THE IMPACT OF FINTECH FIRMS ON BANK PERFORMANCE: ANALYSING THE SOUTH AFRICAN CASE (2009-2021)

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DECLARATION OF ORIGINAL WORK

This page declares that the work produced in this thesis is my work and was conducted whilst completing the degree of Master of Commerce in Financial Markets at Rhodes University. Any work that is not my own has been credited accordingly. I, Simon Simbarashe Runyowa, certify that this thesis has not been submitted for a degree in any other university, Technikon, or college.

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ABSTRACT

The growth of the Fintech Firm sector globally was inevitable, given the changes in consumer behaviour, expectations, and the ever-changing and evolving nature of technology. The sector saw a sharp increase during the 2008 Global Financial Crisis and was driven by digital payments, government policy, less stringent regulation, and technological innovation. Unsurprisingly, South Africa was home to a mature and developing Fintech sector primarily driven by money transfers and mobile payments putting Fintech firms in the same market segment as traditional banks but with a more extensive potential customer base through offering easily accessible and lower-cost services. The relationship between the growth of the Fintech firm sector and Bank performance was widely researched within the literature with varying results.

The study aimed to add to the body of literature and determine the nature of this relationship in the South African context. The study primarily aimed to determine the relationship and impact of the growth of the Fintech firm payments segment on the performance of the South African Banking sector. Additionally, the study aimed to measure the sector's growth by creating a Fintech Growth Index.

Using the Ordinary Least Squares, Fixed Effect and the Generalized Method of Moments estimation techniques, estimations between Bank performance variables and the Fintech growth Index were analysed between 2009 and 2021. Firstly, the study found the growth of the Fintech payments segment to be positive. Secondly, the study found that the growth of the payment segment had a negative relationship and impact on the financial performance of South African banks. The findings of this study have implications for the development and regulatory framework of the South African Fintech sector as well as its interaction with the South African banking sector. Furthermore, policymakers may find that the growth of the Fintech Firm sector has overall positive benefits for financial inclusion for South African consumers. The study recommended that future research be taken to address the gap in the literature regarding the growth of the South African Fintech sector.

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CHAPTER 1: INTRODUCTION

1.1 Research Context

Fintech is "technologically enabled financial innovation that results in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services" (FSB, 2017). Fintech denotes the industrial developments occurring from the convergence of financial services and information technology (IT); Fintech is a compounded phrase comprised of the terms "finance" and "technology" (Slazus and Bick, 2022). Globally, Fintech adoption is expected to increase to an average adoption level of 64% in small to medium enterprises within emerging markets such as South Africa, Mexico, and Singapore set to have higher levels of adoption (EY, 2019).

The growth of the Fintech sector has primarily been driven by digital payments, government policies that foster the development of the industry through Fintech acceleration programs and less stringent regulation, and innovation such as the generation of financial services accessed via mobile devices and the internet (Demirgüç-Kunt et al.,2017, Dube, Simatele and Khumalo, 2021). Money transfers and mobile payments mostly drive fintech adoption in South Africa. (EY, 2019). These high adoption rates can be attributed to two factors: To begin, Fintech firms are focused at tech-savvy consumers, hence lowering the budgetary costs and resource waste of attempting to win away non-responsive clients. Second, Fintech firms provide services to the previously financially underserved population, which is proportionally larger in emerging economies like South Africa (EY, 2017).

Fintech firms offer disruptive and innovative financial services (Thakor, 2020). These firms use these innovative services to offer financial services historically provided by traditional brick-and-mortar banks and, at the same time, invent new financial products such as peer-to-peer (P2P) lending and mobile phone payments (Li et al., 2017,Thakor, 2020). This puts fintech firms in a market segment similar to incumbent banks but with a more extensive potential customer base by offering easily accessible and lower-cost services (Buchak et al., 2018,FSB, 2019). The traditional banking model is therefore under threat in two ways: first, the entry of “neo-banks’’ that offer a fully digital service without the need to invest in costly branch networks (Coetzee, 2019); Second, Fintechs that provide cheaper and more efficient banking solutions (Weichert et al.,2017).

The entrance of three neo-banks, TymeDigital, Discovery Bank and Bank Zero, and the state-owned Postbank into the South African Banking sector has had a potentially disruptive effect on the incumbent institutions (Coetzee, 2018). Due to the threat posed by financial technology firms, South African banks are contemplating forming partnerships with them. Previously, this was not the preferred option due to the complex nature of such a union (Investec, 2019). Still, banks have realised that fintech firms can erode and threaten the bank-client relationship (Coetzee, 2019). Furthermore, the nature of the relationship between the growth of the Fintech firm sector in South Africa and the Banking sector's financial performance is unknown, partly attributed to the lack of a measure for Fintech firm growth.

Various studies apply consumer theory to examine the impact of fintech firms on incumbent financial institutions. Consumer theory states that new products and service offerings, such as those provided by fintech firms, act as either a complement to incumbent financial institution services or a substitute (Aaker and Keller, 1990, Frank, 2008). Therefore, the offerings that fintechs provide benefit incumbent financial institutions if complementary and would negatively affect incumbent financial institutions if they are a substitute for traditional financial offerings (Kaul, 2012). Merton (1995) states that while fintech firms have the potential to develop innovative business models, partnerships between fintech and incumbent banks would be evolutionary. Haddad and Hornuf (2021) add that the growth of fintech firms enhances existing service offerings and rarely are replaced. Additionally, empirical evidence shows that large numbers of existing financial institutions acknowledge the innovation and superiority of fintech business models and incorporate these into their services and products. The emergence of fintechs has resulted in beneficial partnerships for incumbent institutions rather than a threat (PWC, 2016).

Li et al. (2017) state that fintech firms may take over several essential functions of incumbent financial institutions. The absence of legacy infrastructure and minimal organizational complication are advantageous for new market entrants (fintech firms), enabling them to be more agile, innovate more rapidly, and employ revolutionary methods of innovation. (Brandl and Hornuf, 2020). Therefore, it is probable that fintech companies will supplant the ineffective service provisions of established incumbent institutions. This substitution effect aligns with the disruptive innovation theory Christensen (1997), which states that new entrants compete with incumbent institutions by providing superior, cost-effective customer offerings. By doing so, these new entrants replace incumbent institutions within the market. A report by PWC (2016) found that efficiency increases from financial technology resulting from disintermediation significantly lowered consumer transaction costs.

Various studies have found a positive impact on the financial performance and stability of financial markets with the growth of the fintech sector. Safiullah et al. (2022) analysed the effect of the growth of fintech firms on 26 local banks in Malaysia from 2003-2018. They found that the growth of fintech sector positively impacted performance and financial stability. These results were indiscriminate of bank type (Islamic vs conventional) and size. However, it was noted that the effects of fintech growth were less favourable in larger banks compared to smaller banks. Li et al. (2017) investigated the impact of start-up funding on the stock returns of 47 incumbent US retail banks between 2010 and 2016 and observed a positive correlation between fintech growth and bank financial performance..

Various studies in China have also found a positive relationship between fintech and bank performance. Lee et al. (2021) examined the development of fintech in China and its effects on cost efficiency and technology innovation from 2003-2017 and found a positive relationship. Fintech firms also enhanced the technology used by Chinese banks. Chen et al. (2021) and Huang (2018) both examined the impact of fintech innovation (P2P) lending platforms on the Chinese financial system and found a positive relationship between fintech innovation and the performance of financial institutions. Zalan and Toufaily (2017) found that Officials in the Middle East and North Africa (MENA) region were of the opinion that Fintech firms had an economic advantage over traditional banking institutions due to their comparatively lax regulatory framework. This advantage enabled Fintech firms to disrupt the banking sector. In contrast, Zalan and Toufaily (2017) asserted that enforcing strict regulatory obligations on financial services hindered fintech firms from providing reduced fees to customers. The literature on fintech in general and the interaction between fintech and traditional financial institutions in South Africa is limited.

1.2 Problem Statement

The existing literature reveals divergent perspectives on the impact of Fintech sector growth on the financial performance of traditional banks. While some studies suggest that Fintech services may complement traditional banking offerings or serve as substitutes that directly challenge the conventional banking model (Aaker and Keller, 1990; Frank, 2008), empirical evidence remains mixed.

Research conducted in various regions demonstrates both positive and negative associations between Fintech growth and bank performance. For example, studies by Chen et al. (2021) and Huang (2018) observed a positive impact of Fintech growth on bank performance in China. Similarly, Li et al. (2017), using Fintech funding and the number of Fintech acquisitions as proxies for growth, found a positive relationship with bank share prices in the United States. Haddad and Hornuf (2021) also reported a positive association between the growth of Fintech start-ups and bank financial performance across 87 countries, employing the number of Fintech firms as a proxy and using metrics such as ROA, ROE, NIM, and Tobin's Q.

Conversely, Phan et al. (2020) found that Fintech growth negatively affected bank performance in Indonesia, using similar proxies and performance variables as Haddad and Hornuf (2021). These conflicting findings highlight the ambiguity surrounding the impact of Fintech growth on traditional banks, suggesting that the relationship may vary depending on the specific regional context and the proxies used for measurement.

There is a notable gap in empirical research examining the impact of Fintech growth, particularly in the payments segment, on bank financial performance within the South African context. Given this limited focus, this study aims to specifically explore the potential relationship between the growth of Fintech firms in the payments segment and the financial performance of banks in South Africa. This research will contribute to the existing body of knowledge by addressing the gap in understanding how Fintech developments in this segment affect traditional banking within this unique regional

1.3 Research Question

This study seeks to answer:

1. What is the growth trend of Fintech Firm growth in the payments segment in South Africa?
2. What is the nature of the relationship between Fintech Firm growth in the payments segment and bank financial performance?

1.4 Goals of the Research

The overarching goal of this thesis is to critically examine the relationship between the growth of Fintech firms, specifically within the payments segment, and the financial performance of traditional banks in South Africa. By investigating this relationship, the study aims to provide a nuanced understanding of how the evolving Fintech landscape influences banking operations and profitability in the South African context, addressing the existing gaps in empirical research and offering insights for policymakers, financial institutions, and stakeholders in the rapidly changing financial ecosystem .The objectives of this research are, firstly, to measure the growth of fintech firms in South Africa. Secondly, to determine the relationship between the development of Fintech Firms and the performance of South African Banks.

The specific research objectives of this study are:

i. To measure the growth of fintech firms in the payments segment through the creation of a Fintech firm growth Index
ii. To determine the relationship between the growth of fintech firms in the payments segment and the performance of South African Banks

1.5 Methods, Procedures, Techniques and Ethical Consideration

This study is quantitative and falls within a positivist research paradigm, as the goal is to obtain objective evidence on the relationship between the growth of fintech firms and bank financial performance. The study will employ the use of panel data, pooled ordinary least squares and fixed effects regressions as the baseline research method to achieve the primary goal of this study. This methodology aligns with research on the impact of Fintech firms on banks' financial stability by Safiullah et al. (2022). Thereafter, we employ the generalised method of moments (GMM) estimation as a robustness check. This methodology is consistent with empirical research on bank financial performance (Pathan and Faff, 2013). The observation period of the study will range from 2009-2021, as during this period, there is an increase in the number of new fintech firms.

1.5.1. Objective 1

The data sources for the Fintech variable are the National Treasury Website, Genesis Analytics (2020) and the CrunchBase database[1]. Fintech data will be restricted to processes related to the banking sector and the payments segment. Fintech firms in the payments segment facilitate or enable the processing and settlements of payments by performing all or part of the functions necessary to send and receive currency from one party to the other via a digital channel (*Fintech Scoping in South Africa*, 2019).

Various studies, including Phan et al. (2020), use a count of the number of Fintech firms within the market as a proxy for Fintech firm development. Similarly, studies by Cheng and Qu (2020) and Luo et al. (2022) use a Fintech Index as a proxy for Fintech development. This study will employ the use of Fintech firm funding volume, a count of the number of Fintech firms and the number of Deals/Acquisitions for Fintech firms in the payments segment to create an equally weighted index as a measure for the growth of Payment Fintech Firms. To add to the robustness of our study, similar to studies such as Low and Wang (2021) and Li et al. (2017), Fintech firm funding volumes will also be used as a proxy for Fintech firm growth in the robustness check.

1.5.2. Objective 2

Bank data in this study comprises panel data collected from the Thompson Reuters Database Stats SA and the Reserve Bank of South Africa. There are 14 locally controlled banks in South Africa. However, this study is restricted to the five largest banks holding 90.1% of total banking sector assets (SARB, 2020). Yearly data is used from 2009 to 2021. Therefore, the number of observations is 60 (i.e., 5 banks x 12 years). The impact of fintech on bank performance is measured in line with the methodology employed by (Phan et al.,2020). Return on assets (ROA), return on equity (ROE), net interest margin (NIM) are included as Bank performance variables. Stock prices are a performance variable as they more accurately represent current

[1] The CrunchBase database has more than 200,000 firm contributors and is recently cited in publications by (Cumming et al., 2016) ;(*Fintech Scoping in South Africa*, 2019).

knowledge and expectations regarding the future growth and profitability of a company. (Anilowski et al., 2007).

To account for heterogeneity, multiple variables are employed as controls in accordance with the literature on bank performance. (Phan et al., 2020). The following literature from Pathan and Faff (2013), Shaban and James (2018) and Berger et al. (2017) control measures will be deposit growth, capital asset ratio, cost-income ratio, and the loan loss provision. Bank performance might also be influenced by gross domestic product (GDP) throughout the business cycle. Inflation is also included as a control variable due to the literature evidence highlighting the positive relationship between inflation and bank performance (Kasman et al., 2010). Inflation may also harm financial institutions if these institutes fail to adjust their interest rates, leading to increases in costs and a decrease in profits (Haddad and Hornuf, 2021). High market concentration within the banking sector was found to have a material effect on the financial performance and risk-taking of banks (Mishi et al., 2016). Therefore, HHI values will be used as a measure of bank concentration. Bank z-score has widely been used within the literature as a proxy for bank risk or financial stability; various studies stated that the Z-score was a more comprehensive measure of bank risk than other accounting-based measures (Hafeez et al., 2022). Following the methodology employed by Safiullah et al. (2022), this study employs the Ordinary least Squares and Fixed Effects estimations to analyse the relationship of Fintech firms on bank performance. This methodology allows for an overview of the relationships between the dependent and independent terms.

Studies by Shaban and James (2018) and Phan et al. (2020) analyse the effects of Fintech Firms on Bank performance with the use of a generalised method of moments (GMM) dynamic panel estimator. This methodology will be employed as a robustness check. This method allows the explanatory variables to be treated as endogenous using their past values as instruments. First, differences are taken to eliminate unobserved heterogeneity and control for variable bias. Following Wintoki et al. (2012), two lags will be included to capture the persistence of the Banking institutions.

1.6 Significance of the Study

The rapid expansion of Fintech firms in South Africa, particularly in the payments and mobile money segments has introduced significant innovation and disruption to the traditional banking landscape (EY, 2019). This expansion has proliferated the accessibility of cost-effective, technologically advanced financial solutions to previously underserved communities (EY, 2017), and as a result contributed to higher levels of financial inclusivity. Despite this, the impact of this expansion on the financial performance of incumbent banks in South Africa remains ambiguous .The emergence of fully digital “neo banks’’ into the South African Banking sector that potentially have disruptive effect on the incumbent banking institutions (Coetzee, 2018) , further necessitates an examination of this relationship.

This thesis seeks to address this gap in the research by investigating the relationship between Fintech Firm growth in the payments segment and the financial performance of South African commercial banks. By creating a comprehensive measure of Fintech firm growth through the construction of a Fintech Growth Index, this thesis aims to establish a deeper understanding of the influence Fintech Firms have on traditional banking performance. This thesis will contribute valuable insights both policymakers, Fintech Firms, South African banks and investors in the financial industry in developing policies that allow for the efficient operation of the South African financial markets. To the researcher, this study assisted in the understanding of the evolving trends in the Fintech payment segment and its influence on the banking sector. The study also highlighted the relevance of less strict regulation in the growth of the Fintech sector.

1.7 Organisation of the Thesis

This thesis will be organised as follows. Chapter 2 will examine the current knowledge relevant to the definition, structure, and growth of the Fintech firm sector through a literature review. Chapter 3 will examine the structure of the South African Banking sector and the effects of Fintech firm growth within the literature. Chapter 4 outlines the data, methodology and techniques used to conduct the research. Chapter 5 presents the results of the research and discusses the findings. Chapter 6 concludes the thesis with a summary and provides recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter analyses and reviews the literature concerning and related to Fintech Technology, Fintech Firms and the South African Banking sector. The literature in the chapter will mainly look to answer the following questions: What is Fintech, and what defines a Fintech Firm? What theories explain the growth of Fintech Firms? And what is the relationship between fintech firm growth and Bank performance in South Africa?

The chapter, in brief, conceptualises Financial Technology (Fintech) and Fintech Firms and gives an overview of the South African case. Section 2.2 defines Financial Technology and Fintech firms and states the applications and risks associated with Fintech Firms. Section 2.3 investigates the drivers of Fintech Adoption and growth. Section 2.4 analyses the structure of the Fintech segment in the South African context. Section 2.5 surveys the literature and theories explaining the adoption of Fintech and Fintech Firms. Section 2.6 surveys the empirical literature relating to the impact of the development of Fintech Firms on the performance of Banks. Trends within the literature on the effect of Fintech Firms on Bank performance are highlighted. The chapter then concludes with a summary of the main findings in the literature in section 2.7.

2.2 Financial Technology and Financial Technology Firms

2.2.1 Definition of Fintech

Financial Technology is one of the most researched areas in the Finance Industry. The term Fintech is used in literature to represent the innovative and disruptive technologies offerings in the financial services sector. According to Haddad (2018), interest in Fintech as a concept peaked in 2010. Fintech's emergence and sustained growth have been attributed to various reasons within the literature. Anikina et al. (2016) attributed the development of the sector to the cost-effective and innovative approach to financial services offerings provided by Fintech. Haddad (2018) also found that the fintech sector saw an increase in growth after the Global financial crisis, as consumers lost trust in traditional financial institutions.

Although various studies in the literature are of the prevailing opinion that the fourth industrial revolution has started (Yoon et al. 2016), finding a consensus on a unified definition of Fintech in the literature has proven to be complicated (Ryu, 2018). There is currently no widely accepted definition for Fintech within the literature. Bureshaid et al. (2021) find that Fintech's rapid, revolutionary nature creates a challenge in formulating a universal definition. However, various definitions of Fintech highlight the coming together of financial services and information technology. Researchers such as Gomber et al. (2018) argue, however, that fintech has ushered in a new paradigm shift in consumers' lives through the use of new technologies.

