The Impact of Fintech on Employment and Labour Productivity in the South African Banking Sector

by

Mbulelo M. Soyizwapi

submitted in accordance with the requirements for

the degree of

Master's in Economics

at the

UNIVERSITY OF SOUTH AFRICA

SUPERVISOR: Dr. SJ Joubert

CO-SUPERVISOR: Prof TLA Leshoro

DECLARATION

Name: Mbulelo M Soyizwapi

Student number: 57486638

Degree: MASTER OF COMMERCE (MCOM) IN ECONOMICS

Exact wording of the title of the dissertation as appearing on the electronic copy submitted for examination:

"The Impact of Fintech on Employment and Labour Productivity in the South African Banking Sector "

I declare that the above dissertation is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

I further declare that I submitted the dissertation to originality-checking software and that it falls within the accepted requirements for originality.

I further declare that I have not previously submitted this work, or part of it, for examination at Unisa for another qualification or at any other higher education institution.

(The dissertation will not be examined unless this statement has been submitted.)

___________________________ SIGNATURE

_________12/12/2025____________ DATE

ACKNOWLEDGEMENTS

I would like to extend my deepest gratitude to my supervisor, **Dr SJ Joubert**, for your invaluable guidance, encouragement, and patience throughout this research project. Your constructive comments and insightful feedback were instrumental in shaping the quality and direction of this work.

To my co-supervisor, **Prof TLA Leshoro**, I am sincerely grateful for the knowledge and expertise you imparted, particularly in econometrics, which greatly enriched my research. I also wish to thank both of you for your patience and understanding during the many challenges, changes, and pivots that this project required. Your support made navigating those moments possible.

To my **mother**, thank you for your unwavering support and encouragement from the very beginning to the completion of this dissertation. To **Kabelo**, I am grateful for your assistance with planning in the early stages, which provided a strong foundation for this work. To **Unarine**, thank you for your help with editing and for your constant support, which ensured that this dissertation reached its final form.

Finally, I wish to acknowledge the **University of South Africa (UNISA)** for providing the academic environment and resources that enabled me to pursue and complete this research.

ABSTRACT

This study examines the influence of financial technology (Fintech) on labour productivity and employment in South Africa's banking industry from 2010 Q1 to 2022 Q4, a period characterised by significant digital transformation accelerated by the COVID-19 pandemic. Employing the Autoregressive Distributed Lag (ARDL) modelling framework, the analysis estimates both short-term and long-term relationships between fintech adoption and two key economic variables: employment and labour productivity.

The empirical results indicate that fintech adoption initially reduces employment levels due to automation and digital substitution; however, it positively affects employment in the long term through the creation of new roles and the expansion of service offerings. Labour productivity consistently benefits from fintech diffusion, although incremental improvements tend to decrease over time. By focusing on an emerging economy such as South Africa, this research fills a notable gap in existing literature, which has predominantly concentrated on developed countries.

The findings highlight the dual role of fintech as a catalyst for efficiency and a disruptor of traditional employment frameworks. Additionally, the study advocates for balanced policy approaches that leverage the productivity gains associated with fintech while addressing its potential short-term impact on labour displacement. These conclusions offer valuable guidance to policymakers, financial institutions, and technology developers as they navigate the dynamic digital financial ecosystem in South Africa and comparable markets.

Keywords: Autoregressive Distributed Lag, Employment, Fintech, Fintech Adoption, Fintech Diffusion, Labour Productivity.

ABBREVIATIONS AND ACRONYMS

ADF – Augmented Dickey-Fuller Test

AI – Artificial Intelligence

AIC – Akaike Information Criterion

APF – Aggregate Production Function

ARDL – Autoregressive Distributed Lag

ATM – Automatic Teller Machine

BG – Breusch-Godfrey Test

CLRM – Classical Linear Regression Model

CointEq – Cointegration Equation

COVID-19 - Coronavirus Disease 2019

CUSUM – Cumulative Sum Test

CUSUMSQ – Cumulative Sum of Squares Test

DCOVID – Dummy Variable for Coronavirus Disease

DiD – Difference-in-Difference

DW – Durbin-Watson Test

ECM – Error Correction Model

EDP – Electronic Data Processing

EMPLOY – Employment

EVIEWS – Econometric Views

FINTECH – Financial Technology

GDP – Gross Domestic Product

IFWG - Intergovernmental Fintech Working Group

IT – Information Technology

INFL – Inflation Rate

IV-GMM – Instrumental Variable Generalized Method of Moments

LM – Lagrange Multiplier Test

LPROD – Labour Productivity

OLS – Ordinary Least Squares

PC – Personal Computer

PCA – Principal Component Analysis

POS – Point of Sale

PP – Pillips-Perron Test

P2P – Peer to Peer

RBI – Reserve Bank of India

RENB - Random Effects Negative Binomial Regression Model

REPO – Repurchase Rate

SARB – South African Reserve Bank

SEM – Structural Equation Modelling

TFP – Total Factor Productivity

USD – United States Dollar

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Background

Financial technology, commonly referred to as Fintech, encompasses a wide range of services. This includes, but is not limited to, mobile banking apps, payment services, cryptocurrencies, and machine learning. The term fintech is therefore used as an umbrella term to describe innovative technology-enabled financial services and the business models that accompany those services (Mention, 2019). Since the COVID-19 pandemic, the global economy has experienced a rapid transformation and adoption of fintech. Furthermore, this coincides with an increase in the development of several fintech innovations and companies (Fu & Mishra, 2020). This transformation has the potential to reshape both operational efficiencies and labour dynamics.

Adam Smith's "The Wealth of Nations" introduced land, labour, and capital as key factors of production, with entrepreneurship later recognised as a fourth factor (Smith 1776). He emphasised technology's role in enhancing labour productivity. David Ricardo (1817) added to this by highlighting technology's impact on economic output distribution and introducing the law of diminishing returns. However, given the dates of their respective publications, neither of these models explicitly accounted for the rapid and transformative effects of digital technologies and the evolution of factors of production.

The concept of financial technology as an additional, or fifth factor of production, identifies technological innovations as a crucial element in economic production. Success in this new landscape requires embracing fintech as a key pillar of this new factor of production. However, this poses several important questions about possible macroeconomic implications. These include how the adoption of fintech innovations impacts economic growth, productivity, and labour market dynamics. Furthermore, one needs to analyse the potential benefits and risks of these newer fintech innovations and the consequences of what their widespread adoption poses. Thus, this research paper explores fintech's impact on employment and labour productivity within the South African banking sector.

Fintech has significantly transformed and modernised the financial services sector. In addition, it enables the use of advanced technology to introduce innovations and improve established financial services. Furthermore, it also challenges traditional financial institutions by offering the ability to provide financial services more efficiently and in a way that is more accessible to customers. Furthermore, the entry of new players has increased competition, as well as challenges for regulation and consumer protection (Beck, 2020).

Contemporary fintech innovations represent the latest progression in a longstanding history of technological advancements within the financial services sector. In the 1950s, the introduction of early credit cards and electronic data processing (EDP) systems marked the advent of Fintech products, enhancing consumer flexibility and convenience while automating various banking operations (Gibson, 2023). This initial momentum facilitated the emergence of additional technologies.

For instance, the 1960s saw the deployment of automated teller machines (ATMs), affording consumers new methods of accessing funds, alongside the adoption of banking mainframes (Gibson, 2023). The rise of personal computers (PCs) in the 1980s further enabled banks to provide online banking services. By 1998, the proliferation of the internet led to the founding of PayPal, one of the first fintech solutions operating predominantly in an online environment (Gibson, 2023). These foundational developments have paved the way for today's mobile payment applications, blockchain networks, and numerous other innovative financial services.

As of 2024, the global fintech market was valued at USD 347.2 billion and is forecasted to reach USD 1,076.1 billion by 2033 (Tiwari, 2025). This anticipated growth is primarily driven by technological advancements and evolving consumer behaviours (Tiwari, 2025). A notable factor contributing to this expansion is the increasing digitisation of financial services, propelled by the widespread adoption of smartphones and internet connectivity. Digitalisation has enhanced both accessibility and cost-efficiency in the sector, as digital platforms typically incur lower operational expenses compared to traditional physical institutions (Smith, 2020).

One of the primary drivers of fintech adoption is the streamlined experience offered by digital and mobile banking, enabling both businesses and individuals to access financial services without the need to visit physical branches or endure lengthy queues. Traditional financial institutions are also contending with heightened competition, evolving customer expectations, and an increasingly complex regulatory environment. While these challenges have historically impacted established providers, the emergence of fintech introduces additional considerations for these organisations.

Moreover, the emergence of fintech is closely associated with evolving consumer preferences and expectations. Contemporary consumers increasingly seek personalised, convenient, and seamless experiences, areas where traditional service providers may not always excel.

Conversely, fintech firms utilise advanced technologies to deliver financial solutions that address these shifting requirements (Jones, 2018).

Numerous banks have strategically invested in fintech or acquired fintech firms, recognising the imperative to rapidly innovate to maintain competitiveness through enhanced digital services and novel solutions (Vasiljeva & Lukanova, 2016). The integration of traditional banking practices with emerging fintech innovations presents a promising approach to optimally serving clients (Vasiljeva et al, 2016). Nevertheless, increased adoption of digital banking may adversely affect employment at physical branches and introduce technology-related challenges such as service disruptions and connectivity issues.

The heightened digitisation and utilisation of fintech by financial institutions also generate notable macroeconomic considerations. Naoyuki and Sahoko (2020) found that Fintech development enhances banking efficiency, which can increase deposit interest rates. Improved operational efficiency within banks tends to lower lending rates and reduce default losses. Conversely, the same authors note that fintech may decrease transaction costs associated with capital inflows, potentially increasing exchange rate volatility. These factors underscore the prudential implications of fintech for macroeconomic stability.

The COVID-19 pandemic (2020 to 2021) served as a significant catalyst for fintech growth, accelerating the transition to digital financial services as consumers sought contactless and remote banking options (Brown & Lee, 2021). This crisis-induced shift is expected to have enduring effects, further driving the expansion of the fintech sector in the years ahead.

1.2 Overview of Fintech in South African Banking

Since 2010, the South African banking industry has experienced significant transformation due to the growth of financial technology. Driven by increased reliance on digital platforms and ongoing technological advancements, this evolution has facilitated greater financial inclusion and fostered innovation (Louw et al., 2020). Tyme Bank, South Africa's first digital-only bank, illustrates this trend by providing clients with access to its services via its website, online banking facilities, and mobile application. This fundamental shift is redefining customer engagement within the banking sector and highlights the necessity for thorough analysis of fintech's economic impact on the industry.

South Africa's position as the continent's financial hub further strengthens the relevance of this study. The Absa Africa Financial Markets Index (2024) consistently places South Africa at the top of African financial systems reflecting deep capital markets and strong digital infrastructure. These conditions create an environment where fintech innovations can scale rapidly, interact with established financial systems and generate measurable economic effects. This makes South Africa and ideal setting for empirical investigations.

The expansion of digital banking in South Africa is clearly demonstrated by the substantial increase in real-time clearing transactions processed by Bank Serve Africa, the continent's leading automated clearing house. These interbank transaction figures are regularly published in the South African Reserve Bank's quarterly reports. In 2010, the monthly average of processed transactions was approximately 260,000; by 2022, this number had risen markedly to 17.99 million per month. This significant growth reflects the rapid adoption of digital banking services among South Africans and emphasizes the imperative for continued investment in digital infrastructure to satisfy increasing demand for efficient and secure banking solutions.

Africa, as a whole, has experienced accelerated growth in its mobile service industry, with over 620 million mobile connections recorded in September 2011, establishing it as the world's second largest mobile market (Gillwald et al., 2012). Among countries with the highest mobile subscriber counts, South Africa ranks third after Nigeria and Egypt (Gillwald et al., 2012). The widespread availability of mobile devices has contributed to the swift proliferation of mobile applications, including those for banking, providing consumers with enhanced functionality, productivity benefits, and entertainment options (Pranata et al., 2013).

In South Africa, the trend towards mobile-first banking services is notable, with all major banks supporting both Android and iOS smartphone applications, the predominant operating systems globally (Statcounter Global Stats, 2019). This strategic choice underscores the significance of mobile banking within South Africa and highlights its relevance as part of a broader global trend. The prevalence of these apps suggests that they effectively address contemporary consumer needs while positioning banks for future market expansion (Louw et al., 2020). Mobile-centric, locally adapted banking services are poised to become essential to the overall customer experience and serve as a key element of institutional strategy.

Despite these advancements, banked population rates reveal room for progress. By 2019, only 34% of adults in the Southern African region used formal banking services, compared to 70%

in South Africa (Mungai, 2019). However, South Africa continues to face challenges within the global digital economy; as of 2019, just 25% of South Africans utilised debit or credit cards for purchases. Financial inclusion remains hindered by both demand-side factors, such as limited funds, geographic constraints, and scepticism toward financial institutions, and supply-side barriers, including insufficient access to data among lower-income groups and a lack of incentives to target these markets (Mungai, 2019).

Fintech companies are increasingly addressing gaps in the banking sector (Kowalewski, 2023). Nevertheless, unmet needs alone do not guarantee adoption; successful fintech innovations such as M-Pesa in Kenya and WeChat payments in China have typically been propelled by telecommunications firms (Mungai, 2019). As banking continues to undergo a digital and mobile transformation, it is essential for financial institutions to address the diverse requirements of their clientele, which includes providing suitable training for customers who may lack technical expertise. Although digitalization may not be optimal for every market segment, South African banks are prioritizing mobile-first strategies as part of their digital evolution.

All five major banks in South Africa, Absa Bank, Nedbank, Standard Bank, First National Bank, and Capitec Bank, now offer internet-enabled services, enhance online accessibility, and provide zero-rated data applications for smartphone banking. These initiatives benefit both customers and financial institutions, while mobile POS systems enable expanded service provision for informal traders and small businesses (Louw et al., 2020).

1.3 Tyme Bank: South Africa's First Digital-Only Bank

Online banking, encompassing both internet and mobile platforms, has experienced significant growth in the post-COVID era. The COVID-19 pandemic underscored the necessity for digital financial solutions, given the health risks associated with cash handling (Gertze, 2024). Digitalisation presents several advantages over traditional banking methods, including decreased crime rates and enhanced payment security (Gertze, 2024). However, in South Africa, challenges such as limited internet access and increased competition remain prevalent (Gertze, 2024). Despite these obstacles, fintech innovations have the capacity to address gaps left by conventional financial institutions, with Tyme Bank emerging as a notable example.

Tyme Bank, which commenced operations on a limited basis in South Africa in 2018, holds the distinction of being the country's first exclusively digital bank. Owned by Patrice Motsepe’s African Rainbow Capital, Tyme Bank operates without any physical branches, relying entirely on digital channels such as online services, mobile applications, and in-store kiosks (Malinga, 2024). Strategic partnerships with retailers like Pick'n Pay and Boxer facilitate customer engagement through points of presence in their stores.

The bank has demonstrated robust growth, achieving profitability by December 2023 (Malinga, 2024). According to its Chief Commercial Officer, Cheslyn Jacobs, Tyme Bank’s success is attributable to key strategies such as integrating digital services within major retail kiosks, maintaining strong relationships with retail partners, and securing shareholder confidence to raise capital. As of 2024, Tyme Bank operates over 1,000 retail-based kiosks nationwide, which have contributed to approximately 75% of new business growth (Malinga, 2024).

Research on TymeBank indicates that the institution offers lower banking fees compared to traditional competitors, and its online application is free to use (Gertze, 2024). However, the application still requires data usage, whereas some established banks offer data-free options (Gertze, 2024). In terms of trust, areas for improvement remain; users report technical issues such as timeouts, interruptions, and concerns regarding the tap-and-pay feature, which operates without a PIN.

Additional challenges involve international payments and transferring funds from other banks that do not list TymeBank as an option. While these are typical challenges for emerging technologies, Tyme Bank’s growth reflects significant opportunities, particularly in reaching unbanked younger demographics and leveraging increasing internet and mobile accessibility.

Importantly, TymeBank challenges classical economic theories of production factors by operating without brick-and-mortar premises; technology, in this case, substitutes traditional concepts of land in the factor model. As more sectors transition toward fintech solutions, it prompts consideration of technology, and fintech in particular, as a potential fifth factor of production.

1.4 Problem Statement

In line with global trends, South Africa’s banking sector has experienced substantial growth in digital financial services over recent decades, primarily driven by advancements in fintech. By its nature, fintech acts as a disruptive force, challenging established norms and traditional financial service providers through the introduction of innovative technologies. These digital offerings often necessitate enhanced security measures, encompassing mutual authentication, authorisation, and assurance of data privacy and integrity (Kang, 2018). Accordingly, stakeholders must remain vigilant and informed about best practices for client protection and operational continuity within this rapidly evolving environment.

While fintech innovations can improve efficiency and accessibility, they may also contribute to job displacement and erode trust in conventional financial institutions. This trend is exemplified by early fintech platforms such as PayPal, a digital payment solution founded in 1998 that had accrued over 300 million active accounts by 2019 (Wewege, 2020). The proliferation of the internet naturally facilitated the emergence of such platforms; however, as PayPal expanded, it introduced significant competition for banks by offering reduced transaction costs, expedited processing, and flexible payment options. In response, numerous financial institutions developed proprietary online payment services or acquired existing platforms to maintain market relevance (Wewege, 2020).

The Covid-19 pandemic further accelerated the adoption of fintech solutions, compelling both individuals and businesses to seek digital alternatives for their financial activities (Jones & Smith, 2021). For consumers, this shift was evident in the increased utilization of banking applications during periods of restricted physical access to branches. Businesses, such as Kuwait International Bank (KIB), implemented Interactive Voice Response systems to serve customers without dependence on traditional call centres, which were often closed at the height of the pandemic (Naz et al., 2022).

The disruptions induced by the pandemic have expedited the digitisation of financial services, fundamentally altering consumer behaviours and expectations (Brown & Davis, 2020). Such changes, including heightened reliance on digital channels for transactions, are anticipated to persist beyond the immediate crisis (Smith et al., 2020). The transition towards digital solutions holds potential to foster greater financial inclusion, expanding access for underserved populations (Perez & Garcia, 2020). Furthermore, increased digitisation is projected to boost efficiency and reduce costs for both financial institutions and their clients (Gupta & Sharma, 2021). Nonetheless, these developments raise concerns regarding data privacy, cybersecurity, and regulatory compliance (Sullivan & Johnson, 2020).

Overall, the pandemic has not only advanced the adoption of fintech but also precipitated considerable shifts in consumer behaviour and the broader financial landscape. The long-term implications for the economy and society at large require further investigation. Despite rapid fintech expansion, no empirical study has quantified its effects on labour productivity and employment within South Africa's banking sector for the period, creating a critical gap that this research addresses. Therefore, this research endeavours to analyse the economic impact of fintech innovations from 2010 Q1(pre-Covid) to 2022 Q4 (post-Covid) on select variables within South African banking, with the aim of providing novel insights into the interplay between fintech, productivity, and employment in the sector.

1.5 Research Objectives

This study intends to examine the economic effects of fintech innovations on the South African banking sector over the period from 2010 Q1 to 2022 Q4.

The primary objectives are as follows:

1. To evaluate the landscape of fintech adoption, with particular attention to the wider economic ramifications for the South African banking industry.

2. To analyse the economic impact of fintech adoption and diffusion on labour productivity within South African banks.

3. To analyse the economic impact of fintech adoption and diffusion on employment within South African banks.

1.6 Research Questions

This study aims to address the following research questions:

1. In what ways has the adoption of fintech transformed the economic landscape, and what are the broader implications for the South African banking sector?
2. How does fintech adoption and diffusion affect labour productivity among South African banks, as assessed using the ARDL modelling framework?
3. How does fintech adoption and diffusion affect employment levels within South African banks, as assessed through the ARDL modelling framework?

1.7 Hypothesis

- H_0 (Null Hypothesis): Fintech innovations do not have an economic impact on the South African banking sector
- H_1 (Alternative Hypothesis): Fintech innovations have an economic impact on the South African banking sector

1.8 Rationale of the Study

Although much of the existing literature on the economic effects of fintech is concentrated within developed economies, research specific to the South African context remains comparatively scarce (Beck, 2020). Previous studies have primarily examined fintech's role in promoting financial inclusion and operational efficiency (Jones & Williams, 2021), while relatively few have quantified its impact on labour productivity and employment within the banking sector. Addressing this gap is crucial, especially considering the rapid digitisation of financial services, a trend significantly accelerated by the COVID-19 pandemic (Brown & Lee, 2021; Louw, 2020).

Prior research frequently utilises cross-sectional data approaches that aggregate countries with markedly different institutional and technological frameworks (Kowalewski, 2023; Chinoracky et al., 2021), which may obscure effects unique to specific national contexts. This study concentrates on South Africa's banking sector, providing targeted insights into the influence of fintech innovations on labour productivity and employment. The results offer valuable guidance for policymakers and senior leaders within financial institutions, supporting the development of evidence-based strategies to balance labour productivity objectives with employment considerations. Furthermore, the findings contribute meaningfully to the broader discourse on digital transformation in emerging markets.

This study makes key contribution to the existing body of knowledge by first addressing an empirical gap by examining how fintech adoption affects both labour productivity and employment within South Africa's banking sector; an area where prior research largely focuses on financial inclusion, competition and digital disruption rather than these labour market outcomes. Secondly, the study introduces a more precise and sector specific proxy for fintech adoption by utilising electronic fund transfer volumes from the South African Reserve Bank, thereby capturing both institutional adoption and client-side utilisation.

Unlike previous studies, explored in depth in the literature review, that rely on cross-country datasets or focus primarily on financial inclusion, this research provides a banking-sector specific South African focused analysis of fintech's labour implications. By integrating a novel fintech indicator and modelling both productivity and employment dynamics, this study offers empirical insights not previously available for the South African context.

In addition to South Africa's classification as an emerging economy, the country provides a uniquely suitable context for analysing fintech's economic effects because it possesses amongst the most advanced financial markets on the African continent. According to the 2024 Absa Africa Financial Institutions Forum (OMFIF), South Africa ranks first overall across six pillars: market depth, access to foreign exchange, market transparency and regulatory environment, capacity of local investors, macroeconomic opportunity and legal standards. This combination of emerging-market characteristics and highly developed financial infrastructure makes South Africa an analytically valuable case for examining how fintech adoption influences labour productivity and employment within a sophisticated yet evolving banking system.

