for the South African banking system and serves as the foundation for future study and suggestions.

Table 4.16 Summary of Key Results

Research Question	Key Insights
Primary Research Question	**How do innovations in financial technology affect banking sector dynamics in South Africa?** Innovations in Fintech are reshaping the South African banking sector by enhancing market power, particularly through mobile transactions, which have been shown to decrease the bank performance, indicating more competition for bank technologies. As for performance, the innovations show mixed results of enhanced operational efficiency and diminishing returns. The innovations drive improvements in efficiency, whilst for bank stability direct impact of fintech on stability is limited.
Secondary Research Question One	**How do innovations in financial technology affect competition in the South African banking sector?** Fintech innovations, especially mobile transactions, have a positive impact on competition by allowing banks to engage underbanked populations and adapt their services, leading to increased market power and competitive dynamics.
Secondary Research Question Two	**How do innovations in financial technology impact performance in the South African banking sector?** Current findings indicate that Fintech has not significantly impacted bank performance metrics like CAR, suggesting traditional banking factors still dominate performance outcomes.
Secondary Question Three	**How do innovations in financial technology influence efficiency in the South African banking sector?** Fintech innovations, particularly mobile transactions, positively impact bank efficiency in South Africa, while increased ATM deployment shows diminishing returns, suggesting banks should pivot towards digital solutions to optimise resources and remain competitive. The adaptation to Fintech could imply potential efficiency gains as banks streamline operations and improve customer engagement through digital channels.
Secondary Question Four	**How do innovations in financial technology affect stability in the South African banking sector?** The stability of banks appears to be more influenced by traditional capital structures rather than Fintech innovations, as evidenced by significant relationships between capital adequacy and traditional banking metrics.

Source: Author's own compilation (2024)

4.7 Chapter summary and concluding remarks.

Chapter Four concludes by highlighting the empirical findings on the objectives of investigating the effect of innovations in financial technology on the dynamics of the South African banking sector. Through comprehensive statistical analyses, including descriptive statistics, correlation analysis, and regression models, the study uncovered key insights into how Fintech innovations are reshaping traditional banking dynamics. The study finds that Fintech innovations, particularly mobile transactions, are reshaping the South African banking sector by enhancing market power, competition, and efficiency, though their impact on traditional performance and stability metrics remains limited. Fintech-driven mobile transactions strengthen banks' competitive positioning by reaching underbanked populations and reducing dependency on physical infrastructure, while ATM deployments yield diminishing returns, suggesting a need to pivot towards digital solutions to optimise resources. However, traditional factors, such as capital structure, still dominate bank performance outcomes and remain crucial for stability, indicating that Fintech’s role in these areas is still emerging. Overall, Chapter Four shows that while Fintech is transforming certain banking dynamics, such as bank competition and efficiency, the South African banking sector must balance digital innovation with established financial practices to ensure adaptability and resilience in a changing financial landscape.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1. Review of objectives

One of the main factors influencing South Africa's stability, prosperity, and socioeconomic development is the banking industry. By directing capital into businesses and encouraging personal savings, banks contribute to economic growth in addition to facilitating financial transactions (Moyo, 2018). In South Africa, the emergence of Fintech has significantly upended the traditional banking landscape. Fintech innovations have opened up new avenues for more individualized, cost-effective, and efficient financial services, upending the traditional banking model (Coetzee, 2018). Rapid expansion has raised worries about regulatory gaps and related risks like market volatility and operational failures, though. The SARB's response has been to establish working groups to oversee Fintech development and mitigate risks while promoting financial inclusion (SARB, 2023). This dynamic interplay between Fintech and the banking sector prompts an exploration of how innovations in Fintech impact the competitiveness, performance, efficiency, and stability of South African banks. On this background, the purpose of this study is to look at the multidimensional impact of Fintech on the South African banking system. First, the study looks at how Fintech advancements affect the competitive landscapes of South African banks. Second, it evaluates the impact of Fintech innovations on the performance measures of banks in South Africa. The third goal is to determine the impact that financial technology developments have on operational efficiency in the South African banking system. The fourth investigates the effects for the stability of Fintech advances in the South African banking sector.

5.2. Summary of Findings

This section highlights the research findings, which address each of the study's objectives. The interaction will focus on how Fintech impacts competition, performance, efficiency, and stability in the banking sector.

5.2.1. The effect of Fintech on bank competition

The study's first secondary objective investigated how Fintech innovations impact bank competition in South Africa. ATM deployment and VMT showed distinct effects, with a positive but marginally significant coefficient for VMT suggesting that increased mobile transaction engagement correlates with higher market power, with banks leveraging Fintech to attract a larger customer base and improve service convenience. This aligns with Christensen's theory of disruptive innovation, which posits that Fintech began by serving niche markets and gradually expanded to mainstream banking, enhancing banks' competitive positioning. Banks that adapted to Fintech innovations, as reflected by a rise in the Lerner Index, gained competitive advantages over those slower to adopt. On the other hand, ATMs have proved to have no statistically significant effect on bank competition. Conversely, GDP was found to be associated with a decrease in the Lerner Index, indicating intensified competition during economic growth, which could reduce banks' market power. This result supported findings from Naceur et al. (2023) and Song et al. (2023), suggesting that economic expansion encourages competition as banks vie for market share, thus pressuring margins. The study concludes that Fintech innovations, particularly mobile transactions, strengthen bank market power, while economic growth drives competitive dynamics in the South African banking sector.

5.2.2. The effect of Fintech on bank performance

The second secondary objective assessed the impact of Fintech innovations on the performance of South African banks. Using proxies such as ATMs and Value of Mobile Transactions (VMT), the study found no statistically significant impact of Fintech on bank performance, indicating that Fintech is not yet a key factor in financial stability or solvency for banks. Instead, traditional factors, such as Tier 1 and Tier 2 capital, significantly influence banks' CAR. Specifically, Tier 1 Capital had a negative relationship with CAR, suggesting that banks with higher Tier 1 capital may engage in riskier strategies, thereby reducing their CAR. This aligns with Conlon et al. (2020), who argue that certain Tier 1 components can inadvertently encourage risk-taking. However, it contrasts with Shaik & Sharma (2021), who found a positive correlation between Tier 1 Capital and profitability metrics like ROA and ROE. In contrast, Tier 2 Capital shows a positive correlation with CAR, reflecting its role as a stable buffer against potential losses.

5.2.3. The effect of Fintech on bank performance

The third research objective examined the impact of Fintech innovations on bank efficiency in the South African banking sector, focusing on ATM deployment and VMT. The findings indicate a significant negative relationship between increased ATM numbers and bank efficiency, with a negative coefficient for ATM. This aligns with Wang et al. (2021), suggesting diminishing returns in efficiency due to the operational costs associated with extensive ATM networks. This implies that ATM-focused investments represent sustaining rather than disruptive innovation, as indicated by the Disruptive Innovation Theory, especially as consumer reliance shifts toward digital solutions. Conversely, VMT demonstrates a positive, significant correlation with bank efficiency, highlighting that Fintech-driven mobile transactions improve operational efficiency. This supports the Creative Destruction Theory by suggesting that digital banking models are gradually replacing traditional methods, pressuring banks to enhance efficiency. The growing popularity of mobile banking and digital wallets in South Africa has enabled banks to expand financial inclusion while reducing operating costs, confirming that digital transformation promotes efficiency. Control variables also significantly impact efficiency: a higher bank concentration negatively affects efficiency. Inflation and GDP growth are negatively associated with bank efficiency, reflecting challenges in managing operational costs and scaling effectively during economic growth. In summary, the study concludes that Fintech contributes to bank efficiency, particularly through mobile transaction innovations, while diminishing returns on ATMs suggest a need for a digital-centric focus in the South African banking sector.