"Fintech" refers to a collection of cutting-edge information technology solutions implemented by financial service providers, including insurance regulators and institutions. Additionally, the term includes start-up companies and new entrants to the financial services sector (Arner et al., 2015). Bettinger (1972) first described fintech as combining bank experience and information technology expertise. Similar to the definition by Bettinger (1972), Arner et al. (2015) also formally define fintech as a contraction of Financial Technology in reference to technology-enabled financial solutions. Various sources in the literature define fintech as a unique sector or segment of the financial industry. PWC (2016) states that fintech is a rapidly evolving sector within the financial and technology industries, characterized by technology-driven startups and emerging market players that introduce innovative services and products to disrupt the conventional financial services sector. Micu (2016) similarly defines fintech as a new segment within the financial services industry, incorporating a wide range of technologies to facilitate trade, business between corporations, and services in the retail sector. Schueffel (2016) defines fintech as a new term in the financial sector that aims to improve service offerings through technology.

Other studies in the literature refer to Fintech as applications, technology, or digital platforms used to deliver, perform or offer financial services (Arner et al. 2015). Furthermore, in other sources in the literature, Fintech is defined from the business model point of view; Schueffel (2016) .Fintech utilizes software, applications, and online channels to provide financial services to consumers via digital devices like smartphones. Arner et al. (2015) provide a similar, although more succinct, definition, stating that fintech refers to the application of technology to finance. Dorfleitner et al. (2016) define fintech as the innovative business models that can transform the finance industry. KPMG (2019) defines fintech as financial innovation facilitated by technology that results in the development of novel business models, offerings, processes, or applications, thereby impacting financial services provision, institutions, and markets. Table 1 below summaries the main definitions of the term fintech within the literature in the table below:

Table 1: Summary of Fintech Definitions

Definitions	**Source**
Fintech comprises a wide variety of financial services and products, not limited to certain sectors.	(Arner et al., 2015, Schueffel, 2016)
Financial innovation involves the development and distribution of new financial products.	(Farah Husain, 2015)
Fintech enhances the efficacy of its financial system through the application of information technology.	(Haddad and Hornuf, 2021)
Fintech represents a financial service created in the 21st century	(The Payments Association, 2020)
FinTech utilizes contemporary software and technologies.	(Fintech weekly, 2019)
Fintech is the integration of several business models to enhance the financial system.	(Dorfleitner et al., 2016)

Source: Author's compilation

2.2.2 Fintech Applications

Fintech applications have been divided into different market segments depending on the core business model or service offered. Similarly, to the lack of consensus on a definition for Fintech, there is a lack of consensus within the literature on the various segments encompassing the fintech sector.

Various sources in the literature categorise the Fintech industry into four broad segments of other niche segments (Brandl and Hornuf, 2020, Dorfleitner et al., 2016, Thakor, 2020). Three of the four main segments include Financing, Asset Management, and Payments. However, various sources diverge on the last segment. (Brandl and Hornuf, 2020) Argue that the fourth segment represents Fintech applications and products related to API (application programming services). Furthermore, Thakor (2020) argues that Insurance Fintech firms represent the segment. Dorfleitner et al.(2016), however, argue that the Fintech Firms represent the segment that cannot be classified by the three other traditional bank functions. Following Dorfleitner et al. (2016), this study refers to the last segment as ‘Other Fintech’. Additionally, this study adapts the Fintech industry segmentation from the Reserve Bank of South Africa to further detail the subsections of the Fintech industry in South Africa.

The *Asset Management* segment includes Fintech applications that provide financial planning and advisory services, the saving and managing financial assets and wealth-related indicators. The segment hosts firms offering innovative and novel business models (Dorfleitner et al., 2016). The segments included include Fintech applications related to Robo advisory, Digital and Investment Banking and trading platforms.

Robo advisory Fintech applications offer largely automated algorithm-based portfolio management systems that provide investment advice to investors. These applications achieve this with little human interaction(SARB, 2019). These applications can employ advanced algorithms to analyse market performance and match investors' risk preferences to provide returns given the investor’s financial targets(SARB, 2019). Robo advice fintech firms are often financed through advisory fees charged to investors. This fee is calculated as a proportion of the sum of the portfolio. Performance-dependent fees are also implicated (Dorfleitner et al., 2016).

Personal financial management (PFM) Fintech applications use software or app-based services to offer financial planning for private and business clients. These applications focus on administering and presenting financial data (Dorfleitner et al., 2016). To provide these services, PFM applications use Application programming interface (API) technology to connect with financial institutions, which are typically open access and combine the various providers' accounts into a PFM (Thomas Dapp et al., 2015).

The digital bank subsegment is made up of Fintech firms that offer traditional banking products, which include fiat currency accounts with various information technology functionalities. Through the use of innovative technology and by leapfrogging cumbersome legacy traditional banking technology and branch infrastructure, these digital banks can offer conventional banking services and products more efficiently and cheaper than traditional banks (Haddad and Hornuf, 2021). South Africa is home to four challenger digital bank Fintech firms: TymeBank, Discovery Bank, BankZero and Hello Paisa. These four banks, unlike neo-banks that are not required to partner with established incumbent banks, are registered according to the Banks Act as fully registered banks by the South African Reserve Banks (SARB, 2019)

The Finance segment includes Fintech firms offering lending and Capital raising services to private and business clientele. The lending subsegments can be further divided into firms that source alternative financing, online lenders, and lending marketplaces.

Crowdlending fintech firms provide individuals and small businesses with secure loans from contributions or small investments from a large number of people (Dorfleitner et al., 2016). Fintech firms such as FundFind and Jumpstarter provide donation-based/rewards-based lending that does not require a financial return (SARB, 2019). Other Equity-based firms charge borrowers a fee depending on their credit profile and the loan term. On the other hand, other Fintech lenders require a predetermined fee on a percentage of the invested amount. Equity-based crowdlending in South Africa has slowly developed due to a strict regulatory framework. Firms in this space are required to register as an exchange under the Financial Market Act 2012 (SARB, 2019).

Fintech firms that offer alternative financing services to private and business clientele or LendTech can be referred to as capital intermediaries. Firms in this segment offer short-term loans without recourse from the public that vary in term periods from a few days to weeks through the internet or mobile devices (Dorfleitner et al., 2016). These firms follow two distinct business models: Lending marketplaces that act as intermediaries between borrowers and investors without their capital while collecting revenue from fees charged. Online lenders lend their capital from their balance sheets and collect revenue from interest and service fees (SARB, 2019). Similar to large incumbent lending firms, Fintech firms in the lending subsegments are required to register with the National Credit Regulator (NCR) as credit providers (SARB, 2019). The crowdfunding and lending applications of fintech firms in this sector are often viewed as reintermediation rather than disintermediation; however, they are not only disruptive to incumbent insurance firms but also perform investment banking financing activities of traditional banks.

The *Payments* segment refers to Fintech applications and firms that offer payment transactions internationally and nationally (Dorfleitner et al., 2016). P2P (peer-to-peer) applications are included in this definition. These applications allow for the transfer of fiat or virtual currency between individuals. Furthermore, P2P applications allow for real-time currency transfer and are thus faster than traditional offerings from traditional banks (Merritt, 2010).

Fintech firms that offer alternatives to fiat money (virtual currencies), such as the cryptocurrency and blockchain subsegments, would also be included in this segment. Fintech firms such as Luno and VALR offer cryptocurrency-related services in South Africa (SARB, 2019). Blockchain-based assets such as cryptocurrency serve as a virtual substitute for physical currency. Gomber et al. (2017) define Blockchain as a decentralised digitally distributed ledger technology shared among nodes within a computer network to maintain secure digital records. Furthermore, the data stored within these nodes is unchangeable and available publicly(Stulz, 2019).

Fintech firms that offer alternative payment methods, such as Mobile Payments, are also included in the segment. The term "Mobile payment" in the literature generally refers to various services enabled through mobile phones (Merritt, 2010). Fintech firms that offer E-wallets (electronic wallets) fall within this subsegment. An E-wallet is a technology that stores information relating to both digital currency and payment information. This information can then be used to relay payment information via mobile phone or over the internet without re-entering it (Dorfleitner et al., 2016).

The Bigtech segment, although not referenced in the main Fintech segments, is regarded as a particular subset of the broader Fintech sector (Frost et al., 2019). Stulz (2019) defines Bigtech as technology companies whose primary business model is focused on exploiting digital technologies. Fintech firms differ from Bigtech companies in that Fintech firms focus on a specific financial service. In contrast, Bigtech companies often offer financial products as one part of a more extensive set of business lines.

The Bigtech business model comprises two primary characteristics: Firstly, network effects created by e-commerce platforms, messaging software, search engines, and other such technologies. Secondly, technology involving artificial intelligence and big data. (Frost et al., 2019). The Bigtech model and its features at the core allow these firms to observe consumer behaviour, which forms the basis of the Bigtech monetisation strategy (Giya et al., 2021).

Vodacom, the telecommunications firm, has become active in financial services in regions such as East Africa, India and Egypt through its banking-related M-Pesa service. Similarly, Bigtech firms such as Google (Alphabet) and Apple currently provide payment services as bundled packages within South Africa. Google is set to launch current accounts along with its current market offerings, putting in direct competition with traditional banks (Giya et al., 2021)

2.2.3 Risk associated with Fintech.

The operation of Fintech firm presents a wide variety of risks that cut across various sectors and often blend both risks to clients and the financial system. The most prominent risks end users and banking institutions face are Cyber, Operational, Regulatory, and Systemic or Financial Stability risks. Cyber risk encompasses the risks associated with information integrity, availability, or secrecy (Boulianne and Fortin, 2020). Cyber risk can be divided into three components: Malware attacks, Data leakages and Data integrity risk (Najaf et al., 2021). A survey by the Society for World Interbank Financial Telecommunications (SWIFT) found that hackers chose to focus malware attacks on banking intuitions partnered with a Fintech firm by taking advantage of the vulnerabilities in Fintech firms (Vimal, 2019).

Fintech firms were also found to be relatively more vulnerable to data leakages compared to traditional banking intuitions due to their services mostly being digital (Boulianne and Fortin, 2020). Mobile banking plays a pivotal role in the Fintech sector, and therefore, mobile Fintech applications require robust, compactable encryption systems to support Fintech applications. Authors such as Subashini and Kavitha (2011) found that data integrity varied greatly between mobile money applications. These discrepancies ultimately resulted in cyber-security risk for Fintech firms and financial stability risk for the banking institutions they are partnered with.

Operational Risk is defined by the BCSB (2006) as the losses caused by external events or failed internal processes, individuals and systems. However, various studies have found that Fintech firms reduce operational risks through better governance by using more effective data analysis and efficiency of the banking business model. Cheng and Qu (2023) state that Fintech firms may increase operational risks within the Banking sector due to technical reasons. Firstly, the over-reliance on technology would increase the likelihood of operation risks due to business failure caused by inherent flaws in emerging FinTech technology. Secondly, the innovative financial services offered in banks based on Fintech partnering would increase the complexity of the bank business model and, therefore, introduce increased risks of potential operational losses.

Regulatory Risk within the FinTech sector can be attributed to a lack of consistent regulations governing the Fintech firms in part due to their online/digital offerings (Boulianne and Fortin, 2020). Ryu (2018) refers to regulatory risk as an unclear legal status and the lack of universal regulation of Fintech firms. Various papers within the literature attribute less stringent regulation of the Fintech sector as necessary to its development (Anagnostopoulos, 2018). Conversely, non-compliance of laws such as data privacy rules can lead to cyber risk, or they may potentially undermine the stability of the financial markets (Li et al., 2017)

Systemic/financial stability risk refers to the potential for severe adverse effects on the real economy due to the disruption of financial service flows resulting from failures in the entire or specific components of the financial system. (FSB, 2019). Although studies have found various advantages and benefits to the financial stability of the banking sector due to the growth of the Fintech sector, Fintech firms could potentially pose a threat and further endanger the real economy (Vučinić, 2020). FinTech could threaten financial stability through micro and macro-financial channels.

Micro financial risks refer to risks originating from single firms or sectors vulnerable to shocks. Micro financial risk can be attributed to financial or operational sources (FSB, 2017). Financial sources include risks associated with mismatched maturities, liquidity, and leverage, whereas operational sources involve cyber, regulatory, and business risks. Fintech innovations cause macro-financial risk over a more extended period of time; the extent of the risk to financial stability is dependent on the type of innovation and its potential to develop over time (FSB, 2017). Macro financial risk encompasses procyclicality, excess volatility, and contagion. Systemic/Financial stability risk is composed of various risk components. Table 2 below summarises the various risks related to the Fintech firm sector:

Table 2:Summary of Fintech Risk Factors

Impact on Consumer	Risks	Description	Sources
	Privacy and data rights breach	Risk posed by clients granting unauthorized access to their bank information to fintech firms	(Vimal, 2019)
	Lack of Financial literacy	Financial literacy on the part of clients, primarily in developing countries	(Giglio, 2021)
	Financial fraud and inadequate investor safeguards	Financial technology firms are more susceptible to significantly higher levels of fraud due to the ease of assuming fake identities.	(Giglio, 2021)
Impact on Banks and Banking sector			
	Cyber risk	The risk inherent to the integrity, availability, and confidentiality of information	(Boulianne and Fortin, 2020, Najaf et al., 2021, Vimal, 2019)
	Systemic/Financial stability risk	A disruption in financial technology that causes the complete instability of the financial system.	(FSB, 2019)
	Operational risk	The risk associated with ineffective internal processes, procedures, and staff in financial technology firms.	(Basle Committee on Banking Supervision., 2006)
	Default risk	The risk of defaulting on loans within Fintech firms is higher than in traditional lenders.	(Vučinić, 2020)
	Regulatory compliance and Legal risk	The lack of specific laws regulating the Fintech firm sector leads to lax functioning.	(Boulianne and Fortin, 2020)
	High costs	The banking and financial technology sectors experience financial instability due to the high volatility of the cryptocurrency asset market.	(Committee on Banking Supervision, 2017a)

Source: Author’s compilation

2.2.4 Trends in the Growth of the Fintech Industry

Fintech's growth rate within the developed and emerging markets has been high since the end of the global financial crisis. Globally, funding for Fintech start-ups experienced a substantial annual compound growth rate of 41% over the four years leading up to 2017, accumulating to a total value of $40 billion. (PWC, 2017). In a report by EY (2017), fintech adoption by consumers was forecasted to increase to a global average of 52%, with the highest intended use in emerging markets like South Africa, Mexico, and Singapore. In a more recent report by EY (2019), fintech adoption had increased to a global average of 64%. South Africa had a fintech adoption rate of 82%, the highest adoption rate in Africa for emerging markets. The Netherlands, UK and Ireland lead the adoption rates in the developed countries due to the developments in open banking in Europe. The report stated that 96 % of global consumers knew of at least one fintech firm in the money transfer and payments segments.

The growth rates in the adoption of fintech firms can be attributed to various reasons within different regions. EY (2019) stated that the high levels of consumer awareness of fintech firms in India could be linked to the government announcement to decrease the circulation of paper currency in 2017. Similarly, in Russia, the foreign sanctions imposed on banks have raised the profiles of fintech firms that offer remittance and foreign exchange services. In South Africa, consumer fintech adoption has been driven by mobile money and payments. Additionally, the South African retail sector has also primarily driven the adoption of fintech by consumers as retailers partner up with fintech to provide consumers with a broader range of checkout options (Thambo Mthwalo, 2021).

2.3 Drivers of Fintech Adoption and Growth

2.3.1 User Demographics, Mobile phone penetration and Internet Access

Various sources, such as Anagnostopoulos (2018) and Coetzee (2018), find that the changing demographics of financial services consumers and the high internet and mobile phone penetration enable the growth of Fintech applications. Millennials[2] have exhibited varyingly

[2] Those born between 1980 and 2000

different buying patterns and consumer expectations than the older generation, such as baby boomers[3] (KPMG, 2019). Millennials have been found to be averse to in-person interactions with banks, specifically via physical branches and instead prefer interactions via technologically driven channels (Hõbe, 2015). In addition, generation Z[4] consumers will operate in an environment with highly developed remote access (Anagnostopoulos, 2018). These changes in user demographics have resulted in the increased growth of Fintech firms that have been able to address these changes in consumer expectations more rapidly than the traditional banking sector.

Increased Internet penetration and mobile phone growth rates in emerging markets in Africa have contributed to the growth of Fintech firms in the Digital banking and Payments subsegments (Chigada et al., 2017). Similarly, in a report by EY (2019), mobile money transfers were found to be the primary driver of fintech growth on the continent. Chigada et al. (2017) found that the reduction in broadband subscription and smartphone prices was central to the increase in Internet penetration and mobile phone penetration. However, although South Africa and Nigeria had the highest rates of mobile penetration within the continent at 89%, only 15% of adults in South Africa used mobile banking payment applications. With a mobile phone penetration of 82%, Kenya had a mobile banking payment penetration rate of 61% (Poushter and Oates, 2015). Jack and Suri (2014) found that these discrepancies resulted from Kenya's lower rates of traditionally banked consumers in the population and weaker banking sector.

2.3.2 GFC (Global financial crisis)

The global financial crisis and the resulting regulatory gaps that formed have widely been attributed to the boom in the growth of Fintech firms within the literature. The investments in Fintech applications increased by four times compared to investments in venture capital(Anagnostopoulos, 2018). The crisis created a credit crunch, which in turn caused financial difficulties for many firms. As a result, economic output declined, and the rate of unemployment worldwide rose (Campello et al., 2010).

[3] Those born between 1960 and 1979
[4] Those born between 1995 and 2012

During the same period, the credit sector froze, the supply of mortgages fell, and small business credit and lending was withdrawn. Traditional banking institutions were unable and unwilling to lend credit or invest in IT due to the changing regulatory frameworks imposed by governments (Anagnostopoulos, 2018). Hence traditional bank clients lost confidence in the financial system. This unstable financial and regulatory period provided the ground for the novel, innovative offerings of Fintech firms to bridge the gap. These Fintech firms did not need to overcome the growing mistrust and risk aversion by consumers of traditional financial services (Haddad and Hornuf, 2021). Furthermore, the regulatory requirements of financial services providers generated better prospects for entrepreneurs to invest in online banking and Fintech solutions (Anagnostopoulos, 2018).

2.3.3 Changing consumer behaviour

Various sources within the literature refer to the changes in customer expectations as an enabler of Fintech growth. Consumers' expectations from financial service providers continue to evolve as a spin-off result of their interactions with services from other sectors (Anagnostopoulos, 2018). The future of the financial services industry, according to experts, will be characterized by the establishment of significant consumer relationship (Committee on Banking Supervision, 2017b).