1.9 Division of Chapters

The remainder of this study is structured as follows:

Chapter 2 presents a comprehensive literature review, beginning with an examination of relevant theoretical frameworks followed by an empirical evaluation of prior research concerning the impact of fintech on developed and developing economies. Chapter 3 details the methodological approach and data selection, providing rationale for their suitability within the context of the study. Chapter 4 offers an in-depth analysis of the empirical findings. Finally, Chapter 5 concludes the study, delivering recommendations and identifying potential avenues for future research.

CHAPTER 2.

LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive overview of theoretical and empirical literature relevant to understanding the relationship between fintech, labour productivity and employment. Section 2.2 presents the theoretical framework, outlining and examining the aligned viewpoints of Classical, Austrian, and Keynesian economists on the essential contribution of technology to enhancing firm efficiency, as articulated by Smith (1776), Ricardo (1817), Solow (1957), Schumpeter (1942), and Keynes (1936). 2.21 expands on this by examining the theoretical foundations of technological change and its implications for production efficiency. Subsequently, section 2.3 provides the empirical literature review beginning with studies that assess the impact of fintech on employment and labour productivity (2.3.1). This is followed by a review of empirical studies that assess the impact of fintech across both developed (2.3.2) and developing economies (2.3.3). Section 2.3.4 then focuses specifically on fintech within the South African banking sector which identify gaps that this research addresses. Finally, section 2.4 concludes the chapter. Together these sections provide the conceptual and empirical foundation for this study's methodological approach.

2.2 Theoretical Framework

2.2.1 Theoretical Framework for Technology

This section examines the shared perspectives of Smith (1776), Ricardo (1817), Solow (1957), Schumpeter (1942), and Keynes (1936) on the critical role of technology in fostering efficiencies within firms. Collectively, these authors regard technology as both a catalyst and enabler, enhancing the productive capabilities of other factors of production.

Smith (1776), representing Classical economics, delineated three primary factors of production, land, labour, and capital, in his influential work, "The Wealth of Nations." Many scholars subsequently include entrepreneurship as a fourth factor due to its capacity to elevate firm productivity (Glancey et al., 2000; Rico et al., 2019). Factors of production encompass resources necessary for producing goods and services that do not form part of the final product. Smith also acknowledged technological advancement as essential in economic development, terming it the "improvement of the productive powers of labour." He posited those technological innovations, such as machinery, lead to increased productivity and higher output (Smith, 1776).

Other prominent Classical economists, including David Ricardo and Karl Marx, expanded on these concepts. Ricardo (1817), in "Principles of Political Economy and Taxation," emphasized technology's significance in determining output distribution among the production factors. He introduced the "law of diminishing returns," which maintains that adding units of a factor to fixed inputs eventually yields decreasing marginal productivity. Marx, in "Das Kapital" (1867), analysed technology's impact, particularly the use of machinery, in capitalist production models. He argued that technological progress, while increasing productivity, also prompts labour displacement by machines, intensifying labour exploitation by capital.

Solow (1957: 65-94), associated with the neo-Keynesian tradition, advanced Smith's framework by developing the neoclassical model of economic growth. Solow refined the analysis of production factors, emphasizing the roles of labour and capital, with technological innovation as a vital element for sustained growth. The Solow Residual, or total factor productivity (TFP), underscores the contribution of technological innovation to economic output beyond traditional inputs. Solow contended, "Technological change is the only source of sustained increases in productivity and the only possible explanation of differences in growth rates of output per worker across countries" (Solow, 1957, p.65).

The Austrian School of Economics, originating with Carl Menger's "Principles of Economics" (1870s), is characterized by six principal tenets: individualism, subjectivism, marginalism, preferences, opportunity cost, and the temporal structure of consumption and production (Boettke et al., 2003: 446). Renowned for advocating free-market capitalism and limited government intervention, the Austrian School regards technology as an economic phenomenon that enhances both the quantity and quality of output, rather than as a discrete factor (Ciborowski et al., 2019: 132-133). Entrepreneurial activity is central to their perspective, as entrepreneurs identify and apply new technologies to create value, aligning with Classical views.

Austrian economist Joseph Schumpeter, in "Capitalism, Socialism and Democracy" (1942), introduced "creative destruction," illustrating how innovation and technological advancement propel economic development by supplanting outdated methods and products. Friedrich Hayek (1945: 519–530) further emphasized the significance of dispersed knowledge, highlighting how technological change facilitates more efficient resource allocation and economic coordination. Thus, the Austrian School perceives financial technology, like other technological forms, as a positive force for efficiency and entrepreneurship.

The Keynesian School, developed by John Maynard Keynes, prioritizes aggregate demand in determining economic output and inflation (Keynes, 1936). Keynesians assert that active government intervention can stabilize economies (Blinder, 2008:1). Keynes (1936) viewed technology as instrumental in boosting resource efficiency and productivity, thereby fostering growth, which aligns with Classical and Austrian positions. However, he also recognized that technological change could disrupt industries, potentially causing unemployment. Keynes advocated for fiscal policies to mitigate adverse effects by stimulating demand and generating employment opportunities.

Accordingly, if technological advancements result in substantial unemployment, Keynes (1936) noted that reduced consumer spending could weaken aggregate demand. While Keynesian economists affirm technology's pivotal role in long-term economic growth and efficiency gains, they also support policy measures to address negative externalities arising from creative destruction.

In conclusion, Classical, Austrian, and Keynesian economists concur that technology increasingly drives differences in firm-level efficiencies. Smith highlighted technology's role in economic advancement (Smith, 1776), Keynes recognized its importance for resource and productivity expansion (Keynes, 1936), and Schumpeter underscored innovation's transformative power (Schumpeter, 1942). Collectively, these schools view technology as a facilitator and catalyst for the other factors of production.

2.3 Empirical Literature Review

This section provides an overview of empirical research on Fintech, beginning with a review of literature examining the impact of Fintech on productivity and employment. Subsequently, it considers relevant studies on Fintech across both developed and developing economies.

2.3.1 Impact of Fintech on Employment and Labour Productivity

Jiang (2021) examines the implications of fintech developments on employment within the United States, introducing an occupational-level metric of fintech exposure by correlating job task descriptions with fintech patent data. The study reveals that occupations most susceptible to fintech advancements witnessed a significant decline in job postings; nevertheless, such roles also became concentrated more geographically and sectoral (Jiang, 2021). Many organizations responded to fintech-induced disruptions by implementing upskilling initiatives, placing emphasis on candidates who possess hybrid expertise in finance and software, advanced educational credentials, and substantial professional experience (Jiang, 2021). Moreover, financial institutions characterized by robust innovation capabilities demonstrated greater resilience to fintech shocks relative to less innovative entities. Among these, firms driven by internal inventors outperformed those pursuing innovation through acquisitions, particularly in recruitment, sales, investment, and asset returns.

Chinoracky et al. (2021) explore the effects of digital technologies, including fintech, on gross value added, employment, and labour productivity in Slovakia's transport industry. Through an analysis of sectoral data, their findings indicate that although robotics and automation were anticipated to reduce employment, such declines were not universal. Sectors with low to medium digital maturity experienced workforce reductions, whereas those with medium to high levels of digitalisation recorded employment growth (Chinoracky et al., 2021).

Labour productivity rose substantially across the industry, especially in digitally intensive domains such as automated vehicle manufacturing, which surpassed less technologically advanced areas like land transport information systems. While recognizing multiple influencing factors, the authors attribute a portion of this productivity increase to fintech-driven digital transformation (Chinoracky et al., 2021). Their research highlights the differentiated impacts of fintech across sectors, emphasizing the critical role of digital sophistication in determining employment and productivity outcomes.

Ang (2024) investigates the influence of fintech innovation on labour efficiency and productivity in China, focusing on its contributions to mitigating information asymmetry and optimizing resource allocation. In labour-intensive industries such as manufacturing, where labour constitutes roughly two-thirds of production costs, fintech facilitates more effective investment decisions by mitigating moral hazard and adverse selection (Ang, 2024). Leveraging cost-efficient data integration and visualization tools, fintech enhances predictive analytics capabilities, enabling firms to streamline resource deployment.

Ang (2024) further contends that fintech reshapes human capital structures by automating routine functions, thereby decreasing reliance on low-skilled labour and heightening demand for highly skilled personnel (Ang, 2024). These technological advancements expedite both the development and strategic placement of labour, prompting organizations to recalibrate workforce strategies in line with evolving operational requirements, particularly within upstream productive services (Ang, 2024). Overall, the research concludes that fintech has markedly improved traditional financial processes in China, notably by addressing labour misallocations and alleviating informational inefficiencies.

The reviewed literature uniformly affirms that fintech plays a crucial role in advancing labour productivity across various sectors and national contexts. Both theoretical perspectives and empirical evidence from the United States, Slovakia, and China underscore that technological progress via fintech innovation is integral to productivity enhancement. Nevertheless, effective integration of fintech solutions necessitates organizational investment in workforce development, human capital restructuring, and research and development. Therefore, while fintech presents considerable productivity opportunities, its successful adoption requires strategic planning and dedicated investment in both technology and talent.

2.3.2 Fintech in Developed Economies

Developed economies provide favourable conditions for fintech innovation, owing to advanced digital infrastructure and high internet penetration. Nevertheless, fintech firms within these environments tend to remain comparatively smaller than traditional financial institutions (Kowalewski & Pisany, 2023). Drawing from a cross-country analysis, Kowalewski and Pisany employed the Random Effects Negative Binomial (RENB) regression model alongside descriptive statistics on data spanning 2010–2021 to identify determinants of fintech growth. Their findings indicate that fintech enterprises frequently arise in regions with restricted access to loans, suggesting that their expansion is primarily driven by the need to address deficiencies in conventional banking services.

Developed economies provide favourable conditions for fintech innovation, owing to advanced digital infrastructure and high internet penetration. Nevertheless, fintech firms within these environments tend to remain smaller in comparison to traditional financial institutions (Kowalewski & Pisany, 2023). Drawing from a cross-country analysis using panel regression techniques and descriptive statistics, Kowalewski and Pisany examined data spanning 2010–2021 to assess determinants of fintech growth. Their findings indicate that fintech enterprises frequently arise in regions with restricted access to loans, suggesting that their expansion is primarily driven by the need to address deficiencies in conventional banking services.

While technological factors such as information technology infrastructure, mobile connectivity, and broadband access are necessary enablers, Kowalewski's study highlights the critical role of research quality, particularly university-industry collaboration, in promoting fintech innovation. Demographic characteristics are also influential; younger populations typically facilitate fintech formation, whereas older adults in developed economies demonstrate a higher propensity to adopt innovative financial solutions. Moreover, urbanisation contributes to the diffusion of fintech, a phenomenon more pronounced in developed markets (Kowalewski, 2023).

Despite operating in technologically advanced settings, fintech companies in developed countries often target underserved market segments, which are more commonly associated with developing regions. However, Kowalewski (2023) notes that the study did not incorporate regulatory considerations, which may present stricter barriers to entry in developed economies. The findings reaffirm that fintech adoption is closely linked to banking accessibility, positioning financial inclusion at the centre of fintech expansion.

Chinoracky et al. (2021) performed a time series analysis covering the period 2010 to 2019 to evaluate the macroeconomic impact of fintech on GDP growth, employment, and financial sector development in Slovakia. Their model included variables such as employment, labour productivity, and value added. Results suggest that fintech had a positive effect on value added, indicating enhanced economic output. The influence on employment was mixed, with sector-specific outcomes revealing both increases and decreases. Importantly, organisations that embraced digital transformation realised substantial improvements in labour productivity, underscoring the significance of effective fintech integration.

Chenic et al. (2023), utilising an Ordinary Least Squares (OLS) regression model, investigated the relationship between digitisation and key economic indicators across European Union member states covering the period 2011–2021. The research incorporated labour productivity, value added, and export performance to assess the macroeconomic consequences of digital transformation. Findings revealed a statistically significant and positive correlation between digitisation and these indicators, demonstrating that increased digital adoption stimulates productivity, economic output, and export competitiveness (Chenic et al., 2023).

Jeong et al. (2018) applied input-output analysis to South Korean national economic data from 2010 to 2015 to investigate the effects of fintech on inter-industry linkages and aggregate economic performance. Their methodology traced both upstream and downstream impacts of fintech activities across sectors. The study found that, during this timeframe, fintech's macroeconomic influence in South Korea was not statistically significant, indicating that the broader economic effects were still emerging and not yet fully realised.

Berg et al. (2020) employed the Digital Readiness Index to evaluate the potential for fintech to advance financial efficiency and inclusion throughout Europe, using data from 2015 to 2019. The study benchmarked national digital capabilities, including infrastructure, regulatory frameworks, and innovation ecosystems, against fintech adoption metrics. The authors concluded that countries with greater digital readiness are better positioned to leverage fintech for improved financial efficiency and greater inclusion of underserved populations.

Agarwal et al. (2022) utilised difference-in-difference (DiD) analysis to examine the causal impact of fintech adoption on business performance in Singapore from 2015 to 2020. By comparing firms before and after fintech implementation, and employing matched control groups to isolate fintech's effects, the researchers assessed transaction costs, demand, and business growth. Their results indicate that fintech adoption significantly reduced transaction costs and boosted demand, particularly among business-to-consumer firms, while business-to-business entities experienced more modest gains, suggesting sector-specific differences in fintech's benefits.

Naoyuki (2020) adopted a two-stage least squares (2SLS) regression approach to analyse the macroeconomic implications of fintech in Japan over the period 1995 to 2015, addressing potential endogeneity between fintech development and economic outcomes. Variables considered included GDP growth, financial sector efficiency, and regulatory factors. The findings indicate that fintech exerts both positive and negative macroeconomic effects, contingent upon the regulatory environment and stage of adoption. The study emphasises the necessity for updated legal frameworks to accommodate fintech's evolving contributions to Japan's financial system.

Table 2.1 below provides a summary of empirical research regarding the effects of fintech across developed economies. Notably, there is no standardised analytical method; researchers employ diverse methodologies, though the literature review remains prominent. Given the range of approaches and models, the overall impact of fintech on developed economies appears mixed.

Table 2.1. Summary of Findings from Selected Developed Countries

Author	Region	Methodology	Findings
Agarwal et al. (2022)	Singapore	Difference-in-differences analysis	The introduction of fintech has led to reduced transaction costs, increased demand and business growth particularly in business-to-consumer companies, rather than business-to-business companies.
Berg et al. (2020)	Europe	Digital Readiness Index	Fintech has potential for financial efficiency and inclusion gains in the Europe
Chenic et al. (2023)	European Union member states	Linear regression model (OLS)	There is a positive relationship between digitization and productivity, value added and exports.

Chinoracky et al. (2021)	Slovakia	Time series analysis.	Fintech has increased value added. However, it has had different effects on employment, both increases and decreases were observed. Companies also saw an increase in labour productivity as they adapt to the trends of digital transformation.
Jeong et al. (2018)	South Korea	Input-Output analysis	The economic effects of fintech are not significant for the period examined.
Naoyuki (2020)	Japan	Two stage least squares	Fintech has both positive and negative macroeconomic effects and a new legal framework is required

Source: Compilation by author

Although reviewed studies from developed economies provide valuable insights into fintech's macroeconomic and sectoral implications, several analytical gaps remain. As indicated in Table 2.1, current studies predominantly centre on Europe and frequently employ qualitative methodologies utilising secondary data. The findings generally demonstrate either mixed outcomes or a positive influence of fintech on economic output, productivity, demand, and overall growth. Notably, key challenges identified include limitations in data availability and regulatory ambiguity which create existing research gaps.

For instance, Kowalewski and Pisany (2023) identify structural and demographic determinants of fintech formation but do not assess how these dynamics translate into labour-market or productivity outcomes within these institutions. Similarly, Chinoracky et al (2021) and Chenic et al. (2023) report positive associations between digitisation, value added and productivity, yet their analyses do not disentangle whether these gains stem from labour augmentation or labour substitution.

Jeong et al (2018) finds that fintech's inter-industry effects in South Korea were not statistically significant, suggesting that macroeconomic benefits may take time to materialise, while Berg et al. (2020) emphasises digital readiness without examining employment implications. Agarwal et al. (2022) demonstrates how fintech adoption reduces transactional costs and boosts demand, but their firm level analysis does not extend to labour-productivity dynamics.

Finally, Naoyuki (2020) highlights both positive and negative macroeconomic effects, yet the study does not explore how these effects filter down to employment. Collectively these studies show that while fintech enhances efficiency and economic output in developed economies, empirical evidence on its direct effects on labour productivity and employment remains fragmented, underscoring the need for sector specific econometric analysis. Therefore Fintech, as a contemporary research topic, continues to present numerous gaps in the literature within developed countries.

2.3.3 Fintech in Developing Economies

Beck (2020) notes that financial institutions operating in developing countries face significant constraints resulting from both cost and risk factors. Institutions incur fixed transaction and client costs, leading to lower unit costs as transaction volume increases. However, outreach to potential clients with smaller or fewer transactions, particularly in rural areas, remains costly due to the fixed costs associated with Information Technology (IT) systems and support services. Additionally, risks such as rising loan losses or lending to higher-risk borrowers can threaten macroeconomic stability. Consequently, financial inclusion in these contexts is often limited by the ability of financial institutions to effectively manage these cost and risk challenges (Beck, 2020).

Historically, these financial constraints have rendered certain segments of developing economies 'unbankable,' due to low transaction volumes and inadequate documentation, thereby increasing both cost and risk. Recent advances in fintech have catalysed new models aimed at broadening access to financial services, for example, institutions such as Gareem Bank in Bangladesh and BancoSol in Bolivia (Beck, 2020). Gareem Bank's microfinance approach earned international recognition, notably the Nobel Peace Prize in 2006, although some critiques highlight its narrow focus on credit, which may not address all needs of unbanked populations.

Technological advancements over the past decade have significantly reshaped the financial landscape by reducing service delivery costs and enhancing risk management capabilities. The November 2020 Reserve Bank of India (RBI) bulletin credits the fintech sector with lowering transaction costs, optimizing operational expenses, mitigating credit risk, promoting financial inclusion, and supporting contemporary banking infrastructures (Sethi, 2022). India, as the world's second-largest developing economy, is poised to become the largest digital economy globally (Sethi, 2022). With an 87% fintech adoption rate in 2019, far exceeding the global average of 64% according to the EY Fintech Adoption Index, the rapid uptake of fintech solutions has facilitated financial inclusion across regions traditionally underserved by branch banking (Sethi, 2022).

Sethi’s research further demonstrates the role of fintech in lowering transaction costs and strengthening economic development through increased financial accessibility, emphasizing fintech's transformative impact in developing markets. Nevertheless, disparities persist in fintech implementation among developing economies, underscoring the need for continued research to understand its broader implications.

The empirical study by Sethi and Manocha (2022) examined fintech's effects in India over 2001–2020 using an ARDL methodology, highlighting fintech's role in supplementing traditional financial services and extending access to individuals with limited engagement with conventional banks. Their findings indicate that stringent COVID-19 restrictions accelerated fintech adoption among suppliers, regulators, and consumers.

Additionally, the research assessed the influence of fintech on key macroeconomic variables, economic growth, individual income (using official exchange rates), and labour participation, through an index constructed via Principal Component Analysis (PCA). Results suggest that fintech contributed positively to India's economic growth, per capita income, and exchange rate; however, regulatory conditions may have also shaped these outcomes. The study additionally reports a notable decrease in employment opportunities linked to fintech proliferation.

Akinola (2021) adopted a mixed-methods approach to evaluate fintech ecosystems in Sub-Saharan Africa, integrating surveys, interviews, and secondary data. Focusing on the rise of digital payment companies, mobile money platforms, and fintech startups from 2015 to 2020, the study captured perspectives from both users and institutions. Findings indicate that fintech expansion supports economic advancement through improved financial inclusion, enhanced transaction efficiency, and new entrepreneurial opportunities.

Song (2022) utilized a comprehensive econometric framework to investigate the impact of fintech on China's economic growth during 2011–2020, employing neoclassical aggregate production function theory combined with instrumental variable generalized method of moments (IV-GMM) and Dumitrescu and Hurlin panel causality testing. The analysis included subcategories such as third-party payments, digital credit, and insurance services, all of which demonstrated statistically significant positive effects on economic growth, reaffirming the integral role of digital finance in China's macroeconomic progress.

Diep and Canh (2022) conducted a consumer-oriented study of peer-to-peer (P2P) fintech services in Vietnam, utilizing descriptive statistics, reliability testing (Cronbach’s Alpha), factor analysis, and structural equation modelling (SEM). Analysing survey data collected between 2018 and 2021, the research examined variables including customer experience, payment behaviour, and service quality. Findings reveal that P2P fintech platforms are redefining payment trends, with users increasingly favouring digital avenues over traditional banking due to superior customer experiences.

While these reviewed studies provide insights into fintech’s role in expanding financial access and improving operational efficiency across developing economies, several limitations emerge upon closer examination. Much of the literature relies on broad cross-country panels (Fu & Mishra, 2020; Gillwald et al., 2012), which obscures institutional and labour market differences that shape how fintech affects employment and productivity.

2.3.4 Fintech in South African Banking

Fintech has become a significant driver of innovation in South Africa’s banking sector, introducing technologies such as mobile payments, digital lending, and big data analytics (IFWG, 2021). Regulatory initiatives, including the Intergovernmental Fintech Working Group, have supported this evolution by promoting frameworks that balance innovation with financial stability. Despite these developments, empirical research remains limited, with most studies focusing on competition and inclusion rather than productivity or labour outcomes

Mhlongo et al. (2025) employed panel regression on JSE-listed banks for the period 2000–2023 to examine fintech's influence on competition and performance. Their findings indicate that fintech adoption has intensified competition, particularly through mobile transactions, but has not significantly improved profitability metrics, suggesting that traditional banking structures remain dominant.