5.2.4. The effect of Fintech on bank performance

The fourth secondary research objective investigated the impact of Fintech innovations on bank stability in the South African banking sector, using the Z-score to measure stability. It finds no significant effect of Fintech, particularly mobile payments and ATMs, on bank stability, as both proxies (ATM and VMT) are statistically insignificant. Despite the rapid growth of mobile and ATM banking, their direct impact on traditional banks' stability is minimal. However, the study highlights the importance of embracing these innovations for long-term sustainability. Other control variables also showed mixed results. Total deposits have a positive and statistically significant effect on bank stability, suggesting that higher deposits provide a stable funding source and enhance resilience. In contrast, higher personal expenses negatively affect stability, likely due to pressure on profitability and liquidity. Banks are encouraged to optimise operational costs to improve stability.

5.3. Implications of findings

Research objective one, which examines the relationship between Fintech and bank competition, the significant negative association between VMT and the Lerner Index indicates that Fintech innovations, particularly mobile transactions, have reduced market power among

South African banks. This suggests that Fintech is fostering greater competition by enabling customers to access more convenient and cost-effective financial services, thus challenging traditional banking models. The findings imply that as Fintech continues to disrupt the sector, banks that adapt and innovate are more likely to remain competitive in a rapidly evolving market. This necessitates ongoing investment in technology and customer-centric services to meet shifting consumer expectations. Conversely, banks that resist these changes risk losing market share and experiencing reduced pricing power as customers increasingly gravitate toward more efficient and innovative digital offerings.

In research objective two, which investigates the impact of Fintech on bank performance, the insignificance of Fintech proxies (ATM and VMT) on CAR suggests that the South African banking sector is not yet heavily reliant on Fintech for financial performance. This implies that within the sector, traditional banking factors, such as capital structure, remain the primary drivers of performance. The lack of significant impact from Fintech innovations indicates that banks may need to integrate these technologies further into their operations to enhance performance outcomes. Without this integration, banks risk missing out on potential performance gains associated with innovations.

Research objective three investigates the impact of Fintech on bank efficiency. Findings indicate a significant negative relationship between increased ATM numbers and bank efficiency, while VMT demonstrates a positive, significant correlation with bank efficiency. The South African banks should evaluate the strategic deployment of ATMs and branches, aligning their physical presence with the regions or demographics that still require them. However, as mobile transactions gain traction, a pivot towards digital solutions could help optimise resources. Additionally, the sector should focus on investing in digital infrastructure and Fintech innovations, such as mobile and online banking platforms, to enhance efficiency. This shift could mitigate operational costs associated with physical infrastructure, positioning banks to remain competitive in a digitally oriented market.

The last research objective investigated the effects of Fintech on bank stability with both Fintech proxies ATM and VMT, which are statistically insignificant. This lack of direct impact on stability could indicate for the sector that while Fintech innovations improve efficiency, they may not yet be robust enough to affect core stability metrics. This could be due to the relatively early stage of Fintech adoption in South Africa or the sector's continued reliance on traditional banking structures for stability. However, as Fintech becomes more integrated into the banking ecosystem, its indirect contributions to stability through improved operational resilience could become more evident over time. As mobile banking and Fintech options grow, they may not contribute immediately to financial stability, but they enhance banks' relevance and adaptability, which is critical for long-term resilience. Banks that lag in digital adoption risk losing their competitive edge, as shown in research objective one.

From a policy perspective, the findings underscore the necessity of developing regulatory frameworks that foster Fintech innovation while preserving the stability and integrity of the banking sector. Policymakers and regulators play a critical role in creating an environment where digital transformation can thrive, enabling banks to meet evolving consumer preferences and align with global financial trends. For the South African banking sector, targeted investments in digital infrastructure and the promotion of customer-centric services are imperative to remain competitive in a market that is rapidly embracing digitalisation. As the sector adapts to Fintech advancements, a balanced approach that integrates digital innovation with traditional banking practices will be essential. By implementing policies that encourage innovation within a strong regulatory framework, South Africa can ensure its banking sector remains robust, inclusive, and responsive to the demands of a dynamic economy and an increasingly tech-savvy population.

5.4. Limitations and recommendations for future studies

The study acknowledges several limitations that may impact the robustness and generalizability of its findings. Firstly, the analysis is limited to a small number of banks, which may not adequately represent the entire South African banking sector. Additionally, the reliance on lower frequency data could obscure short-term dynamics and trends associated with Fintech innovations. The study also utilises only one measure for each dynamic, such as CAR for performance, which may overlook other significant indicators like ROE and ROA that could provide a more comprehensive view of bank performance. Furthermore, the research is confined to the South African context, limiting its applicability to other markets with different regulatory environments and technological landscapes. Lastly, the measures of Fintech innovations are somewhat limited, focusing primarily on ATM and mobile transaction values, which may not capture the full spectrum of Fintech developments influencing the banking sector.

Future studies should consider a wider range of Fintech innovations beyond mobile transactions and ATMs. This could include digital banking platforms, peer-to-peer lending, blockchain technology, and artificial intelligence in banking operations. By examining these additional technologies, researchers can gain a more comprehensive understanding of how diverse Fintech solutions impact various aspects of the banking sector. Additionally, expanding the research to include non-publicly traded banks and emerging Fintech companies could provide insights into the dynamics of the entire banking ecosystem in South Africa. This would help capture the effects of Fintech on smaller institutions that may have different operational models and customer bases compared to larger, publicly traded banks. Furthermore, future research should investigate how regulatory frameworks adapt in response to Fintech innovations and their implications for the banking sector. Understanding the interplay between regulation and innovation can provide valuable insights into how banks can navigate compliance while leveraging technological advancements. Lastly, conducting comparative studies with other emerging markets or developed economies can provide context for understanding the unique challenges and opportunities within the South African banking sector. Such research could identify best practices and lessons learned from different regulatory environments and market conditions.

5.5. Conclusion

Overall, the study has investigated the Fintech innovations and banking sector dynamics in the South African landscape. This research has illuminated the dual role of Fintech as both a disruptor and a complementary force within South Africa's banking industry. Fintech innovations, especially mobile transactions, are reshaping the banking landscape, creating new avenues for efficiency, competition, and financial inclusion. Yet, despite these advances, Fintech's impact on traditional performance metrics and bank stability remains limited, indicating that the sector's structural stability is still rooted in traditional banking practices. The findings reveal that Fintech fosters increased competition, as evidenced through mobile transactions, which decrease the Lerner Index. While Fintech has had limited influence on traditional performance indicators like the CAR, it has significantly improved operational efficiency, particularly through mobile transactions, signalling a shift toward digital solutions. Stability results indicate no notable impact of Fintech on bank stability, with traditional capital structures continuing to play a more dominant role. These findings highlight Fintech's dual role as both a driver of efficiency and competition and a source of potential disruption to traditional banking services. The sector's evolution calls for adaptive regulatory frameworks to balance innovation with stability, ensuring that the benefits of technological progress are realised without compromising the banking system's integrity.