Gomber et al. (2018) found that Fintech firms earning a reputation for customer-centricity along with innovative and novel technology applications to traditional banking products have been at the forefront of the disruption of the traditional banking model. The growth of Fintech can be attributed to the slow response by traditional banking institutions to react to changing consumer behaviour and change from a product-oriented approach to a more client-centric one (Anagnostopoulos, 2018). As a result, a larger shift in the market share of traditional banks in favour of Fintech firms has been forecasted within the sector (Watson, 2016) . Consumers expect efficient, user-tailored, timely services and a more consumer-focused personal relationship with their financial service providers. Consumers expect to be treated as individuals by their service providers (Anagnostopoulos, 2018). Similarly, PWC (2016) found that consumers at the core of the financial system would expect cutting-edge KYC (know your client), personalised consumer experience and virtually managed offerings. This customer-centric approach has been championed by large technologically proficient companies such as

Apple and Amazon. Therefore, there is a demand for better, cheaper, and more efficient services driving the growth of Fintech firms (Haddad and Hornuf, 2021).

2.3.4 Fintech Regulatory Environment

The regulatory frameworks around Fintech firms have had both enabling and restrictive implications for Fintech growth. Anagnostopoulos (2018) found that the new regulatory requirements on traditional banking restricting large deposits as a source of banks' funding have been largely abolished following the GFC. These regulations carry large financial penalties for institutions engaging in practices considered less stable for the efficient operation of the financial system. These regulatory gaps following the GFC have enabled fintech firms to leapfrog the banking, financial compliance, and payment regulations of traditional banks (Anagnostopoulos, 2018).

However, Brandl and Hornuf (2020) state that often, fintech firms do not fully comply with financial regulations and therefore take advantage of regulatory arbitrage through legal exemptions, potentially undermining the stability of the financial markets (Li et al., 2017). The risks associated with a lack of regulatory oversight have been acknowledged in the South African context, given the increasing growth of Fintech firms (SARB, 2019). Evidence suggests, however, that more stringent regulation of Fintech firms has a restrictive effect on the growth of the sector. Zalan and Toufaily (2017) found evidence that increased regulation on fintech firms within the MENA region led to a decrease in the growth rate of fintech firms.

2.4 Fintech in South Africa

Various studies in the literature have identified the money transfers and mobile payments sectors as drivers of fintech firm growth in South Africa(EY, 2019, Slazus and Bick, 2022). Underpinning the growth of the payments segments in South Africa is the increased mobile phone and internet penetration. As the prices fall to gain access to smart mobile devices, the growth of Fintech firms is likely to increase. However, the regulatory framework around fintech in South Africa has proven to be both an enabler and deterrent to the entrance of new fintech market entrants. The following section is limited in scope to fintech applications directly related to traditional banking offerings.

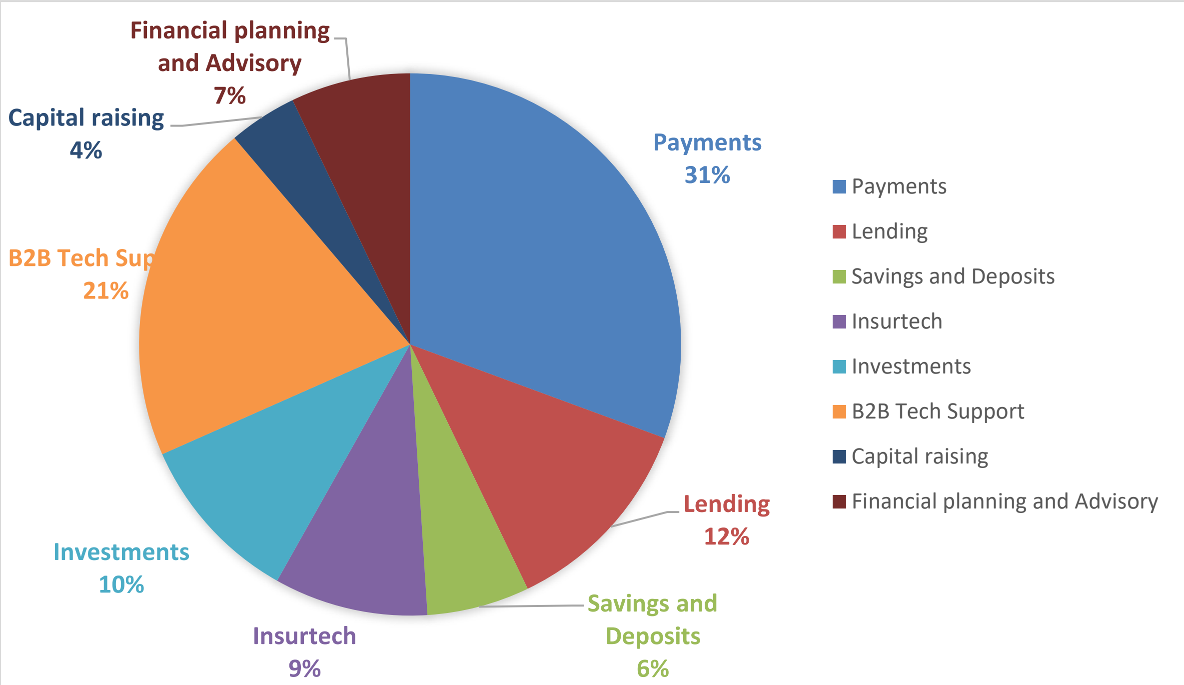

Figure 1: Segmentation of Fintech firms in South Africa
Source: (SARB, 2019)

As of 2019, the South African fintech sector has at least 217 active and operational fintech firms (SARB, 2019). Similar to global trends, the largest, most mature segment is the Payments segment, accounting for approximately 31% of all fintech firms. Firstly, the segment's growth has been driven by increased access to smart devices and internet penetration. Secondly, the growing retail sector and the need for efficient online payment services (EY, 2019). The segment accounts for 6% of the total transactional volume addressable market, the rest being addressed by traditional banking firms (SARB, 2019). The fintech payments segment, however, is expected to grow above the total payments segment by 4% as mobile devices and internet connectivity become more affordable. Regulatory frameworks within the payments segments within global markets have enabled the segment's growth as incumbent banks are now required to share data with fintech firms. These policy changes have yet to be reflected within the South African banking framework. Although expected to grow above the market, fintech firms in the payments are limited due to the regulatory requirement that these firms partner with incumbent banks(SARB, 2019).

The lending subsegment is the second largest segment in South Africa, with 28 fintech, 18 of which service the lenders online. The segment is responsible for 1.49% of the addressable Lending market, which equates to R 9.8 billion. The sector's growth has been attributed to increased consumer demand due to previously underserved consumers not being served by formal incumbent financial service providers. Lending Fintech firms are required to register as credit service providers with the NCR (National Credit Regulator). Similarly to the payments segment, the fintech lending segment is expected to outgrow the lending market by 3% in 2025 and provide loans valued at R13 billion (SARB, 2019).

The savings and deposits segments represent only 6% of the entire fintech firm segment and historically is highly regulated. There are 14 fintech firms in the segment, four of which are digital challenger banks (SARB, 2019). These banks include Tymebank, Discovery, BankZero and Hello Paisa. Currently, the segment services 1% of the 28.7 million banked persons in the sector. These digital banks are required to obtain banking licenses and are subject to liquidity and capital reserve requirements by the Reserve Bank of South Africa (SARB, 2019). Although the sector is heavily regulated to allow for the efficient operation of South African financial markets, and bank licenses being prohibitively expensive and difficult to acquire, the subsegment is expected to outgrow the deposit sector by 7% (SARB, 2019).

The investment financial sector has been largely only accessible to middle to high-income earners; however, the Investment fintech subsector has made retail investing more accessible to a broader range of consumers (Haddad and Hornuf, 2021). There are 175 JSE (Johannesburg Stock Exchange) registered stockbrokers responsible for broking trades for individual clients; however, Fintech firms such as EasyEquities have made it possible for investors to trade without these intermediaries (SARB,2019). The subsegment comprises 22 fintech firms, ten offering cryptocurrency trading services and eight retail trading platforms. Luno and Project Ubuntu are domestic trading platforms that have allowed cryptocurrency trading via mobile devices. Similar to the deposit and savings subsegment, four of the five major South African Banks offer online trading services and are represented in the Investment subsegment(SARB, 2019). Since 2016, the FCSA has registered five licenses to alternative exchange platforms; these platforms will remove the oligopoly once held by the JSE and SAFEX (SA Future Exchange). The Reserve Bank of South Africa states that 1.392% of 68 million trades at the JSE in cryptocurrencies and on alternative exchanges were executed by fintech firms. Growth in the segment has been restricted by regulatory changes regarding the legality of cryptocurrency as legal tender in South Africa (PWC, 2017, SARB, 2019).

A handful of fintech firms represent the capital raising segment, with most of these firms being crowdfunding applications. Most of the firms in this segment use the rewards-based crowdfunding model (SARB, 2019). The segment is represented by firms such as FundFind, JumpStart and Thundafund. These platforms collectively raised R 429 million and funded 4581 projects, exceeding traditional incumbent venture capital firms that only funded 98 in 2015 (SARB, 2019). Although the segment has the potential to support more significant volumes of funding, regulatory pressures hamper growth within the segment. Regulatory uncertainty with regard to Equity based fundraising has resulted in only one fintech firm offering funding using the equity-based model. Although the segment is most prevalent within the North American and European markets, the sector is not expected to grow within the South African market due to regulatory pressures (SARB, 2019).

2.5 Theoretical Literature Review

2.5.1 Introduction

This section discusses the various theories that can be attributed to the growth of Fintech and Fintech firms within a global and South African context. Firstly, in 2.5.2, the Substitution and Consumer theories are discussed, followed by 2.5.3 Diffusion of Innovation and 2.5.4, the Technology Acceptance Model. The section then ends with a conclusion of the theoretical framework.

2.5.2 Microeconomic theory of Consumer theory

Central to the phenomenal growth of fintech adoption is the consumer theory. The theory is applied by various studies, such as those by (Haddad and Hornuf, 2021, Li et al., 2017,Phan et al., 2020,Almulla and Aljughaiman, 2021), who have attributed the growth of fintech firms partly to the consumer theory. The consumer theory explains how new service and product offerings, such as those developed by fintech firms, act as either a complement when used jointly with existing incumbent offerings or a substitute if they can replace the incumbents' offerings by satisfying the same need (Aaker and Keller, 1990). The Consumer theory attempts to determine the effect on rational consumers' demand preferences for goods and services as they attempt to maximise their utility given their preferences and budgetary constraints (Barten and Böhm, 1982). Furthermore, the theory highlights the distinction between complementary and substitute products.

According to the consumer theory, the income and substitution effects can be used to determine the rationale of consumers' choices when faced with a change in the cost associated with their preferred bundle of goods. The income effect is influenced by budgetary constraints, which are determined by the value of total wealth at the disposal of the consumer. Consumer demand is negatively affected by changes in prices due to fluctuations in income, as predicted by the income effect. (Barten and Böhm, 1982). Similarly, the substitution effect, according to (Christensen, 1997) predicts the relationship between consumer preference for different commodities.

Aaker and Keller (1990) state that substitute products or service offerings are those that can easily replace and satisfy the consumer's needs in place of the product or service in the same context. Goods and service offerings that can be used in conjunction with the original service are referred to as complementary goods. Various authors in the literature refer to the consumer theory in predicting the adoption of Fintech services. In the context of consumers' budgetary constraints, Fintech services have proven to be cheaper and more efficient than incumbent traditional financial institutions (Haddad and Hornuf, 2021).

The Consumer theory argues that consumer demand for financial services is predicted by price differentials between similar services and products by traditional banks and Fintech Firms. Fintech firms would, therefore, have a negative effect on the demand and profitability of traditional banking services. Fintech offerings and products can also be complementary in nature due to the innovative and novel business models employed by Fintech firms. Incumbent banking institutions are therefore positively impacted as the complimentary effects increase the demand for both Fintech and banking services (Li et al.,2017)

2.5.3 Disruptive Innovation Theory

The disruptive innovation theory by Christensen (1997) states that new market entrants that offer successful substitutes for traditional services and target overlooked markets disrupt traditional retail banks by providing cost-effective services and goods to consumers. The theory of disruptive innovation differentiates between disruptive innovation and sustaining innovation. Sustaining innovation targets existing consumers and can be either incremental improvements or radical development. Both instances allow firms to sell innovative offerings to customers at a premium. However, disruptive innovations start in low-end or new markets, i.e. (unbanked and underbanked market segments)(Christensen et al., 2016). These overlooked markets include the underbanked and unbanked segments that do not offer traditional retail banks profitable returns through traditional labour-intensive service offerings(Almulla and Aljughaiman, 2021). Christensen et al. (2016) further clarify that disruptive innovation takes time, and complete substitution of incumbent banks' by fintech firms would take decades. Ferrari et al. (2016) found that fintech firms have already initiated a disruptive evolution due to their ability to offer alternative services and products to consumers in an innovative and efficient manner.

Fintech firms have provided consumers with significantly lower transactional costs due to increased efficiency in part through disintermediation (PWC, 2016). These efficiencies can be accomplished by Blockchain technology, regarded as the most disruptive and prominent fintech innovation, by making the clearing and settlements of financial offerings in the financial sector more cost-effective (Arner et al., 2015). Fintech companies have created many services such as mobile and quick money transfers, automated asset management, and data management (Villeroy de Galhau, 2016).

These sustaining innovations allow fintech firms to exploit the outdated legacy information technology used by incumbent banks and financial institutions and their slow response to adapting to new technologies to gain a foothold in the market (Brandl and Hornuf, 2020). Established banks face challenges in their ability to swiftly embrace new technology due to the regulatory constraints that are put on them as fully compliant entities (E. Lee, 2017). Empirical evidence has shown, however, that fintech firms in specific segments have not affected the performance of incumbent banks. This is partly due to disruptive technologies that allow fintech firms to attract consumers that traditional banks otherwise do not serve (Haddad and Hornuf, 2021). As evidenced in studies by Jack and Suri (2016), the growth of fintech in the mobile money and banking services segment in Kenya did not affect the financial performance of traditional banks as these fintech firms mainly targeted the under and unbanked consumers.

2.5.4 Diffusion of Innovation Theory

A further applicable model to the growth of fintech is the Diffusion of Innovation theory. Everette Roger proposed the theory as an earlier technology acceptance theory. Rogers (1995) defines diffusion of innovation as a process in which innovation is spread through various channels over a period through society. The theory suggests that the adoption of innovation relies on a client-centred strategy to effectively communicate the benefits of the innovation to potential users. Innovation, in this case, refers to a new idea, practice, or service that consumers see as novel (Roger et al., 2009). Various studies, such as those by Coetzee (2019) and Alwi et al. (2019), have applied the innovation of fintech to the diffusion of innovation theory.

The diffusion of innovation theory posits that the spread of new technology is influenced by four key factors: invention, communication channel, time, and social systems. (Roger et al., 2009). Rogers also suggested five characteristics in his model vital to explaining the rate of technology adoption: relative advantage, trialability, compatibility, complexity, and observability. The theory further stated that consumers would likely adopt innovative technology if it met all five constructs (Roger et al., 2009).

While the Diffusion of Innovation theory is commonly used in fintech adoption literature, other studies suggest that not all five qualities are necessary to assess perceived utility and adoption of innovation. Hamdan et al., (2021) found that there was no unanimity among researchers in applying the theory to study phenomena related to fintech adoption. Hubert et al., (2019) argues that it is crucial to incorporate only four specific criteria from the diffusion of innovation theory, excluding relative advantage.

However, relative advantage was found to predict both perceived usefulness in the context of E-learning (Lee et al., 2011). Similarly, relative advantage was found to positively affect the attitude towards adopting internet banking (Shih and Fang, 2004). Lou et al. (2017) used only the complexity, trialability and relative advantage characteristics to determine the perceived usefulness and adoption of fintech in industries. However, in a study by Lee et al. (2011), observability was found to positively predict the effect on the perceived usefulness of technology. Mutahar et al. (2017) discovered that analysing the adoption of mobile banking may be effectively done by focusing on three key characteristics: compatibility, trialability, and observability. However, Siddik et al., (2014) argues the diffusion of innovation theory is entirely applicable to understanding the uptake of new technology, including fintech.

In a report by Min et al., (2019), a sixth characteristic, social influence, was included as being vital in explaining technology adoption. According to Roger et al. (2009) the diffusion of innovation theory is a social process that spreads an innovation by consumers talking to other consumers about the adoption of an innovation. And as such, social characteristics is vitally essential when explaining an individual's mobile technology adoption (Suprateek et al., 2003).

2.5.5 Technology Acceptance Model

Various studies, such as those by Hamdan et al. (2021) and Hubert et al. (2019), find the Diffusion of Innovation theory similar and complementary to the Technology Acceptance Model in terms of explaining the adoption of information technology. These studies argue that the Technology Acceptance Model employs constructs that are a subset of the perceived innovation characteristics. Therefore, combining the two theories could lead to a more comprehensive knowledge compared to studying each one separately. (Bureshaid et al., 2021).

The Technology Acceptance Model was developed by Davis (1989). Since then, the model has been widely applied by researchers partly to its usefulness in predicting consumer intention to adopt the technology by using the Perceived Usefulness (PU) and Perceived Ease of Use contracts (PEU) (Davis, 1989). The primary goal of the Technology Acceptance model is to analyse how external factors influence consumers' internal beliefs, attitudes, and intentions. According to Davis (1989), PU and PEU are the key variables that determine and forecast technology usage, with additional factors playing a minor role in explaining the variance in users' technology acceptance beliefs. Some studies suggest that external variables are influenced by PU and PEU, offering a deeper insight into the factors affecting PU and PEU. The presence of these variables is essential to explaining the adoption of technology (Olushola et al., 2017). Furthermore, a third variable was shown to be relevant in explaining the consumers' intention to adopt the technology. According to Lee and Shin (2018), the concept of risk associated with any new technological innovation was necessary to include in the technology acceptance model.

The Technology Acceptance Model is highly regarded as a framework that predicts users' intention to adopt a technology (Akturan and Tezcan, 2012). Various studies, including one by

Wentzel et al. (2013), regard the Technology Acceptance approach and its modifications as the most proven approach for analysing technology uptake. According to Chigada et al. (2017), the most common theory used to investigate the adoption of mobile money technologies in Africa was the technologies Acceptance Model.

In the context of fintech services, many researchers support the Technology Acceptance Model as an excellent model for explaining the consumers' adoption of technology (Lee and Shin, 2018). Bagozzi (2007), however, argues that the Technology Acceptance Model has a broad scope of limitations, particularly concerning the theory's neglect of group, social and cultural aspects of technology adoption. Many empirical research suggest combining the Technology Acceptance Model with theories that can adapt to the fast pace of technological advancements and enhance explanatory capabilities (Bureshaid et al., 2021, Carter and Bélanger)

2.2.6 Assessment of Theory

Various theoretical frameworks have been applied to exploring the adoption of Financial Technologies across literature. Central to the theories regarding the adoption of fintech is the consumer's attitude towards the economic benefits, novelty or innovative business models, usefulness, and ease of use of technology. The central theme concerning the Consumer theory is the consumers' appetite for cost-effective, efficient service offerings. The Disruptive innovation theory builds on the Consumer theory and states that consumers gravitate towards innovative and new business models underserviced in the market. Both the Diffusion of Innovation and Technology acceptance model attempt to explain the adoption of technology concerning the consumers' attitude towards perceived usefulness and perceived ease of use.