Coetzee (2018) investigated the strategic implications of fintech on South African retail banks using a qualitative, post-positivist approach during 2018. The study identifies several key trends. Namely, technology-based skills are becoming mandatory for staff and regulators. Furthermore, client interaction policies are shifting toward remote-based distribution with physical branches declining in relevance as digital-only competitors enter the market. The diminishing importance of branches has direct implications for employment within the banking sector, underscoring the need for studies like the present one that examine how fintech-driven structural changes affect labour productivity and workforce dynamics.

Mungai (2019) adopted a mixed-methods design, combining quantitative analysis of FinScope data (2012–2015) with interviews to assess fintech's role in financial inclusion and digital disruption. The research reveals that while approximately 80% of adults are financially included through formal banking channels, structural barriers persist for low-income groups despite high mobile penetration. Fintech has improved access and transaction efficiency but has not fully addressed systemic challenges related to affordability and infrastructure.

Collectively, these studies demonstrate fintech's growing influence on competition, strategic positioning, and inclusion within South Africa's banking sector. However, to date, its influence on labour productivity and employment outcomes remains unexplored, underscoring the necessity of localized research into these aspects.

Table 2.2 below provides a summary of empirical studies addressing fintech effects in developing countries. While quantitative modelling predominates, with varied methodological approaches, most studies conclude that fintech adoption positively influences economic outcomes.

Table 2.2. Summary of Findings from Developing Countries

Author	Region	Methodology	Findings
Akinola (2021)	Sub-Saharan Africa	Surveys, personal interviews and secondary data analysis	The development of digital payments business and FinTech ecosystems are having a synergistic positive impact on the economic well-being of developing countries.
Coetzee (2018)	South Africa	Qualitative (post-positivist, strategic analysis)	Fintech innovations have influenced the declining relevance of branches with increasing digital only competitors.
Diep and Canh (2022)	Vietnam	Descriptive statistics, Testing the reliability of Cronbach's Alpha scale, Exploratory factor analysis and confirmatory factor analysis and Testing of SEM structural models using IBM SPSS Statistics and IBM SPSS Amos	P2P Fintech provides products with a better customer experience, and there is a change in customer payment trends with users increasingly favouring digital channels over traditional banking methods.
Mhlongo et al. (2025)	South Africa	Panel regression on JSE-listed banks	Fintech increases competition but does not significantly improve profitability.
Mungai (2019)	South Africa	Mixed methods (Finscope data + interviews)	Fintech improves financial inclusion and transaction efficiency,

			but structural barriers persist.
Sethi (2022)	India	Principal component analysis (PCA) and ARDL framework	Fintech adoption has supported India's economic growth, income per capita and official exchange rate.
Song (2022)	China	The neoclassical aggregate production function (APF), the instrumental variable generalized method of moments and Dumitrescu and Hurlin causality test	Fintech and the sub measures of third-party payment, credit, and insurance have a statistically significant positive effect on China's economic growth

Source: compilation by author

Although the reviewed studies provide valuable insights into fintech's role in expanding financial access and supporting economic development across developing economies, several limitations remain. Beck (2020) highlights how fintech helps overcome long-standing cost and risk barriers, yet the analysis does not quantify how these improvements translate into labour-market or productivity outcomes within financial institutions. Similarly, Sethi (2022) demonstrate that fintech reduces transactional costs and promotes financial inclusion across India, but their findings on employment are mixed with evidence of enhanced access and declining job opportunities. Akinola's (2021) mixed-methods study captures the growth of fintech ecosystems but focuses primarily on inclusion and entrepreneurship, rather than productivity and labour dynamics. Song (2022) shows that digital finance significantly contributes to China's economic growth, yet the study does not examine whether these gains stem from labour augmentation or labour substitution. Likewise, Diep and Canh (2022) document shifting consumer behaviour in Vietnam without assessing broader economic or employment effects. Collectively these studies highlight important trends but leave unresolved questions regarding both short and long-run implications of fintech for labour productivity and employment in developing country banking sectors, underscoring the need for more targeted sector specific empirical research.

2.4 Conclusion

This chapter examined the convergent views of Classical, Austrian, and Keynesian economists, all acknowledging the significant influence of technology on firm-level efficiencies. The consensus among these theories underscores technology's growing impact on differentiating operational effectiveness across enterprises. Each school regards technology as both a facilitator and a catalyst for other production factors.

Additionally, the chapter evaluated empirical findings from developed and developing countries. Despite fintech's emergence as a contemporary research area, substantial gaps persist in both regions. The literature typically reports either mixed outcomes or a positive relationship between fintech and variables such as output, productivity, demand, and growth. Furthermore, the scarcity of prior empirical studies focused on South Africa underscores the novelty of this research and its potential contribution to knowledge, as it provides localized insights into fintech’s impact on labour dynamics and productivity in South African banking, an area that remains largely unexplored.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter delineates the data sources and methodological strategies implemented in this study. To assess the influence of Fintech on selected variables within South Africa's banking sector, the Autoregressive Distributed Lag (ARDL) framework is employed. As highlighted in the literature review (Chapter 2), previous studies have adopted this approach. The ARDL framework is particularly suited to this analysis due to its capacity to accommodate variables of mixed integration orders and its robustness in evaluating data characteristics. The methodology adopts a systematic procedure comprising the identification of fintech indicators, data collection, ARDL modelling, cointegration analysis, as well as diagnostic and stability testing.

The subsequent sections of this chapter are organised as follows: Section 3.2 describes the data sources and details the model specification; Section 3.3 explains the econometric estimation techniques and their application; Section 3.4 addresses the diagnostic tests conducted to ensure reliability and model stability; Section 3.5 defines the principal terms and variables utilised in the research; and Section 3.6 offers concluding remarks summarising the methodological approach.

3.2 Data Sources, Model Specification and Definitions

This study utilises quarterly time series data covering the period from 2010Q1 to 2022Q4, resulting in a total of 52 observations. The endpoint of 2022Q4 was selected based on the availability of complete and reliable data. The dataset is suitable for analysis as it encompasses both the perspectives of banks and their clients. The selected timeframe enables the research to capture the transformation within South Africa's fintech sector. The year 2010 represents a notable juncture when significant developments in contemporary FinTech innovation and digital financial services began to emerge (IFWG, 2020). Furthermore, commencing the analysis in 2010 allows for examination of trends prior to the COVID-19 pandemic, thus facilitating an assessment of the acceleration in FinTech adoption during the pandemic.

The pandemic is widely recognised for expediting digital transformation and increasing the adoption of FinTech solutions, primarily due to social distancing measures and economic disruptions (Arner et al., 2020; Ozili, 2020). The collected data comprises the number of electronic fund transfers processed during the period (serving as the fintech indicator), the index of employment levels in financial institutions (representing employment level), total gross operating income for the banking sector (which, divided by employment level, yields labour productivity), the repo rate, and the inflation rate. The data is sourced from the South African Reserve Bank. The number of electronic fund transfers acts as the explanatory variable, as elaborated in Section 3.2.2 below.

3.2.1 Definition of Terms

3.2.1.1 Fintech

Leong and Sung (2018) describe fintech as "a cross-disciplinary subject that combines finance, technology management and innovation management." Their expanded definition encompasses "any innovative ideas that improve financial service processes by proposing technology solutions tailored to various business contexts. These ideas may also give rise to new business models or even entirely new enterprises."

Mention (2019) further develops this concept, characterising fintech as a broad array of services including mobile banking applications, payment platforms, cryptocurrencies, and machine learning applications. Mention (2019) therefore regards fintech as a comprehensive term encompassing innovative, technology-enabled financial services and the associated business models.

While Mention's (2019) definition reflects current developments in fintech, it does not necessarily surpass the scope offered by Leong and Sung (2018). Mention highlights the evolving nature of fintech innovations, noting the importance of an inclusive definition that can accommodate a wide range of developments, businesses, and processes. Consequently, the definition provided by Leong et al. remains valuable for its blend of specificity and adaptability, offering a robust foundation for examining the complexities of fintech and its influence on the financial industry. Accordingly, for the purposes of this study, 'Fintech' refers to a broad spectrum of innovative technologies that enhance financial services and their related business models.

3.2.1.2 Fintech Adoption and Diffusion

Fintech adoption and diffusion, as considered in this research, pertain to both the implementation of fintech innovations by banks within the South African banking sector and the extent to which these fintech instruments are utilised by the banks' clients. While a bank may introduce a new fintech innovation (adoption), its impact cannot be fully assessed unless clients actively engage with the service. Consequently, analysing the volume of digital transactions conducted via banks enables an evaluation of not only the level of fintech adoption within the sector but also the rate of client engagement (diffusion) with these fintech solutions.

3.2.1.3 Employment and Unemployment

In this research, employment is defined as the deployment of labour resources to produce goods and services. This encompasses both full-time and part-time personnel. Accordingly, the employment rate denotes the metrics and indices used to assess the proportion of individuals who are employed relative to those who are unemployed.

3.2.1.4 Labour Productivity

Labour productivity, as defined in this research, denotes the quantity of output generated per unit of labour input. Typically, productivity is assessed by measuring output per hour worked or per worker, contingent upon the chosen employment metric. Thus, productivity serves as an indicator of both efficiency and competitiveness, illustrating the effectiveness of labour utilisation within the production process.

Classical economic theory, particularly Adam Smith's work (1776), underscores the significance of the division of labour as a primary factor influencing productivity. Smith's foundational concept of the "invisible hand" posits that free markets facilitate efficient resource allocation, thereby maximising productivity. Additionally, specialization enables workers to concentrate on distinct tasks, enhancing expertise and minimising time lost due to task-switching, which further bolsters productivity (Smith, 1776). In Robert Solow's neoclassical growth model, technological advancement is identified as a critical determinant of sustained economic growth and labour productivity. According to Solow (1956), absent technological progress, economies are subject to diminishing returns to capital and labour. Consequently, productivity growth is realised when technological improvements enable increased output from unchanged labour inputs.

3.2.2 Explanation of variables

3.2.2.1 Fintech Indicator

The selection of an appropriate fintech indicator is crucial for accurately capturing the extent of fintech adoption and its impact on relevant banking sector variables. In this study, the fintech indicator functions as a key variable to assess how fintech adoption influences core banking outcomes such as employment and productivity. By effectively representing the spread of fintech, the indicator enables the model to estimate both short-term and long-term relationships between fintech and economic performance. A reliable proxy is especially significant in the ARDL model, which requires robust variables to reflect nuanced dynamic adjustments over time.

Previous research on fintech adoption has utilised various fintech-related metrics as indicators or proxies (Sethi et al., 2022: 8). For instance, Narayan et al. (2018) employed the number of fintech firms to analyse macroeconomic effects of fintech in Indonesia, while Sethi (2022) examined the impact of fintech adoption in India by selecting the number of ATMs and mobile and fixed broadband subscriptions, primarily due to limitations in available data on financial service providers from 2001 to 2020.

To measure fintech adoption and diffusion in South Africa's banking sector, this study distinguishes itself from prior work by employing electronic transaction volumes as the primary indicator. This approach reflects the level of digital banking activity facilitated through financial technology, offering a suitable proxy for the degree of fintech integration within the sector. Specifically, the variable used is the number of electronic fund transfers (SARB KBP1264), as reported by the South African Reserve Bank.

This metric encompasses all digital transaction channels, including mobile banking, internet banking, banking applications, and other bank-specific digital products (SARB, 2024). Consequently, this study replaces previously selected indicators (ATMs, mobile and broadband subscriptions, number of fintech firms) with electronic transaction volumes to more comprehensively capture fintech adoption and diffusion within South Africa's banking industry.

3.2.2.2 Dependent Variables

The dependent variables utilized in this study are the employment index (Employ) and labour productivity (LProd). These variables were selected based on their relevance as demonstrated in prior research referenced in the literature review, where similar metrics were employed.

Employment (Employ), as defined in this context, is measured by an index provided by the South African Reserve Bank that reflects employment levels within private sector financial institutions (KBP7007). While banks constitute a significant proportion of these institutions, the data also encompasses non-banking entities such as insurance companies. Due to limitations regarding banking-specific employment data, this variable serves as a proxy for banking sector employment.

Labour productivity (LProd) is assessed based on the efficiency with which the banking sector utilises its human resources to generate output. Specifically, it is calculated as the gross operating income of the banking sector divided by the employment level.

The interest rate (IR), specifically the repurchase rate (repo rate), is the primary monetary policy instrument employed by the South African Reserve Bank (SARB) to manage inflation (Leshoro 2014:524). Its inclusion in the model is warranted given its significant influence on borrowing costs for both banks and their clientele. Similarly, the inflation rate (INF) captures the pace at which general price levels increase over time, reducing purchasing power (Munyeka, 2014:120). Inflation is incorporated into the model due to its effects on consumer behaviour and its interaction with interest rates.

To enhance model interpretability and address heteroskedasticity, select variables were transformed using natural logarithms. Logging labour productivity, employment, and fintech variables assists in linearizing exponential relationships and stabilising variance across observations. This transformation facilitates elasticity interpretation of coefficients, with logged variables indicated by the prefix L_ in estimation outputs.

Additionally, a dummy variable was introduced in the labour productivity model to account for structural shifts during the COVID-19 pandemic. This binary indicator equals 1 for quarters within the pandemic period (2020Q1-2021Q4) and 0 otherwise, allowing the regression to capture disruptions in labour productivity arising from reduced economic activity, lockdown measures, and the accelerated adoption of digital solutions. The dummy variable was omitted from the employment model due to diagnostic issues, such as potential overfitting or multicollinearity.

A squared term for the fintech variable was also included in both models to detect nonlinear effects, thereby capturing either diminishing or increasing impacts of fintech adoption on labour productivity and employment.

In alignment with established theoretical frameworks and empirical evidence, this research posits that greater adoption and diffusion of fintech within South Africa's banking sector will positively influence labour productivity. Conversely, a negative association is anticipated between fintech adoption and employment levels, reflecting the potential for digital transformation to displace labour within financial institutions.

3.2.3 Model specification

Two models, equation 3.1 and 3.2, will be estimated in this study. Labour Productivity (LProd) and Employment (Employ) and the functional form of the models will take the following shape:

- Model 1: Labour Productivity as the dependent variable

$$LLProd = \beta_0 + \beta_1 LFintech + \beta_2 LFintech^2 + \beta_3 Repo + \beta_4 INFL + \beta_5 DCovid + \varepsilon_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where:

LLprod is the natural logarithm of labour productivity, calculated as Gross Income / Labour Input.

LFintech is the natural logarithm of the number of electronic fund transfers, used as a proxy for fintech adoption and diffusion.

$LFintech^2$ is squared term of the fintech indicator, included to capture potential nonlinear effects of fintech adoption.

Repo represents the repurchase rate (interest rate)

INFL represents the inflation rate

DCovid is a binary variable equal to 1 during the COVID-19 pandemic period (2020Q2 – 2021Q4) and 0 otherwise, used to isolate pandemic-related structural effects.

β_0 represents the intercept or constant term in the regression equation (the value of the dependant variable when the independent variable is zero.

β_1 to β_5 are the coefficients associated with each explanatory variable, indicating the magnitude and direction of their impact on the dependent variable.

ε1 denote the error term or residuals in each regression equation, capturing the difference between the actual and predicted values of the dependent variable.

- Model 2: Employment as the dependent variable

$$LEmploy = \beta_0 + \beta_1 LFintech + \beta_2 LFintech^2 + \beta_3 Repo + \beta_4 INFL + \varepsilon_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.2)$$

Where:

LEmploy denotes the natural logarithm of employment levels, as measured by the South African Reserve Bank Index for private sector financial institutions. The remaining variables retain their definitions as previously outlined.

As illustrated in equations 3.1 and 3.2 above, this study estimates the coefficients within the ARDL framework to evaluate the effects of fintech adoption on labour productivity and employment, respectively.

3.3 Econometric Estimation Technique

3.3.1 Stationarity tests

One of the key concerns in time series econometrics is stationarity. A time series is classified as stationary when its mean and variance remain constant over time. Moreover, the covariance between any two periods is determined solely by the lag between them, rather than by the specific time at which it is calculated (Gujarati, 2010).

While early approaches often assumed that time series were stationary or displayed stationarity around a deterministic trend, recent advancements in econometric theory indicate that many time series are non-stationary (Nkoro, 2016). Consequently, time series data may deviate from their mean over time, and non-stationarity can result in misleading or inaccurate classical regression estimates (Gujarati, 2010). To address this challenge, econometric analysis has increasingly focused on cointegration, which provides a robust framework for assessing long-run equilibrium among variables (Nkoro, 2016). Cointegration essentially tests whether variables that are stationary at levels exhibit co-movement in the long run. Notably, the ARDL approach does not necessitate pretesting for unit roots. Nevertheless, in this study, the unit root test will be applied to ensure the variables are not integrated of order two [I(2)].

Prior to implementing any modelling framework, it is essential to evaluate the stationarity of the data. In this research, stationarity is examined using unit root tests, specifically the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) methods, which have been widely adopted in comparable studies (Sethi et al., 2022).

The ADF and PP tests (see Equations 3.3 and 3.4 below) incorporate lagged differences of the dependent variable to account for autocorrelation. The specific form of the test equations may vary according to the characteristics of the data.

1. No constant or trend: Used when the data is purely random or stochastic.
2. With a constant: Used for data with a non-zero average (mean).
3. With a constant and trend: Used when the data shows a clear upward or downward trend over time.

Augmented Dickey Fuller Test (ADF Test):

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{\{t-1\}} + \sum_{\{i=1\}}^{\{p\}} \delta_i \Delta Y_{\{t-i\}} + \epsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

Phillips-Perron Test (PP):

$$\Delta \mathrm{Yt} = \alpha + \beta \mathrm{t} + \gamma Y_{t-1} + \epsilon \mathrm{t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

The null hypothesis (H_0 : γ = 0) states that the series has a unit root (non-stationary)

The alternative hypothesis (H_1 : γ < 0) indicates stationarity.

Where:

- ΔY_t = Dependent Variable
- α = Intercept.
- β = time trend coefficient.
- t = Time trend.
- γ = Coefficient testing the null hypothesis.
- δ_i = Coefficients of lagged terms.
- p = Number of lagged differences.
- ϵ_t = Error term.

The test statistic obtained from is evaluated against critical values from non-standard distributions, as established by Dickey and Fuller (Dickey et al., 1979). Referencing relevant literature that investigates analogous data contexts (Sethi et al., 2022), this study posits that the unit root tests are expected to indicate the presence of both stationary and non-stationary time series variables. This would support the application of a mixed-order model, such as the Autoregressive Distributed Lag (ARDL) model. Should all variables be stationary at level [I(0)], the Ordinary Least Squares (OLS) method is considered suitable. If all variables are integrated of order one [I(1)], the ARDL approach remains applicable. When variables comprise a combination of I(0) and I(1), the ARDL model is identified as the preferred estimation technique.

3.3.2 ARDL Bounds Co-integrating test and Error Correction Model (ECM) approach

The Autoregressive Distributed Lag (ARDL) cointegration technique serves as a robust method for identifying long-run relationships among variables with differing integration orders (i.e., both stationary and non-stationary series). This approach also facilitates the reparameterization of time series into the Error Correction Model (ECM), thereby establishing a connection between short-run dynamics and long-run associations among variables. Consequently, the ARDL framework is widely utilised in econometric analysis to investigate dynamic interactions in time series data, accommodating both short-term and long-term effects (Kripfganz, 2018).

The theoretical basis of the ARDL methodology is grounded in cointegration theory, which describes an equilibrium relationship over the long run among non-stationary variables (Yussuf, 2022). When cointegration exists, deviations from equilibrium are typically transitory, as the variables tend to adjust over time to restore balance (Yussuf, 2022).

A notable advantage of the ARDL model lies in its versatility: it permits the examination of cointegrating relationships involving variables that are either stationary, non-stationary, or a combination thereof (integration of order zero, I(0), and order one, I(1)) (Nkoro, 2016). However, in the context of mixed orders of integration, the dependent variable is required to be I(1). This flexibility renders the ARDL model particularly attractive for empirical economic research, where datasets often comprise variables of different integration orders. It should be noted, however, that the applicability of ARDL is limited to cases involving only I(0) and I(1) variables; it is not suitable for variables integrated of order two or higher. Through the ARDL approach, both short- and long-run dynamics can be estimated within a single equation, thereby eliminating the necessity for separate estimations associated with traditional cointegration techniques.

The standard specification of the ARDL model for analysing the relationship between a dependent variable Y and an independent variable X is as follows (Gujarati, 2010):

$$Y_t = c + \sum_{\{i=1\}}^{\{p\}} \alpha_i Y_{\{t-i\}} + \sum_{\{j=0\}}^{\{q\}} \beta_j X_{\{t-j\}} + \epsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3.5)$$

where:

- Y_t is the dependent variable at time t
- X_t is the independent variable at time t,
- α_i and β_j are the coefficients of lagged terms,
- c is a constant,
- ϵ_t is the error term,
- p and q are the lag orders for Y and X, respectively.