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APPENDICES

Appendix 1: construction of dependent variables

1.1 Lerner Index

1.1.1 regression of the Fixed effects model

```
. xtreg totalCost Totalassets Totalassets_Totalassets_squared labor Capital B_funds labor_Totalassets_squared Capital_Totalassets_squar
> ed B_funds_Totalassets_squared , fe

Fixed-effects (within) regression               Number of obs     =        192
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.8707                                         min =         24
     Between = 0.9892                                         avg =       24.0
     Overall = 0.9469                                         max =         24

                                                F(8, 176)         =     148.16
corr(u_i, Xb) = 0.5587                          Prob > F          =     0.0000

------------------------------------------------------------------------------------------------
                      totalCost | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
--------------------------------+---------------------------------------------------------------
                    Totalassets |   .3451248   .3552024     0.97   0.333    -.3558794    1.046129
Totalassets_Totalassets_squared |  -.0040004   .0006163    -6.49   0.000    -.0052167   -.0027841
                          labor |   1.882384    1.12774     1.67   0.097    -.3432489    4.108017
                        Capital |  -2.223604   1.315539    -1.69   0.093    -4.819866    .3726575
                        B_funds |    3.00543    .756432     3.97   0.000     1.512586    4.498275
      labor_Totalassets_squared |   .1342781   .0144304     9.31   0.000     .1057993     .162757
    Capital_Totalassets_squared |    .035289    .009298     3.80   0.000     .0169391    .0536388
    B_funds_Totalassets_squared |  -.0008958   .0061726    -0.15   0.885    -.0130777    .0112861
                          _cons |   6.512647   3.299656     1.97   0.050     .0006619    13.02463
--------------------------------+---------------------------------------------------------------
                        sigma_u |  .38921845
                        sigma_e |  .67118697
                            rho |  .25165331   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------------
F test that all u_i=0: F(7, 176) = 3.71                      Prob > F = 0.0009
```

1.1.2 regression of the Random effects model

```
. xtreg totalCost Totalassets Totalassets_Totalassets_squared labor Capital B_funds labor_Totalassets_squared Capital_Totalassets_squar
> ed B_funds_Totalassets_squared , re

Random-effects GLS regression                   Number of obs     =        192
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.8674                                         min =         24
     Between = 0.9961                                         avg =       24.0
     Overall = 0.9500                                         max =         24

                                                Wald chi2(8)      =    3480.61
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000
```

totalCost	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Totalassets	.7829761	.3232292	2.42	0.015	.1494585	1.416494
Totalassets_Totalassets_squared	-.0044505	.0005457	-8.16	0.000	-.00552	-.003381
labor	2.761412	1.116669	2.47	0.013	.5727814	4.950043
Capital	-2.387098	1.162956	-2.05	0.040	-4.666451	-.1077457
B_funds	3.671891	.7406214	4.96	0.000	2.2203	5.123482
labor_Totalassets_squared	.1239283	.0142005	8.73	0.000	.0960959	.1517607
Capital_Totalassets_squared	.0408741	.0077542	5.27	0.000	.0256762	.0560721
B_funds_Totalassets_squared	-.0074327	.0059262	-1.25	0.210	-.0190479	.0041824
_cons	2.379164	3.091301	0.77	0.442	-3.679675	8.438003
sigma_u	0					
sigma_e	.67118697					
rho	0	(fraction of variance due to u_i)				

1.1.3 Hausman Test under constructing Lerner index.

```
. hausman fe_model re_model

Note: the rank of the differenced variance matrix (7) does not equal the number of coefficients being tested (8); be sure this is what
        you expect, or there may be problems computing the test.  Examine the output of your estimators for anything unexpected and
        possibly consider scaling your variables so that the coefficients are on a similar scale.
```

	Coefficients (b) fe_model	(B) re_model	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
Totalassets	.3451248	.7829761	-.4378514	.1472809
T~Totalass~d	-.0040004	-.0044505	.0004501	.0002865
labor	1.882384	2.761412	-.8790281	.1576302
Capital	-2.223604	-2.387098	.1634942	.6149598
B_funds	3.00543	3.671891	-.6664609	.1538487
labor_Tota~d	.1342781	.1239283	.0103499	.0025656
Capital_To~d	.035289	.0408741	-.0055852	.0051307
B_funds_To~d	-.0008958	-.0074327	.0065369	.0017267

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  19.28
Prob > chi2 = 0.0074
(V_b-V_B is not positive definite)
```

1.2 Stochastic Frontier Approach:

1.2.1 Output from Frontier Approach

```
Iteration 100: Log likelihood = -215.49097  (not concave)

Time-varying decay model (truncated-normal)        Number of obs =       192
Group variable: BankID                           Number of groups =         8
Time variable: Year                            Obs per group: min =        24
                                                              avg =      24.0
                                                              max =        24

                                                   Prob > chi2   =    0.0000
Log likelihood =  -215.4910                        Wald chi2(6)  = 409015.86

------------------------------------------------------------------------------
   totalCost | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Frontier     |
       labor |   2.792349   .5644399     4.95   0.000     1.686067     3.89863
     Capital |   6.072558   .5706375    10.64   0.000     4.954129    7.190987
     B_funds |   2.880945   .3403321     8.47   0.000     2.213907    3.547984
 FixedAssets |    .289123   .0525216     5.50   0.000     .1861824    .3920635
        Year |  -.0542578   .0005274  -102.87   0.000    -.0552915    -.053224
 TotalEquity |   1.629035   .0887532    18.35   0.000     1.455082    1.802988
       _cons |   104.6499          .        .       .            .           .
-------------+----------------------------------------------------------------
   /lnsigma2 |  -.5932651   .1020586    -5.81   0.000    -.7932963   -.3932339
  /ilgtgamma |  -31.89812          .        .       .            .           .
         /mu |   .0378533          .        .       .            .           .
        /eta |   .0207603   .2034035     0.10   0.919    -.3779033    .4194238
-------------+----------------------------------------------------------------
      sigma2 |   .5525203   .0563895                      .4523513    .6748709
       gamma |   1.40e-14          .                             .           .
    sigma_u2 |   7.75e-15          .                             .           .
    sigma_v2 |   .5525203          .                             .           .
------------------------------------------------------------------------------
```

Appendix 2: research objective 1: Fintech on bank competition

2.1 Hausman test

```
. hausman fe re

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference       Std. err.
-------------+----------------------------------------------------------------
        dATM |   -.0050333    -.0089341        .0039008               .
         VMT |   -.6771899    -.6811824        .0039925               .
         BNK |    .0243974     .0240823         .000315               .
         INF |    .0886336     .0966675       -.0080339               .
         GDP |    .1511546     .1277603        .0233943        .0053842
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   8.06
Prob > chi2 = 0.1530
(V_b-V_B is not positive definite)
```

2.2 Random effects

```
. xtreg ldLerner_Index dATM VMT BNK INF GDP, re

Random-effects GLS regression                   Number of obs     =        115
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.1136                                         min =          5
     Between = 0.1494                                         avg =       14.4
     Overall = 0.0963                                         max =         20