2.6 Empirical literature review

2.6.1 Strategic Impact of Fintech firms on Banks

Although technology has already been integrated into products and service offerings by traditional banks for decades, it has largely been restricted to the automation of back-office operations (Coetzee, 2018). Fintech firms are increasingly entering traditional banking services' service chain through their cheaper, more efficient value propositions. Therefore, the direction banks take strategically is vital to ensure their relevancy(Weichert et al., 2017).

Various researchers, such as Hedley et al. (2015), argue that non-traditional banking competitors or Fintech firms have the technological expertise, resources, and consumer goodwill to eradicate traditional banks in the near future. Hedley et al. (2015) , however, put forward factors that might stop this from occurring. Firstly, the regulatory framework that traditional banks thrive in may restrict the fintech firm from entering the market. Secondly, traditional banks have the added advantage of necessary networks that could negate competitive pressure from Fintech firms; lastly, traditional banks are perceived as a less risky prospect for consumers.

Fintech firms have redefined and refined various financial offerings and created completely new business models that have not previously been serviced by traditional banks. Emerging technological innovations such as AI, Quantum computing, Mobile Internet, and Self-learning algorithms are revolutionising the financial sector (Dapp et al., 2015). Therefore, researchers argue that due to disintermediation, the innovative and efficient financial services offerings, traditional banks will need to adapt their strategies to partner with Fintech firms to continue to provide cost-efficient banking services (Arner et al., 2015). Therefore, the offerings provided by fintech firms could be beneficial to incumbent banks in the former case and affect the profitability of incumbent banks in the latter (Kaul, 2012).

Therefore, existing offerings and services by incumbent banks have been improved with innovative business models without the need to replace established ones (Merton, 1995). This collaborative and complementary partnership has the potential to be mutually beneficial to both incumbent banks and fintech firms. Incumbent banks are introduced to innovative, cheaper, and more efficient banking solutions. Fintech firms benefit through the earnings from offering the service (PWC, 2017).

Studies by Shu and Strassmann (2005) and (Martín-Oliver and Salas-Fumás (2008) found that information technology added value to incumbent financial institutions due to the reduction of transactional costs, improvements in service quality and the optimisation of business structures. Incumbent institutions have recognized the innovation of fintech firms and integrated them and their services into their traditional business models, as demonstrated by empirical evidence. (Brandl and Hornuf, 2020). Jerome Bagley et al. (2016) found that although banks in the US adopted banking apps and web 2.0 technologies, South African banks were slow in incorporating banking applications. However, in a more recent report, Coetzee (2018) found that banking apps were the third most downloaded after social media and messaging applications in South Africa. The growth and adoption of fintech firms have, therefore, benefited these incumbent banks rather than be a threat (PWC, 2016). Although fintech firms have developed innovative and revolutionary business models, partnerships between banks and fintech firms have developed over time (Haddad and Hornuf, 2021).

2.6.2 Empirical evidence of the relationship between Fintech firms on Bank performance

Empirical evidence relating to the growth of fintech firms and their relationship with retail bank performance in the South African context has been limited. However, in a global context, various studies relating to the relationship between fintech firm development and bank financial performance have found positive and negative. Li et al. (2017) found a positive relationship between Fintech start-ups on retail banks' share prices. The report examined the relationship between 47 retail banks in the United States and the start-up funding of fintech firms. The study was conducted between 2010 and 2016. In the report, the relationship between fintech firm funding and retail bank share prices was positive, indicating that the development of fintech firms positively affected incumbent retail banks. Furthermore, a second proxy, the growth rate of deals or acquisitions by fintech start-ups, was found to have a positive relationship with the share prices of retail banks (Li et al., 2017).

Similarly, Haddad and Hornuf (2021) found that the relationship between fintech start-ups and incumbent banks' financial performance was positive. The study period was between 2005 and 2018 and included a large sample of incumbent institutions from 87 countries. Unlike the report by Li et al. (2017), the study used the growth rate of fintech startups as the proxy for fintech firm development. The paper also used ROA, ROE, NIM and Tobin's Q as bank performance variables. The report also examined the effect of fintech start-up development on the default risk of incumbent financial institutions. The study concluded that fintech start-up development decreased stock volatility and systematic risk of financial institutions (Haddad and Hornuf, 2021).

Safiullah and colleagues (2022) studied how Fintech companies affect the financial stability of banks in Malaysia . 26 banks from the emerging market, were analysed to investigate the impact of Fintech firms on bank financial stability and cost efficiency. The report also analysed the impact of Fintech firm development on banks of different sizes, bank types (Islamic vs conventional), and corporate governance levels. Safiullah et al. (2022) employed a similar methodology to (Haddad and Hornuf, 2021) by employing the growth rate of Fintech firms as a proxy for Fintech firm development. Using a Dynamic panel GMM regression and a correlation matrix, they concluded that the development of Fintech firms was positively related to financial stability. Larger banks were found to have less of a positive relationship with Fintech development. Similarly, low governance and Islamic banks were also positively correlated with Fintech firm development (Safiullah et al., 2022).

Phan et al. (2020) investigated the growth of Fintech firms on bank performance in Indonesia. Using a sample of 41 banks and Fintech development data, the report found that Fintech firm development negatively influenced bank performance. Similar to Safiullah et al. (2022) and Haddad and Hornuf (2021), the report employed the growth rate of Fintech Firms as a proxy for Fintech firm development. The study focused on NIM , ROE, ROA, and YEA to measure bank performance from 1998 to 2016. Fintech firm development was found to predict bank performance negatively. Specifically, the Fintech proxy was found to predict NIM, ROE, ROA, and YEA negatively. The paper also studied the relationship of Fintech development with bank size and age. Fintech development was found to affect the performance of smaller banks positively; however, the effect was largely negative regardless of bank characteristics (Phan et al., 2020).

Almulla and Aljughaiman (2021) examined the impact of Fintech firm development and Fintech services on bank performance in the United Arab Emirates (UAE), Saudi Arabia, and Bahrain. The study was from 2014 to 2019, and the sample included 40 listed banks within the three regions. The study additionally endeavoured to analyse the relationship between Fintech firm growth and conventional (CB)and Islamic banks (IB). Similar to the findings by (Phan et al., 2020), it was found that the growth of Fintech firms in each region had a negative effect on the performance of conventional banks; however, the relationship with Islamic banks was insignificant. Furthermore, the relationship between Fintech services offered by banks and bank performance was also negative. The study used a similar methodology to (Phan et al., 2020) and Haddad and Hornuf (2021) by using Fintech firm growth and the dynamic GMM (generalised method of moments) to estimate the regression.

Nikita Sari (2020) investigated the effect of Fintech firm growth in the Peer-to-Peer lending (P2P) segment on bank financial performance in Indonesia. The study period was from 2015 to 2019 and used data from 109 registered banks. Using a similar methodology to Phan et al (2020) and Hadda and Hornuf (2021), the author investigated the relationship between bank performance variables such as ROA, ROE, and NIM and the growth of Fintech firms.

Additional proxies for Fintech Firm growth included the number of lender accounts, borrower accounts with fintech firms, and the number of transactions with fintech firms. These variables and fintech firm growth were found to have a negative relationship with bank performance variables (Nikita Sari, 2020). This result was consistent with (Phan et al., 2020, Almulla and Aljughaiman, 2021).

Low and Wong (2021) conducted a study investigating the relationship between Fintech firm growth and the financial performance of Banks in six ASEAN countries. The study investigated the demand and supply side Fintech development factors and their impact on the stock returns of 70 banks in ASEAN nations from 2012 to 2018. The supply side variables or proxies consisted of Fintech company funding volume, number of deals, number of Fintech firms formed, and their growth rates. These variables were regressed against the stock returns within a panel analysis. The study employs a similar methodology to (Li et al., 2017) by using the Fama and French Five-Factor Asset Pricing Model.

The study established a positive relationship between the expansion of Fintech and the stock returns of banks in Singapore and the Philippines. However, the was an insignificant negative relationship between bank share prices in Indonesia and an insignificant positive relationship in Vietnam. Fintech growth in Malaysia and Thailand showed no effect on bank financial performance(Low and Wong, 2021). The positive relationship between Fintech firm funding, the growth rate of Fintech firm funding and bank share prices was consistent with Li et al. (2017). The positive relationship between Fintech firm growth rates and bank financial performance is consistent with results by (Haddad and Hornuf, 2021)

2.7 Assessment of Fintech

The growth of Fintech and Fintech firms globally has been studied in detail, and various studies in the literature point to the many effects fintech has had on the banking and financial system. Various studies in the literature refer to factors such as the 2007-2008 global financial crisis as a catalyst in the growth of the segment (Thakor, 2020). In emerging markets in Africa, Fintech firm growth has been primarily attributed to the growth of mobile money and mobile phone transactions (Jack and Suri, 2014).

Many sources in the literature characterise Fintech Firms as disruptors in the financial and banking sector (Dorfleitner et al., 2016, Haddad and Hornuf, 2021). These studies find that these firms not only replace existing traditional financial and banking institutions but also invent new innovative business models not currently serviced by traditional financial and banking institutions. Furthermore, Fintech firms are more efficient and cost-effective in their provision of service offerings traditionally offered by incumbents (PWC, 2016). However, in contrast, authors such as Watson (2016) argue that Fintech firms are also enablers of traditional financial and banking institutions. Partnerships between Fintech Firms and traditional financial institutions result in positive financial outcomes for Fintech firms and incumbent institutions.

Studies on the effects of Fintech Firm growth on the Bank financial performance have produced varied and polarising findings. Haddad and Hornuf (2021) provided empirical evidence showing a positive correlation between the expansion of Fintech firms and the financial performance of banks. Studies by Li et al. (2017), Low and Wong (2021), and Safiullah et al. (2022) similarly showed a strong correlation between the growth of Fintech companies and the financial performance of banks. Fintech firm growth and Fintech firm funding resulted in a positive effect on Bank financial performance. These results are consistent with the outcomes of Fintech firms forming partnerships with banking institutions. However, other authors found that the development of the Fintech Firm industry had a negative relationship with bank financial performance (Almulla and Aljughaiman, 2021, Phan et al., 2020). These papers found that as the number of Fintech Firms increased, Bank financial performance was negatively affected.

The regulatory frameworks with which Fintech Firms operate were found to have a great impact on the growth of the sector and its relationship with bank financial performance(Slazus and Bick, 2022). Strict financial regulations and oversight negatively affected the growth of the sector. In contrast, in markets with less restrictive regulation, the sector showed higher growth rates.

The South African Fintech sector is regarded as the most developed within the African continent (EY, 2019, Soutter et al., 2019). 31% of South African Fintech firms are in the payments and mobile money segment. However, South African retail banks account for more than 94% of the total payment transactional volume (SARB, 2019). Furthermore, the segment is forecasted to outgrow the entire payments market by 4%. In South Africa, Banking institutions and Fintech firms are highly regulated. The regulatory framework in South Africa requires Fintech firms in the payments segment to partner with traditional retail banking institutions(SARB, 2019).

Given the empirical evidence and regulatory context in which Fintech Firms operate in South Africa, this study will investigate the relationship between South African bank financial performance and the development in the payment Fintech segment.

CHAPTER 3 : THE SOUTH AFRICAN BANKING SECTOR

3.1 Introduction

This chapter examines and reviews the structure of the South African banking sector as well as the regulatory environment in which it operates. The South African Banking sector is regarded as highly efficient and stable within the literature. This chapter delves into the structure, financial performance and the regulation that define the sector. The chapter attempts to answer three questions: How is the banking sector structured? What is the regulatory framework, and how does this affect the efficiency and stability of the sector?

This chapter begins with a brief introduction to the South African banking sector. Section 3.2 explores the sector's structure and highlights the concentration level in the sector. Section 3.3 reviews key financial performance indicators and stability metrics. Section 3.4 surveys the literature concerning the regulatory environment and comments on the risk-averse nature of South Africa's Banks. The chapter then concludes with a summary of the main findings within the literature in section 3.5.

3.2 Structure of the Banking Sector

The South African Banking sector is widely regarded as one of the most developed in the world (Schwab, 2016). The South African banking system is driven by strict global international standards, best practices and functions in an environment challenged by high socioeconomic imbalances (SARB, 2017). The sector is efficiently regulated by the South African Reserve Bank (SARB) and comprises commercial banks, investment institutions, and savings organizations.

Although regarded internationally, Coetzee (2019) found that South African banks have lagged behind their counterparts in the internal banking community. Coetzee (2019) further states that the slow response to fintech firms by retail banks can be attributed to the risk-averse nature of South African retail banks due to stringent regulatory requirements in the banking sector.

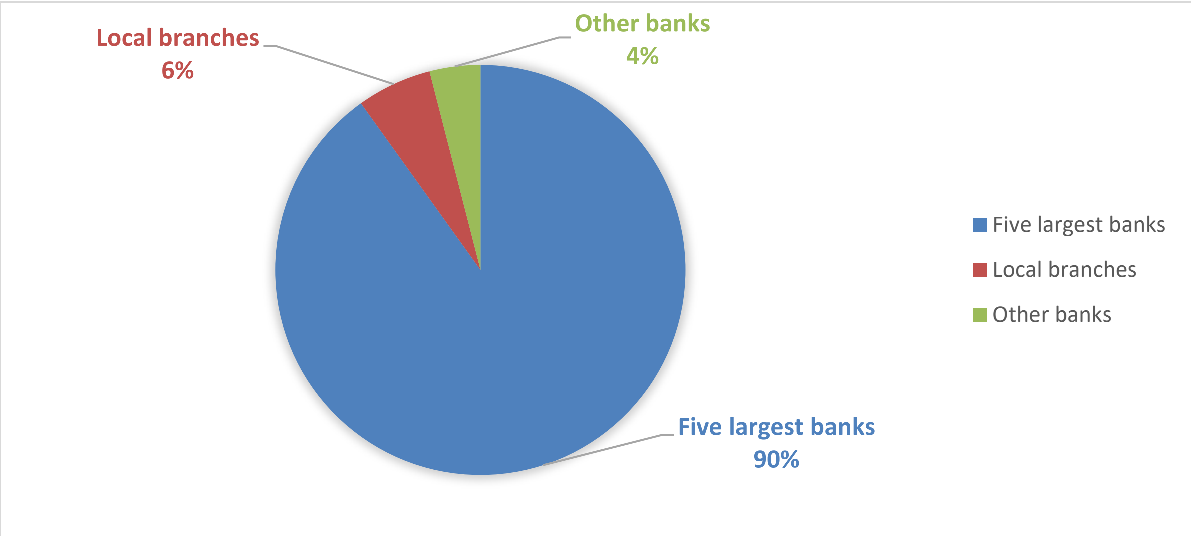

Figure 2: Segmentation of the South African Banking sector
Source: (SARB, 2021)

According to Figure 2, the total asset value held by South Africa's banks was R 6.457 trillion in 2021. The banking sector consists of 18 registered banks, 4 mutual banks, 13 local branches of international banks, and 30 foreign banks with recognized local representative offices, as stated by the prudential authorities. The South African retail banking sector is highly concentrated, with the five largest banks representing 90% of the total bank assets, with digital banks TymeBank and Discovery making up 0.03 and 0.19%, respectively (SARB, 2021). Similarly, the World Bank's five-bank asset concentration ratio is 99.89% for the South African banking sector; this statistic further suggests that the sector is highly concentrated. The World Bank Lerner index statistics for South Africa increased from 0.149% in 2009 to 0.23%, indicating a deterioration in the sector's competitiveness levels.

3.3 Financial Performance

The South African banking sector compares favourably to other developed countries and is ranked 11th out of 138 nations in its financial market development. In terms of bank soundness and the affordability of financial services, the South African banking sector ranked 2nd and 27th, respectively(World Bank, 2017). The sector has experienced consistent growth, as evidenced by the growth of total bank assets from R 2,967 trillion in 2009 to R 6.457 trillion in 2021. ROA, ROE and NIM trends have remained relatively consistent (SARB, 2021). Similarly, bank Z-scores in the banking sector remained relatively consistent, suggesting that the high concentration within the sector did not directly affect the risk-taking nature of the larger banks.