The Bounds Testing procedure is utilized to assess the presence of long-run relationships among variables by testing the null hypothesis of no cointegration. The outcome is based on the calculated F-statistic: if it exceeds the upper bound critical value, the null hypothesis is rejected, signifying a long-run relationship. Conversely, if the F-statistic does not surpass the lower bound, the null hypothesis is retained, indicating no cointegration. If the value falls between the bounds, the result remains inconclusive and may necessitate additional analysis or alternative cointegration methods to verify any long-run association. Upon confirming cointegration, the ARDL framework is employed to estimate both the short-run dynamics and the long-run equilibrium relationships among the variables. The models specified within the ARDL framework are outlined as follows:

- Model 1: Labour Productivity as the dependent variable

$$\begin{aligned}\Delta\,\mathrm{LLprod_t} = {}& \beta_0 + \sum_{\{i=1\}}^{\{n\}} \alpha_1\Delta\,\mathrm{LLprod_{t-i}} + \sum_{\{i=1\}}^{\{n\}} \alpha_2\Delta\,\mathrm{LFintech_{t-i}} + \sum_{\{i=1\}}^{\{n\}} \alpha_3\Delta\,\mathrm{LFintech^2_{t-i}} \\ & + \sum_{\{i=1\}}^{\{n\}} \alpha_4\Delta\,\mathrm{Repo_{t-i}} + \sum_{\{i=1\}}^{\{n\}} \alpha_5\Delta\,\mathrm{INFL_{t-i}} + \sum_{\{i=1\}}^{\{n\}} \alpha_6\Delta\,\mathrm{DCovid_{t-i}} \\ & + \phi_1\mathrm{LLprod_{\{t-1\}}} + \phi_2\mathrm{LFintech_{\{t-1\}}} + \phi_3\mathrm{LFintech^2_{\{t-1\}}} + \phi_4\mathrm{Repo_{\{t-1\}}} \\ & + \phi_5\mathrm{INFL_{\{t-1\}}} + \phi_6\mathrm{DCovid_{\{t-1\}}} \\ & + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.6)\end{aligned}$$

- Model 2: Employment as the dependent variable

$$
\begin{aligned}
\Delta\, L\mathrm{Employt}_t \;=\; & \beta_0 + \sum_{\{i=1\}}^{\{n\}} \alpha_1\, \Delta\, LEmployt_{t-i} + \sum_{\{i=1\}}^{\{n\}} \alpha_2\ \Delta \mathrm{L}Fintech_{t-i} \\
& + \sum_{\{\mathrm{i}=1\}}^{\{\mathrm{n}\}} \alpha_3 \Delta\ \mathrm{LFintech}^2_{\mathrm{t-i}} + \sum_{\{i=1\}}^{\{n\}} \alpha_4\ \ \Delta\, Repo_{t-i} + \sum_{\{i=1\}}^{\{n\}} \alpha_5\, \Delta INF_{t-i} \\
& + \phi_1 L\mathrm{Employt}_{\{t-1\}} + \phi_2 LFintech_{\{t-1\}} + \phi_3 \mathrm{LFintech}^2_{\{\mathrm{t-1}\}} \\
& + \phi_4 Repo_{\{t-1\}} + \phi_5 INF_{\{t-1\}} \\
& + \mu_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3.7)
\end{aligned}
$$

The ARDL model may be further developed into an Error Correction Model (ARDL-ECM). This framework elucidates the adjustment process whereby short-run dynamics converge towards the long-run equilibrium. The rate of this adjustment is represented by the coefficient of the one-period lagged error correction term, which must be negative, statistically significant, and less than zero to indicate a stable long-run relationship (Nkoro, 2016). The ECM can be formulated as follows:

$$
\begin{aligned}
\Delta\, LLProd_t \;=\; & \beta_0 + \sum_{\{i=1\}}^{\{n\}} \alpha_1\ \Delta\, LLProd_{t-1} + \sum_{\{i=1\}}^{\{n\}} \alpha_2\ \Delta Fintech_{t-1} \\
& + \sum_{\{\mathrm{i}=1\}}^{\{\mathrm{n}\}} \alpha_3 \Delta\ \mathrm{LFintech}^2_{\mathrm{t-i}} + \sum_{\{i=1\}}^{\{n\}} \alpha_4\ \ \Delta\, Repo_{t-1} + \sum_{\{i=1\}}^{\{n\}} \alpha_5\ \Delta INF_{t-1} \\
& + \sum_{\{\mathrm{i}=1\}}^{\{\mathrm{n}\}} \alpha_6 \Delta\ \mathrm{DCovid}_{\mathrm{t-i}} + \lambda ECM_{\{t-1\}} \\
& + \mu_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.8)
\end{aligned}
$$

The one-period lag error correction term serves as an indicator of the extent to which disequilibrium from the preceding quarter is corrected. Its coefficient is an adjustment parameter that should be negative, less than one, and statistically significant; this value indicates how quickly variables revert to long-run equilibrium.

ARDL models enable researchers to estimate cointegration within a single equation, facilitating both estimation and interpretation, particularly in small samples where traditional cointegration methods may lack reliability. Additionally, ARDL methodology provides unbiased and efficient estimates of long-run relationships, even when explanatory variables are endogenous, thus offering robustness against common endogeneity issues in economic data (Nkoro, 2016). Upon confirming cointegration via the bounds test, it is necessary to estimate both the long- and short-run coefficients, with the former reflecting the equilibrium relationships among variables over time.

3.3.3 Sample Size and Model Limitations

The study acknowledges that the quarterly dataset spanning 2010Q1 -2022Q4 provides a relatively small sample for ARDL estimation, particularly once lags and first differences are incorporated, which reduces the effective number of observations and may affect the precision of estimated coefficients. Nevertheless, the ARDL framework remains appropriate for this analysis, as it is recommended for small-sample time-series settings and accommodates variables with mixed integration orders while estimating both short-run and long-run dynamics within a unified structure (Pesaran, Shin & Smith, 2001).

Although alternative approaches such as OLS with Newey-West corrections were considered, these models do not allow for the modelling of long-run equilibrium relationships which are central to the study's objectives. The findings should therefore be interpreted with awareness of the small-sample constraint, but the methodological choice remains justified given the nature of the research questions and data availability.

3.4 Diagnostic and Specification Tests

Maintaining the reliability and precision of model estimates is essential in empirical research. To evaluate the validity of model assumptions and to detect potential issues such as heteroskedasticity or parameter instability, researchers employ various diagnostic tests. These assessments are instrumental in ensuring the integrity of regression results. The subsequent sections will examine four key diagnostic procedures utilized in this study: the residual diagnostic test, which identifies heteroskedasticity; the stability test, which assesses the presence of parameter instability in regression models; the normality test, which determines whether residuals conform to a Gaussian distribution; and the autocorrelation test, which evaluates serial dependence among error terms.

3.4.1 Residual Diagnostic Test

Heteroskedasticity arises when the variance of the error terms in a regression model varies with the independent variables. This occurrence violates a key assumption of classical linear regression, which requires that error terms maintain constant variance (homoscedasticity). Although the presence of heteroskedasticity does not bias the estimates of regression coefficients, it renders the standard errors unreliable, potentially resulting in inaccurate hypothesis testing outcomes (Brooks, 2008).

The Breusch-Pagan Godfrey test is commonly employed to detect heteroskedasticity. Unlike other procedures, this test is particularly suitable for models with a moderate sample size and offers a robust mechanism for determining whether the variance of error terms remains constant across various levels of the independent variables. The null hypothesis asserts that the error terms possess constant variance (homoscedasticity); a significant test statistic (either F-statistic or chi-square) suggests evidence of heteroskedasticity (Breusch & Pagan, 1979; Godfrey, 1978).

When heteroskedasticity is identified, Ordinary Least Squares (OLS) estimates remain unbiased; however, standard error calculations become invalid. Remedial measures include transforming the data using the natural logarithm to stabilize variance, or employing Generalized Least Squares (GLS), which addresses heteroskedasticity by assigning weights to observations according to their variance (Greene, 2008). These approaches enhance the reliability and validity of regression analysis findings.

In addition to homoscedasticity, the Classical Linear Regression Model (CLRM) assumes the absence of correlation among error terms. Violation of this assumption leads to serial correlation, also known as autocorrelation (Brooks, 2008; Gujarati, 2010). The Durbin-Watson (DW) test is widely used to identify first-order autocorrelation by evaluating the relationship between consecutive error terms. A statistically significant DW statistic results in the rejection of the null hypothesis of no autocorrelation (Gujarati, 2010). However, the DW test is inappropriate for models incorporating lagged dependent variables or higher-order autocorrelation, as its detection capability is limited to adjacent error terms.

Consequently, this research utilizes the Breusch-Godfrey (BG) test, which facilitates the detection of higher-order serial correlation by including multiple lags of the error term in the auxiliary regression (Brooks, 2008). The null hypothesis of no autocorrelation is rejected if the BG test's chi-square statistic attains statistical significance. Serial correlation yields consequences analogous to those of heteroskedasticity, such as inefficient parameter estimation and compromised standard errors.

Furthermore, the CLRM presumes that error terms follow a normal distribution, characterized by symmetry about the mean and a kurtosis of three. Deviations from normality can be evaluated using the Jarque-Bera test, where rejection of the null hypothesis occurs if the p-value is statistically significant or if the residual histogram deviates markedly from a bell-shaped distribution (Brooks, 2008; Gujarati, 2010).

3.4.2 Stability Test

The Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests are recognized tools for detecting parameter instability in regression models. These methods are frequently favoured over alternatives such as the Chow test due to their independence from prior knowledge regarding the nature of parameter variation (Caporale & Pittis, 2004). Both tests operate under the null hypothesis that model parameters remain stable over time, with the alternative hypothesis indicating the presence of parameter instability.

The CUSUM test evaluates cumulative changes in residuals, which represent the discrepancies between observed and predicted values. If model parameters are stable, the CUSUM statistic should be approximately zero. A deviation of the CUSUM statistic beyond the standard error band of ±2 signals a significant shift, prompting rejection of the null hypothesis in favour of the alternative (Brooks, 2008).

In addition, the CUSUMSQ test evaluates changes in the variance of residuals. The statistic generated by this test ranges from zero to one, and concerns regarding parameter stability arise when it surpasses the standard error boundaries of ±2 (Brooks, 2008). Both the CUSUM and CUSUMSQ tests function as robust tools for monitoring model stability over time and detecting structural breaks or shifts in data patterns.

Moreover, the Ramsey RESET test is frequently utilized to assess model specification. Under its null hypothesis, the model is presumed to be correctly specified; however, a significant F-statistic or chi-square statistic indicates potential misspecification, warranting rejection of the null hypothesis (Brooks, 2008).

3.5 Conclusion

This chapter presents the methodology adopted to achieve the research objectives. The study primarily utilizes the ARDL approach due to its suitability for mixed-order variables and its empirical relevance to the research aims. Unit root testing is undertaken to evaluate the stationarity of the variables. Following ARDL bounds testing, the Error Correction Model (ECM) is applied to estimate both short-run and long-run coefficients. The subsequent chapter will provide a detailed analysis of the data and discuss the findings of the econometric assessment.

CHAPTER 4

DATA ANALYSIS AND EMPIRICAL RESULTS

4.1 Introduction

This chapter outlines the empirical results obtained through the implementation of the ARDL modelling framework. The analyses were conducted using EViews12 econometric software to carry out the required statistical computations. The findings from the ARDL models pertaining to labour productivity and employment are presented in distinct sections to facilitate a clear and comprehensive discussion of each dynamic.

Section 4.2 presents the outcomes of the unit root tests, which identify the order of integration of the time series variables. Section 4.3 investigates the cointegration relationships among the variables; it details the results of the ARDL bounds testing procedure and provides an analysis of both long-run and short-run coefficients, as estimated by the ARDL and ARDL-ECM methodologies. Section 4.4 summarises the results of various diagnostic tests. The chapter concludes with section 4.5, which offers final observations and remarks.

4.2 Unit Root Test Results

To evaluate the stationarity characteristics of the time series variables, both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were utilised. The corresponding results are detailed in Table 4.1. Prior to applying these tests, visual examination of the time series plots (refer to Appendix B) was performed to identify potential deterministic trends, thereby informing the selection between models incorporating solely an intercept or both an intercept and a trend in the ADF and PP procedures.

The variables Employment (Employ), Labour Productivity (LProd), and fintech exhibit pronounced upward trends over time, necessitating the inclusion of both intercept and trend components in their respective test specifications. Furthermore, fintech, employment, and labour productivity were log-transformed before testing and estimation. This logarithmic transformation not only standardises the distributions of variables with marked trends but also enables interpretation of estimated coefficients as elasticities, enhancing their economic relevance. It is noteworthy that unit root tests were conducted on the logged series, ensuring the order of integration aligns precisely with the ARDL model’s functional form. In contrast, Inflation (Infl) and the Repo Rate (Repo), which demonstrate volatile yet mean-reverting behaviour without consistent trends, were evaluated using intercept-only models.

The ADF test outcomes indicate that employment, labour productivity, fintech, the repo interest rate, and inflation are all non-stationary at level, but achieve stationarity after first differencing (see Table 4.1). The null hypothesis of a unit root is rejected at the 1% significance level for the first-differenced forms. As such, these variables are classified as integrated of order one, I(1). Consistent with these findings, the Phillips-Perron test results presented in Table 4.1 confirm that employment, labour productivity, fintech, the repo rate, and the inflation rate remain non-stationary at level but become stationary after first differencing.

In conclusion, both the ADF and PP tests robustly demonstrate that the variables are I(1). Since none of the variables are integrated of order two, I(2), employing the ARDL bounds testing approach is appropriate. This model is particularly suitable for the integration structure observed and ensures compliance with underlying statistical assumptions.

Table 4.1 Augmented Dickey-Fuller (ADF) and Phillips-Perrons (PP) Unit Root Test Results (t-Statistic)

ADF Test (t-statistic)					Conclusion
	Level		First Difference		
Variables	Intercept	Intercept and Trend	Intercept	Intercept and Trend	
L_Employ	-2.650	-2.028	-6.751***	-7.084***	I(1)
L_Lprod	-0.658	-3.823**	-7.325***	-7.224***	I(1)
L_Fintech	1.355	-1.905	-8.335***	-7.035***	I(1)
Repo	-2.583	-	-6.601***	-	I(1)
Infl	-2.846*	-	-7.624***	-	I(1)
PP test (t-Statistic)					
L_Employ	-2.688*	-2.116	-6.752***	-7.084***	I(1)
L_Lprod	-0.079	-3.823**	-19.234***	-21.220***	I(1)
L_Fintech	1.025	-2.262	-9.858***	-13.209***	I(1)
Repo	-2.679*	-	-6.636***	-	I(1)

Infl	-3.371**	-	-7.708***	-	I(1)

Source: Author's calculations

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

4.3 ARDL bounds cointegrating test results

4.3.1 Labour Productivity

The existence of a long-term cointegrating relationship between labour productivity and its explanatory variables was examined utilizing the ARDL bounds testing method. As detailed in Table 4.2, the analysis employed the AIC-selected optimal lag structure of ARDL (2,2,2,3,0,0). The computed F-statistic of 3.532 exceeds both the upper bound critical value (3.38) and lower bound critical value (2.39) at the 5% significance level, while falling between the respective 1% critical values. These results provide statistical evidence of cointegration among labour productivity, fintech, inflation, and the repo rate at the 5% significance threshold; however, this evidence is insufficient to confirm cointegration at the more stringent 1% level. Consequently, there appears to be a long-run equilibrium relationship among these variables, characterised by moderate strength during the period analysed.

Table 4.2 Labour Productivity – Model 1 F-Bound Test for Cointegration

Dependant Variable	Regressors	Asymptotic Critical Values						F-Statistic (Bound Test)
		10%		5%		1%		
		I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	
L_LProd	L_Fintech, L_Fintech_SQ, INFL, REPO, D_COVID	2.08	3.00	2.39	3.38	3.06	4.15	3.532**

Source: Author's calculations

Notes: ** denotes statistical significance at 5 % levels.

The Long-run and short-run effects are derived through the application of the ARDL model and ARDL-ECM model. The results of the coefficients are displayed in Table 4.3 below.

Table 4.3 Long and Short Run Estimated Coefficients – Labour Productivity

Long Run Estimated Coefficients – Labour Productivity				
Dependant	Regressors	Coefficients	Std. Error	t-Statistic
L_LPROD	L_FINTECH	-7.652	22.425	-0.341
	L_FINTECH_SQ	0.336	0.884	0.381
	INFL	17.732**	7.958	2.228
	REPO	6.530	4.133	1.580
	D_COVID	0.349*	0.197	1.767
	C	55.034	141.750	0.388
Short Run Estimated Coefficients – Labour Productivity				
Dependent	Regressor	Coefficient	Std.Error	t-Statistic
L_LProd	D(L_PROD(-1))	-0.504***	0.123	-4.089
	D(L_FINTECH)	18.032***	4.033	4.472
	D(L_FINTECH(-1))	16.975***	4.699	3.612
	D(L_FINTECH_SQ)	-0.688***	0.156	-4.401
	D(L_FINTECH_SQ(-1))	-0.654***	0.181	-3.606
	D(INFL)	1.503**	0.637	2.359
	D(INFL(-1))	-1.578**	0.750	-2.103
	D(INFL(-2))	-0.952	0.584	-1.629
	CointEq (-1)	-0.189***	0.035	-5.394

Source: Author’s calculations

Notes: *, ** and *** denote statistical significance at 10%, 5% and 1 % levels, respectively.

The long-run estimated coefficient of L_FINTECH is −7.652, reflecting a negative yet statistically insignificant relationship between Fintech adoption and labour productivity throughout the study period (see Table 4.3). This outcome suggests that variations in Fintech adoption, as measured by the model, do not exert a significant long-term impact on labour productivity within South Africa’s banking sector. Similarly, the squared term, L_FINTECH_SQ, presents a coefficient of 0.336, which is also statistically insignificant, indicating no evidence of nonlinear long-run effects associated with Fintech.

These results imply that Fintech's ability to improve productive efficiency within the banking industry may be limited by external factors. According to Keynesian theory, technological advancement does not inherently lead to increased productivity or employment without sufficient demand and supportive institutional frameworks (Keynes, 1936). Structural constraints, including inadequate digital skills, infrastructure gaps, and uneven adoption across client segments, may hinder Fintech's capacity to enhance productivity. In line with Keynesian perspectives, it is evident that investment in human capital and favourable macroeconomic conditions are essential for realizing the full productivity benefits of Fintech.

The coefficient for inflation (INFL) stands at 17.732, positive and statistically significant at the 5% level, suggesting that a 1% rise in inflation correlates with a 17.7% increase in measured labour productivity over the long term. This effect likely reflects nominal output changes during periods of inflation rather than genuine improvements in operational efficiency. Conversely, the repo rate (REPO) is positive, with a coefficient of 6.530, but lacks statistical significance, indicating no substantial long-run relationship between interest rates and labour productivity.

The COVID-19 dummy variable (D_COVID) has a coefficient of 0.349, positive and marginally significant at the 10% level. This may indicate a temporary uptick in labour productivity during the initial phase of the pandemic, possibly attributable to accelerated digital adoption and operational adjustments.

Collectively, these findings deviate from Solow's (1957, 1969) neoclassical growth model, which emphasizes technological progress as a principal driver of sustained productivity growth. Within the context of South Africa, the absence of statistically significant Fintech effects implies that its transformative potential in the banking sector remains nascent. Realizing these benefits will depend on investments in human capital, robust institutional support, and expanded digital infrastructure.

These findings are broadly consistent with empirical evidence from other economies. For example, Chinoracky et al. (2021) also reported that digitisation raises productivity primarily in the short run, with long run gains depending on firm digital maturity and other complementary investments. Similarly, Ang (2024) finds that fintech improves labour allocation efficiency in China, however, the magnitude if these gains diminish as adoption intensifies. This mirrors the diminishing marginal effects observed in the squared fintech term in this study. By contrast Chenic et al. (2023) identifies strong long run productivity improvements in EU countries, suggesting that South Africa's weaker long-run effects may reflect structural constraints such as skills shortages and uneven digital readiness.

It is noteworthy that short-run coefficients are presented in differenced form. According to the results (see Table 4.3), the first lag of labour productivity (D(L_PROD(-1))) is negative and highly significant at the 1% level, with a coefficient of −0.504. This signifies a pronounced short-term adjustment effect, where increases in productivity during the preceding period are partially offset in the current period, indicating a tendency toward short-term corrections following shocks.

The first lag of Fintech adoption (D(L_FINTECH(-1))) is positive and highly significant at the 1% level, with a coefficient of 16.975, indicating that a 1% increase in Fintech adoption in the prior period leads to a 17% increase in current labour productivity. The contemporaneous effect (D(L_FINTECH)) is likewise positive and highly significant at the 1% level, with a coefficient of 18.032, signifying immediate gains in labour productivity following Fintech adoption. However, the squared terms reveal a different dynamic: D(L_FINTECH_SQ) holds a coefficient of −0.688 at the 1% significance level, and D(L_FINTECH_SQ(-1)) is −0.654, both statistically significant and negative. These findings suggest that while Fintech fosters short-term productivity improvements, there is evidence of diminishing marginal returns or corrective responses when adoption accelerates excessively.

From a classical economic standpoint, this phenomenon reflects the law of diminishing marginal productivity of capital (Smith, 1776; Ricardo, 1817). Initial investments in Fintech produce notable productivity gains, but subsequent increments contribute increasingly less, and poorly integrated adoption may even reduce efficiency due to duplication, systemic friction, or adjustment costs.

Short-run effects of inflation are mixed. The second lag (D(INFL(-2))) is negative and statistically insignificant, while the first lag (D(INFL(-1))) is negative and significant at the 5% level, with a coefficient of −1.578. By contrast, the contemporaneous coefficient (D(INFL)) is positive and significant at the 5% level, at 1.503, suggesting that the impact of inflation shifts over time, with a 1% increase resulting in a 1.5% rise in labour productivity.

The error correction term (CointEq(-1)), with a coefficient of −0.189, is negative and highly significant at the 1% level, confirming a stable long-run equilibrium relationship among the variables. The magnitude of the coefficient indicates that approximately 18.9% of any disequilibrium between labour productivity and its long-term determinants is corrected each quarter, representing a moderate pace of adjustment as short-run deviations are gradually reconciled over time.

4.3.2 Employment

The existence of a long-run relationship between Employment (Employ) and its explanatory variables was evaluated using the ARDL bounds testing approach to cointegration. As presented in Table 4.4, the results are derived from the AIC-selected optimal lag structure of ARDL(5,5,5,2,3). The computed F-statistic of 14.083 surpasses both the lower and upper critical bounds, 4.37 and 3.29, respectively, at the 1% significance level. These findings provide evidence for a statistically significant cointegrating relationship among employment, fintech, the square of fintech, inflation, and the repo rate, thereby indicating a stable long-run equilibrium among these variables throughout the study period.

Table 4.4 F-Bound Test for Cointegration – Employment

Dependant Variable	Regressors	Asymptotic Critical Values						F-Statistic (Bound Test)
		10%		5%		1%		
		I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	
L_Employ	L_Fintech, L_Fintech_SQ, INFL, REPO,	2.2	3.09	2.56	3.49	3.29	4.37	14.083***

Source: Author's calculations

Notes: *** denotes statistical significance at 1% levels.