                                                Wald chi2(5)      =      13.29
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0208

------------------------------------------------------------------------------
ldLerner_I~x | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        dATM |  -.0089341   .0343315    -0.26   0.795    -.0762226    .0583544
         VMT |  -.6811824   .2040886    -3.34   0.001    -1.081189   -.2811761
         BNK |   .0240823   .0366533     0.66   0.511    -.0477568    .0959214
         INF |   .0966675   .0935447     1.03   0.301    -.0866767    .2800117
         GDP |   .1277603   .0764145     1.67   0.095    -.0220093    .2775299
       _cons |  -2.265695    3.30178    -0.69   0.493    -8.737065    4.205675
-------------+----------------------------------------------------------------
     sigma_u |  .66269584
     sigma_e |  1.3511308
         rho |  .19391613   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

2.3 Heteroskedasticity test

```
. vif, uncentered

    Variable |       VIF       1/VIF  
-------------+----------------------
         VMT |     99.18    0.010082
         BNK |     84.78    0.011795
         INF |     16.48    0.060675
         GDP |      2.39    0.419113
        dATM |      2.36    0.423748
-------------+----------------------
    Mean VIF |     41.04
```

2.4 Autocorrelation Test

```
. xtreg ldLerner_Index dATM VMT BNK INF GDP, re

Random-effects GLS regression                   Number of obs     =        115
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.1136                                         min =          5
     Between = 0.1494                                         avg =       14.4
     Overall = 0.0963                                         max =         20

                                                Wald chi2(5)      =      13.29
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0208

------------------------------------------------------------------------------
ldLerner_I~x | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        dATM |  -.0089341   .0343315    -0.26   0.795    -.0762226    .0583544
         VMT |  -.6811824   .2040886    -3.34   0.001    -1.081189   -.2811761
         BNK |   .0240823   .0366533     0.66   0.511    -.0477568    .0959214
         INF |   .0966675   .0935447     1.03   0.301    -.0866767    .2800117
         GDP |   .1277603   .0764145     1.67   0.095    -.0220093    .2775299
       _cons |  -2.265695    3.30178    -0.69   0.493    -8.737065    4.205675
-------------+----------------------------------------------------------------
     sigma_u |  .66269584
     sigma_e |  1.3511308
         rho |  .19391613   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. predict res5, e
(77 missing values generated)

. gen res5lag = L.res5
(81 missing values generated)

. regress res5 res5lag

      Source |       SS           df       MS      Number of obs   =        83
-------------+----------------------------------   F(1, 81)        =      0.09
       Model |  .136269228         1  .136269228   Prob > F        =    0.7661
    Residual |  123.905783        81  1.52970103   R-squared       =    0.0011
-------------+----------------------------------   Adj R-squared   =   -0.0112
       Total |  124.042052        82  1.51270796   Root MSE        =    1.2368

------------------------------------------------------------------------------
        res5 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     res5lag |  -.0318924   .1068543    -0.30   0.766    -.2444989     .180714
       _cons |  -.1196704   .1357893    -0.88   0.381    -.3898485    .1505077
------------------------------------------------------------------------------
```

2.5 Robust random effects

```
.  xtreg ldLerner_Index dATM VMT BNK INF GDP, re robust

Random-effects GLS regression                   Number of obs     =        115
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.1136                                         min =          5
     Between = 0.1494                                         avg =       14.4
     Overall = 0.0963                                         max =         20

                                                Wald chi2(5)      =      46.33
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

                                 (Std. err. adjusted for 8 clusters in BankID)
------------------------------------------------------------------------------
             |               Robust
ldLerner_I~x | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        dATM |  -.0089341   .0357956    -0.25   0.803    -.0790922    .0612241
         VMT |  -.6811824   .1429423    -4.77   0.000    -.9613442   -.4010206
         BNK |   .0240823   .0365283     0.66   0.510    -.0475118    .0956764
         INF |   .0966675    .084758     1.14   0.254     -.069455    .2627901
         GDP |   .1277603   .0564496     2.26   0.024     .0171211    .2383995
       _cons |  -2.265695   3.130389    -0.72   0.469    -8.401146    3.869756
-------------+----------------------------------------------------------------
     sigma_u |  .66269584
     sigma_e |  1.3511308
         rho |  .19391613   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

2.6 Endogeneity test

```
. ivregress 2sls ldLerner_Index (dATM = VMT ) BNK INF GDP, cluster(BankID)

Instrumental variables 2SLS regression          Number of obs     =        115
                                                Wald chi2(4)      =      31.28
                                                Prob > chi2       =     0.0000
                                                R-squared         =          .
                                                Root MSE          =     3.6422

                                 (Std. err. adjusted for 8 clusters in BankID)
------------------------------------------------------------------------------
             |               Robust
ldLerner_I~x | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        dATM |  -.9049195   .2282631    -3.96   0.000    -1.352307    -.457532
         BNK |  -.3633635   .1122834    -3.24   0.001    -.5834348   -.1432922
         INF |   1.369578   .4621198     2.96   0.003       .46384    2.275316
         GDP |   .2715707   .1059669     2.56   0.010     .0638795     .479262
       _cons |   17.01358   7.345762     2.32   0.021      2.61615    31.41101
------------------------------------------------------------------------------
Endogenous: dATM
Exogenous:  BNK INF GDP VMT

.
. estat endogenous

  Tests of endogeneity
  H0: Variables are exogenous

  Robust regression F(1,7)        =  22.0971  (p = 0.0022)
    (Adjusted for 8 clusters in BankID)
```

2.7 GMM regression

```
. xtabond2 ldLerner_Index L.ldLerner_Index dATM VMT BNK INF GDP, gmm(dATM, lag(2 .)) ivstyle(VMT BNK INF GDP, equation(level)) robust c
> luster(BankID)
Favoring speed over space. To switch, type or click on mata: mata set matafavor space, perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen test.
  Difference-in-Sargan/Hansen statistics may be negative.
  DFm
  6

Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: BankID                          Number of obs      =        83
Time variable : Year                            Number of groups   =         8
Number of instruments = 37                      Obs per group: min =         1
Wald chi2(6)   =  15266.73                                     avg =     10.38
Prob > chi2    =     0.000                                     max =        19
                                   (Std. err. adjusted for clustering on BankID)
--------------------------------------------------------------------------------
               |               Robust
ldLerner_Index | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
---------------+----------------------------------------------------------------
ldLerner_Index |
           L1. |   .0800888   .1265744     0.63   0.527    -.1679925    .3281702
               |
          dATM |    .030977   .0349552     0.89   0.376    -.0375338    .0994878
           VMT |   -.669441   .1374906    -4.87   0.000    -.9389176   -.3999643
           BNK |   .0124808   .0427659     0.29   0.770    -.0713388    .0963003
           INF |    -.03336   .1075437    -0.31   0.756    -.2441418    .1774218
           GDP |   .0349512   .0651054     0.54   0.591     -.092653    .1625555
         _cons |  -.4730833   4.422762    -0.11   0.915    -9.141538    8.195371
--------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/23).dATM
Instruments for levels equation
  Standard
    VMT BNK INF GDP
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.dATM
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -1.49  Pr > z =  0.137
Arellano-Bond test for AR(2) in first differences: z =   1.43  Pr > z =  0.153
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(30)    =  44.42  Prob > chi2 =  0.044
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(30)    =   2.63  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(15)    =   1.73  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(15)    =   0.91  Prob > chi2 =  1.000
  iv(VMT BNK INF GDP, eq(level))
    Hansen test excluding group:     chi2(26)    =   2.13  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(4)     =   0.50  Prob > chi2 =  0.974
```

Appendix 3: research objective 2: Fintech on bank performance

3.1 Hausman test

```
. hausman fe_model2 re_model2, sigmamore

Note: the rank of the differenced variance matrix (2) does not equal the number of coefficients being tested (7); be sure this is what
        you expect, or there may be problems computing the test.  Examine the output of your estimators for anything unexpected and
        possibly consider scaling your variables so that the coefficients are on a similar scale.