Of the 5 largest banks in the South African banking sector, Capitec has the highest return on assets, peaking at 11% during the study period. The remaining 4 banks maintained a ROA range of between 1% and 3%. The higher returns for Capitec can be attributed to the bank's low-cost business model. Furthermore, Capitec was founded in 2001, making it the youngest bank in the largest five groupings; however, it was ranked the best bank in the world in 2017 by Lafferty's Global bank survey (Banking Association of South Africa, 2017). The Individual return on assets for each the five largest banks in South Africa are plotted in figure 3 below:

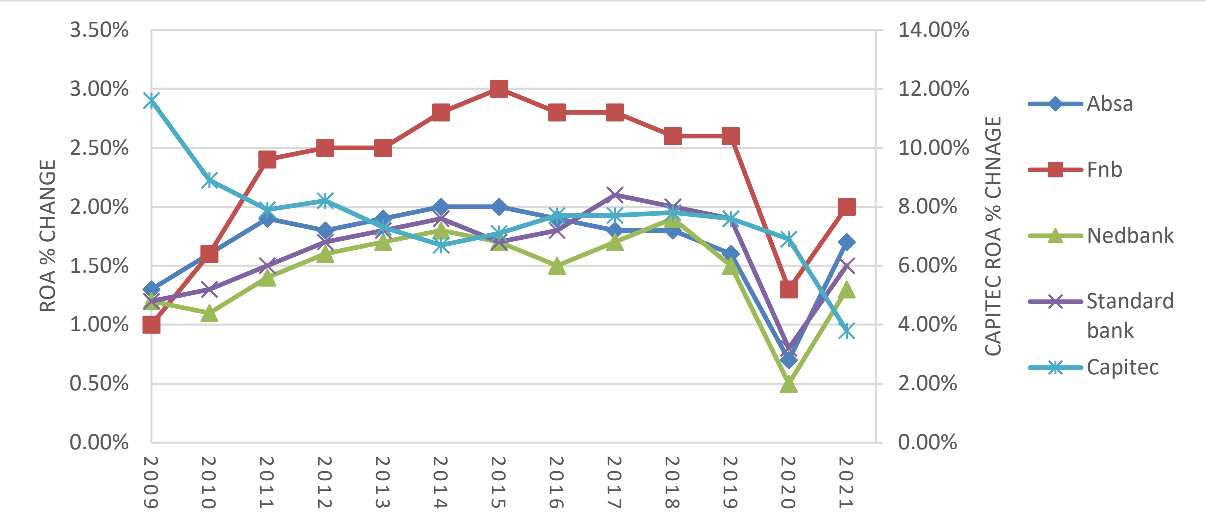

Figure 3: Return on Assets of the Five Largest Banks
Source: (SARB, 2021)

Similarly, according to Figure 4, the return on equity for the largest five banks followed a similar pattern to the return on assets trend. There was an uptick in the ROE from the start of 2008, coinciding with the tail end of the global financial crisis. ROE within the banks remained stable until 2020, coinciding with the start of the COVID-19 pandemic. Capitec Bank remained the outlier with the highest rates ROE within the period. FNB had the second-highest ROE, with the rest of the banks ranging between 15% and 25%. Figure 4 highlights the trends in ROE below:

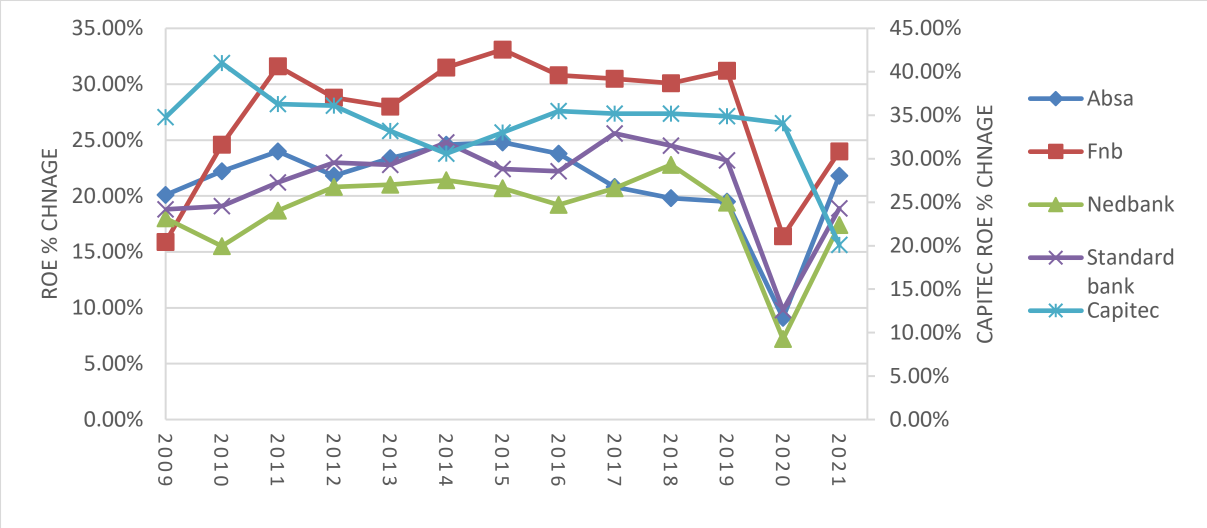

Figure 4 : Return on Equity of the Five Largest Banks
Source: (SARB, 2021)

Bank Share prices within the South African banking sector followed similar trends, with Capitec again being the outlier. The four remaining banks had similar and steady share prices within the study period. Market sentiment is positive for Capitec in part due to the Bank's Earnings per share within the period. Capitec has a high EPS accounting; furthermore, the total shareholder return was high due to Capitec's generous dividends. Figure 5 details the share prices within the study period of the five largest banks:

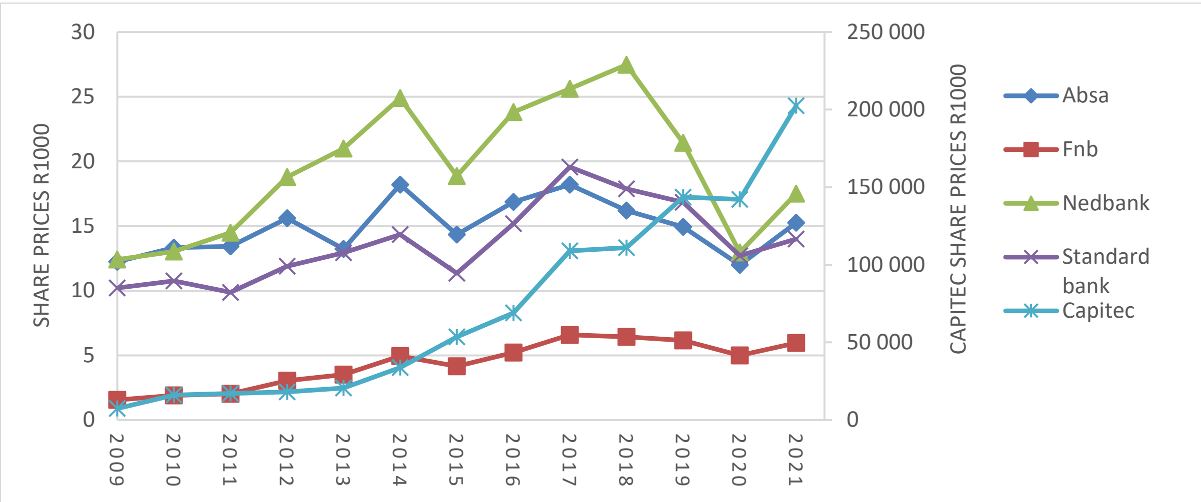

Figure 5 : Bank share prices of the Five Largest Banks
Source: (SARB, 2021)

Bank Z-scores during the period remained relatively consistent. FNB and Capitec had the lower financial stability score relative to the rest of the banks. Furthermore, ABSA Bank was the class-leading bank in terms of financial stability. The five banks follow a similar trend, ranging between 10% and 30%. The trend dipped in 2020, coinciding with the COVID-19 pandemic. However, the sector recovered to pre-COVID levels the following year. Figure 6 highlights the bank Z scores during the period:

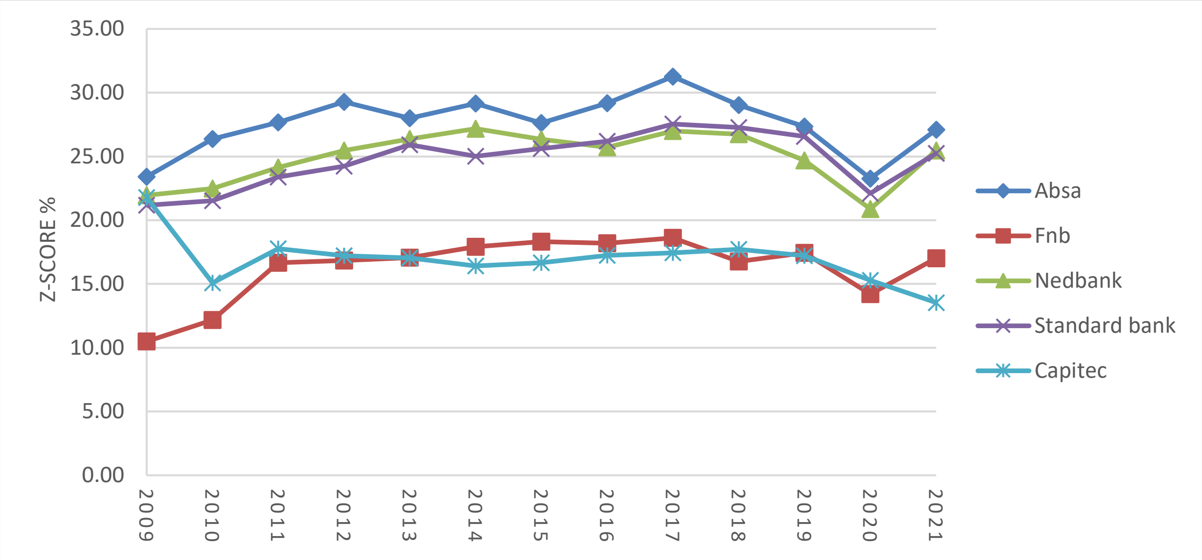

Figure 6 : Bank Z scores of the Five Largest Banks

Source: Thompson Reuter database (2021)

Various studies categorize the South African banking sector as highly concentrated during the study period (Coetzee, 2018). Similarly, Mishi et al. (2016) categorized the sector as being monopolistic and concentrated around the five largest banks. During the study period, bank concentration remained high, as evidenced by the Herfindahl–Hirschman Index in Figure 7. Furthermore, bank financial stability and bank concentration over the period followed the same trend. This is consistent with studies by Coetzee (2019) and that found that high bank concentration was highly correlated with banks' financial stability.

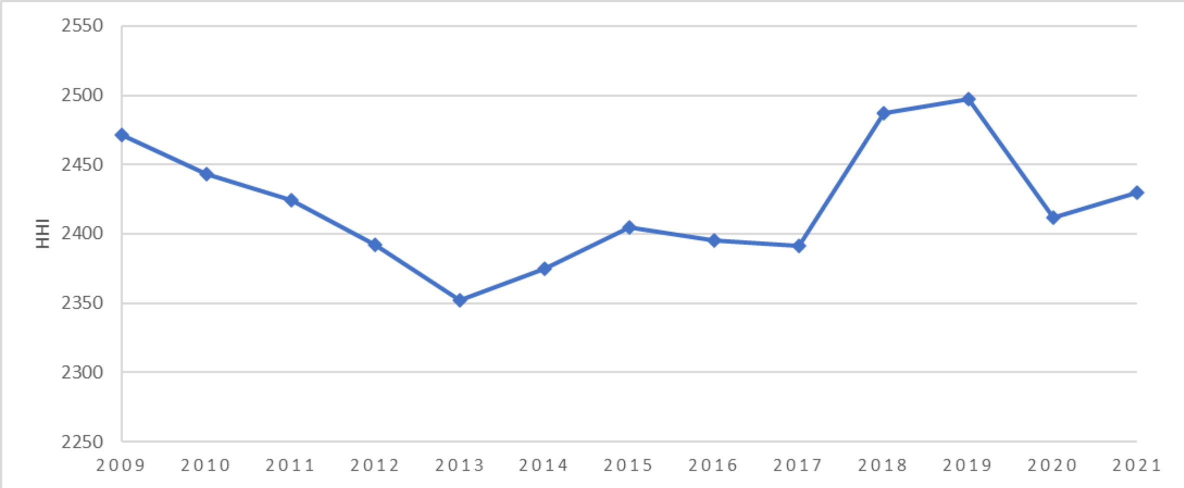

Figure 7 : HHI for the Five Largest Banks
Source: STATS SA

3.4 Regulation

The risk-averse nature of South African banks can be attributed to various attributes specific to the regulatory and socioeconomic environment in which banks operate. Firstly, Coetzee (2018) argue that the NCA (National Credit Act) (34 of 2005) that came into effect in 2007, and escalating housing prices forced stricter rules on banking sector lending, marketing, and option pricing activities. The NCA, unlike the more lenient consumer credit law before it (Coetzee, 2019), resulted in a banking sector that was required to be more conservative and risk-averse. Secondly, the Reserve Bank of South Africa requires retail banks in South Africa to be fully compliant with capital standards set by the Basel Committee on Banking Supervision since the nineties. Furthermore, following the GFC, the FSRA was passed, requiring banks to move towards the Twin-Peaks framework for regulation (Coetzee, 2018). These regulatory shifts resulted in South African banks being regulated by both the Prudential Authority and the FSCA (Financial Services Conduct Authority) (Coetzee, 2019). This supervisory environment has created a stable, trustworthy banking environment as banks become more conservative in their business operations.

Thirdly, South African banks have historically ventured less into high-risk corporate and investment banking activities and instead invested more in retail and commercial banking (Coetzee, 2019). Before 2009, banks such as JPMorgan and Chase and Deutsche Banks were the leaders in investment banking offerings. However, the four largest South African Banks, including Fintech Banks such as Tymebank, Discovery Bank and BankZero, have since increased their investment banking offerings. This tendency by South African banks to scale bank offerings in the investment banking sector has been regarded as one of the main reasons the banking sector was able to avoid the adverse effects of the GFC (BASA, 2019). Fourthly, the South African banking sector currently does not have a (DIS) Deposit Insurance Scheme. However, the South African reserve bank is in the process of establishing a DIS. Although the South African banking sector is regarded as highly contracted, the regulatory and supervisory oversight inherent in the system has not required a DIS. The Reserve Bank of South Africa has placed Banks such as the African Bank under curatorship for failing to meet recapitalisation requirements. Retail banks are, therefore, obligated to operate within strict regulatory guidelines, further enforcing the risk-averse nature of South African retail banks (Coetzee, 2019).

Coetzee (2019) argues that another major contributor to the slow response by South African banks to the growth of Fintech firms is the outdated and detached legacy systems traditionally used by the retail banking industry. The incorporation of data-driven and integrated management information systems has been delayed due to these old and outdated technologies (Partner and Brinckmann, 2017). These ageing systems can be characterised as being cumbersome and are usually difficult to integrate with emerging technologies in Fintech due to their closed-lopped architecture. These closed-looped systems tend to be rigid and prevent the introduction of new banking offerings (Marinc, 2013). Fintech banks such as Discovery, TymeBank and, BankZero and Capitec have the benefit of not having legacy systems and are therefore able to focus on investing in operational systems that are digital and real-time. These firms do not need to overcome resistance to the fundamental changes in pushing for a frictionless customer experience (Partner and Brinckmann, 2017).

3.5 Assessment of the South African Banking Sector

Various studies in the literature regard the South African banking sector as world-class in its efficiency and regulation (Moyo, 2018). The sector is mainly comprised of five large commercial banks that control 90% of the total assets within the sector, the largest being Standard Bank, with a market share of 24%. Fintech banks such as TymeBank and Discovery, however, have recently moved into the sector. However, these banks command a far lower market share at 0.22% of the total bank assets in 2021 (SARB, 2021).

Although the sector is considered efficient (Coetzee, 2019), the 5 banks asset concentration ratio suggests that the sector is highly concentrated around the five largest banks. Various studies in the literature have found a positive relationship between high levels of market concentration within the banking sector and bank financial stability (Coetzee, 2019); this result is consistent with the Z-scores of the South African banking sector. Similarly, the ROA, ROE and NIM values of the five largest banks remained consistent throughout the study period (SARB, 2021)

The South African Banking sector follows stringent regulatory laws applied by the Reserve Bank of South Africa; this stringent environment has resulted in banks adopting a risk-averse nature in response to regulation and allowed for the efficient operation of the financial system. The SARB requires that financial institutions fully comply with the standards set by the Basel Committee on Banking Supervision. Additionally, the FSRA requires that financial institutions move toward the Twin-Peaks regulatory framework (Coetzee, 2018). In effect, the South African banking sector is regulated by both the Prudential Authority and the FSCA; this has had the effect of a stable sector; however, studies have argued that this has also resulted in the slow growth of the Fintech Banking sector. The Payments Association of South Africa, although not a member of the SARBS' Intergovernmental Fintech Working Group (IFWG), regulates banks and third-party payment providers and requires that these parties register as payment service providers or third-party payment providers (TPPS). Non-bank members of Fintech firms may participate in the national system via a sponsorship agreement with an established banking entity licensed for settlements and clearing (SARB, 2019). The requirements of the National Payment System Act effectively enforce partnerships between non-registered Fintech Firms and Incumbent registered banks.

CHAPTER 4: DATA, METHODOLOGY AND TECHNIQUES

4.1 Introduction

This chapter begins by describing the methods and techniques undertaken to conduct the research and achieve the objectives of this study. The research paradigm is described in section 4.2. Section 4.3 describes the data used, the data sources, and the rationale for selecting the time period used. Section 4.4 will then explain the facets of the research methodology, estimation variables and the techniques used. Section 4.5 describes the robustness check and the associated methodology. Section 4.6 then concludes this chapter.

4.2 Research Paradigm

This quantitative study falls within a positivist research paradigm popularised by Austine Comte (1856). This research aims to obtain objective evidence on the relationship between the growth of Fintech firms in the payments segment and bank financial performance and analyse the impact Fintech firms have on Bank financial performance.

The empirical evidence in the previous chapter highlighted the divergence in the relationship between Fintech firm development and bank financial performance. Various sources in the literature found statistically significant relationships between the development of the Fintech firm sector and bank financial performance. Similarly, other sources found the relationship to be negative. Furthermore, there is a divergence in quantitative measures for the development of Fintech firms within the various sources. Given the empirical evidence within the literature and structure of the South African Fintech, Banking and Regulatory frameworks, this study aims to test the hypothesis that Fintech firm growth has a negative impact on bank financial performance.

To test our hypothesis, the study constructs a Fintech Index consisting of Fintech firm growth proxies used within the literature and assumes that the Index accurately measures the growth of the Fintech payments segment. Additionally, this study employs the use of Bank performance variables employed in various studies such as (Phan et al., 2020) and (Safiullah et al., 2022). Furthermore, the Fintech Index is then used to determine the relationship between Fintech firm development and bank financial performance using the Ordinary Least Squares and Fixed Effects estimation techniques in EViews. Additionally, this research uses the GMM (Generalised methods of moments) estimation as a robustness check to prove the empirical evidence of the relationship between Fintech firm development and bank financial performance in our initial OLS and FE regression analysis.

4.3 Data and Data Sources

The data sources for the Fintech variables are the National Treasury Website, Genesis Analytics and the CrunchBase database[5]. Fintech data will be restricted to processes related to the banking sector and the payments segment. Fintech firms in the payments segment that facilitate or enable the processing and settlements of payments by performing all or part of the functions necessary to send and receive currency from one party to the other via a digital channel (SARB, 2019). Fintech firms that provide mobile point of sale, Crypto, cross-border, closed-loop mobile wallets, payments aggregators and 3rd party payment providers are included in this Payments segment. The data is collected between 2009 and 2021 and collapsed into yearly data. The study started after the start of the global financial crisis to avoid any shock or influence that would have affected our data set. Furthermore, there was a noted uptick in the segment's growth following the GFC as noted in the literature in Chapter 2.

Bank performance data comprises panel data collected from the Thompson Reuters Database, Stats SA and the Reserve Bank of South Africa. Although there are 14 listed banks in South Africa, this study is restricted to the five largest retail banks holding 90.1% of total banking sector assets (SARB, 2020). These banks include Nedbank, Absa, First National Bank, Standard Bank and Capitec. Bank panel data is restricted to four variables: ROA (Return on assets), ROE (Return on equity), NIM (Net interest margin) and Bank share prices. Included on bank-specific variables are control variables that include CAP (Ratio of equity to assets), CTI (Cost to income ratio), LLP (loan loss provision), DG (Growth of deposits), ZS (Z-scores) and HHI (Bank concentration). Data is collected for the period between 2009 and 2021 and is then collapsed into yearly data.

[5] The CrunchBase database has more than 200,000 firm contributors and is recently cited in publication by (Haddad and Hornuf, 2021; Phan et al., 2020; SARB, 2019)

This study also considered macroeconomic variables such as the growth rate of annual GDP (Gross domestic product) and the annual Inflation rate. These variables were sourced from Stats SA and the Reserve Bank of South Africa. Similar to the Fintech firm and Bank performance variables, data is collected between 2009 and 2021 and is then collapsed into yearly data.