The Long-run and short-run effects are derived through the application of the ARDL model and ARDL-ECM model. The results of the long-run and short run coefficients are displayed in Table 4.5 below.

Table 4.5 Long Run and Short Run Estimated Coefficients – Employment

Long Run Estimated Coefficients – Employment				
	Regressors	Coefficients	Std. Error	t-Statistic
L_Employ	L_FINTECH	4.670**	1.771	2.638
	L_FINTECH_SQ	-0.189**	0.069	-2.756
	INFL	0.077	0.247	0.310
	REPO	1.172***	0.397	2.950
	C	-24.344**	11.416	-2.132
Short Run Estimated Coefficients – Employment				
Dependent	Regressor	Coefficient	Std.Error	t-Statistic
L_Employ	D(L_Employ(-1))	0.129	0.116	1.114
	D(L_Employ(-2))	0.158	0.122	1.296
	D(L_Employ(-3))	-0.173	0.125	-1.386
	D(L_Employ(-4))	0.324***	0.119	2.724
	D(L_FINTECH)	-2.074	1.534	-1.351
	D(L_FINTECH(-1))	-10.785***	1.461	-7.383
	D(L_FINTECH(-2))	-12.983***	1.766	-7.352
	D(L_FINTECH(-3))	-12.684***	1.734	-7.313
	D(L_FINTECH(-4))	-8.463***	2.032	-4.165
	D(L_FINTECH_SQ)	0.085	0.059	1.431
	D(L_FINTECH_SQ(-1))	0.432	0.058	7.481
	D(L_FINTECH_SQ(-2))	0.518	0.069	7.411
	D(L_FINTECH_SQ(-3))***	0.507	0.069	7.386
	D(L_FINTECH_SQ(-4))***	0.336	0.079	4.234
	D(INFL)	0.040	0.155	0.256
	D(INFL(-1))*	-0.267	0.141	-1.899
	D(REPO)***	0.930	0.273	3.402

	D(REPO(-1))	0.047	0.258	0.183
	D(REPO(-2))***	-0.761	0.260	-2.92
	CointEq (-1)***	-0.593	0.058	-10.183

Source: Author's calculations

Notes: ** and *** denote statistical significance at 10%, 5% and 1 % levels, respectively.

The long-run estimated coefficients presented in Table 4.5 indicate a statistically significant yet non-linear association between Fintech adoption and employment in South Africa's banking sector. The linear Fintech coefficient (L_Fintech) is positive (4.670) and statistically significant at the 5% level, suggesting that, at initial stages of development, increased Fintech adoption correlates with higher employment, such that a 1% rise in Fintech corresponds to a 4.67% increase in employment.

Conversely, the squared Fintech term (L_Fintech_SQ) is negative (–0.189) and also statistically significant at the 5% level, pointing to diminishing returns and potential adverse effects as Fintech intensity grows; specifically, each 1% increment is linked to a 0.189% decrease in employment. Notably, the negative impact from the squared term is less pronounced than the positive effect of the linear term, implying that higher Fintech adoption may exert downward pressure on employment, but the initial benefits outweigh subsequent reductions. Thus, the net long-run effect of Fintech on employment in South Africa's banking sector remains modestly positive.

The long run inverted U-shaped pattern identified here aligns with international evidence. Jiang (2021) shows that fintech exposure in the United States initially increases demand before reducing routine employment. This is consistent with the positive linear and negative squared fintech effects found in this study. Likewise, Sethi (2022) reports declining employment opportunities in India as fintech adoption accelerates, reinforcing the labour-substitution effect observed at higher levels of fintech diffusion. However, Akinola (2021) notes that fintech ecosystems in Sub-Saharan Africa can generate new entrepreneurial and support-service roles, which may explain the modest net positive long-run employment effect observed in South Africa.

This inverted U-shaped relationship aligns with Keynes's (1936) framework in The General Theory of Employment, Interest and Money, where technological innovation initially stimulates effective demand and fosters job creation through multiplier effects. In the short term, Fintech can expand banking employment by elevating demand for complementary roles in IT support, system integration, and product innovation.

Simultaneously, the findings reflect Classical theory, notably Ricardo's (1821) Principles of Political Economy and Taxation, which posits that technological progress substitutes capital for labour, reducing workforce requirements for routine functions. As such, evidence from South Africa demonstrates both compensatory effects described by Keynes in early phases of innovation and displacement effects noted by classical economists during advanced automation, resulting in the observed inverted U-shaped employment trend.

The Repo rate coefficient is positive (1.172) and statistically significant at the 1% level, indicating that a 1% increase in policy rates is associated with a 1.17% rise in banking sector employment, whereas a 1% decrease corresponds to a 1.17% reduction. This counterintuitive finding may reflect sector-specific dynamics, whereby tighter monetary policy enhances margins and operational expansion, indirectly supporting employment. In contrast, the inflation coefficient (0.077) is positive but statistically insignificant, signifying no discernible long-run influence of inflation on banking sector employment over the period studied. The constant term (–24.344) is negative and statistically significant at the 5% level, representing the baseline employment level when explanatory variables reach zero-log values.

In summary, these results demonstrate that the employment impact of Fintech is inherently non-linear, initially generating jobs before ultimately reducing them, albeit to a lesser extent than the initial creation. Consequently, the net long-run effect remains marginally positive, while interest rate policy exerts a robust and statistically significant influence. Inflation appears not to significantly affect long-term employment dynamics in South Africa's banking sector.

Short-run results in Table 4.5 offer insights into the dynamic adjustment of employment in response to changes in fintech activity, macroeconomic conditions, and deviations from long-run equilibrium. The one-period lag error correction term (CointEq (-1)) is negative and statistically significant at the 1% level, with a coefficient of -0.593, signifying that approximately 59% of any short-run disequilibrium is corrected within a quarter, a relatively rapid adjustment indicative of strong mean reversion towards the long-run path following shocks.

Regarding employment's autoregressive structure, most short-run lags are statistically insignificant except for the fourth lag (D(L_Employ (-4))), which is positive and significant

(0.324) at the 1% level. This outcome suggests that changes in employment materialise over several periods, likely reflecting hiring or restructuring delays within the banking industry.

The short-run influence of Fintech on employment is notable and non-linear. While the contemporaneous effect (D(L_FINTECH)) is negative (-2.074) and statistically insignificant, all four subsequent lags are negative and highly significant at the 1% level, ranging from -10.785 in the first lag to -8.463 in the fourth. These findings imply that increased Fintech adoption persistently reduces employment in the short term, potentially due to automation, digitalization of processes, and decreased demand for certain roles as technology is integrated.

Conversely, the squared Fintech term (D(L_FINTECH_SQ)) reveals a mitigating factor: though the contemporaneous coefficient (0.085) is insignificant, all four lags are positive and statistically significant at the 1% level, spanning from 0.432 in the first lag to 0.336 in the fourth. These results suggest that while initial Fintech adoption may temporarily reduce employment, sustained Fintech engagement generates new employment opportunities, particularly in areas related to digital platform management, cybersecurity, and specialised client services. This dynamic underpins a U-shaped short-run adjustment process—initial job losses followed by partial recovery as the sector adapts to technological advancements, consistent with the inverted U-shaped pattern observed in the long run.

From a classical economic perspective, this supports the notion that technological progress may temporarily displace labour, but ultimately boosts productivity, lowers costs, and increases output, thereby reintegrating workers into emerging sectors (Ricardo, 1817).

The macroeconomic variables tested in the model present a varied picture in the short run. The contemporaneous effect of inflation is negligible (0.040), with its first lag being weakly significant at the 10% level and negative (-0.267), suggesting inflationary pressures may slightly delay employment losses. The repo rate yields a significant immediate positive effect on employment (0.930), likely reflecting temporary profitability improvements supporting hiring or retention; however, by the second lag, this relationship turns negative (-0.761), highlighting that extended elevated interest rates may eventually constrain employment growth through increased borrowing and operating costs.

In conclusion, the short-run dynamics reveal that Fintech adoption initially disrupts employment, but subsequent lags show an increase as the banking sector acclimatises to new technological paradigms. Macroeconomic conditions, particularly interest rate shifts, play a moderating role, while inflation's influence is limited and delayed. Collectively, these findings underscore the transitional nature of technological change, wherein immediate disruptions may be offset over time by the emergence of new, technology-driven roles.

4.4 Diagnostic Test Results

Table 4.6 and Figures 4.1 and 4.2 present the outcomes of the diagnostic tests performed. These results demonstrate that the ARDL models estimated for Labour Productivity and Employment successfully passed a comprehensive suite of diagnostic evaluations.

The labour productivity (Lprod) model exhibits sound specification overall. Residual diagnostics indicate the absence of significant issues pertaining to autocorrelation, heteroskedasticity, or normality. Specifically, the LM test for serial correlation is not significant (F-statistic = 0.191, $p = 0.827$), indicating no concern regarding serial correlation. The Breusch–Pagan–Godfrey heteroskedasticity test (F-statistic = 0.765, $p = 0.697$) supports the presence of homoscedastic residuals, and the Jarque–Bera normality test (1.752, $p = 0.416$) further confirms the normal distribution of residuals.

The Ramsey RESET test yields a borderline result (F-statistic = 4.120, $p = 0.051$), meeting significance at the 5% level, which could suggest minor nonlinearity or omitted variables; however, the evidence is limited and does not materially affect the model's validity. Stability diagnostics provide additional confirmation of robustness: both CUSUM and CUSUM of squares plots (Figure 4.1) remain within critical bounds, with only brief periods approaching these limits. Importantly, the model restores and sustains stability across most of the sample, which highlights the reliability of the estimates.

For the employment (Employ) model, the diagnostic assessments confirm that it is generally well-specified. The Breusch–Godfrey LM test indicates no serial correlation (F-statistic = 0.715, $p = 0.501$), and the Breusch–Pagan–Godfrey test shows no evidence of heteroskedasticity (F-statistic = 0.670, $p = 0.830$). The Jarque–Bera normality test (1.706, $p = 0.426$) supports the assumption of normal residuals.

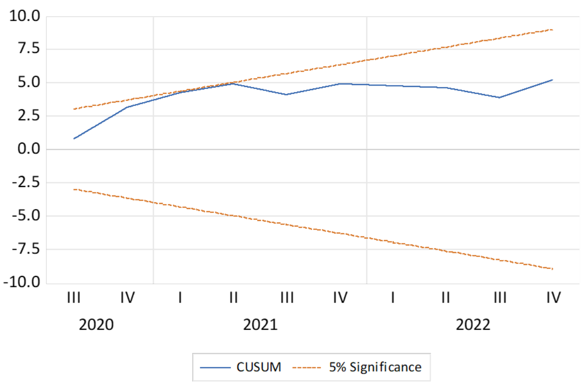
Additionally, the Ramsey RESET test is insignificant (F-statistic = 0.361, $p = 0.554$), confirming appropriate functional form specification. The stability diagnostics corroborate these findings, as both CUSUM and CUSUM of squares plots (Figure 4.2) remain comfortably within critical bounds throughout the evaluation period, affirming stable parameter estimates.

Collectively, all null hypotheses are retained, which suggests a robust and reliable specification. Nonetheless, results pertaining to labour productivity should be interpreted with measured caution.

Table 4.6 Diagnostic Tests

Source: Author's calculations

Test	Null hypothesis	Labour Productivity			Employment	
		Statistic		Prob.	Statistic	Prob.
Serial Correlation LM Test: Breush-Godfrey	Residuals are not serially correlated.	F-Stat:	0.191	0.827	0.715	0.501
		Obs*R-Squared	0.578	0.749	3.135	0.208
Heteroskedasticity Test: Breusch-Pagan-Godfrey	Residuals are homoscedastic (no heteroskedasticity).	F-Stat:	0.765	0.697	0.670	0.830
		Obs*R-Squared	11.736	0.628	19.843	0.706
Normality Test	Error term is normally distributed	Jarque Bera	1.752	0.416	1.706	0.426
Ramsey RESET Test	The model is correctly specified.	F-Statistic:	4.120	0.051	0.361	0.554
		t-Statistic	2.030	0.051	0.601	0.554



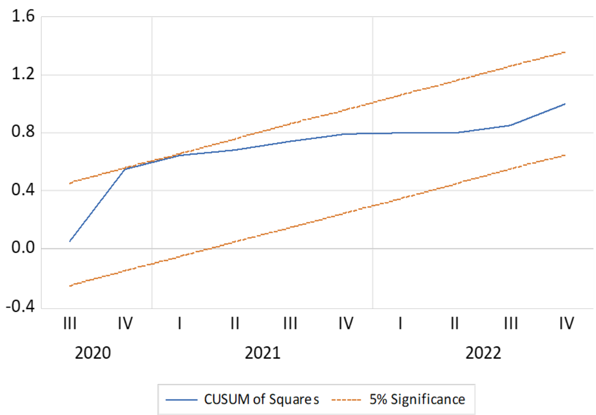


Figure 4.1 Labour Productivity CUSUM and CUSUM of Squares Test Results

Source: Author's compilation

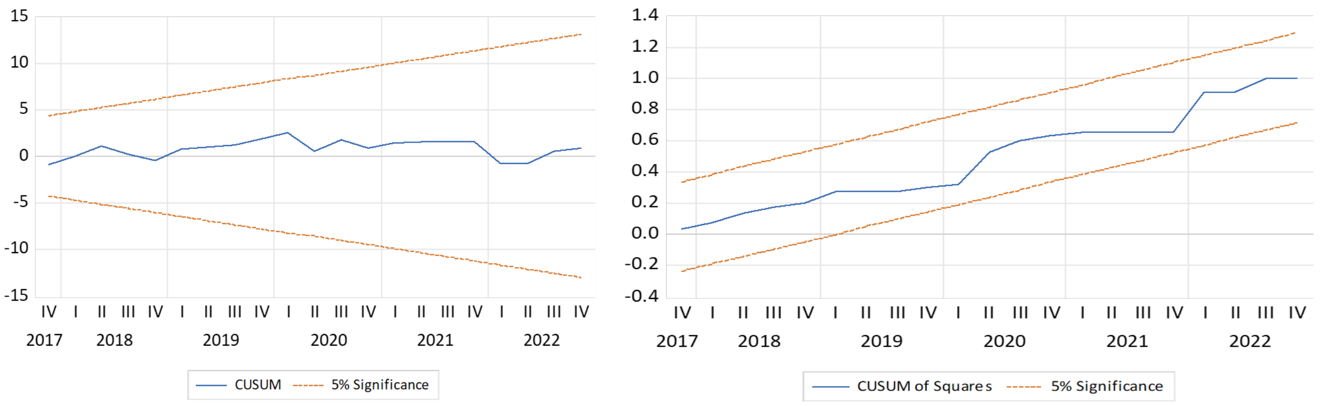


Figure 4.2 Employment CUSUM and CUSUM of Squares Test Results

Source: Author's compilation

4.5 Conclusion

The ARDL analysis provided in this chapter indicates that Fintech's impact on South Africa's banking sector from 2010Q1 to 2022Q4 is marked by limited long-term effects but significant, non-linear short-term fluctuations. The lack of notable long-run influences on labour productivity contrasts with Solow's (1957) neoclassical growth model, which emphasizes technological advancement as a persistent driver of productivity and economic expansion. This outcome implies that Fintech's transformative potential is largely dependent on supporting factors such as human capital development, robust institutions, and infrastructure enhancement.

In terms of employment, the findings reveal an inverted U-shaped pattern consistent with Keynes's (1936) framework which states that initial innovation can boost effective demand and employment via multiplier effects, yet as technology adoption progresses, Ricardo's (1821) classical theory suggests that capital increasingly replaces labour, ultimately resulting in employment reductions at advanced stages. The observed short-run outcomes support this transitional trajectory: although Fintech implementation yields immediate productivity improvements and deferred profitability gains, these are moderated by diminishing returns, labour displacement, and eventual recovery effects as the sector acclimates to new technological norms. Collectively, the empirical results highlight Fintech's dual function as both a driver of efficiency and a source of disruption.

CHAPTER 5

CONCLUSION

5.1 Introduction

This chapter summarises the main findings and recommendations, while direction for future research is also provided. Section 5.2 reviews the primary findings in relation to the stated research objectives. Section 5.3 offers informed insights and practical recommendations derived from the results. Section 5.4 discusses prospective avenues for further academic inquiry. Section 5.5 concludes with a synthesis of the implications of fintech adoption and diffusion within the South African banking sector.

5.2 Summary of Findings

This section synthesises the principal findings from the study's three core objectives; namely, to evaluate the landscape of fintech adoption, to analyse the economic impact of fintech adoption and diffusion on labour productivity in South African banks and lastly, to analyse the economic impact of fintech adoption and diffusion on employment within South African banks. Collectively these findings offer insights into the economic ramifications of fintech adoption within South Africa's banking sector.

The study's first objective examines the landscape of fintech adoption and diffusion, emphasizing its broader economic impact on the South African banking industry. A review of existing literature indicates that fintech innovations have fundamentally altered traditional financial systems in both developed and developing economies, albeit with varying outcomes. In advanced markets, fintech enhances operational efficiency and reduces transaction costs, particularly through customer-centric innovations (Mention, 2019; Beck, 2020). Conversely, developing economies encounter more intricate circumstances, where the influence of fintech is shaped by factors such as digital infrastructure, regulatory frameworks, and levels of financial literacy (Fu & Mishra, 2020; Naoyuki, 2023; Beck, 2020).

The literature generally asserts that fintech serves as a catalyst for enhanced efficiency. However, the sustained economic impact is governed by complementary investments and policy measures, highlighting that fintech's efficacy is determined by the structural and institutional conditions present within each economy.

Within South Africa, the proliferation of digital banking platforms, including for example Tyme Bank, and the notable increase in digital transactions reported by the South African Reserve Bank (SARB), exemplify robust fintech adoption (Louw et al., 2020). Despite these advancements, the broader economic implications remain multifaceted. Existing scholarship suggests that while fintech can foster financial inclusion and improve efficiency, its overall impact is contingent upon institutional readiness, encompassing infrastructure, human capital, and adaptability (Brown & Orsagh, 2021; Kowalewski, 2023). Additional concerns regarding technological unemployment and potential labour displacement are consistent with Keynesian viewpoints and the observations of Vasiljeva & Lukanova (2016), who discuss the disruptive nature of emerging technologies.

The second objective evaluates the effect of fintech adoption on labour productivity in South African banks utilising an ARDL modelling approach. Results from the bounds test indicate a cointegrating relationship, signifying a stable long-run equilibrium among the examined variables. Over the long term, fintech adoption reveals negative but statistically insignificant effects on labour productivity, while inflation demonstrates a positive and significant impact. The absence of non-linear long-run effects is evidenced by the statistical insignificance of the squared fintech term. These findings suggest that the capacity of fintech to bolster long-term labour productivity may be limited by structural constraints, such as the availability of digital infrastructure, workforce competencies, and institutional preparedness.

Short-run analysis, in contrast, identifies a strong and statistically significant positive correlation between fintech adoption and labour productivity. Both current and lagged fintech indicators exhibit immediate positive effects, although diminishing marginal returns are highlighted by the negative significance of squared terms.

The third objective explores the effect of fintech adoption on employment. The ARDL bounds test confirms a statistically significant cointegrating relationship, with long-term results indicating a modestly positive and significant effect of fintech on employment. The negative and significant squared fintech term points to an inverted U-shaped dynamic: initial fintech adoption stimulates job creation, but further adoption imposes downward pressure on employment growth.

In the short run, employment demonstrates a U-shaped response: early fintech adoption leads to reductions in employment across several lags, yet the positive and significant squared fintech term suggests partial recovery as firms adapt to technological changes. Error correction terms in both models are negative and significant, confirming stable long-run relationships. Adjustment towards equilibrium occurs at different rates, with approximately 18.9% of disparities in labour productivity resolved quarterly, compared to a swifter 59.3% correction rate for employment.

Collectively, these findings illustrate the nuanced opportunities and risks associated with fintech adoption in South African banking. While short-term gains in labour productivity underscore optimistic perspectives regarding efficiency (Jones & Williams, 2018), the lack of statistically significant long-term productivity benefits suggests that persistent infrastructural and institutional challenges may hinder sustained improvement (Brown & Orsagh, 2021).

Employment effects reveal a complex dynamic: significant short-term job displacement aligns with classical theories of technological unemployment (Ricardo, 1817; Dutta, 2006), whereas modest long-term gains reflect the creation of new roles in digital services, which supports both Keynesian multiplier effects and classical substitution theory. The observed diminishing returns further imply that excessive fintech adoption could ultimately dampen employment growth.

From a policy standpoint, these insights advocate for a balanced strategy, maximizing the advantages of fintech for productivity and inclusion while proactively addressing short-term job losses, digital inequality, and regulatory shortcomings. As recommended by Louw et al. (2020) and Geoffrey (2022), trust, demographic preparedness, and clear institutional frameworks are vital for effective fintech integration.

These results correspond closely to patterns documented in the empirical literature review. The short run productivity gains align with findings from Chinoracky et al. (2021) and Ang (2024), who show that fintech enhances efficiency but requires sustained investment to generate durable long-term improvements. The employment dynamics also mirror international evidence from Jiang (2021) and Sethi (2022). These studies observe initial job displacement followed by the emergence of new tech-complementary roles, while Akinola (2021) highlights the potential for fintech ecosystems to stimulate new employment channels in African markets. The South African experience therefore fits within broader global trends, while also reflecting local structural constraints.

The analysis provides partial support for the alternative hypothesis (H2), which posits that fintech innovations have economic impacts on the South African banking sector. The association between fintech adoption and increased labour productivity is validated in the short term but not in the long term. Similarly, employment effects are evident in the short run, with fintech diffusion contributing to reduced employment, while long-term findings reveal a more complex, non-linear pattern.

In conclusion, the results reflect both classical and Keynesian interpretations of technological advancement, short-term disruption followed by long-term adjustment. This study contributes to the body of literature by demonstrating that fintech's economic effects are dynamic, non-linear, and contextually dependent. Echoing Chinoracky et al. (2021) and Ang (2024), the research emphasizes the productivity potential of fintech, while noting that realization of these benefits in South Africa may be tempered by structural and institutional limitations. Ultimately, fintech is evolving as a productive resource, and its comprehensive inclusion within production theory alongside labour and capital remains a compelling avenue for future research.