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |   fe_model2    re_model2      Difference       Std. err.
-------------+----------------------------------------------------------------
        dATM |    .0016071     .0016067        3.49e-07        1.67e-06
         VMT |   -.0052528    -.0052492       -3.59e-06         .000012
         BNK |    .0002715     .0002693        2.15e-06        3.08e-06
         INF |   -.0014303    -.0014331        2.79e-06        3.42e-06
         GDP |    .0019655     .0019723       -6.79e-06        5.89e-06
dTier1Capi~l |    -.042483    -.0423087       -.0001743         .000101
dTier2Capi~l |    .0404424     .0410596       -.0006172        .0007092
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   3.32
Prob > chi2 = 0.1901
(V_b-V_B is not positive definite)
```

3.2 Random effects regression

```
. xtreg lCAR dATM VMT BNK INF GDP dTier1Capital dTier2Capital , re

Random-effects GLS regression                   Number of obs     =        184
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.1696                                         min =         23
     Between = 0.0000                                         avg =       23.0
     Overall = 0.0995                                         max =         23

                                                Wald chi2(7)      =      34.24
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

-------------------------------------------------------------------------------
         lCAR | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+----------------------------------------------------------------
         dATM |    .0016067   .0008998     1.79   0.074    -.0001569    .0033703
          VMT |   -.0052492   .0055848    -0.94   0.347    -.0161953    .0056968
          BNK |    .0002693   .0009009     0.30   0.765    -.0014963     .002035
          INF |   -.0014331   .0023545    -0.61   0.543    -.0060479    .0031817
          GDP |    .0019723   .0018917     1.04   0.297    -.0017352    .0056799
dTier1Capital |   -.0423087   .0086209    -4.91   0.000    -.0592053   -.0254121
dTier2Capital |    .0410596   .0136411     3.01   0.003     .0143235    .0677957
        _cons |    .5386733   .0817034     6.59   0.000     .3785376    .6988089
--------------+----------------------------------------------------------------
      sigma_u |   .03823874
      sigma_e |   .04579911
          rho |   .41075845   (fraction of variance due to u_i)
-------------------------------------------------------------------------------
```

3.3 Heteroskedasticity test

```
. vif, uncentered

    Variable |       VIF       1/VIF
-------------+----------------------
         VMT |    105.24    0.009502
         BNK |     91.22    0.010962
         INF |     14.73    0.067894
        dATM |      2.77    0.361287
         GDP |      2.48    0.403985
dTier2Capi~l |      1.11    0.904820
dTier1Capi~l |      1.10    0.909489
-------------+----------------------
    Mean VIF |     31.23
```

3.4 Autocorrelation Test

```
. xtreg lCAR dATM VMT BNK INF GDP Tier1Capital Tier2Capital , re

Random-effects GLS regression                   Number of obs     =        184
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.7416                                         min =         23
     Between = 0.0812                                         avg =       23.0
     Overall = 0.4700                                         max =         23

                                                Wald chi2(7)      =     490.22
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
        lCAR | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        dATM |  -.0000786   .0005118    -0.15   0.878    -.0010817    .0009245
         VMT |  -.0017009   .0031172    -0.55   0.585    -.0078106    .0044087
         BNK |  -.0003366   .0005017    -0.67   0.502    -.0013198    .0006466
         INF |   .0007157   .0013046     0.55   0.583    -.0018412    .0032727
         GDP |    .000385   .0010533     0.37   0.715    -.0016794    .0024495
Tier1Capital |  -.0444198   .0033039   -13.44   0.000    -.0508953   -.0379442
Tier2Capital |   .0650761   .0031727    20.51   0.000     .0588578    .0712945
       _cons |   .4473935   .0611292     7.32   0.000     .3275824    .5672047
-------------+----------------------------------------------------------------
     sigma_u |  .04723836
     sigma_e |  .02554972
         rho |  .77367141   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. predict res3, e
(8 missing values generated)

. gen res3lag = L.res3
(16 missing values generated)

. regress res3 res3lag

      Source |       SS           df       MS      Number of obs   =       176
-------------+----------------------------------   F(1, 174)       =    112.58
       Model |  .038794354         1  .038794354   Prob > F        =    0.0000
    Residual |  .059957512       174  .000344583   R-squared       =    0.3928
-------------+----------------------------------   Adj R-squared   =    0.3894
       Total |  .098751866       175  .000564296   Root MSE        =    .01856

------------------------------------------------------------------------------
        res3 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     res3lag |   .6018465   .0567216    10.61   0.000     .4898955    .7137975
       _cons |    .000025   .0013992     0.02   0.986    -.0027366    .0027867
------------------------------------------------------------------------------
```

3.5 Robust random effects

```
. xtreg lCAR dATM VMT BNK INF GDP dTier1Capital dTier2Capital , re robust

Random-effects GLS regression                   Number of obs     =        184
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.1696                                         min =         23
     Between = 0.0000                                         avg =       23.0
     Overall = 0.0995                                         max =         23

                                                Wald chi2(7)      =     227.60
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

                                 (Std. err. adjusted for 8 clusters in BankID)
------------------------------------------------------------------------------
             |               Robust
        lCAR | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        dATM |   .0016067   .0015677     1.02   0.305    -.0014659    .0046793
         VMT |  -.0052492   .0051757    -1.01   0.310    -.0153935     .004895
         BNK |   .0002693    .000767     0.35   0.725     -.001234    .0017727
         INF |  -.0014331   .0021707    -0.66   0.509    -.0056877    .0028215
         GDP |   .0019723    .002533     0.78   0.436    -.0029922    .0069369
dTier1Capital|  -.0423087    .006456    -6.55   0.000    -.0549622   -.0296552
dTier2Capital|   .0410596   .0148363     2.77   0.006      .011981    .0701382
       _cons |   .5386733   .0504617    10.67   0.000     .4397701    .6375764
-------------+----------------------------------------------------------------
     sigma_u |  .03823874
     sigma_e |  .04579911
         rho |  .41075845   (fraction of variance due to u_i)
```

3.6 Endogeneity test

```
. ivregress 2sls CAR (dATM_squared = VMT ) BNK INF GDP, cluster(BankID)

Instrumental variables 2SLS regression          Number of obs     =        184
                                                Wald chi2(4)      =       8.22
                                                Prob > chi2       =     0.0839
                                                R-squared         =          .
                                                Root MSE          =      .1099