4.4 Model Specification and Theoretical Framework

4.4.1 Pooled Ordinary Least Squares

The Ordinary Least Squares (OLS) method is a statistical method capable of establishing the line of best fit of a model and addressing the minimum sum of the square residuals (Gujarati, 2003). The method is commonly used in regression analysis and estimation within banking or financial performance studies (Mustafa, 2020). The pooled OLS method assumes that the intercept and slope coefficients stay constant across time and cross-section and that the residual term captures the variation over time and cross-section (Gujarati, 2003). The multiple linear regression can be stated as follows:

$$Y_{i.t} = \alpha_i + \beta_1 X_{1,t} + \beta_2 X_{2i,t} + \beta_3 X_{3i,t} + \varepsilon_{i,t} \dots \quad (1)$$

Where:

$Y_{i.t}$: represents the dependent variable.

α_i : represents the constant intercept

β_1 : is the independent term coefficient.

X : represents the independent variable.

$\varepsilon_{i,t}$: represents the error term.

t : represents the time period.

Gujarati (2003) states that the Pooled OLS methodology makes the following assumptions: Firstly, the independent explanatory variables are assumed to be exogenous, meaning they are not correlated with the error term. Secondly, the model assumes homoscedasticity, meaning the error term has a constant variance. Thirdly, there is no serial correlation and the error term is assumed not to be correlated across time for a given cross-sectional unit. Lastly, the error term has a zero mean. The Pooled OLS model for this study is adapted from Phan et el., (2020).

However, this study includes three additional variables being: A second bank performance lagged variable ($PER_{i,t-2}$) , the (Z-score ($ZS_{i,t}$) , and HHI ($HHI_{i,t}$) variables . The OLS estimation regression be stated as follows:

$$PER_{i.t} = \alpha_i + \beta_1 FINTECH_{i,t} + \beta_2 PER_{i,t-1} + \beta_3 PER_{i,t-2} + \beta_4 DG_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 LLP_{i,t} + \beta_8 ZS_{i,t} + \beta_9 HHI_{i,t} + \beta_{10} GDP_{i,t} + \beta_{11} INF_{i,t} + \varepsilon_{i,t} \quad (2)$$

Where:

$PER_{i.t}$: represents one of the four bank performance variables; ROA, ROE, NIM and Bank stock prices; α represents the intercept coefficient.

$\beta_1 FINTECH_{c,t}$ represents Fintech firm variable (Fintech Firm development index). $\beta_2 PER_{i,t-1}$ represents the first lagged bank performance variable.

$\beta_3 PER_{i,t-2}$ represents the second lagged bank performance variable.

$\beta_4 DG_{i,t}$ represents the DG control variable.

$\beta_5 CAP_{i,t}$ represents the CAP control variable.

$\beta_6 CTI_{i,t}$ represents the CTI control variable.

$\beta_7 LLP_{i,t}$ represents the LLP control variable.

$\beta_8 ZS_{i,t}$ represents the Z-score control variable.

$\beta_9 HHI_{i,t}$ represents the HHI control variable.

$\beta_{10} GDP_{i,t}$ represents the GDP control variable.

$\beta_{11} INF_{i,t}$ represents the INF control variable and the $\varepsilon_{i,t}$ represents the error term with mean zero and constant variance over time.

4.4.2 Fixed Effects

Various studies in the literature employ the Fixed effects model over the Ordinary least squares model in the estimation of Bank financial performance. Heffernan and Fu (2010) and Derbali (2021) employed NIM,ROA and ROE in determining the attributes of bank financial performance within their respective studies. Both studies concluded that the Fixed effects model was the appropriate model within the context. Furthermore, although the Fixed effects model builds from the Pooled OLS model, the FE model differs regarding the underline assumptions. The FE model does not assume a constant intercept across all cross-sectional units but instead allows for entity-specific characteristics that are constant over time but vary across entities (Gujarati, 2003). In line with similar studies in literature , this study, therefore, employs the use of the Fixed effects model in our methodology.

The OLS and FE models both assume the exogenous nature of the independent variables. However, the FE model controls for the time-invariant unobserved variables and thus makes it more robust to various forms of endogeneity (Gujarati, 2003). The FE model can be described as a classic model with dummy variables, and the model also validates the standard OlS assumptions through its residual structure(Gujarati, 2003). The FE model can be stated as follows:

$$Y_{i.t} = \alpha_i + \beta_1 X_{1,t} + \beta_2 X_{2i,t} + \beta_3 X_{3i,t} + \varepsilon_{i,t} \ldots \qquad (3)$$

Where:

$Y_{i.t}$: represents the dependent variable.

α_i : represents the intercept (variable)

β_1 : is the independent term coefficient.

X : represents the independent variable.

$\varepsilon_{i,t}$: represents the error term.

t : represents the time period.

4.4.3 Diagnostic Testing

The model variables are tested using the F-statistic to confirm statistical significance; R and Adjusted R-squared tests are also included to evaluate the overall quality and appropriateness of our regressions. Similar studies such as Safiullah et al. (2022) follow a similar approach.

4.4.4 Fintech Variables

Studies in the literature differ in the variable used as a proxy for Fintech firm growth. Studies by Phan et al. (2020) and Haddad et al. (2021) incorporate a count of the number of Fintech Firms as a proxy for Fintech Firm growth. In contrast, various empirical studies, such as those by Low and Wong (2021) and Li et al. (2017), use Fintech firm start-up funding as a proxy for Fintech firm development and the Number of Fintech firm deals/Acquisitions. Furthermore, this research incorporates Fintech Firm Funding in the study as a proxy for Fintech firm development within South Africa. Monthly funding data between 2009 and 2021 is collapsed into yearly data.

4.4.5 Fintech Sample Size and Selection Criteria

The Fintech firms in the study were selected based on their market segment within the South African Fintech sector. The study incorporated the categorization by the Fintech Scoping study, and the Genesis Analytics report . These firms were restricted to the payments segment consisting of Mobile money, Peer to Peer, Crypto payments, Money Remittances and mPos Firms. These firms were then cross referenced with the Crunchbase database where Fintech funding, Fintech firm deal acquisition and Fintech firm incorporation/start year were available. The sample consisted of 68 Fintech firms in total across the 2009 to 2021 study period.

4.4.6 Fintech Index Construction

Our Fintech explanatory variable is an equally weighted index comprising the three most appropriate Fintech growth proxies applicable to South Africa. These include the total number of Fintech firm acquisitions per year, the total number of Fintech firms per year and the total funding of Fintech firms per year. The summation or total value of each proxy is calculated between 2009 to 2021. The data is then normalised by dividing each proxy series by its maximum value to create a scale between 0 and 1. The index for each year is then created by the addition of one 1/3rd of each normalised proxy value (normalised Fintech funding + normalised Count of number of Fintech firms + normalised number of Fintech deal acquisitions). These proxies were selected based on studies by (Low and Wong, 2021, Phan et al., 2020), as well as the availability of data.

4.4.7 Bank Financial Performance Variables

The impact of Fintech on bank performance is measured in line with the methodology employed by Phan et al. (2020). Similar to studies by Phan et al. (2020), Haddad et al. (2021), Low and Wong (2021) and Li et al. (2017), this study employs ROA (Return on assets), ROE (Return on equity, and NIM (Net interest margin) as proxies for bank financial performance. Furthermore, similar to studies by Low and Wong (2021), this study also includes bank stock prices as a proxy for banks’ financial performance. Stock returns better reflect current information about and expectations of the firm future growth and profitability (Anilowski et al., 2007).

4.4.8 Bank Control Variables

Included in our estimation are bank firm-specific control variables. Studies such as Phan et al. (2020), Haddad et al.(2021), and Low and Wang(2021) include the use of control variables to increase the explanatory power of their regression analysis. CAP measures the ratio of equity to total assets; studies by Thakor and Mehran (2011) found a positive relationship between capital and Bank performance; in contrast, Osborne et al. (2012) found that higher CAP values resulted in poor bank financial performance. Therefore, it is expected that CAP either has a positive or negative effect on bank performance. CTI is determined by calculating the ratio of a bank’s operating cost against the income generated. A higher CTI value indicates low bank efficiency and will, therefore, affect the bank’s performance negatively (Athanasoglou et al. 2008).

LLP is a proxy for credit risk; the variable is considered a reserve to cover any potential defaults on loans, shielding the bank’s profitability and capital positions (Betty and Liao, 2011). Various studies suggest that LLP can be used as a future predictor of bank performance. Athanasoglou et al. (2008) argue that banks exposed to high levels of credit risk experience decreased bank profitability. Therefore the priori expectation of the e relationship between LLP and bank financial performance indicators is negative.

DG measures the growth of deposits within banks. Increases in deposit growth indicate business expansion within the banking sector; however, increases in DG have been attributed to increased competition within the banking sector and thus have the potential to reduce profitability for banks within the sector. Various sources indicate that DG negatively and positively affects bank performance (Dietrich and Wanzenried, 2014). Therefore, the priori expectations of DG still need to be discovered in our study.

The Z-score variable has been widely employed in literature as a proxy for bank financial stability or risk-taking behaviour due to its relative ease of calculation. The variable was developed by (Boyd and Runkle, 1993) . Furthermore, various studies, such as Zhang et al.

(2015), employ the use of the variable within the context of the banking sector. Studies such as Mishi and Khumalo (2019) employed the variable as a proxy for financial stability within the South African context. Higher Z-score values are associated with a lower probability of bank insolvency. The Z-score variable employed in this study can be derived from accounting data within the banking sectors.

The Herfindahl-Hirschman Index (HHI) is a market concentration index used to measure the size of firms in relation to the industry they operate in and indicates the level of competition within that industry. The index can be viewed as a weighted sum of firms' market share where the weighting is proportional to the market shares (Herfindahl, 1950, Hirschman, 1946). Studies such as Demirgüç-Kunt et al. (2017) have used the index to measure bank concentration. Similarly, Mishi et al. (2016) employed the index within the South African context.

The HHI values range from between 0 to 1000. For sectors, the sector can be described as less concentrated, with each firm having an equal market share. Where the sector can be described as monopolistic. Where each firm controls 1 % market share, and this would define a competitive market. Studies such as Mishi et al. (2016) state that HHI scores of 1000 and less indicate a non-concentrated market, 1000 to 1800 a discreetly concentrated and 1800 and above as highly concentrated.

4.4.9 Macroeconomic Control Variables

Macroeconomic variables are included to address potential country-specific heterogeneity. This study includes GDP (Gross Domestic Product) to account for the influences on bank performance due to the variations in the business cycle. During periods of reduced growth in the GDP (recession), bank profitability is negatively affected due to increases in credit losses. Furthermore, bank profits are expected to be procyclical, given that economic growth influences net income from lending activities. Various studies have highlighted the impact of GDP on bank financial performance (Dietrich and Wanzenried, 2014).

Finally, this study includes INF (inflation) as a control variable due to inflation influencing bank financial performance. Studies by Athanasoglou et al. (2008) indicate that inflation is positively related to bank profitability, given that increases in the inflation level do not undermine economic activity or increase faster than wages and other operating activities. There is, however, an unknown prior expectation regarding inflation in this study.

4.5 Robustness Check

4.5.1 GMM Model

The OLS and FE model specifications are commonly employed in panel data analysis literature. However, these models lose their predictive power when lagged dependent variables are introduced into the estimation. Furthermore, there is a risk of bias if the regressors are correlated with the lagged dependent variables to an extent (Heffernan and Fu, 2010). Blundell and Bond (1998) developed the difference GMM model to tackle this issue and expanded it to incorporate the system GMM model specification, incorporating lagged levels and differenced levels. Roodman (2006) contended that both models were appropriate for scenarios involving panels with a small number of time periods and a high number of cross-sectional units, where the independent variables may not be exogenous. The models also account for fixed individual effects, heteroscedasticity, and autocorrelation (Roodman,2006).

Furthermore, various studies such as Phan et al. (2020) , Haddad and Hornuf (2021) and Safiullah et al. (2022) include the GMM model to analyse bank performance-related regressions. The Generalized Method of Moments (GMM) is a method used in the estimation of statistical models. The GMM makes use of moment conditions that are functions of the model parameters and data, such that at the parameter's true value, their expected value tends to zero. The GMM method controls for the endogeneity of the lagged variable in the panel model, and unobserved panel heterogeneity. furthermore, the model controls for omitted variable bias and measurement errors (Blundell and Bond, 1998).

4.5.2 Difference GMM

The difference model corrects endogeneity by transforming all regressors through first differencing, which also removes the fixed effects. Finally, the first difference-lagged dependent variable is then regressed with its past levels; therefore, changes in the dependent variable are assumed to be represented by Equation 4.

The initial Difference GMM model can be formally stated as:

$$lnY_{i,t} = \Phi lnY_{i,t-1} + \beta X'_{i,t} + (\eta_i + \varepsilon_{it}) \quad (4)$$

The transformed model can be stated as:

$$\Delta lnY_{i,t} = \Phi \Delta lnY_{i,t-1} + \beta \Delta X'_{i,t} + \Delta\varepsilon_{it} \quad (5)$$

The model then becomes:

$$\Delta u_{i,t} = \Delta\eta_i + \Delta\varepsilon_{it} \quad (6)$$

Where:

$Y_{i,t}$ represents the persistent dependent variable.

Φ represents the variable to be estimated for the lagged dependent variable.

$X'_{i,t}$ represents the explanatory variables in the model.

4.5.3 System GMM

The System GMM model can be formally stated as:

$$lnY_{i,t} = \Phi lnY_{i,t-1} + \beta X'_{i,t} + (\eta_i + \varepsilon_{it}) \quad (7)$$

Where:

$Y_{i,t}$ represents the persistent dependent variable.

Φ represents the variable to be estimated for the lagged dependent variable.

$X'_{i,t}$ represents the explanatory variables in the model.

The System GMM model assumes that equation 1 is a random walk model. The model uses more explanatory variables when compared to the difference GMM estimation (Blundell and Bond, 1998).

The GMM model follows from equation 1, however the model excludes both the Z-score and HHI variables. Our GMM model continues from the Ordinary Least Squares regression. However, in keeping consistent with the methodology used with the methodology employed by Phat et al. (2020) and Haddad et al. (2021), the variables are modified as per the methodology.

$PER_{i.t}$ represents one of the four bank performance variables; ROA, ROE, NIM and Bank stock prices; α represents the intercept coefficient.

$\beta_1 FINTECH_{c,t-1}$ represents lagged Fintech firm variable (Fintech firm funding).

$\beta_2 PER_{i,t-1}$ represents the first lagged bank performance variable.

$\beta_3 PER_{i,t-2}$ represents the second lagged bank performance variable.

$\beta_4 DG_{i,t}$ represents the DG control variable.

$\beta_5 CAP_{i,t}$ represents the CAP control variable.

$\beta_6 CTI_{i,t}$ represents the CTI control variable.

$\beta_7 LLP_{i,t}$ represents the LLP control variable.

$\beta_8 GDP_{c,t}$ represents the GDP control variable.

$\beta_9 INF_{c,t}$ represents the INF control variable and the $\varepsilon_{i,t}$ represents the error term with mean zero and constant variance over time.

Similarly, to the approach by Phat et al. (2020) and Haddad et al. (2021), this study tests the null hypothesis of the GMM regression that Fintech firm funding negatively influences bank financial performance in South Africa. First, differences are taken to eliminate unobserved heterogeneity and control for variable bias. Following Wintoki et al. (2012), two lags will be included to capture the persistence of the Banking institutions. Our model is repeated for all four bank performance variables represented by $PER_{i.t}$.

4.5.4 Diagnostic Test

We determine variable validity using the Hansen (1982) J test or the Sargan (1985) test of over-identifying restrictions. These tests test the null hypothesis of the overall validity of the variables used in the estimation. Failure to reject the null hypothesis would validate the use of the variables in the model. Variables with Probability values greater than 0.9 would be deemed invalid.

A test for autocorrelation/serial correlation of the error term is then done by testing whether the null hypothesis that the differenced error term is first and second-order serially correlated. Failure to reject the null hypothesis of no second-order serial correlation implies that the original error term is serially uncorrelated and the moment's conditions are correctly specified. Arellano-Bond or AR (2) values greater than 0.05 indicate some levels of autocorrelation.

4.6 Summary of Variables

Table 3 below summarizes the variables used in the methodologies outlined in the chapter. The table includes the formula for each variable, priori expectation regarding the relationship of the variable with bank financial performance based on literature and the source of the variables.

Table 3: Summary - Variable Definition

Dependent Variable	**Formula**	**Priori Expectation**	**Source**
Fintech firm funding	Summation of total funding per year	Positive/Negative	CRUNCHBASE
Fintech Acquisitions	Summation of total acquisitions per year	Positive/Negative	CRUNCHBASE
Fintech firm count	Summation of total firms per year	Positive/Negative	CRUNCHBASE
Fintech Index	$= \sum FINETCH\ FIRM\ FUNDING + \sum FINETCH\ FIRM\ ACQUISTIONS + \sum FINTECH\ FIRM\ COUNT$	Positive/Negative	CRUNCHBASE
Bank performance variables			
ROA	$= \frac{NET\ INCOME}{TOTAL\ ASSET} \times 100$		SARB
ROE	$= \frac{NET\ INCOME}{TOTAL\ EQUITY} \times 100$		SARB
NIM	$= \frac{INVESTMENT\ INCOME - INTEREST\ EXPENSES}{AVERAGE\ EARNING\ ASSET} \times 100$		THOMPSON REUTERS
Bank Share Prices	Average Share price per year		THOMPSON REUTERS
Control Variable			
CAP	$= \frac{CURRENT\ ASSEST}{CURRENT\ LIABILITIES}$	Positive	THOMPSON REUTERS
LLP	$= \frac{LOAN\ LOSS\ PROVISON}{TOTAL\ LOANS}$	Negative	THOMPSON REUTERS
CTI	$= \frac{OPERATING\ COSTS}{OPERATING\ INCOM}$	Negative	THOMPSON REUTERS
HHI	$= s_1^2 + s_2^2 + s_3^2 + \cdots s_n^2 +$	Negative	STATS SA
Z-Scores	$= \frac{ROA + CAR}{\delta(ROA}$	Negative	STATS SA
GDP	Yearly GDP	Positive	STATS SA
INF	Yearly Inflation	Positive/Negative	STATS SA

Source: Author

4.7 Chapter Summary

Chapter 4 discusses the research design, data sources, and model specifications employed to investigate the objectives of this study and determine the nature of the relationship between Fintech firm growth in the payments segment and bank financial performance. Furthermore, the independent and dependent variables and the a priori expectations of the variable coefficients are identified. The advantages of the chosen model specification are stated with reference to empirical studies in Chapter 2—furthermore, the model diagnostics tests and their respective results. The results obtained from the methodology explained in Chapter 4 are provided in Chapter 5.investigate the objectives of this study and determine the nature of the relationship between Fintech firm growth in the payments segment and bank financial performance. Furthermore, the independent and dependent variables are identified as well as the a priori expectations of the variable coefficients. The advantages of the chosen model specification are stated with reference to empirical studies in Chapter 2. Furthermore, the model diagnostics tests and their respective results. The results obtained from the methodology explained in Chapter 4 are provided in Chapter 5.