5.3 Insights and Recommendations

Drawing on the principal insights and empirical results of this study, the following recommendations are advanced to inform policy formulation and strategic decision-making within South Africa's banking sector.

Policymakers are encouraged to facilitate innovation in financial technology (fintech) and promote the adoption and diffusion of fintech solutions. The findings reveal a robust and statistically significant short-term relationship between fintech integration and labour productivity. Consequently, decision-makers in banking, regulatory authorities, and other stakeholders should support digital adoption initiatives, such as investments in mobile banking platforms, digital payment systems, and customer-facing fintech innovations, that can generate immediate efficiency improvements.

In addition, it is advisable for companies to invest in both digital infrastructure and human capital to achieve sustainable long-term benefits. The absence of a significant long-run effect of fintech on labour productivity underscores the need for complementary factors, including an enhanced digital infrastructure, comprehensive employee training, and institutional readiness. Collaborative efforts by government and industry stakeholders to broaden broadband access in underserved communities, elevate digital literacy, and foster fintech start-ups as well as education and skills development, are essential.

Moreover, the management of short-term employment displacement resulting from fintech adoption requires attention. Empirical evidence indicates that increased fintech adoption may temporarily reduce employment levels during the first two years. To mitigate these challenges, policymakers should implement active labour market policies, including retraining programs for obsolete roles, digital upskilling towards emerging fintech-driven job markets, and transitional support for displaced workers, to facilitate workforce adaptation and minimize structural unemployment.

Finally, long-term employment gains associated with fintech adoption can be maximized through sustained innovation. While the study demonstrates eventual employment growth after the initial period of adjustment, returns tend to diminish over time. Stakeholders should therefore cultivate innovation ecosystems by supporting fintech entrepreneurs, advancing platform development, and creating opportunities in fields such as cybersecurity, data analytics, and digital compliance, thereby helping to sustain positive employment trends in the evolving digital economy.

5.4 Areas for Future Research

This study offers valuable insights into the influence of fintech on employment and labour productivity within South Africa's banking sector. Nonetheless, several avenues remain for further research:

Future studies may consider evaluating the expanding role of Artificial Intelligence (AI) in financial services. While the integration of AI was not addressed per se in this study, its increasing prevalence, through innovations such as chatbots, predictive analytics, and algorithmic lending, presents new opportunities for investigation. Subsequent research could explore how AI both disrupts and enhances productivity, employment, and financial performance.

Another promising direction would be to broaden the scope beyond the banking sector. Researchers might apply similar methodologies to other areas of the financial services industry, including insurance, asset management, and fintech startups, to determine if comparable trends exist across different segments in South Africa.

Additionally, future research could benefit from alternative methodological approaches. While this study employed a time series ARDL framework, panel data techniques such as panel ARDL or fixed effects models could facilitate comparative analyses across provinces or countries. This would enable assessment of how fintech's impact on productivity and employment varies according to institutional, regulatory, or infrastructural contexts. Furthermore, implementing nonlinear models like threshold regression or quantile regression may reveal whether the effects of fintech differ at various levels of adoption or economic development. Adopting these methodologies could provide a deeper understanding of fintech's economic implications.

5.5 Conclusion

This study examined the impact of fintech adoption and diffusion on employment and labour productivity within the South African banking sector between 2010Q1 and 2022Q4. Using a quantitative methods framework, the research uncovered both long and short-run dynamics, showing that the impacts of fintech are complex, nonlinear and shaped by the existing economic and technological conditions.

The findings confirmed that fintech adoption significantly boosts labour productivity in the short-run, but its long-run impact remains statistically insignificant. This suggests that sustained productivity gains require complementary investments in infrastructure, skills and institutional capacity. For employment, fintech exerts a short-run displacement, followed by partial recovery, with a modest net positive impact in the long-run. These results align with both Keynesian and Classical interpretations of technological change,

By incorporating control variables such as inflation and the repo rate, the study also demonstrated that macroeconomic conditions play a moderate role in shaping fintech's economic outcomes. Further, the inclusion of a COVID-19 dummy variable captures the structural shifts triggered by the pandemic, reinforcing the importance of adaptability in times of crisis.

However, this study recognises that the quarterly dataset provides a relatively small sample for ARDL estimation, particularly once lags and first differences are incorporated. While this may affect the precision of some coefficients, the ARDL framework remains suitable for small-sample time-series analysis, and the findings offer meaningful insights into the evolving relationship between fintech, labour productivity and employment in South Africa’s banking sector.

This research contributes to the growing body of literature on fintech’s economic implications by offering empirical analysis within the context of a developing country. Further, it underscores the need for balanced policy approaches that promote innovation while also protecting workers. As fintech continues to grow, its influence on employment and productivity will remain a critical area of inquiry. The aim of this study was to establish a foundational understanding of these dynamics within the South African context, emphasising the need for continued research, adaptive policy frameworks, and strategic investment to ensure that technological innovation fosters both inclusive and sustainable growth.

APPENDICES

Appendix A: Tables

Table A1 Utilised Data

Date	Fintech	Employ	Gross Operating Income	Lprod	Infl	Repo
Quarterly	Millions	Index	Total Banks	Gross Operating Income/Employment Index	Monthly % Averaged for Quarter	Monthly % Averaged for Quarter
	SARB Code: KBP1264	SARB Code: KBP7007	SARB BA120 Forms	Calculated by Author	SARB CPI Headline Index	SARB
2010 Q1	203713	91,8	R 37 204 289	R 405 275	7,7%	7,0%
2010 Q2	209970	93,5	R 37 543 101	R 401 530	4,5%	6,5%
2010 Q3	213892	94,4	R 38 976 375	R 412 885	3,4%	6,3%
2010 Q4	222522	95,5	R 41 784 325	R 437 532	3,4%	5,7%
2011 Q1	216959	95,3	R 40 063 230	R 420 391	3,8%	5,5%
2011 Q2	225365	96,7	R 41 284 502	R 426 934	4,7%	5,5%
2011 Q3	235085	97,7	R 43 454 744	R 444 777	5,4%	5,5%
2011 Q4	239617	97,1	R 45 354 239	R 467 088	6,0%	5,5%
2012 Q1	236597	97,5	R 45 714 241	R 468 864	6,1%	5,5%
2012 Q2	242548	98,2	R 47 960 205	R 488 393	5,7%	5,5%
2012 Q3	247877	98,4	R 47 675 197	R 484 504	5,2%	5,0%
2012 Q4	259742	98,1	R 55 124 742	R 561 924	5,7%	5,0%
2013 Q1	247378	98,6	R 50 116 443	R 508 280	5,7%	5,0%
2013 Q2	251853	99,2	R 50 345 200	R 507 512	5,7%	5,0%
2013 Q3	261279	99,8	R 53 393 980	R 535 010	6,2%	5,0%
2013 Q4	265808	99	R 55 753 039	R 563 162	5,4%	5,0%
2014 Q1	257493	99,1	R 52 498 945	R 529 757	5,9%	5,5%
2014 Q2	263845	98,3	R 55 488 552	R 564 482	6,5%	5,5%
2014 Q3	266982	98,2	R 59 792 176	R 608 882	6,3%	5,8%
2014 Q4	275949	98,5	R 60 766 731	R 616 921	5,7%	5,8%
2015 Q1	257891	99,1	R 59 436 981	R 599 768	4,2%	5,8%
2015 Q2	262263	99,4	R 58 405 508	R 587 581	4,6%	5,8%
2015 Q3	267783	100,1	R 59 110 616	R 590 516	4,7%	6,0%
2015 Q4	276541	101,4	R 64 249 393	R 633 623	4,8%	6,2%
2016Q1	265752	101,2	R 63 493 153	R 627 403	6,5%	6,8%
2016 Q2	275052	101,1	R 65 803 705	R 650 877	6,2%	7,0%

2016 Q3	280577	100,6	R 65 474 180	R 650 837	6,0%	7,0%
2016 Q4	286725	101,4	R 69 624 821	R 686 635	6,6%	7,0%
2017 Q1	278790	100,8	R 66 009 554	R 654 857	6,3%	7,0%
2017 Q2	286588	100,9	R 68 005 474	R 673 989	5,3%	7,0%
2017 Q3	293881	100,9	R 71 126 201	R 704 918	4,8%	6,8%
2017 Q4	308122	101,1	R 72 675 034	R 718 843	4,7%	6,8%
2018 Q1	305452	101,2	R 69 568 753	R 687 438	4,0%	6,8%
2018 Q2	336188	101,8	R 73 323 035	R 720 266	4,5%	6,5%
2018 Q3	356615	102,4	R 72 098 360	R 704 086	5,0%	6,5%
2018 Q4	369789	103,2	R 77 055 856	R 746 665	4,9%	6,7%
2019 Q1	372346	103,9	R 71 718 213	R 690 262	4,2%	6,8%
2019 Q2	404805	104	R 75 648 730	R 727 392	4,4%	6,8%
2019 Q3	412523	103,9	R 73 528 843	R 707 689	4,1%	6,5%
2019 Q4	445015	103,6	R 78 699 731	R 759 650	3,7%	6,5%
2020 Q1	407758	104,2	R 76 142 855	R 730 738	4,5%	5,9%
2020 Q2	367716	96,9	R 69 753 310	R 719 848	2,4%	3,9%
2020 Q3	433491	96,5	R 72 942 862	R 755 885	3,1%	6,5%
2020 Q4	479824	96,2	R 75 653 434	R 786 418	3,2%	6,5%
2021 Q1	441827	96,1	R 75 826 382	R 789 036	3,1%	5,9%
2021 Q2	457267	96,4	R 79 377 215	R 823 415	4,8%	3,9%
2021 Q3	454244	97,4	R 78 997 126	R 811 059	4,9%	3,5%
2021 Q4	529112	96,9	R 83 104 222	R 857 629	5,4%	3,7%
2022 Q1	498456	96,2	R 80 236 383	R 834 058	5,8%	4,1%
2022 Q2	463928	96,2	R 86 138 483	R 895 410	6,6%	4,6%
2022 Q3	518205	97	R 88 112 475	R 908 376	7,6%	5,8%
2022 Q4	556071	96,6	R 94 527 880	R 978 549	7,4%	6,8%

Table A2 Labour Productivity Model Estimation

Dependent Variable: L_LPROD
Method: ARDL
Date: 08/09/25 Time: 14:09
Sample (adjusted): 2010Q4 2022Q4
Included observations: 49 after adjustments
Maximum dependent lags: 3 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (3 lags, automatic): L_FINTECH L_FINTECH_SQ INFL REPO D_COVID
Fixed regressors: C
Number of models evaluated: 3072
Selected Model: ARDL(2, 2, 2, 3, 0, 0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
L_LPROD(-1)	0.306848	0.152671	2.009867	0.0524
L_LPROD(-2)	0.503948	0.146101	3.449307	0.0015
L_FINTECH	18.03231	5.123855	3.519286	0.0013
L_FINTECH(-1)	-2.505236	6.867579	-0.364792	0.7175
L_FINTECH(-2)	-16.97492	5.879457	-2.887159	0.0067
L_FINTECH_SQ	-0.688382	0.198508	-3.467778	0.0014
L_FINTECH_SQ(-1)	0.097685	0.264837	0.368849	0.7145
L_FINTECH_SQ(-2)	0.654335	0.227131	2.880878	0.0068
INFL	1.503315	0.815025	1.844502	0.0738
INFL(-1)	0.273720	0.955347	0.286514	0.7762
INFL(-2)	0.626439	0.958769	0.653379	0.5179
INFL(-3)	0.951548	0.678473	1.402485	0.1698
REPO	1.235464	0.758180	1.629513	0.1124
D_COVID	0.066015	0.023591	2.798377	0.0084
C	10.41274	23.11680	0.450441	0.6553

R-squared	0.985256	Mean dependent var	13.36901
Adjusted R-squared	0.979185	S.D. dependent var	0.213690
S.E. of regression	0.030830	Akaike info criterion	-3.873874
Sum squared resid	0.032317	Schwarz criterion	-3.294746
Log likelihood	109.9099	Hannan-Quinn criter.	-3.654154
F-statistic	162.2868	Durbin-Watson stat	2.105515
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Source: author's calculations

Table A3 Labour Productivity Long-Run Form and Bounds Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(L_LPROD)
Selected Model: ARDL(2, 2, 2, 3, 0, 0)
Case 2: Restricted Constant and No Trend
Date: 08/11/25 Time: 18:39
Sample: 2010Q1 2022Q4
Included observations: 49

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.41275	23.11680	0.450441	0.6553
L_LPROD(-1)*	-0.189204	0.096852	-1.953545	0.0590
L_FINTECH(-1)	-1.447850	3.720973	-0.389105	0.6996
L_FINTECH_SQ(-1)	0.063639	0.144449	0.440561	0.6623
INFL(-1)	3.355023	0.851888	3.938338	0.0004
REPO**	1.235464	0.758180	1.629513	0.1124
D_COVID**	0.066015	0.023591	2.798377	0.0084
D(L_LPROD(-1))	-0.503948	0.146101	-3.449307	0.0015
D(L_FINTECH)	18.03231	5.123855	3.519286	0.0013
D(L_FINTECH(-1))	16.97492	5.879456	2.887159	0.0067
D(L_FINTECH_SQ)	-0.688382	0.198508	-3.467778	0.0014
D(L_FINTECH_SQ(-1))	-0.654335	0.227131	-2.880878	0.0068
D(INFL)	1.503315	0.815025	1.844502	0.0738
D(INFL(-1))	-1.577988	0.846852	-1.863356	0.0711
D(INFL(-2))	-0.951548	0.678473	-1.402485	0.1698

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_FINTECH	-7.652313	22.42504	-0.341240	0.7350
L_FINTECH_SQ	0.336348	0.883927	0.380516	0.7059
INFL	17.73229	7.958017	2.228230	0.0326
REPO	6.529795	4.132985	1.579922	0.1234
D_COVID	0.348911	0.197476	1.766850	0.0862
C	55.03444	141.7498	0.388251	0.7003

EC = L_LPROD - (-7.6523*L_FINTECH + 0.3363*L_FINTECH_SQ + 17.7323
*INFL + 6.5298*REPO + 0.3489*D_COVID + 55.0344)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	3.532603	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
Actual Sample Size	49		Finite Sample: n=50	
		10%	2.259	3.264
		5%	2.67	3.781
		1%	3.593	4.981
			Finite Sample: n=45	
		10%	2.276	3.297
		5%	2.694	3.829
		1%	3.674	5.019

Source: author’s calculations

Table A4 Labour Productivity Error Correction Regression and Short Run Coefficients

ARDL Error Correction Regression
Dependent Variable: D(L_LPROD)
Selected Model: ARDL(2, 2, 2, 3, 0, 0)
Case 2: Restricted Constant and No Trend
Date: 08/11/25 Time: 18:40
Sample: 2010Q1 2022Q4
Included observations: 49

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(L_LPROD(-1))	-0.503948	0.123226	-4.089620	0.0003
D(L_FINTECH)	18.03231	4.032566	4.471671	0.0001
D(L_FINTECH(-1))	16.97492	4.699649	3.611956	0.0010
D(L_FINTECH_SQ)	-0.688382	0.156402	-4.401372	0.0001
D(L_FINTECH_SQ(-1))	-0.654335	0.181455	-3.606054	0.0010
D(INFL)	1.503315	0.637245	2.359085	0.0242
D(INFL(-1))	-1.577988	0.750310	-2.103114	0.0429
D(INFL(-2))	-0.951548	0.584023	-1.629298	0.1125
CointEq(-1)*	-0.189204	0.035079	-5.393702	0.0000

R-squared	0.701283	Mean dependent var	0.017610
Adjusted R-squared	0.641540	S.D. dependent var	0.047475
S.E. of regression	0.028424	Akaike info criterion	-4.118772
Sum squared resid	0.032317	Schwarz criterion	-3.771295
Log likelihood	109.9099	Hannan-Quinn criter.	-3.986940
Durbin-Watson stat	2.105515		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.532603	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

Source: author's calculations

Table A5 Employment Model Estimation

Dependent Variable: L_EMPLOYMENT
Method: ARDL
Date: 08/12/25 Time: 16:13
Sample (adjusted): 2011Q2 2022Q4
Included observations: 47 after adjustments
Maximum dependent lags: 5 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (5 lags, automatic): L_FINTECH L_FINTECH_SQ INFLATION REPO
Fixed regressors: C
Number of models evaluated: 6480
Selected Model: ARDL(5, 5, 5, 2, 3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
L_EMPLOYMENT(-1)	0.536567	0.177443	3.023883	0.0062
L_EMPLOYMENT(-2)	0.028717	0.237992	0.120663	0.9051
L_EMPLOYMENT(-3)	-0.331469	0.232981	-1.422732	0.1688
L_EMPLOYMENT(-4)	0.497709	0.212373	2.343565	0.0285
L_EMPLOYMENT(-5)	-0.324294	0.159254	-2.036325	0.0539
L_FINTECH	-2.073868	1.870043	-1.108995	0.2794
L_FINTECH(-1)	-5.943173	2.274891	-2.612509	0.0159
L_FINTECH(-2)	-2.197734	1.460646	-1.504631	0.1466
L_FINTECH(-3)	0.299178	1.346787	0.222142	0.8263
L_FINTECH(-4)	4.220704	1.864781	2.263377	0.0338
L_FINTECH(-5)	8.463248	2.744002	3.084271	0.0054
L_FINTECH_SQ	0.085124	0.072528	1.173682	0.2531
L_FINTECH_SQ(-1)	0.234588	0.088211	2.659396	0.0143
L_FINTECH_SQ(-2)	0.086263	0.057064	1.511680	0.1448
L_FINTECH_SQ(-3)	-0.010855	0.052592	-0.206400	0.8384
L_FINTECH_SQ(-4)	-0.171267	0.072309	-2.368537	0.0271
L_FINTECH_SQ(-5)	-0.335779	0.107190	-3.132564	0.0048
INFLATION	0.039837	0.204353	0.194944	0.8472
INFLATION(-1)	-0.261791	0.252510	-1.036756	0.3111
INFLATION(-2)	0.267343	0.180810	1.478588	0.1534
REPO	0.930037	0.403473	2.305079	0.0310
REPO(-1)	-0.188232	0.557330	-0.337739	0.7388
REPO(-2)	-0.808157	0.501484	-1.611530	0.1213
REPO(-3)	0.760972	0.339382	2.242231	0.0354
C	-14.43011	9.137143	-1.579280	0.1285

R-squared	0.971409	Mean dependent var	4.599113
Adjusted R-squared	0.940218	S.D. dependent var	0.024576
S.E. of regression	0.006009	Akaike info criterion	-7.086464
Sum squared resid	0.000794	Schwarz criterion	-6.102343
Log likelihood	191.5319	Hannan-Quinn criter.	-6.716133
F-statistic	31.14450	Durbin-Watson stat	2.214071
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Source: author's calculations

Table A6 Employment Long-Run Form and Bounds Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(L_EMPLOYMENT)
Selected Model: ARDL(5, 5, 5, 2, 3)
Case 2: Restricted Constant and No Trend
Date: 08/13/25 Time: 15:20
Sample: 2010Q1 2022Q4
Included observations: 47

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-14.43012	9.137143	-1.579282	0.1285
L_EMPLOYMENT(-1)*	-0.592770	0.138288	-4.286504	0.0003
L_FINTECH(-1)	2.768356	1.511533	1.831488	0.0806
L_FINTECH_SQ(-1)	-0.111926	0.059140	-1.892543	0.0717
INFLATION(-1)	0.045390	0.144485	0.314149	0.7564
REPO(-1)	0.694620	0.224384	3.095682	0.0053
D(L_EMPLOYMENT(-1))	0.129337	0.151838	0.851810	0.4035
D(L_EMPLOYMENT(-2))	0.158054	0.178409	0.885909	0.3852
D(L_EMPLOYMENT(-3))	-0.173415	0.193565	-0.895900	0.3800
D(L_EMPLOYMENT(-4))	0.324293	0.159254	2.036324	0.0539
D(L_FINTECH)	-2.073869	1.870043	-1.108996	0.2794
D(L_FINTECH(-1))	-10.78539	2.024364	-5.327792	0.0000
D(L_FINTECH(-2))	-12.98312	2.439743	-5.321514	0.0000
D(L_FINTECH(-3))	-12.68395	2.505446	-5.062550	0.0000
D(L_FINTECH(-4))	-8.463240	2.744001	-3.084270	0.0054
D(L_FINTECH_SQ)	0.085124	0.072528	1.173682	0.2531
D(L_FINTECH_SQ(-1))	0.431638	0.079845	5.405946	0.0000
D(L_FINTECH_SQ(-2))	0.517901	0.096503	5.366696	0.0000
D(L_FINTECH_SQ(-3))	0.507046	0.099094	5.116795	0.0000
D(L_FINTECH_SQ(-4))	0.335779	0.107190	3.132563	0.0048
D(INFLATION)	0.039837	0.204352	0.194945	0.8472
D(INFLATION(-1))	-0.267343	0.180810	-1.478588	0.1534
D(REPO)	0.930038	0.403473	2.305079	0.0310
D(REPO(-1))	0.047185	0.349071	0.135174	0.8937
D(REPO(-2))	-0.760972	0.339382	-2.242230	0.0354

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_FINTECH	4.670201	1.770690	2.637503	0.0150
L_FINTECH_SQ	-0.188818	0.068511	-2.756026	0.0115
INFLATION	0.076572	0.246938	0.310086	0.7594
REPO	1.171821	0.397231	2.949975	0.0074
C	-24.34353	11.41612	-2.132382	0.0444

EC = L_EMPLOYMENT - (4.6702*L_FINTECH -0.1888*L_FINTECH_SQ + 0.0766*INFLATION + 1.1718*REPO - 24.3435)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	14.08319	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	47		Finite Sample: n=50	
		10%	2.372	3.32
		5%	2.823	3.872
		1%	3.845	5.15
			Finite Sample: n=45	
		10%	2.402	3.345
		5%	2.85	3.905
		1%	3.892	5.173