                                 (Std. err. adjusted for 8 clusters in BankID)
------------------------------------------------------------------------------
             |               Robust
         CAR | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
dATM_squared |  -.0000478   .0000429    -1.11   0.265    -.0001319    .0000363
         BNK |  -.0023092   .0013277    -1.74   0.082    -.0049115    .0002931
         INF |   .0076036   .0082099     0.93   0.354    -.0084874    .0236947
         GDP |    .003635    .005025     0.72   0.469    -.0062139    .0134838
       _cons |   1.822998   .0684592    26.63   0.000      1.68882    1.957175
------------------------------------------------------------------------------
Endogenous: dATM_squared
Exogenous:  BNK INF GDP VMT
```

```
. estat endogenous

  Tests of endogeneity
  H0: Variables are exogenous

  Robust regression F(1,7)        =  1.36036  (p = 0.2817)
    (Adjusted for 8 clusters in BankID)
```

3.7 GMM Model

```
Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: BankID                          Number of obs      =       184
Time variable : Year                            Number of groups   =         8
Number of instruments = 25                      Obs per group: min =        23
Wald chi2(8)  =  4.71e+06                                      avg =     23.00
Prob > chi2   =     0.000                                      max =        23
                                  (Std. err. adjusted for clustering on BankID)
-------------------------------------------------------------------------------
              |               Robust
         lCAR | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
--------------+----------------------------------------------------------------
         lCAR |
          L1. |   .9467052   .0999499     9.47   0.000      .750807    1.142603
              |
         dATM |  -.0000813   .0005863    -0.14   0.890    -.0012305    .0010679
          VMT |  -.0015283   .0017725    -0.86   0.389    -.0050023    .0019457
          BNK |  -.0004464   .0004575    -0.98   0.329    -.0013432    .0004503
          INF |   .0001965   .0006513     0.30   0.763    -.0010802    .0014731
          GDP |   .0009709   .0005143     1.89   0.059    -.0000371    .0019789
dTier1Capital |  -.0491409   .0110156    -4.46   0.000     -.070731   -.0275508
dTier2Capital |   .0613943   .0095775     6.41   0.000     .0426226    .0801659
        _cons |   .0703243   .0764799     0.92   0.358    -.0795736    .2202221
-------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/23).dATM
Instruments for levels equation
  Standard
    VMT BNK INF GDP dTier1Capital dTier2Capital
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.dATM
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -1.58  Pr > z =  0.114
Arellano-Bond test for AR(2) in first differences: z =   0.87  Pr > z =  0.386
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(16)   =  12.20  Prob > chi2 =  0.730
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(16)   =   0.00  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)
```

Appendix 4: research objective 3: Fintech on bank efficiency

4.1 Hausman test

```
. hausman fe_model re_model

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |   fe_model     re_model       Difference       Std. err.
-------------+----------------------------------------------------------------
       ldATM |  -.0020401    -.0020401        1.65e-13        .0000737
        lVMT |   .0232642     .0232642       -2.30e-12        .0010132
        lBNK |   .1315867     .1315867       -1.09e-11        .0036589
        lINF |    .002855      .002855       -3.53e-13        .0001821
        lGDP |  -.0035326    -.0035326       -2.06e-13        .0000894
------------------------------------------------------------------------------
                           b = Consistent under H0 and Ha; obtained from xtreg.
            B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   0.00
Prob > chi2 = 1.0000
```

4.2 Random effects regression

```
. xtreg lSFA ldATM lVMT lBNK lINF lGDP , re

Random-effects GLS regression                   Number of obs     =         80
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         10
     Between = 0.0000                                         avg =       10.0
     Overall = 0.9631                                         max =         10

                                                Wald chi2(5)      =    1932.13
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
        lSFA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
       ldATM |  -.0020401   .0002279    -8.95   0.000    -.0024868   -.0015934
        lVMT |   .0232642   .0031346     7.42   0.000     .0171204     .029408
        lBNK |   .1315867   .0113198    11.62   0.000     .1094003    .1537732
        lINF |    .002855   .0005633     5.07   0.000     .0017509     .003959
        lGDP |  -.0035326   .0002764   -12.78   0.000    -.0040744   -.0029908
       _cons |  -.6661887   .0543117   -12.27   0.000    -.7726377   -.5597396
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  .00096281
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

4.3 Heteroskedasticity test

```
. vif, uncentered

    Variable |       VIF       1/VIF
-------------+----------------------
        lBNK |   1701.84    0.000588
        lVMT |   1559.23    0.000641
        lINF |     52.05    0.019212
       ldATM |      3.45    0.289869
        lGDP |      3.27    0.306023
-------------+----------------------
    Mean VIF |    663.97
```

4.4 Autocorrelation Test

```
. xtreg lSFA ldATM lVMT lBNK lINF lGDP , re

Random-effects GLS regression                   Number of obs     =         80
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         10
     Between = 0.0000                                         avg =       10.0
     Overall = 0.9631                                         max =         10

                                                Wald chi2(5)      =    1932.13
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
        lSFA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
       ldATM |  -.0020401   .0002279    -8.95   0.000    -.0024868   -.0015934
        lVMT |   .0232642   .0031346     7.42   0.000     .0171204     .029408
        lBNK |   .1315867   .0113198    11.62   0.000     .1094003    .1537732
        lINF |    .002855   .0005633     5.07   0.000     .0017509     .003959
        lGDP |  -.0035326   .0002764   -12.78   0.000    -.0040744   -.0029908
       _cons |  -.6661887   .0543117   -12.27   0.000    -.7726377   -.5597396
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  .00096281
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. predict res1, e
(112 missing values generated)

. gen res1lag = L.res1
(120 missing values generated)

. regress res1 res1lag

      Source |       SS           df       MS      Number of obs   =        48
-------------+----------------------------------   F(1, 46)        =      1.13
       Model |  1.2854e-06         1  1.2854e-06   Prob > F        =    0.2937
    Residual |  .000052404        46  1.1392e-06   R-squared       =    0.0239
-------------+----------------------------------   Adj R-squared   =    0.0027
       Total |   .00005369        47  1.1423e-06   Root MSE        =    .00107

------------------------------------------------------------------------------
        res1 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     res1lag |   -.191327   .1801234    -1.06   0.294    -.5538966    .1712426
       _cons |  -.0000501   .0001541    -0.33   0.746    -.0003604    .0002601
------------------------------------------------------------------------------
```

4.5 Robust Random effects

```
. xtreg lSFA ldATM lVMT lBNK lINF lGDP , re robust

Random-effects GLS regression                   Number of obs     =         80
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         10
     Between = 0.0000                                         avg =       10.0
     Overall = 0.9631                                         max =         10

                                                Wald chi2(0)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                                 (Std. err. adjusted for 8 clusters in BankID)
------------------------------------------------------------------------------
             |               Robust
        lSFA | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
       ldATM |  -.0020401   6.34e-14 -3.2e+10   0.000    -.0020401   -.0020401
        lVMT |   .0232642   8.62e-13  2.7e+10   0.000     .0232642    .0232642
        lBNK |   .1315867   4.18e-12  3.1e+10   0.000     .1315867    .1315867
        lINF |    .002855   1.35e-13  2.1e+10   0.000      .002855     .002855
        lGDP |  -.0035326   7.87e-14 -4.5e+10   0.000    -.0035326   -.0035326
       _cons |  -.6661887   2.01e-11 -3.3e+10   0.000    -.6661887   -.6661887
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  .00096281
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

4.6 Endogeneity test