CHAPTER 5: PRESENTATION AND DISCUSSION OF RESULTS

5.1 Introduction

The relationship between the Fintech Firm Index, Fintech Firm Funding and bank financial performance variables is estimated in this section of the study. The chapter presents the findings of the models estimated in Chapter 3. The chapter is composed of six major sections. Following the introduction, section 4.2 presents the descriptive statistics to analyse the univariate characteristics of the data employed. This is followed by the correlation matrixes in section 4.3. In section 4.4, we present and interpret the results of the OLS and FE regression models set out in Chapter 4. Section 4.5 comprises the robustness check. Furthermore, the correct specification of the GMM model is identified, and the regression results are presented. Section 4.5 summarises the results of the regressions and concludes the chapter.

5.2 Descriptive Statistics

Table 4 presents the descriptive statistics of the variables employed in the study. The descriptive statistics indicate that the mean value of bank share price is 26.14, indicating a rand value of R26,140.00 with a minimum value of 1.55 or R1550.00 and a maximum of R202,546.00, indicating a high level of variance in share prices amongst the banks in the study period. Bank ROA had a mean value of 2.9 % and a maximum value of 11 %. Bank ROE values in the period had a mean value of 24.4 % and a maximum value of 41 %. Nim values over the same period had a mean value of 4.5 % with a maximum value of 11,2 %. The ROE, ROA and NIM, bank performance variables, showed low levels of variance within the study period, with most of the banks performing similarly.

Bank concentration measured by the HHI variable had a minimum value of 2352 and a maximum of 2497, indicating that bank concentration was consistently high during the study period. HHI scores above 1800 are described as highly concentrated within the literature (Mishi and Khumalo, 2019) . The results indicate that the sector can be categorised as oligopolistic in nature. Bank Z-Scores had a mean value of 22.1 % and a minimum of 10.5%, indicating a significant variance in the bank risk-taking appetite during the period. This result could confirm that each bank has a markedly different risk-taking approach.

The remaining control variables have positive minimum values except for DG and GDP. CAP, CTI and LLP have mean values of 17 %, 53 % and 1.5 %, respectively. DG had a mean value of 9% and a minimum value of -9.4%, indicating a period of negative deposit growth within the retail banking sector.

The mean GDP shows that during the period of study, the South African economy grew at a rate of 1.07% on average. Furthermore, there was a period of negative economic growth with a GDP value of -6.34% during the study period. Both DG and GDP had negative minimum values in 2009, during the start of the observation period. The level of inflation for the period under study indicates an average inflation level of 4.98%. Inflation during the period remained within a 3% and 6% band. However, there were periods in which it slightly exceeded the 6 per cent band.

The Fintech Firm growth Index variable had a minimum value in 2009 and a maximum value of 67.3 % in 2021, indicating a positive trend across the study period. The growth within the sector follows global trends, with an increase in the sector's growth following the global financial crisis. Figure 8 below highlights the trend in the sector:

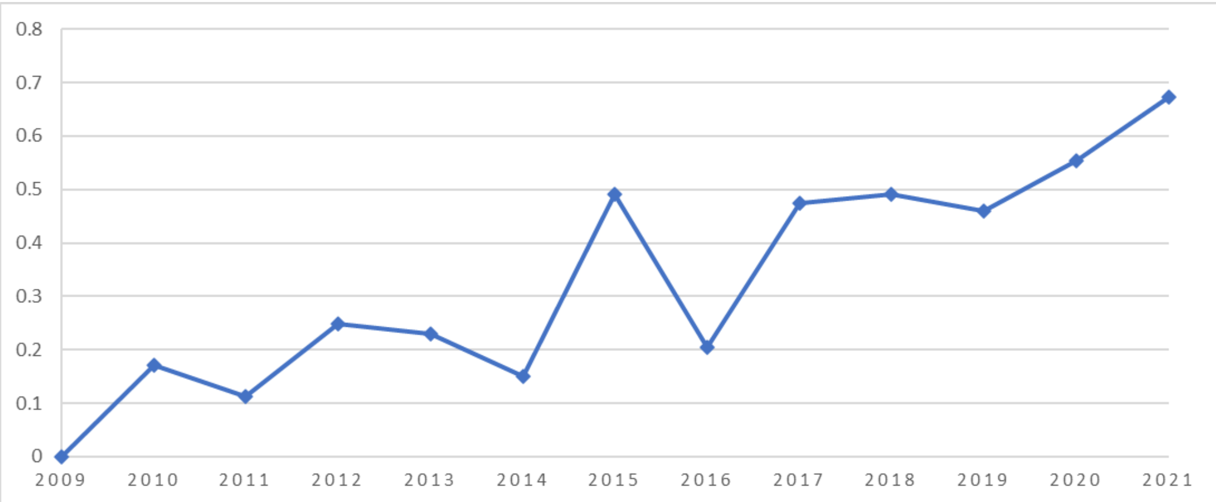

Figure 8: Fintech Firm growth Index
Source: Authors calculation

Table 4: Descriptive Statistics

	SHARE PRICES (R1000)	NIM	ROA	ROE	CAP	CTI	DG	LLP	HHI	ZS	GDPGR	INFL	F.INDEX
Mean	24.98765	0.044853	0.029415	0.244815	0.173187	0.533234	0.1494	0.03426	2421.077	22.10908	1.11588	5.101	0.327585
Median	14.5	0.0431	0.019	0.23	0.1333	0.559	0.099	0.0107	2412	23.27	1.413826	5.263	0.248679
Maximum	202.546	0.112	0.116	0.41	0.421	0.622	1.219	0.1871	2497	31.26	4.913097	6.764	0.672619
Minimum	1.55	0.0286	0.005	0.072	0.112	0.32	-0.094	0.0048	2352	10.49	-6.342471	3.172	0
Std. Dev.	36.78662	0.015173	0.025199	0.070797	0.08299	0.07375	0.232266	0.048529	42.23902	5.087109	2.646948	1.040371	0.198166
Skewness	3.178926	2.636583	1.668403	0.102963	1.501167	-1.719573	3.184552	1.651573	0.373993	-0.257235	-1.523753	-0.386544	0.091042
Kurtosis	12.93925	10.7322	4.579123	2.748216	3.639588	4.696761	13.99105	4.084569	2.191268	1.892333	5.479598	2.252154	1.7763
Jarque-Bera	377.0299	200.7344	36.90891	0.286544	23.95032	39.21795	437.04	32.7358	3.286642	4.039762	41.80502	3.13337	4.145365
Probability	0	0	0	0.866518	0.000006	0	0	0	0.193337	0.132671	0	0.208736	0.125848
Sum	1624.197	2.4669	1.912	15.913	10.5644	34.127	9.711	2.2269	157370	1437.09	72.53248	331.565	21.293
Sum Sq. Dev.	86608.35	0.012432	0.04064	0.320786	0.413245	0.342661	3.452632	0.150723	114184.6	1656.236	448.4054	69.27176	2.513261

Source: Author's calculations using Eviews

5.3 Correlation Matrix

A correlation matrix was also estimated to analyse the linear relationship between the dependent bank performance variables of interest and the Fintech Firm Index.

5.3.1. Bank share price Correlation Matrix

Table 5 presents the Bank share price correlation matrix and indicates a positive linear relationship between bank share price and FINTECHINDEX, ZSCORES, CTI, CAP, DG, GDP and INFLATION variables. Furthermore, the CAP and ZSCORES variables are statistically significant at the 10 % and 1 % respectively. The positive relationship between CAP and bank performance is in line with findings by (Dietrich and Wanzenried, 2014). The relationship between DG and bank share price is also in line with our priori expectations. LLP and HHI, however, have a negative relationship with bank share prices with the latter being statistically significant at the 10 % level. The negative relationship between CTI and bank financial performance also conforms with our priori expectations. The positive relationship between Bank share price, GDP and INFLATION also conforms with out priori expectations.

Table 5 : Correlation Matrix: Bank Share Price

Probability	Bank Share Price	CAP	CTI	DG	LLP	ZS	HHI	GDP	INFL	F.INDEX
Bank Share Price	1									
CAP	0.526299*	1								
	0.0963									
CTI	0.474228	0.36659	1							
	0.1406	0.2675								
DG	0.182065	0.7353	0.31772	1						
	0.5921	0.0099	0.3410							
LLP	-0.571262*	-0.4058	-0.4684	0.04903	1					
	0.0664	0.2156	0.1462	0.8862						
ZSCORES	0.793242***	0.62093	0.59154	0.48819	-0.6806	1				
	0.0036	0.0415	0.0552	0.1276	0.0212					
HHI	-0.091512	-0.1221	-0.0752	-0.2632	-0.2020	-0.262037	1			
	0.789	0.7206	0.826	0.4342	0.5514	0.4363				
GDP	0.439199	0.53927	0.1831	0.18806	-0.7651	0.700847	-0.1231	1		
	0.1765	0.0869	0.5900	0.5798	0.0061	0.0163	0.7184			
INFLATION	0.199918	0.26152	-0.5393	0.14684	-0.1928	0.287081	-0.2182	0.44423	1	
	0.5556	0.4373	0.0869	0.6666	0.5701	0.392	0.5192	0.44423		
FINTECH INDEX	0.13652	0.53068	0.48611	0.33543	-0.1428	0.032654	0.16377	-0.0831	-0.451556	1
	0.689	0.0931	0.1295	0.3133	0.6754	0.9241	0.6304	0.8082	0.1633	

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.3.2. Net Interest Margin Correlation Matrix

Table 6 presents the net interest margin correlation matrix and indicates a positive linear relationship between bank share price and CAP, CTI, DG, ZSCORES, GDP and FINTECHINDEX. The CAP, CTI, FINTECHINDEX and ZSCORES variables are statistically significant at the 10 %, 10%, 10% and 5% level. These positive linear relationships are in line with our priori expectations expect for CTI. Similar to the bank share correlation matrix results LLP and HHI have negative relationship with bank share prices, with the former being significant at the 10 % level. Additionally, the negative relationship between INLFATION and bank financial performance is also negative also, however the result is not statistically significant.

Table 6 Correlation Matrix : Net Interest Margin

Correlation, Probability	**NIM**	**CAP**	**CTI**	**DG**	**LLP**	**ZSCORE**	**HHI**	**GDP**	**INFL**	**F.INDEX**
NIM	1									
CAP	0.531009*	1								
	0.0928									
CTI	0.721597*	0.36659	1							
	0.0122	0.2675								
DG	0.348253	0.7353	0.31772	1						
	0.2939	0.0099	0.3410							
LLP	-0.551242*	-0.4058	-0.4684	0.04903	1					
	0.0788	0.2156	0.1462	0.8862						
ZSCORES	0.67852**	0.62093	0.59154	0.48819	-0.6806	1				
	0.0217	0.0415	0.0552	0.1276	0.0212					
HHI	-0.237389	-0.1221	-0.0752	-0.2632	-0.2020	-0.262037	1			
	0.4821	0.7206	0.826	0.4342	0.5514	0.4363				
GDP	0.251279	0.53927	0.1831	0.18806	-0.7651	0.700847	-0.1231	1		
	0.4561	0.0869	0.5900	0.5798	0.0061	0.0163	0.7184			
INFLATION	-0.070632	0.26152	-0.5393	0.14684	-0.1928	0.287081	-0.2182	0.44423	1	
	0.8365	0.4373	0.0869	0.6666	0.5701	0.392	0.5192	0.1711		
FINTECH INDEX	0.574316*	0.53068	0.48611	0.33543	-0.1428	0.032654	0.16377	-0.0831	-0.451556	1
	0.0646	0.0931	0.1295	0.3133	0.6754	0.9241	0.6304	0.8082	0.1633	

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.3.3. Return on Assets Correlation Matrix

Table 7 presents the return on assets correlation matrix and indicates a linear positive relationship between return on assets and CAP, CTI, DG, GDP, ZSCORES, GDP and INFLATION. The positive relationship between the dependent variable, ZSCORES, GDP and INFLATION are statistically significant at the 1%,1% and 5% level. Furthermore, these results are in line with our expectations. CTI has a negative and with ROA, this result is not line with our priori expectations however, the relationship is not statistically significant. The negative relationship between FINTECHINDEX and ROA differs from the previous two bank performance variables but is not statistically significant. The negative relationship between

FINTECH and ROA is in line with findings by (Phan et al., 2020). Similarly, the HHI and LLP variables are negatively correlated to the dependent variable, with the latter, being statistically significant at the 1% level. The negative relationship is in line with studies in the literature.

Table 7 Correlation Matrix: ROA

Correlation, Probability	ROA	CAP	CTI	DG	LLP	ZS	HHI	GDP	INFL	F.INDEX
ROA	1									
CAP	0.406712	1								
	0.2145									
CTI	0.297271	0.36659	1							
	0.3747	0.2675								
DG	0.202479	0.7353	0.31772	1						
	0.5505	0.0099	0.341							
LLP	-0.785924***	-0.4058	-0.4684	0.049025	1					
	0.0041	0.2156	0.1462	0.8862						
ZSCORES	0.868165***	0.62093	0.59154	0.488186	-0.6806	1				
	0.0005	0.0415	0.0552	0.1276	0.0212					
HHI	-0.268995	-0.1221	-0.0752	-0.2632	-0.202	-0.262	1			
	0.4238	0.7206	0.826	0.4342	0.5514	0.4363				
GDP	0.82909***	0.53927	0.1831	0.188055	-0.7651	0.70085	-0.1231	1		
	0.0016	0.0869	0.5900	0.5798	0.0061	0.0163	0.7184			
INFLATION	0.526311*	0.26152	-0.5393	0.146835	-0.1928	0.28708	-0.218183	0.444226	1	
	0.0963	0.4373	0.0869	0.6666	0.5701	0.392	0.5192	0.1711		
FINTECH INDEX	-0.183531	0.53068	0.48611	0.335432	-0.1428	0.03265	0.163768	-0.083061	-0.451556	1
	0.5891	0.0931	0.1295	0.3133	0.6754	0.9241	0.6304	0.8082	0.1633	

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.3.4. Return on Equity Correlation Matrix

Table 8 presents the return on equity correlation matrix and indicates a linear positive relationship between return on equity and CAP, CTI, ZSCORES GDP, and INFLATION. Similar to the correlation matrix for return on assets, the ZSCORE, GDP and INFLATION variables have a statistically significant relationship with the dependent variable and are significant at the 10%, 1% and 5% level . Furthermore, the positive relationships are in line with studies in the literature and meet our expectations except for the CTI variable. The relationship between the FINTECH variable and ROE is negative unlike the ROA results. Additionally, the FINTECH variable is not statistically significant. DG, LLP and HHI have a negative relationship with ROE, apart from DG these results are in line with the literature however, none of the relationships are statistically significant.

Table 8 : Correlation Matrix: ROE

Correlation ,Probability	ROE	CAP	CTI	DG	LLP	ZS	HHI	GDP	INFL	F.INDEX
ROE	1									
CAP	0.203431	1								
	0.5485									
CTI	0.018722	0.366586	1							
	0.9564	0.2675								
DG	-0.021434	0.735302	0.317723	1						
	0.9501	0.0099	0.3410							
LLP	-0.700112	-0.405842	-0.468436	0.049025	1					
	0.0164	0.2156	0.1462	0.8862						
ZSCORES	0.666664*	0.620927	0.59154	0.488186	-0.680577	1				
	0.0251	0.0415	0.0552	0.1276	0.0212					
HHI	-0.251977	-0.122124	-0.075215	-0.263201	-0.2020	-0.262037	1			
	0.4548	0.7206	0.826	0.4342	0.5514	0.4363				
GDP	0.838027***	0.53927	0.183101	0.188055	-0.765081	0.700847	-0.1231	1		
	0.0013	0.0869	0.5900	0.5798	0.0061	0.0163	0.7184			
INFLATION	0.614024**	0.261524	-0.539306	0.146835	-0.192801	0.287081	-0.218183	0.444226	1	
	0.0445	0.4373	0.0869	0.6666	0.5701	0.392	0.5192	0.1711		
FINTECH INDEX	0.387108	0.53068	0.486106	0.335432	-0.142775	0.032654	0.163768	-0.083061	-0.451556	1
	0.2395	0.0931	0.1295	0.3133	0.6754	0.9241	0.6304	0.8082	0.1633	

***** Indicate significance at the 1% level** ***Source: Author's calculations in Eviews***
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

5.4 Estimation Results of OLS and FE regressions

In this section the results of the regression estimations of the Ordinary least squares and Fixed effects are presented. The regressions for each Bank performance variable against the Independent Fintech Firm Index and control variables are repeated for bank share price, net interest margin, return on equity and return on assets.

5.4.1 Bank share price OLS/FE estimation

The results presented in Table 9 reveal that there is a positive relationship between the lagged FINTECHINDEX variable and bank Share price. The coefficient of FINTECHINDEX is 3.089782 and 2.686542 for the OLS and FE regression respectively, however, the variable is not statistically significant in both instances. Given this result, a relationship between the variables cannot be proven. The 1st and 2nd lagged bank share variables are positively related to bank share prices, are statistically significant at the 1% level and this result follows our priori expectations that previous bank share prices predict current bank share prices. The empirical results also indicate that the coefficient of the CAP of which is the ratio of equity to assets is negative and statistically significant at the 10% and 5% level with coefficients of -124.0368 and -182.049 respectively. This suggests that CAP negatively predicts bank share prices. This result deviates from the bank share correlation matrix and does not meet our expectations.

In line with the priori expectations, the empirical results reveal that CTI negatively predicts dependent variable in both OLS and FE regressions. The CTI coefficient has a value of -32.09223 and -9.85415 respectively, however, this result is not statistically significant. The LLP variable, similar to CTI has a negative coefficient. LLP has a coefficient value of 249.1959 and 642.5295, furthermore, these results are significant at the 10% and 1% level respectively. This indicates that LLP positively predicts bank share prices in our model. The ZSCORE Ols and Fe regression coefficients are -0.45251 and 1.906026 respectively and indicate opposing predictive relationships with the dependent variable. Both coefficients are statistically significant at the 5% level. The bank share correlation matrix results however are in line with the regression results suggesting a positive relationship when controlled for fixed effects in the model. The HHI Ols and Fe variable coefficients are -0.024746 and -0.026496 respectively, however none of the variables are statistically insignificant. This result would meet our priori expectations and well as aligned with the literature. The Ols coefficients for the DG variable are -18.16693 with the Fe coefficient being -10.37725. The Ols regression is statistically significant at the 1% however the Fe coefficient was not statistically significant. This result does suggest that DG negatively predicts Bank share price however, although this does not align with our priori expectations.