Source: author's calculations

Table A7 Employment Error Correction Regression and Short Run Coefficients

ARDL Error Correction Regression
Dependent Variable: D(L_EMPLOYMENT)
Selected Model: ARDL(5, 5, 5, 2, 3)
Case 2: Restricted Constant and No Trend
Date: 08/13/25 Time: 15:20
Sample: 2010Q1 2022Q4
Included observations: 47

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(L_EMPLOYMENT(-1))	0.129337	0.116151	1.113524	0.2775
D(L_EMPLOYMENT(-2))	0.158054	0.121913	1.296451	0.2083
D(L_EMPLOYMENT(-3))	-0.173415	0.125124	-1.385945	0.1797
D(L_EMPLOYMENT(-4))	0.324293	0.119036	2.724329	0.0124
D(L_FINTECH)	-2.073870	1.534462	-1.351529	0.1903
D(L_FINTECH(-1))	-10.78539	1.460718	-7.383627	0.0000
D(L_FINTECH(-2))	-12.98313	1.765692	-7.352995	0.0000
D(L_FINTECH(-3))	-12.68395	1.734285	-7.313645	0.0000
D(L_FINTECH(-4))	-8.463243	2.032103	-4.164770	0.0004
D(L_FINTECH_SQ)	0.085125	0.059500	1.430656	0.1666
D(L_FINTECH_SQ(-1))	0.431638	0.057695	7.481316	0.0000
D(L_FINTECH_SQ(-2))	0.517901	0.069880	7.411282	0.0000
D(L_FINTECH_SQ(-3))	0.507046	0.068652	7.385707	0.0000
D(L_FINTECH_SQ(-4))	0.335779	0.079300	4.234292	0.0003
D(INFLATION)	0.039837	0.155416	0.256327	0.8001
D(INFLATION(-1))	-0.267343	0.140758	-1.899310	0.0707
D(REPO)	0.930038	0.273384	3.401948	0.0026
D(REPO(-1))	0.047185	0.257812	0.183022	0.8565
D(REPO(-2))	-0.760972	0.260394	-2.922385	0.0079
CointEq(-1)*	-0.592770	0.058209	-10.18349	0.0000

R-squared	0.884439	Mean dependent var	0.000288
Adjusted R-squared	0.803119	S.D. dependent var	0.012224
S.E. of regression	0.005424	Akaike info criterion	-7.299230
Sum squared resid	0.000794	Schwarz criterion	-6.511933
Log likelihood	191.5319	Hannan-Quinn criter.	-7.002965
Durbin-Watson stat	2.214071		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	14.08319	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37

Source: author's calculations

Table A8 Labour Productivity Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.190931	Prob. F(2,32)	0.8271
Obs*R-squared	0.577832	Prob. Chi-Square(2)	0.7491

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 08/11/25 Time: 18:40
Sample: 2010Q4 2022Q4
Included observations: 49
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_LPROD(-1)	0.068410	0.317446	0.215500	0.8307
L_LPROD(-2)	-0.034064	0.302745	-0.112516	0.9111
L_FINTECH	-0.692071	5.383878	-0.128545	0.8985
L_FINTECH(-1)	-1.186036	7.925984	-0.149639	0.8820
L_FINTECH(-2)	1.202938	7.248483	0.165957	0.8692
L_FINTECH_SQ	0.026111	0.208363	0.125317	0.9011
L_FINTECH_SQ(-1)	0.044958	0.304676	0.147559	0.8836
L_FINTECH_SQ(-2)	-0.045688	0.278799	-0.163875	0.8709
INFL	-0.061646	0.841390	-0.073267	0.9420
INFL(-1)	-0.039323	1.016356	-0.038691	0.9694
INFL(-2)	-0.049713	0.990878	-0.050171	0.9603
INFL(-3)	-0.082334	0.723980	-0.113725	0.9102
REPO	-0.056544	0.786300	-0.071912	0.9431
D_COVID	-0.001366	0.026198	-0.052141	0.9587
C	4.034938	25.12933	0.160567	0.8734
RESID(-1)	-0.148722	0.361566	-0.411327	0.6836
RESID(-2)	-0.066511	0.308713	-0.215444	0.8308

R-squared	0.011792	Mean dependent var	-3.80E-14
Adjusted R-squared	-0.482311	S.D. dependent var	0.025947
S.E. of regression	0.031591	Akaike info criterion	-3.804104
Sum squared resid	0.031935	Schwarz criterion	-3.147758
Log likelihood	110.2006	Hannan-Quinn criter.	-3.555088
F-statistic	0.023866	Durbin-Watson stat	1.985962
Prob(F-statistic)	1.000000		

Source: author’s calculations

Table A9 Labour Productivity Heteroskedasticity Breusch-Pagan-Godfrey Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.764874	Prob. F(14,34)	0.6971
Obs*R-squared	11.73617	Prob. Chi-Square(14)	0.6275
Scaled explained SS	5.991588	Prob. Chi-Square(14)	0.9667

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/11/25 Time: 18:41
Sample: 2010Q4 2022Q4
Included observations: 49

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.331589	0.753924	-1.766211	0.0863
L_LPROD(-1)	-0.001768	0.004979	-0.355099	0.7247
L_LPROD(-2)	-0.000527	0.004765	-0.110625	0.9126
L_FINTECH	0.109955	0.167108	0.657990	0.5150
L_FINTECH(-1)	0.153143	0.223977	0.683745	0.4988
L_FINTECH(-2)	-0.049817	0.191751	-0.259801	0.7966
L_FINTECH_SQ	-0.004190	0.006474	-0.647245	0.5218
L_FINTECH_SQ(-1)	-0.005946	0.008637	-0.688448	0.4958
L_FINTECH_SQ(-2)	0.001803	0.007408	0.243446	0.8091
INFL	0.000118	0.026581	0.004448	0.9965
INFL(-1)	0.003110	0.031157	0.099811	0.9211
INFL(-2)	0.021443	0.031269	0.685748	0.4975
INFL(-3)	-0.021397	0.022128	-0.967008	0.3404
REPO	-0.021081	0.024727	-0.852560	0.3999
D_COVID	-0.000721	0.000769	-0.937622	0.3551

R-squared	0.239514	Mean dependent var	0.000660
Adjusted R-squared	-0.073628	S.D. dependent var	0.000970
S.E. of regression	0.001005	Akaike info criterion	-10.71992
Sum squared resid	3.44E-05	Schwarz criterion	-10.14079
Log likelihood	277.6380	Hannan-Quinn criter.	-10.50020
F-statistic	0.764874	Durbin-Watson stat	2.302736
Prob(F-statistic)	0.697051		

Source: author’s calculations

Table A10 Labour Productivity Ramsey Reset Test

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: L_LPROD L_LPROD(-1) L_LPROD(-2) L_FINTECH L_FINTECH(-1) L_FINTECH(-2) L_FINTECH_SQ L_FINTECH_SQ(-1) L_FINTECH_SQ(-2) INFL INFL(-1) INFL(-2) INFL(-3) REPO D_COVID C

	Value	df	Probability
t-statistic	2.029660	33	0.0505
F-statistic	4.119519	(1, 33)	0.0505
Likelihood ratio	5.764134	1	0.0164

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.003586	1	0.003586
Restricted SSR	0.032317	34	0.000950
Unrestricted SSR	0.028730	33	0.000871

LR test summary:

	Value
Restricted LogL	109.9099
Unrestricted LogL	112.7920

Unrestricted Test Equation:
Dependent Variable: L_LPROD
Method: Least Squares
Date: 08/11/25 Time: 18:42
Sample: 2010Q4 2022Q4
Included observations: 49

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_LPROD(-1)	5.293454	2.461307	2.150668	0.0389
L_LPROD(-2)	8.712250	4.046754	2.152898	0.0387
L_FINTECH	304.4694	141.2164	2.156048	0.0385
L_FINTECH(-1)	-43.74439	21.35567	-2.048374	0.0485
L_FINTECH(-2)	-300.3915	139.7564	-2.149394	0.0390
L_FINTECH_SQ	-11.61407	5.386581	-2.156112	0.0385
L_FINTECH_SQ(-1)	1.704595	0.831327	2.050450	0.0483
L_FINTECH_SQ(-2)	11.58485	5.389994	2.149326	0.0390
INFL	25.55938	11.87838	2.151757	0.0388
INFL(-1)	5.024369	2.512945	1.999395	0.0539
INFL(-2)	10.38989	4.897313	2.121550	0.0415
INFL(-3)	16.25677	7.568988	2.147813	0.0392
REPO	21.77739	10.14725	2.146137	0.0393
D_COVID	1.125821	0.522668	2.153989	0.0386
C	164.2274	78.94978	2.080150	0.0454
FITTED^2	-0.608227	0.299681	-2.029579	0.0505

R-squared	0.986892	Mean dependent var	13.36901
Adjusted R-squared	0.980934	S.D. dependent var	0.213690
S.E. of regression	0.029506	Akaike info criterion	-3.950693
Sum squared resid	0.028730	Schwarz criterion	-3.332956
Log likelihood	112.7920	Hannan-Quinn criter.	-3.716325
F-statistic	165.6395	Durbin-Watson stat	2.392431
Prob(F-statistic)	0.000000		

Source: authors calculations

Table A11 Employment Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.714725	Prob. F(2,20)	0.5014
Obs*R-squared	3.135133	Prob. Chi-Square(2)	0.2086

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 08/13/25 Time: 15:21
Sample: 2011Q2 2022Q4
Included observations: 47
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_EMPLOYMENT(-1)	0.132863	0.220272	0.603178	0.5532
L_EMPLOYMENT(-2)	-0.209766	0.298346	-0.703097	0.4901
L_EMPLOYMENT(-3)	0.166049	0.277797	0.597735	0.5567
L_EMPLOYMENT(-4)	-0.081365	0.225787	-0.360362	0.7224
L_EMPLOYMENT(-5)	-0.004083	0.165990	-0.024596	0.9806
L_FINTECH	-0.622340	2.028050	-0.306866	0.7621
L_FINTECH(-1)	0.837709	2.413901	0.347036	0.7322
L_FINTECH(-2)	0.525322	1.547593	0.339444	0.7378
L_FINTECH(-3)	-0.090379	1.369283	-0.066004	0.9480
L_FINTECH(-4)	0.457966	1.970661	0.232392	0.8186
L_FINTECH(-5)	-1.285504	2.984803	-0.430683	0.6713
L_FINTECH_SQ	0.023872	0.078652	0.303507	0.7646
L_FINTECH_SQ(-1)	-0.032731	0.093655	-0.349481	0.7304
L_FINTECH_SQ(-2)	-0.020620	0.060490	-0.340877	0.7368
L_FINTECH_SQ(-3)	0.003522	0.053477	0.065853	0.9481
L_FINTECH_SQ(-4)	-0.017652	0.076454	-0.230889	0.8197
L_FINTECH_SQ(-5)	0.050853	0.116797	0.435395	0.6679
INFLATION	-0.001058	0.211521	-0.005004	0.9961
INFLATION(-1)	-0.068041	0.263923	-0.257807	0.7992
INFLATION(-2)	0.059092	0.190147	0.310767	0.7592
REPO	-0.013483	0.410153	-0.032874	0.9741
REPO(-1)	-0.138051	0.582156	-0.237137	0.8150
REPO(-2)	0.311017	0.572177	0.543568	0.5927
REPO(-3)	-0.140639	0.364187	-0.386173	0.7034
C	1.065901	9.347879	0.114026	0.9104
RESID(-1)	-0.233764	0.283758	-0.823815	0.4198
RESID(-2)	0.301406	0.317129	0.950420	0.3532

R-squared	0.066705	Mean dependent var	-2.66E-14
Adjusted R-squared	-1.146579	S.D. dependent var	0.004155
S.E. of regression	0.006088	Akaike info criterion	-7.070392
Sum squared resid	0.000741	Schwarz criterion	-6.007541
Log likelihood	193.1542	Hannan-Quinn criter.	-6.670434
F-statistic	0.054979	Durbin-Watson stat	1.863963
Prob(F-statistic)	1.000000		

Source: author's calculations

Table A12 Employment Heteroskedasticity Breusch Pagan Godfrey Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.669775	Prob. F(24,22)	0.8303
Obs*R-squared	19.84279	Prob. Chi-Square(24)	0.7057
Scaled explained SS	4.889489	Prob. Chi-Square(24)	1.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/13/25 Time: 15:21
Sample: 2011Q2 2022Q4
Included observations: 47

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.040296	0.042823	0.941001	0.3569
L_EMPLOYMENT(-1)	0.000302	0.000832	0.362915	0.7201
L_EMPLOYMENT(-2)	9.21E-05	0.001115	0.082582	0.9349
L_EMPLOYMENT(-3)	0.000387	0.001092	0.354324	0.7265
L_EMPLOYMENT(-4)	0.000113	0.000995	0.113408	0.9107
L_EMPLOYMENT(-5)	4.84E-05	0.000746	0.064802	0.9489
L_FINTECH	-0.008765	0.008764	-1.000062	0.3282
L_FINTECH(-1)	-0.004590	0.010662	-0.430520	0.6710
L_FINTECH(-2)	0.004308	0.006846	0.629244	0.5357
L_FINTECH(-3)	-0.009682	0.006312	-1.533875	0.1393
L_FINTECH(-4)	0.013050	0.008740	1.493249	0.1496
L_FINTECH(-5)	-0.001232	0.012860	-0.095830	0.9245
L_FINTECH_SQ	0.000338	0.000340	0.994403	0.3308
L_FINTECH_SQ(-1)	0.000184	0.000413	0.444998	0.6607
L_FINTECH_SQ(-2)	-0.000166	0.000267	-0.622237	0.5402
L_FINTECH_SQ(-3)	0.000373	0.000246	1.514913	0.1440
L_FINTECH_SQ(-4)	-0.000505	0.000339	-1.488746	0.1508
L_FINTECH_SQ(-5)	4.34E-05	0.000502	0.086474	0.9319
INFLATION	0.001236	0.000958	1.290354	0.2103
INFLATION(-1)	-0.001159	0.001183	-0.979082	0.3382
INFLATION(-2)	-0.000367	0.000847	-0.432706	0.6694
REPO	-0.000336	0.001891	-0.177940	0.8604
REPO(-1)	-0.000124	0.002612	-0.047613	0.9625
REPO(-2)	-0.000228	0.002350	-0.096915	0.9237
REPO(-3)	-0.000280	0.001591	-0.176306	0.8617

R-squared	0.422187	Mean dependent var	1.69E-05
Adjusted R-squared	-0.208154	S.D. dependent var	2.56E-05
S.E. of regression	2.82E-05	Akaike info criterion	-17.81254
Sum squared resid	1.74E-08	Schwarz criterion	-16.82842
Log likelihood	443.5946	Hannan-Quinn criter.	-17.44220
F-statistic	0.669775	Durbin-Watson stat	2.243398
Prob(F-statistic)	0.830342		

Source: authors calculations

Table A13 Employment Ramsey Reset Test

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: L_EMPLOYMENT L_EMPLOYMENT(-1) L_EMPLOYMENT(-2) L_EMPLOYMENT(-3) L_EMPLOYMENT(-4) L_EMPLOYMENT(-5) L_FINTECH L_FINTECH(-1) L_FINTECH(-2) L_FINTECH(-3) L_FINTECH(-4) L_FINTECH(-5) L_FINTECH_SQ L_FINTECH_SQ(-1) L_FINTECH_SQ(-2) L_FINTECH_SQ(-3) L_FINTECH_SQ(-4) L_FINTECH_SQ(-5) INFLATION INFLATION(-1) INFLATION(-2) REPO REPO(-1) REPO(-2) REPO(-3) C

	Value	df	Probability
t-statistic	0.600968	21	0.5543
F-statistic	0.361163	(1, 21)	0.5543
Likelihood ratio	0.801445	1	0.3707

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	1.34E-05	1	1.34E-05
Restricted SSR	0.000794	22	3.61E-05
Unrestricted SSR	0.000781	21	3.72E-05

LR test summary:

	Value
Restricted LogL	191.5319
Unrestricted LogL	191.9326

Unrestricted Test Equation:
Dependent Variable: L_EMPLOYMENT
Method: Least Squares
Date: 08/13/25 Time: 15:22
Sample: 2011Q2 2022Q4
Included observations: 47

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_EMPLOYMENT(-1)	18.32169	29.14990	0.628533	0.5364
L_EMPLOYMENT(-2)	0.983236	1.582966	0.621135	0.5412
L_EMPLOYMENT(-3)	-11.28240	17.94985	-0.628551	0.5364
L_EMPLOYMENT(-4)	16.97689	27.00980	0.628545	0.5364
L_EMPLOYMENT(-5)	-11.05758	17.59232	-0.628546	0.5364
L_FINTECH	-71.53902	113.8674	-0.628266	0.5366
L_FINTECH(-1)	-202.7054	322.4964	-0.628551	0.5364
L_FINTECH(-2)	-75.29887	119.8200	-0.628433	0.5365
L_FINTECH(-3)	10.46111	16.71113	0.625997	0.5381
L_FINTECH(-4)	144.3220	229.6301	0.628498	0.5365
L_FINTECH(-5)	288.6184	459.1754	0.628558	0.5364
L_FINTECH_SQ	2.935263	4.671882	0.628283	0.5366
L_FINTECH_SQ(-1)	8.001748	12.73049	0.628550	0.5364
L_FINTECH_SQ(-2)	2.955982	4.703750	0.628431	0.5365
L_FINTECH_SQ(-3)	-0.380572	0.608302	-0.625630	0.5383
L_FINTECH_SQ(-4)	-5.856134	9.317637	-0.628500	0.5365
L_FINTECH_SQ(-5)	-11.45171	18.21904	-0.628557	0.5364
INFLATION	1.327113	2.119980	0.626003	0.5381
INFLATION(-1)	-8.959847	14.25819	-0.628400	0.5365
INFLATION(-2)	9.106614	14.48849	0.628541	0.5364
REPO	31.86643	50.70559	0.628460	0.5365
REPO(-1)	-6.525514	10.40203	-0.627331	0.5372
REPO(-2)	-27.53871	43.81362	-0.628542	0.5364
REPO(-3)	25.92769	41.24903	0.628565	0.5364
C	-564.9300	902.3025	-0.626098	0.5380
FITTED^2	-3.600415	5.900986	-0.610138	0.5483

R-squared	0.971892	Mean dependent var	4.599113
Adjusted R-squared	0.938431	S.D. dependent var	0.024576
S.E. of regression	0.006098	Akaike info criterion	-7.060963
Sum squared resid	0.000781	Schwarz criterion	-6.037477
Log likelihood	191.9326	Hannan-Quinn criter.	-6.675818
F-statistic	29.04496	Durbin-Watson stat	2.220623
Prob(F-statistic)	0.000000		

Source: authors calculation

Appendix B: Figures

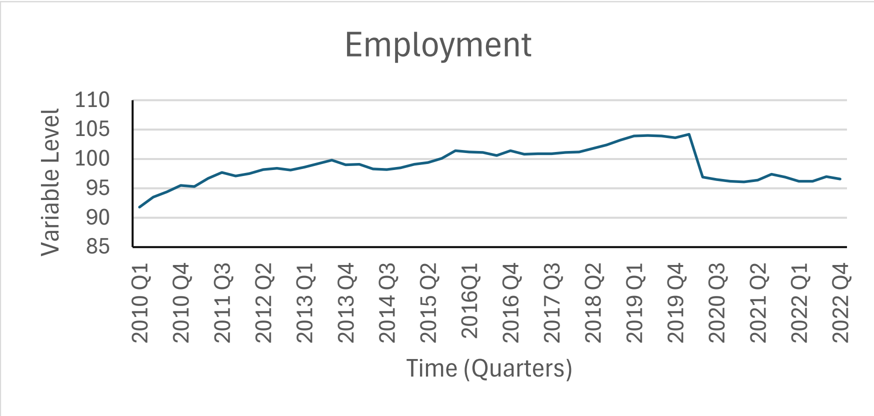


Figure B1. Time Series Plot of Employment (2010Q1-2022Q3)

Source: compiled by author

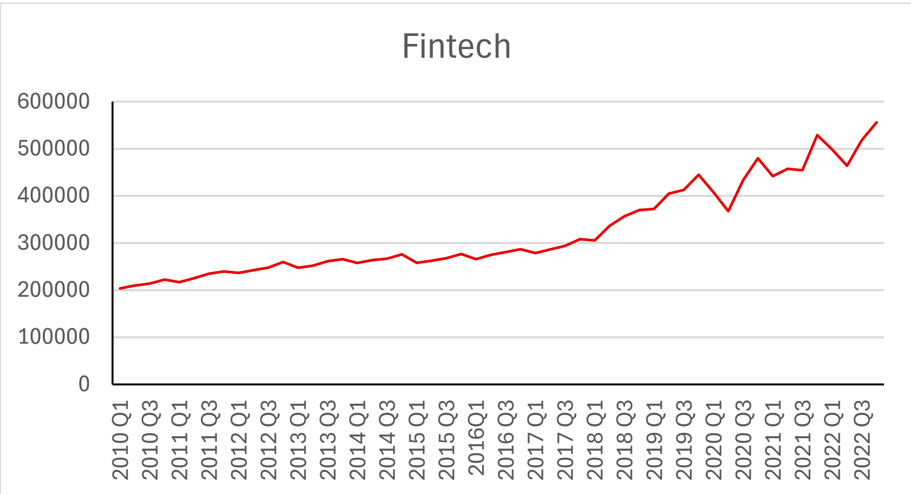


Figure B2 Time Series Plot of Fintech (2010Q1-2022Q3)