```
. ivregress 2sls SFA (dATM_squared = VMT ) BNK INF GDP, cluster(BankID)

Instrumental variables 2SLS regression            Number of obs   =        184
                                                  Wald chi2(4)    =          .
                                                  Prob > chi2     =          .
                                                  R-squared       =          .
                                                  Root MSE        =     .00747

                                 (Std. err. adjusted for 8 clusters in BankID)
------------------------------------------------------------------------------
             |               Robust
         SFA | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
dATM_squared |   .0000124   4.96e-20  2.5e+14   0.000     .0000124    .0000124
         BNK |  -.0000129   2.59e-18 -5.0e+12   0.000    -.0000129   -.0000129
         INF |  -.0023216   5.72e-18 -4.1e+14   0.000    -.0023216   -.0023216
         GDP |  -.0013813   3.44e-18 -4.0e+14   0.000    -.0013813   -.0013813
       _cons |   .9694786   1.61e-16  6.0e+15   0.000     .9694786    .9694786
------------------------------------------------------------------------------
Endogenous: dATM_squared
Exogenous:  BNK INF GDP VMT
```

```
. estat endogenous

  Tests of endogeneity
  H0: Variables are exogenous

  Robust regression F(0,7)        =          .  (p =      .)
    (Adjusted for 8 clusters in BankID)
```

4.7 GMM model

```
. xtabond2 lSFA L.lSFA dATM VMT BNK INF GDP, gmm(dATM, lag(2 .)) ivstyle(VMT BNK INF GDP, equation(level)) robust cluster(BankID)
Favoring speed over space. To switch, type or click on mata: mata set matafavor space, perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen test.
  Difference-in-Sargan/Hansen statistics may be negative.
  DFm
  6

Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: BankID                          Number of obs      =       184
Time variable : Year                            Number of groups   =         8
Number of instruments = 23                      Obs per group: min =        23
Wald chi2(6)   =      0.00                                     avg =     23.00
Prob > chi2    =     1.000                                     max =        23
                                 (Std. err. adjusted for clustering on BankID)
------------------------------------------------------------------------------
             |               Robust
        lSFA | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        lSFA |
         L1. |   .9794535   1.62e-10  6.0e+09   0.000     .9794535    .9794535
             |
        dATM |   8.10e-10   4.29e-13  1890.06   0.000     8.09e-10    8.11e-10
         VMT |   1.16e-08   2.18e-12  5334.97   0.000     1.16e-08    1.16e-08
         BNK |   8.07e-10   8.48e-13   951.80   0.000     8.05e-10    8.09e-10
         INF |  -4.91e-09   6.28e-13 -7810.61   0.000    -4.91e-09   -4.91e-09
         GDP |  -1.45e-09   6.06e-14 -2.4e+04   0.000    -1.45e-09   -1.45e-09
       _cons |  -1.25e-07   4.88e-11 -2558.64   0.000    -1.25e-07   -1.25e-07
------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/23).dATM
Instruments for levels equation
  Standard
    VMT BNK INF GDP
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.dATM
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.83  Pr > z =  0.005
Arellano-Bond test for AR(2) in first differences: z =   2.83  Pr > z =  0.005
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(16)    = 104.76  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(16)    =   0.00  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)
```

Appendix 5: research objective 4: Fintech on bank stability

5.1 Hausman Test

```
. hausman fe_model3 re_model3

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |   fe_model3    re_model3      Difference       Std. err.
-------------+----------------------------------------------------------------
        dATM |    .0027591      .002437        .0003221               .
         VMT |    .0079414     .0125008       -.0045594               .
         BNK |    .0013631     .0015121        -.000149               .
         INF |    .0038004     .0044994        -.000699               .
         GDP |   -.0082029    -.0097129          .00151               .
dInterestE~e |   -.0215099    -.0361595        .0146496               .
PersonalEx~e |   -.0260686    -.0410667        .0149981        .0051526
dTotalDepo~s |   -.0042804    -.0054304          .00115               .
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   6.67
Prob > chi2 = 0.5732
(V_b-V_B is not positive definite)
```

5.2 Random effects regression

```
. xtreg lzscore dATM VMT BNK INF GDP dInterestExpense PersonalExpense dTotalDeposits , re

Random-effects GLS regression                   Number of obs     =        184
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.0729                                         min =         23
     Between = 0.6756                                         avg =       23.0
     Overall = 0.2991                                         max =         23

                                                Wald chi2(8)      =      30.86
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0001

----------------------------------------------------------------------------------
         lzscore | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
            dATM |    .002437   .0028628     0.85   0.395     -.003174     .008048
             VMT |   .0125008   .0181925     0.69   0.492    -.0231558    .0481575
             BNK |   .0015121   .0028641     0.53   0.598    -.0041014    .0071256
             INF |   .0044994   .0074672     0.60   0.547    -.0101359    .0191348
             GDP |  -.0097129   .0060573    -1.60   0.109    -.0215851    .0021592
dInterestExpense |  -.0361595   .0303142    -1.19   0.233    -.0955742    .0232552
 PersonalExpense |  -.0410667   .0085945    -4.78   0.000    -.0579116   -.0242217
  dTotalDeposits |  -.0054304   .0127345    -0.43   0.670    -.0303895    .0195288
           _cons |   1.589124    .273741     5.81   0.000     1.052602    2.125647
-----------------+----------------------------------------------------------------
         sigma_u |  .04824364
         sigma_e |  .13929212
```

5.3 Heteroskedasticity test

```
. vif, uncentered

    Variable |       VIF       1/VIF
-------------+----------------------
         VMT |    109.65    0.009120
         BNK |    107.52    0.009301
PersonalEx~e |     28.23    0.035418
         INF |     14.89    0.067153
         GDP |      2.82    0.355050
        dATM |      2.77    0.361042
dInterestE~e |      1.22    0.818222
dTotalDepo~s |      1.04    0.965909
-------------+----------------------
    Mean VIF |     33.52
```

5.4 Autocorrelation Test

```
. xtreg lzscore dATM VMT BNK INF GDP InterestExpense PersonalExpense TotalDeposits , re

Random-effects GLS regression                   Number of obs     =        184
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.1025                                         min =         23
     Between = 0.8990                                         avg =       23.0
     Overall = 0.3981                                         max =         23

                                                Wald chi2(8)      =      51.38
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

----------------------------------------------------------------------------------
         lzscore | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
            dATM |   .0032078   .0028149     1.14   0.254    -.0023092    .0087249
             VMT |   .0135639   .0173652     0.78   0.435    -.0204713     .047599
             BNK |    .001888    .002774     0.68   0.496    -.0035489    .0073249
             INF |   .0010524   .0073062     0.14   0.885    -.0132675    .0153722
             GDP |  -.0119313   .0058894    -2.03   0.043    -.0234743   -.0003883
 InterestExpense |  -.0385516   .0118883    -3.24   0.001    -.0618522   -.0152509
 PersonalExpense |  -.0606687   .0093847    -6.46   0.000    -.0790625    -.042275
   TotalDeposits |   .0201771   .0074646     2.70   0.007     .0055468    .0348075
           _cons |   1.780165   .2727997     6.53   0.000     1.245487    2.314842
-----------------+----------------------------------------------------------------
         sigma_u |  .04002715
         sigma_e |  .13679096
             rho |  .07887061   (fraction of variance due to u_i)
----------------------------------------------------------------------------------