Source: compiled by author

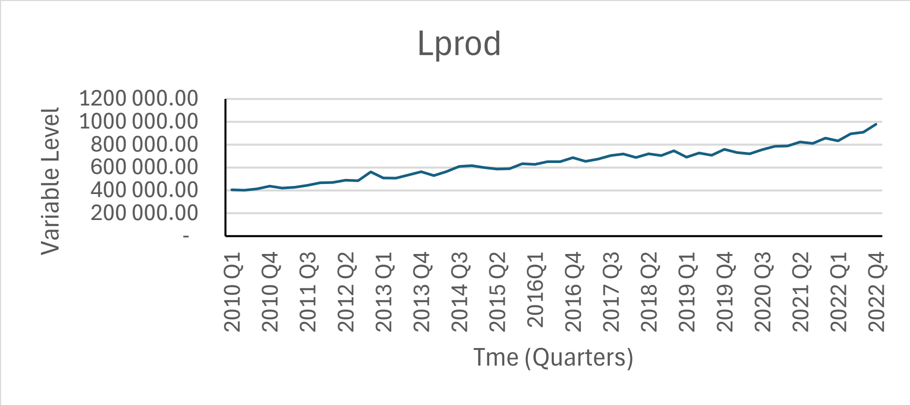


Figure B3 Time Series Plot of Labour Productivity (2010Q1-2022Q3)

Source: compiled by author

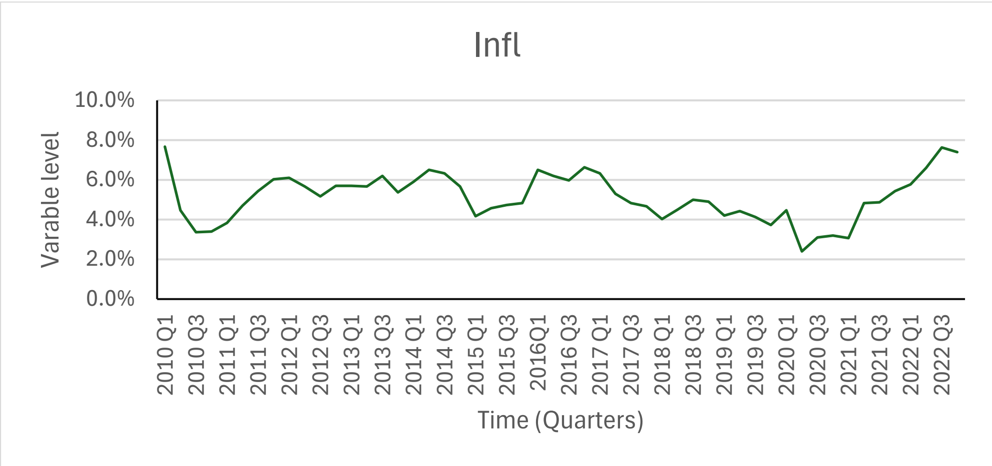


Figure B4. Time Series Plot of Inflation Rate (2010Q1-2022Q3)

Source: compiled by author

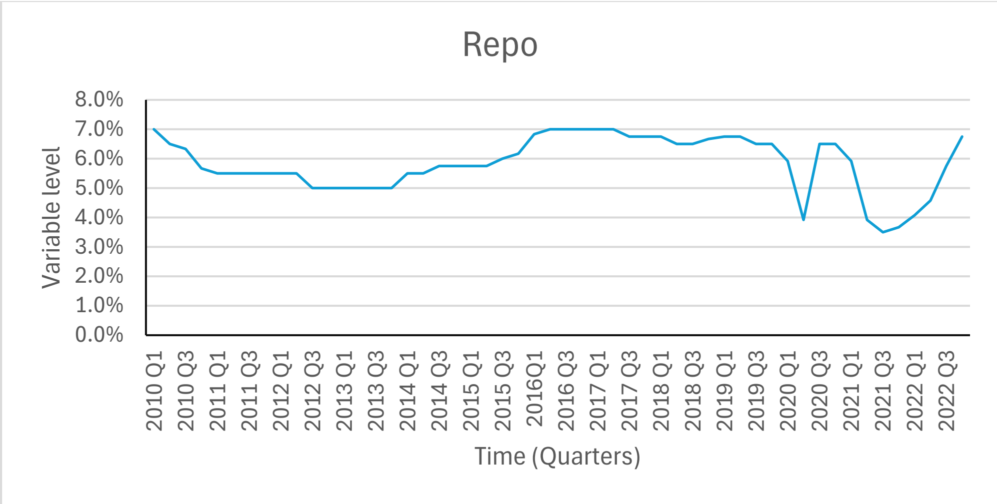


Figure B5. Time Series Plot of Repo Rate (2010Q1-2022Q3)

Source: compiled by author

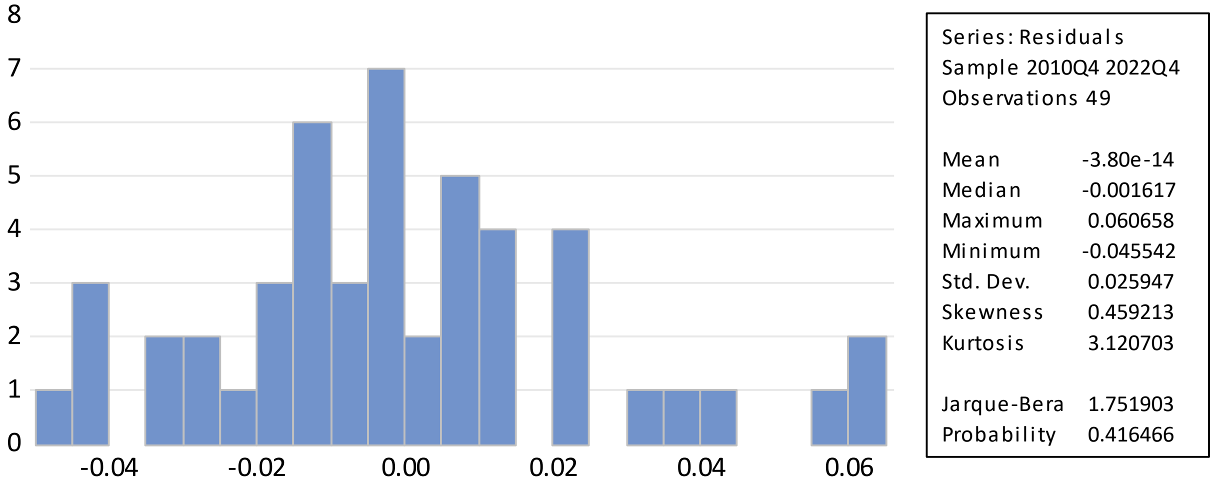


Figure B6 Labour Productivity Jarque-Bera Normality Test

Source: compiled by author

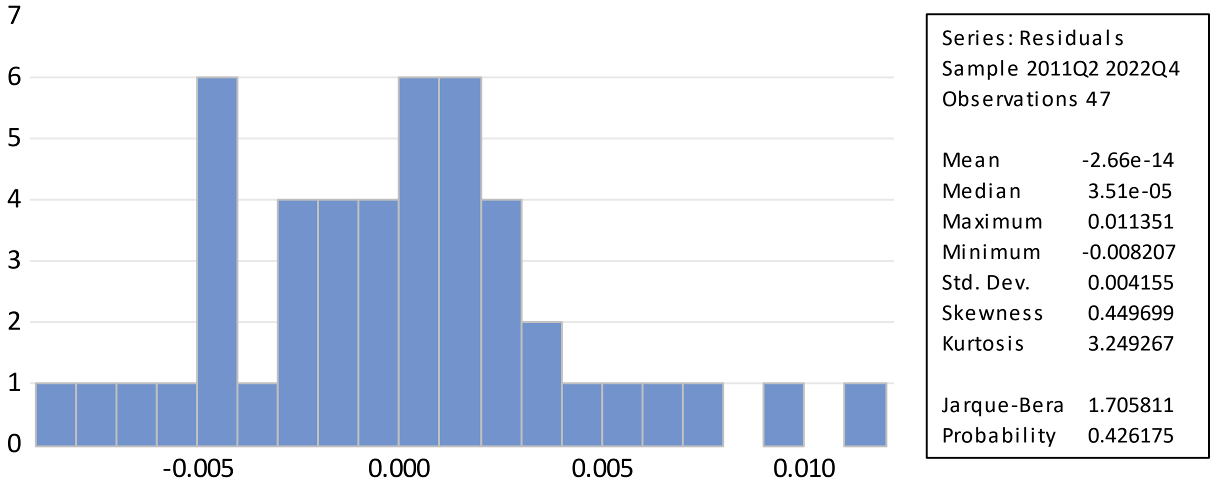


Figure B7 Employment Jarque-Bera Normality Test

Source: compiled by author

REFERENCES

- Agarwal, S. Qian, W. Ren, Y. Tsai, H and Yeung, B (2022) The Real Impact of FinTech: Evidence from Mobile Payment Technology. Agarwal: NUS Business School, National University of Singapore. P1-13.

- Akinola, O (2021) Electronic banking business in Sub-Saharan Africa: Socio-economic impact and the activities of FinTech ecosystems. *International Journal of Management Research & Economics* P27-33 [Online]. Available from: https://doi.org/10.51483/IJMRE.1.1.2021.27-33

- Ang, J . Yan, Z. Xiao, T. Yuan, C and Wang, J (2024) Impact of Fintech on labour allocation efficiency in firms: Empirical evidence from China. *Global Finance Journal*, 62, p.101011.

- Arner, D. Auer, R and Frost, J (2020). The Rise of the Fintech Era. BIS Working Papers No. 762. Bank for International Settlements.

- Beck, T (2020). Fintech and financial inclusion: Opportunities and pitfalls (No. 1165). *ADBI working paper series*, P1-8. [Online]. Available from: https://www.adb.org/publications/fintech-financial-inclusion-opportunities-pitfalls

- Beck, T. Chen, T. Lin, C and Song, F (2016) Financial Innovation: The Bright and the Dark Sides. *Journal of Banking & Finance*, 72, pp.28–51.

- Berg, G. Guadamillas, M. Natarajan, H. and Sarkar, A (2020) Fintech in Europe and Central Asia: Maximizing Benefits and Managing Risks

- Blinder, A.S (2008). Keynesian economics. The concise encyclopedia of economics, The Library of Economics and Liberty p2. [Online]. Available from: https://studynotesunisa.co.za/wp-content/uploads/2018/12/Scanned-notes-6.pdf

- Boettke, P & Leeson,P (2003). "The Austrian school of economics: 1950-2000." Blackwell companion to the history of economic thought. Oxford: Basil Blackwell Publishers :p445-454.

- Breusch, T.S. & Pagan, A.R.(1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47(5), pp.1287–1294

- Brooks, C (2008) *Introductory Econometrics for Finance*. 2nd ed. Cambridge University Press.

- Brown, A & Davis, B (2020). The Impact of COVID-19 on Fintech. *Journal of Financial Technology*, 22(4), p67-82.

- Brown, C & Lee, D (2021). Fintech Adoption in the Wake of COVID-19: A Global Perspective. *International Journal of Finance and Economics*, 25(4), p543-567.

- Brown, G & Orsagh, C (2021). Fintech and the Macroeconomy: New Approaches, Risks, and Policy Challenges. *Federal Reserve Bank of New York Staff Reports*, p959.

- Brown, I. Cajee, Z. Davies, D & Stroebel, S (2003). Cell phone banking: predictors of adoption in RSA—an exploratory study. *International Journal of Information Management*, 23(5), p381-394.

- Caporale, G.M & Pittis, N (2004) Cumulative Sum (CUSUM) Tests for Parameter Stability: An Application to the Demand for Money in the UK. *Oxford Bulletin of Economics and Statistics,* 66(4), pp. 537-554.

- Chenic, A.S. Burlacu, A. Dobrea, R.C. Tescan, L (2023) The Impact of Digitalization on Macroeconomic Indicators in the New Industrial Age. *Electronics*, 12, 1612. [Online]. Available from: https://doi.org/10.3390/ electronics12071612

- Ciborowski, R.W. Kargol-Wasiluk, A. & Zalesko, M (2019). Time, Capital, and Technological Progress in the Austrian School of Economics. Studies in Logic, Grammar and Rhetoric, 57(1), pp.123-144.

- Chinoracky, R. Kurotova, J & Janoskova, P (2021), Measuring the impact of digital technologies on transport industry – macroeconomic perspective, *Transportation Research Procedia,* Volume 55, 2021, p434-441, ISSN 2352-1465, [Online]. Available from: https://doi.org/10.1016/j.trpro.2021.07.092.

- Coetzee, J. (2018). Strategic implications of Fintech on South African retail banks. *South African Journal of Economic and Management Sciences*, 21(1), 1-11. [Online]. Available from: https://doi.org/10.4102/sajems.v21i1.2455

- Diep, N and Canh, T (2022) Impact analysis of peer-to-peer Fintech in Vietnam's banking industry. *Journal of International Studies*, 15(3), p173-185

- Dickey, D.A. & Fuller, W.A. (1979), Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association*, vol. 74, no. 366a, pp. 427–431.

- Dutta, S (2006) Introductory Economics (Micro and Macro): A Textbook for Class XII, New Age International, New Delhi, p120-125

- Fu, J & Mishra, M (2020). The Global Impact of Covid-19 on Fintech Adoption, Swiss Finance Institute Research Paper No. 20-38 *Journal of Financial Intermediation,* *Forthcoming.* p11 [Online]. Available from: https://www.kaggle.com/jcyzag/covid19-lockdown-dates-by-country

- Gertze, L & Petersen, F (2024). Factors influencing the acceptance and use of a South African online bank. *South African Journal of Information Management*, 26(1), p.1759.

- Gibson, A. (2023) 'The Evolution of Fintech: A Historical Perspective', LinkedIn, 25 September. Available at: https://www.linkedin.com/pulse/evolution-fintech-historical-perspective-abigail-gibson

- Glancey, K.S & McQuaid, R.W (2000). Introduction to Entrepreneurship. In: Campling, J. (eds) Entrepreneurial Economics. Palgrave Macmillan, London. [Online]. Available from https://doi.org/10.1057/9780333981245_1 p1-2.

- Godfrey, L.G., (1978). Testing for higher order serial correlation in regression equations when the regressors include lagged dependent variables. *Econometrica*, 46(6), pp.1303–1310.

- Gillwald, A., Moyo, M. and Stork, C. (2012) Understanding Broadband in South Africa, Research ICT Africa. Available at: https://researchictafrica.net (Accessed: 13 November 2025).

- Gujarati, D & Porter, D (2010) Essentials of Econometrics. Fourth Edition, edition. McGraw-Hill International Edition. New York. P381-383.

- Gupta, Mayank & Sharma, Aditya. (2021). Fear of missing out: A brief overview of origin, theoretical underpinnings and relationship with mental health. *World Journal of Clinical Cases*. 9. 4881-4889. 10.12998/wjcc.v9.i19.4881.

- Hayek, F.A (1945). The Use of Knowledge in Society. *American Economic Review*, 35(4), p519-530.

- IFWG (Intergovernmental Fintech Working Group) (2020). Fintech Innovation in South Africa: A Review of the Market and Regulatory Landscape.

- Jeong, Y. Park, H and Park, C. (2018) An Analysis of Economic Effect of The Fintech Industry P1-58. *Journal of Information Technology Services*. [Online]. Available from: https://doi.org/10.9716/KITS.2018.17.1.047

- Jiang, W., Tang, Y., Xiao, R.J. and Yao, V. (2021). Surviving the FinTech disruption (No. w28668). *National Bureau of Economic Research*.

- Jones, D. & Williams J.C. (2018). Fintech and the Financial System. *Federal Reserve Bank of St. Louis Review,* 100(4), p337-350.

- Jones, L & Smith, K (2021). Fintech Adoption in the Wake of COVID-19. *Journal of Financial Innovation,* 28(1), p45-58.

- Kang, J. (2018) 'Mobile payment in Fintech environment: trends, security challenges, and services', Human-centric Computing and Information Sciences, 8(32), pp. 1–16. doi: 10.1186/s13673-018-0155-4.

- Keynes, J.M (1936). The General Theory of Employment, Interest, and Money. Macmillan. Cambridge, UK

- Kowalewski, O & Pisany, P (2023). The rise of fintech: A cross-country perspective, Technovation, Volume 122, p17-19.

- Le, T . Mai, H. Phan, D. Nguyen, M. Le, H (2021). Fintech Innovations: The Impact of Mobile Banking Apps on Bank Performance in Vietnam. *International Journal of Research and Review,* 8(4), pp.391-401.

- Leong, K & Sung, A (2018) FinTech (Financial Technology): What is It and How to Use Technologies to Create Business Value in Fintech Way? *International Journal of Innovation, Management and Technology,* vol. 9, no. 2, p74-78. [Online]. Available From: http://www.ijimt.org /index.php?m=content&c=index&a=show&catid=93&id=1138

- Leshoro, T (2014) Does the Repurchase Rate Affect Inflation in South Africa? An Empirical Analysis Using an Impulse Response Function. *Journal of Economics and Behavioral Studies.* Vol.6 No.7. pp524-531, [Online]. Available from: https://ojs.amhinternational.com/index.php/jebs/article/view/513/513

- Louw, C & Nieuwenhuizen, C. (2020). Digitalisation strategies in a South African banking context: A consumer services analysis. *South African Journal of Information Management*, 22(1), p1-8.

- Malinga, S (2024). ITWeb TV: TymeBank prepares to become full-service bank. P1. [Online] Available from: https://www.itweb.co.za/article/itweb-tv-tymebank-prepares-to-become-full-service-bank/KPNG8v8NyApM4mwD

- Mhlongo, N., Kunjal, D., & Muzindutsi, P.-F. (2025). The influence of Fintech innovations on bank competition and performance in South Africa. Modern Finance, 3(2), 1–12. [Online]. Available from: https://doi.org/10.61351/mf.v3i2.252

- Mungai, K (2019). The economic impact of FinTech in the South African banking industry: A case of digital disruption. P1- [Online] Available from: file:///C:/Users/CP368011/Downloads/mungai_arts_2019_24.pdf

- Marx, K (1996). Das Kapital: A critique of political economy, Washington, D.C.: Eagle.

- Mention, A. L. (2019). The Future of Fintech. *Research-Technology Management*, 62(4), 59–63. https://doi.org/10.1080/08956308.2019.1613123

- Munyeka, W (2014) The relationship between economic growth and inflation in the South African economy. *Mediterranean journal of social sciences*, 5(15), pp.119-129.

- Naoyuki, Y & Sahoko, K (2020). The Macroeconomic Effects of Fintech. *Policy Research Institute, Ministry of Finance, Japan, Public Policy Review*, Vol.16, No.4. p17-18.

- Narayan, S & Sahminan, S (2018). Has Fintech Influenced Indonesia's Exchange Rate and Inflation? *Bulletin of Monetary Economics and Banking*, Vol.21, No.2 (2018), p177-190.

- Naz, F. Karim, S & Houcine, A (2022). Fintech Growth during COVID-19 in MENA Region: Current Challenges and Future prospects. *Electronic Commerce Research* vol. 24, p371–392.

- Nkoro, E. and Uko, A.K. (2016) 'Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation', Journal of Statistical and Econometric Methods, 5(4), pp. 63–91

- Ozili, P (2020) COVID-19 in Africa: Socioeconomic Impact, Policy Response and Opportunities. *International Journal of Sociology and Social Policy*, 40(9/10), pp. 1–20.

- Perez, J & Garcia, M (2020). Fintech and Financial Inclusion: Opportunities and Challenges. *International Journal of Financial Studies*, 8(3), p32-48.

- Pesaran, M.H., Shin, Y. & Smith, R.J. (2001) Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16, p289-326

- Pranata, I. Athauda, R & Skinner, G (2013). Determining Trustworthiness and Quality of Mobile Applications Mobile Wireless Middleware, Operating Systems, and Applications. p192-206

- Ricardo, D (1817). Principles of Political Economy and Taxation. London: John Murray.

- Rico, P & Cabrer-Borrás, B (2019). "Entrepreneurial capital and productive efficiency: the case of the Spanish regions", *Technological and Economic Development of Economy,* 25(6), pp. 1363-1379. doi: 10.3846/tede.2019.10549.

- Schumpeter, J.A (1942). Capitalism, Socialism and Democracy. Routledge. New York: Harper & Brothers.

- Sethi, P and Manocha, R (2022). Impact of Fintech Adoption on Select Macroeconomic Variables in India: An ARDL Approach. *IIMS Journal of Management Science* p1–25 © The Author(s) 2022 DOI: 10.1177/0976030X221139662 [Online]. Available from: https://journal.iimshillong.ac.in/ doi/pdf/10.1177/0976030X221139662.pdf

- Smith, A (1776). An Inquiry into the Nature and Causes of the Wealth of Nations. p47-53 W. Strahan and T. Cadell. London

- Smith, A (2020). Digital Disruption in Banking: The Challenges and Opportunities of Fintech. *Journal of Banking and Finance*, 15(3), p112-125.

- Smith, J (2020). Digital Transformation in Financial Services: The Impact of COVID-19. *Journal of Financial Technology*, 19(2), p15-28.

- Solow, R.M (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics,* 39(3), p312-320

- Solow, R.M (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics,* 70(1), p65-94

- Song, N and Appiah-Otoo, I (2022) The Impact of Fintech on Economic Growth: Evidence from China School of Management and Economics, *University of Electronic Science and Technology of China*. P2-17.

- South African Reserve Bank (2024) Online Statistical Query. Available at https://www.resbank.co.za/en/home/what-we-do/statistics/releases/online-statistical-query (Accessed: 15 November 2024).

- Statcounter Global Stats, (2019), Mobile operating system market share worldwide 2018, viewed 25 August 2019, [Online]. Available from: https://gs.statcounter.com/os-market-share/mobile/worldwide/#monthly-201801-201812.

- Sullivan, T & Johnson, D (2020). Fintech Regulation and Policy in the Post-COVID-19 Era. *Journal of Financial Regulation*, 12(4), p567-582.

- Tiwari, A. (2025) 'Global Fintech Market: Growth, Trends, and Future Outlook', LinkedIn, 20 August. Available at: LinkedIn article (Accessed: 13 November 2025).

- Vasiljeva, T & Lukanova, K (2016). Commercial Banks and Fintech Companies in the Digital Transformantion: Challenges for the Future. *Journal of Business Management*, 2016 No.11. p25-33

- Wewege, Luigi & Lee, Jeo & Thomsett, Michael. (2020). Disruptions and Digital Banking Trends. *Journal of Applied Finance & Banking* Vol.10 No. 6. 1792-6599. P25-35

- Yussuf, A.A. (2022) 'Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation', International Journal of Research Publications, 109(1), pp. 1–12