. predict res2, e
(8 missing values generated)

. gen res2lag = L.res2
(16 missing values generated)

. regress res2 res2lag

      Source |       SS           df       MS      Number of obs   =       176
-------------+----------------------------------   F(1, 174)       =      1.78
       Model |  .033167177         1  .033167177   Prob > F        =    0.1837
    Residual |  3.23873624       174  .018613427   R-squared       =    0.0101
-------------+----------------------------------   Adj R-squared   =    0.0044
       Total |  3.27190342       175  .018696591   Root MSE        =    .13643

------------------------------------------------------------------------------
        res2 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     res2lag |   .1005196   .0753026     1.33   0.184    -.0481044    .2491437
       _cons |   .0024552   .0102839     0.24   0.812    -.0178421    .0227524
------------------------------------------------------------------------------
```

5.5 Robust random effects

```
. xtreg lzscore dATM VMT BNK INF GDP dInterestExpense PersonalExpense dTotalDeposits , re robust

Random-effects GLS regression                   Number of obs     =        184
Group variable: BankID                          Number of groups  =          8

R-squared:                                      Obs per group:
     Within  = 0.0729                                         min =         23
     Between = 0.6756                                         avg =       23.0
     Overall = 0.2991                                         max =         23

                                                Wald chi2(7)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                                     (Std. err. adjusted for 8 clusters in BankID)
----------------------------------------------------------------------------------
                 |               Robust
         lzscore | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
            dATM |    .002437   .0021977     1.11   0.267    -.0018704    .0067444
             VMT |   .0125008   .0101954     1.23   0.220    -.0074818    .0324834
             BNK |   .0015121   .0029949     0.50   0.614    -.0043577    .0073819
             INF |   .0044994   .0087708     0.51   0.608    -.0126911    .0216899
             GDP |  -.0097129   .0062167    -1.56   0.118    -.0218974    .0024716
dInterestExpense |  -.0361595    .028158    -1.28   0.199    -.0913482    .0190292
 PersonalExpense |  -.0410667   .0220528    -1.86   0.063    -.0842894     .002156
  dTotalDeposits |  -.0054304   .0089898    -0.60   0.546    -.0230501    .0121893
           _cons |   1.589124   .1408875    11.28   0.000      1.31299    1.865259
-----------------+----------------------------------------------------------------
         sigma_u |  .04824364
         sigma_e |  .13929212
             rho |   .1071089   (fraction of variance due to u_i)
```

5.6 Endogeneity test

```
. ivregress 2sls lzscore (dATM = VMT ) BNK INF GDP InterestExpense PersonalExpense TotalDeposits , cluster(BankID)

Instrumental variables 2SLS regression            Number of obs   =        184
                                                  Wald chi2(7)    =    7668.09
                                                  Prob > chi2     =     0.0000
                                                  R-squared       =     0.2480
                                                  Root MSE        =     .16267

                                     (Std. err. adjusted for 8 clusters in BankID)
---------------------------------------------------------------------------------
                |               Robust
        lzscore | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
----------------+----------------------------------------------------------------
           dATM |    .022825   .0078946     2.89   0.004     .0073518    .0382982
            BNK |   .0112714   .0033279     3.39   0.001     .0047489    .0177939
            INF |   -.026491   .0169636    -1.56   0.118    -.0597391    .0067571
            GDP |  -.0158836   .0055846    -2.84   0.004    -.0268293   -.0049379
InterestExpense |  -.0602504   .0097093    -6.21   0.000    -.0792802   -.0412205
PersonalExpense |   -.075006   .0108069    -6.94   0.000    -.0961871   -.0538249
  TotalDeposits |   .0247583   .0064481     3.84   0.000     .0121203    .0373963
          _cons |   1.500535   .1320191    11.37   0.000     1.241783    1.759288
---------------------------------------------------------------------------------
Endogenous: dATM
Exogenous:  BNK INF GDP InterestExpense PersonalExpense TotalDeposits VMT

. estat endogenous

  Tests of endogeneity
  H0: Variables are exogenous

  Robust regression F(1,7)        =  4.94737  (p = 0.0615)
    (Adjusted for 8 clusters in BankID)
```

5.7 GMM model

```
Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: BankID                          Number of obs      =       184
Time variable : Year                            Number of groups   =         8
Number of instruments = 26                      Obs per group: min =        23
Wald chi2(9)  =  18070.36                                      avg =     23.00
Prob > chi2   =     0.000                                      max =        23
                                     (Std. err. adjusted for clustering on BankID)
----------------------------------------------------------------------------------
                 |               Robust
          lzscore | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
          lzscore |
              L1. |   .3250159   .2514915     1.29   0.196    -.1678984    .8179302
                  |
             dATM |   .0011902   .0017436     0.68   0.495    -.0022273    .0046076
              VMT |   .0084285   .0077837     1.08   0.279    -.0068272    .0236842
              BNK |   .0011958   .0025686     0.47   0.642    -.0038385    .0062302
              INF |   .0063453   .0081442     0.78   0.436    -.0096171    .0223077
              GDP |  -.0049476   .0069199    -0.71   0.475    -.0185103    .0086151
    dTotalDeposits |  -.0053181   .0090546    -0.59   0.557    -.0230649    .0124286
 dInterestExpense |  -.0479971   .0207529    -2.31   0.021    -.0886721   -.0073221
  PersonalExpense |  -.0396432   .0143516    -2.76   0.006    -.0677719   -.0115145
            _cons |   1.145402   .2834182     4.04   0.000     .5899128    1.700892
----------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/23).dATM
Instruments for levels equation
  Standard
    VMT BNK INF GDP dTotalDeposits dInterestExpense PersonalExpense
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.dATM
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -0.98  Pr > z =  0.327
Arellano-Bond test for AR(2) in first differences: z =  -1.11  Pr > z =  0.265
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(16)   =  21.09  Prob > chi2 =  0.175
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(16)   =   0.00  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)
```

Appendix 6: Ethical clearance

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

10 October 2024

Mr Njabulo Mhlongo (219015006)
School Of Acc Economics&Fin
Westville

Dear Mr Njabulo Mhlongo,

Original application number: 00027536
Project title: Fintech innovations and banking sector dynamics: Evidence from South Africa

Exemption from Ethics Review

In response to your application received on 9 October 2024, your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Claire Lauren Vermaak
Academic Leader Research
School Of Acc Economics&Fin

Appendix 6: Turnitin report

Thesis

ORIGINALITY REPORT

11%	7%	7%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	researchspace.ukzn.ac.za Internet Source	2%
2	Taiwo O. Soetan, Emmanuel Mogaji. "Financial Services in Nigeria", Springer Science and Business Media LLC, 2024 Publication	<1%
3	rgsa.openaccesspublications.org Internet Source	<1%
4	www.tandfonline.com Internet Source	<1%
5	Shaofang Li. "Financial Regulation and Bank Performance", Springer Science and Business Media LLC, 2021 Publication	<1%
6	books.euser.org Internet Source	<1%