In terms of the macroeconomic variables, the results indicate that GDP has a positive impact on bank performance. The GDP coefficients are 1.473996 and 0.922886 and indicates that GDP positively predicts bank share prices. Furthermore, the variables are statistically significant at the 1% and 5% level. This is in line with our priori expectations. In contrast, the INFL variable has a positive statistically insignificant coefficient. This result does not align with both the literature and our priori expectations.

The diagnostic tests indicate that the probability of the Adjusted R-squared test is 0.982983 and 0.982983, which suggests that a high proportion of the variability of bank share prices can be explained by our variables in the models estimated. Both models have Durbin-Watson statistics that are close to 2 confirming our model does not show signs of autocorrelation in the residuals.

Table 9 OLS and FE regression: Bank share price

Dependent Variable: Bank share price		
Variables	**Pooled OLS**	**Fixed Effects**
BANKSHAREPRICE (-1)	0.530216*** (0.121018)	0.452195*** (0.104918)
BANKSHAREPRICE (-2)	0.771817*** (0.128086)	0.980371*** (0.119462)
FINTECHINDEX	3.089782 (5.983018)	2.686542 (5.206967)
CAP	-124.0368* (61.29998)	-182.049** (75.01649)
CTI	-32.09223 (31.39876)	-9.85415 (32.65255)
DG	-18.16693** (6.926287)	-10.37725 (6.725922)
LLP	249.1959* (106.0046)	642.5295*** (123.0968)
ZSCORES	-0.45251** (0.215431)	1.906026** (0.640592)
HHI	-0.024746 (0.020422)	-0.026496 (0.016947)
GDPGR	1.473996*** (0.459713)	0.922886** (0.400747)
INFLATIONR	0.387751 (1.451392)	0.549684 (1.216523)
CONSTANT	96.0479 (53.58070)	28.69919 (47.17346)
F-Statistic	268.8236	290.6136
R-squared	0.986654	0.991809
Adjusted R-squared	0.982983	0.988396
Durbin-Watson stat	1.989799	2.288501

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.4.2 Net Interest Margin OLS/FE estimation

Similarly, to the estimation results for the bank share price dependent variable, the results presented in table 10 reveal there is a positive relationship between Fintech firm growth and net interest margin dependent variable. The coefficient of the FINTECHINDEX variable is 0.006517 and is statistically significant at the 10% level for the Ols regression. This result indicates that the variable positively predicts net interest margin and bank financial performance. The first lagged NIM variable positively predicts the current net interest margin variable. The variable has a coefficient of 1.213310 and 0.871850 respectively, both being statistically significant at the 1% level. However, the second lagged NIM variable negatively predicts current net interest margin. The results suggest that successive past lags of NIM may not be a precise indictor of current values. Both coefficients are not statistically significant therefore the relationship cannot be determined.

The CAP control variable has a positive coefficient for the Fe regression that is statistically significant at the 5% level. Furthermore, this result aligns with the net interest margin correlation matrix and our priori expectations. The CTI coefficient for both regression is positive however the variable is statistically insignificant. This does correlate with the NIM correlation matrix results. The LLP variable similarly has positive coefficients 0.261890 and 0.229069 respectively, with both being statistically significant at the 1% and 10% level. Although not line with the literature and our priori expectations these results suggest that LLP positively predicts net interest margin. The ZSCORE variable has a negative, and statically insignificant coefficient for the Ols regression, however the coefficient for the Fe regression has a value of 0.000277 and is statistically significant at the 5% level. This suggests that ZSCORES and therefore bank risk taking positively predicts net interest margin in our model. The market concentration variable HHI is has a positive coefficient for both regression models however, both coefficients are statistically insignificant.

The DG variable has a negative coefficients for both the Ols and Fe regressions, both however, are statistically insignificant. The GDP variable similarly has a positive coefficient for both models, and both are statistically significant. The INFLTION variable has a coefficient of 0.002665 and 0.001849 and are statistically significant at the 1% and 10% respectively. This is in line with our priori expectations.

The diagnostic tests indicate that the probability of the Adjusted R-squared test is 0.940285 and 0.948728 similarly to the previous models, this suggests that a high proportion of the variability of net interest margin can be explained by our variables in the models estimated. The Durbin-Watson statistics for both modes are within an acceptable range and confirm there is no evidence of autocorrelation.

Table 10 : OLS and FE regression: Net Interest Margin

Dependent Variable: NIM		
Variables	**Pooled OLS**	**Fixed Effects**
NIM (-1)	1.213310*** (0.166297)	0.871850*** (0.219496)
NIM (-2)	-0.264705 (0.169885)	-0.266159 (0.189157)
FINTECHINDEX	0.006517* (0.003619)	0.004081 (0.003587)
CAP	-0.069313 (0.051219)	0.037072** (0.063467)
CTI	0.037143 (0.031911)	0.025643 (0.032190)
DG	-0.011950 (0.008228)	-0.009843 (0.007956)
LLP	0.261890*** (0.076380)	0.229069* (0.112197)
ZSCORES	-0.000165 (0.000118)	0.000277** (0.000473)
HHI	1.38E-07 (1.23E-05)	9.51E-06 (1.20E-05)
GDPGR	0.000408 (0.000281)	4.50E-05 (0.000309)
INFLATIONR	0.002665*** (0.000936)	0.001849* (0.000919)
CONSTANT	-0.023604 (0.038970)	-0.044913 (0.039176)
F-Statistic	59.69060	51.57744
R-squared	0.956306	0.967486
Adjusted R-squared	0.940285	0.948728
Durbin-Watson stat	2.599741	2.775928

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.4.3 Return on Asset OLS/FE estimation

Unlike the previous bank performance dependent variables, the coefficient of the FINTECHINDEX variable is negative in the OlS and FE regression. However, the coefficient is only statistically significant at the 10% level in the Fe model. This result suggests that Fintech firm growth negatively predicts return on asset and bank financial performance. The first lagged ROA variables are both positively and negatively related to current ROA and have coefficients of 0.878030 and -0.300540, respectively. However, only the OlS coefficient is statistically significant at the 1% level. The second lagged ROA coefficients are positive, and not statistically significant. This suggests that later previous values of ROA have less predictive power on current ROA values. This aligns with our priori expectations that the previous year's ROA predict current ROA although the second lagged variables are statistically insignificant.

The CAP OlS and FE coefficients are -0.007044 and -0.135076, respectively. However, only the Fe coefficient statically significant at a 5% level. This suggests a negative predictive relationship with ROA. This result does not align with our priori expectation or the literature. The CTI coefficients are -0.086367 and -0.155129, respectively. However, only the OlS variable is statistically significant at the 5% level. This result suggests a negative predictive relationship with ROA. This result aligns with our priori expectation and literature. The ZSCORE variables coefficient are 0.000154 and 0.003690 respectively, however only the Fe coefficient is statistically significant at the 1 % level. These results suggest that bank risk taking positively predicts return on equity according to our Fe model. The DG, HHI and LLP variables show opposing results for both the Ols and Fe regressions, the variable coefficients are not statistically significant for both models and therefore no conclusion can be made on their predictive powers.

In terms of the macroeconomic variables, the results indicate that both GDP and INFLATION have an opposing impact on bank performance. The GDP and INFLATION OlS coefficients are positive and but statistically insignificant. The Fe coefficients are negative and similarly, not statistically significant. Given these results there is no conclusive evidence of a relationship between GDP and INFLATION in our models.

The diagnostic tests indicate that the probability of the Adjusted R-squared test is 0.941363 and 0.971714 respectively which suggests that a high proportion of the variability of return on assets can be explained by our variables in the models estimated. The Durbin-Watson statistics for both modes are within an acceptable range and confirm there is no evidence of autocorrelation.

Table 11 : OLS and FE regression: ROA

Dependent Variable: ROA		
Variables	**Pooled OLS**	**Fixed Effects**
ROA (-1)	0.878030*** (0.273441)	-0.300540 (0.261987)
ROA (-2)	0.036332 (0.182606)	0.169298 (0.128732)
FINTECHINDEX	-0.005604 (0.007315)	-0.009181* (0.005205)
CAP	-0.007044 (0.068879)	-0.135076** (0.061299)
CTI	-0.081030** (0.037560)	-0.002283 (0.029987)
DG	0.005782 (0.008639)	0.013410 (0.006815)
LLP	-0.124454 (0.102820)	0.020691 (0.089241)
ZSCORES	0.000154 (0.000239)	0.003690*** (0.000616)
HHI	1.28E-05 (2.18E-05)	2.09E-05 (1.53E-05)
GDPGR	0.000722 (0.000479)	-0.000421 (0.000403)
INFLATIONR	0.000675 (1.451392)	-6.12E-05 (0.001115)
CONSTANT	0.012593 (0.001577)	-0.073207 (0.043604)
F-Statistic	75.43241	117.8026
R-squared	0.954010	0.980034
Adjusted R-squared	0.941363	0.971714
Durbin-Watson stat	1.476254	1.008203

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.4.4 Return on Equity OLS/FE estimation

The results presented in table 12 suggest there is a negative relationship between the FINTECHINDEX variable and the ROE bank performance variable. The Fintech variable has a negative coefficient of -0.060802 and -0.037074 respectively and therefore suggest that Fintech firm growth negatively predicts current ROE values. Although this result is consistent with the previous estimations, the FINTECHINDEX variable is not statistically significant.

The first lag of ROE variable has a positive coefficient of 0.581798 and 0.092066 with only the Ols coefficient being statistically significant at the 1 % level. These results suggests that the previous year's ROE positively predicts current ROE. In contrast, the second lag of ROE has a negative coefficient of -0.032724 and -0.242762, with the Fe coefficient being statistically significant at the 5% level. This result therefore suggest that successive lags of ROE negatively predict current ROE. LLP has coefficients of -2.168034 and -1.328672 respectively with both being statistically significant at the 1% level. Therefore, the model suggest LLP negatively predicts ROE, which is in line with our priori expectations and literature. CTI has coefficients of -0.733822 and -0.073102 respectively, however only the Ols coefficient is statistically significant at the 1% level. This result suggests that CTI negatively predicts ROE, which is in line with our priori expectations and the literature.

The CAP and ZCORES both have evidence of opposing effects on the dependent variable. The CAP coefficients are 0.658493 and -0.671981 respectively, with the coefficients being statistically significant at the 10% and 5% level. Both ROA and ROE have a negative relationship with the CAP variables. This result does not align with our priori expectations or the literature however our mode suggests that CAP negatively predicts ROE. ZCORE has coefficients of -0.001298 and 0.019299 respectively with the Fe coefficient being statistically significant at the 1% level. Although not in line with our priori expectations and the literature, this result indicates that bank risk taking positively predicts return on equity in out model. Both the DG and HHI coefficients in our model are statistically insignificant and therefore there is no conclusive evidence of the predictive power of either variable.

In terms of the macroeconomic variables, the results indicate that GDP has a positive impact on bank performance. The GDP coefficients are 0.009971 and 0.003958 with both being statistically significant at the 1% and 5% level. This indicates that GDP positively predicts return on equity. This is in line with our priori expectations. The INFL variable has a negative statistically insignificant coefficient of -0.001588 and -0.000275.

The diagnostic tests indicate that the probability of the Adjusted R-squared test is 0.766648 and 0.930279 respectively which suggests that a high proportion of the variability of return on assets can be explained by our variables in the models estimated. The Durbin-Watson statistics for both modes are within an acceptable range and confirm there is no evidence of autocorrelation.

Table 12 : OLS and FE regression: ROE

Dependent Variable: ROE		
Variables	**Pooled OLS**	**Fixed Effects**
ROE (-1)	0.581798*** (0.155768)	0.092066 (0.105933)
ROE (-2)	-0.032724 (0.197207)	-0.242762** (0.114301)
FINTECHINDEX	-0.060802 (0.043362)	-0.037074 (0.024566)
CAP	0.658493* (0.331698)	-0.671981** (0.286422)
CTI	-0.733822*** (0.199496)	-0.073102 (0.138680)
DG	0.050935 (0.046202)	0.017097 (0.029818)
LLP	-2.168034*** (0.632560)	-1.328672*** (0.422814)
ZSCORES	-0.001298 (0.001654)	0.019299*** (0.002665)
HHI	7.39E-05 (0.000134)	5.73E-05 (7.39E-05)
GDPGR	0.009971*** (0.002874)	0.003958** (0.001874)
INFLATIONR	-0.001588 (0.009411)	-0.000275 (0.005225)
CONSTANT	0.319423 (0.365549)	-0.074702 (0.209430)
F-Statistic	16.23219	46.36546
R-squared	0.816979	0.950785
Adjusted R-squared	0.766648	0.930279
Durbin-Watson stat	1.825256	1.637559

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

5.5 Robustness Check

5.5.1 Estimation Results of Dynamic Panel Data Estimator

In choosing between the difference and system GMM, the study followed the approach of Bond et al (2001) and Presbitero (2006). The steps are as follows:

1. The lagged value of the dependent variable (autoregressive model) should first be estimated through the Pooled Ordinary Least Square (OLS) technique as well as the Fixed effects (FE) models.

2. After estimations, the coefficient of the lagged value of the dependent variable which was obtained through OLS is regarded as the upper-bond estimate. On the other hand, the corresponding FE estimate will be considered to be the lower bond estimate.

3. In the event that the difference GMM estimate obtained is closer to or below the FE estimate, the system GMM estimator will be preferred.

5.5.2 Bank share price GMM estimation

Table 13 : GMM Regression : Bank share price

Dependent Variable: Bank Share price						
Variables	**Pooled OLS**	**Fixed effect**	**One step diff GMM**	**Two step diff GMM**	**One step sys GMM**	**Two step system GMM**
BANK SHARE PRICE(-1)	0.464067** (0.136670)	0.516327 (0.113982)	0.534260 (0.109063)	0.438385 (0.126594)	0.703714 (0.471965)	0.382642 (0.125877)
BANK SHARE PRICE(-2)	0.848154*** (0.149682)	0.875594 (0.124505)	0.825831** (0.115436)	0.863001 (0.138162)	0.474474 (0.534613)	0.892019 (0.140758)
FINTECH(-1)	-0.116171* (0.067255)	-0.153180** (0.072005)	-0.149504** (0.071456)	-0.091204* (0.072367)	-0.137772* (0.077846)	-0.115015** (0.072974)
CAP	-0.132483** (0.01405)	-0.662853 (0.774943)	0.355446** (0.121939)	-67.76705 (60.52567)	-0.119963 (0.355773)	23.09105 (33.79579)
CTI	-0.523070 (.204013)	-0.664574 (0.312902)	-0.226336 (0.926561)	-42.70162 (32.25622)	1.076082*** (0.012783)	-77.56012 (26.37495)
LLP	0.229166* (0.114733)	0.5160341 (0.112117)	-0.469785* (0.225851)	-20.04267 (7.241880)	0.047609 (0.053468)	-21.03453 (7.407506)
GDP	1.205031** (0.478897)	1.302319 (0.408862)	0.464146 (0.11556)	-0.611743 (0.773747)	-0.1383124*** 0.003889)	-0.435186 (0.787292)
INFL	0.794506 (1.330978)	0.473006 (1.113745)	1.215295 (0.392034)	- 1.109761 (0.427328)	- 0.874766*** (0.070213)	0.933181 (0.426538)
Constant	36.90035* (20.81359)	22.33965 (17.84673)	0.786662 (0.32401)	0.166114 (1.261148)	-0.129762*** (0.029947)	0.382642 (0.125877)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic	299.1021	292.6627				
AR(2)			-0.976479	0.984288	0.953501	0.980921
Hansen statistic			0.2206726	0.588176	0.317860	0.819557

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

Looking at the results presented on Table 13, the Pooled OLS results indicate that the lagged value of bank share price is 0.464067. On the other hand, the value of the lagged estimate using the differenced GMM estimator is 0.534260. This result suggests that there is no significant difference in magnitudes of the two estimators. Following the approach employed by Bond et al (2001) and Presbitero (2006), the one step difference GMM estimator became the appropriate technique to use for the data.

The results presented in Table 13 reveal that there is a negative relationship between the lagged Fintech variable and Bank Share price. The coefficient of Fintech is -0.149504 and is statistically significant at the 5 % level. This result indicates that Fintech firm funding negatively predicts bank share prices and bank financial performance. The 1st and 2nd lagged bank share variables are positively related to bank share prices and these follow our priori expectations that previous bank share prices predict current bank share prices. The empirical results also indicate that the coefficient of the CAP of which is the ratio of equity to assets is positive and statistically significant at the 5% level and has a value of 0.355446. This suggest that CAP positively predicts bank share prices. This result is in line with the bank share correlation matrix and is supported within the literature.

In line with the priori expectations, the empirical results reveal that CTI negatively predicts dependent variable. The CTI value has a value of -0.226336; however, this result is not statistically significant. The LLP variable, similar to CTI has a negative coefficient. LLP has a coefficient value of -0.469785 and is significant at the 10% level. This indicates that LLP negatively predicts bank share prices in our model. In terms of the macroeconomic variables, the results indicate that GDP has a positive impact on bank performance. The GDP coefficient is 0.464146 and indicates that GDP positively predicts bank share prices. This is in line with our priori expectations. In contrast, the INFL variable has a positive statistically insignificant coefficient. This result does not align with both the literature and our priori expectations.

The diagnostic tests indicate that the probability of the AR (2) test is 0.976479, which is insignificant, suggesting that there is no second order serial autocorrelation in the model estimated. The diagnostic tests also indicate that the Hansen J-statistic for overidentification restrictions is 0.2206726, indicating the validity of the instruments.

5.5.3 Net Interest Margin GMM estimation

Table 14 GMM regression : NIM

Dependent Variable: NIM						
Variables	**Pooled OLS**	**Fixed effect**	**One step diff GMM**	**Two step diff GMM**	**One step sys GMM**	**Two step system GMM**
NIM(-1)	1.159787 (0.183112)	0.987742 (0.189979)	1.216927** (0.184125)	0.255343 (0.065378)	1.306342 (1.726325)	0.724779 (3.234494)
NIM(-2)	-0.321098 (0.183112)	-0.322231 (0.196756)	-0.328708** (0.180049)	4.72E-05 (2.55E-05)	-0.087864 (2.078677)	0.566267 (3.783572)
FINTECH(-1)	6.43E-05 (4.12E-05)	5.78E-05 (4.26E-05)	-0.287357* (0.143758)	0.126509 (0.055273)	0.000102 (0.000354)	0.041188 (0.000575)
CAP	0.013214 (0.058641)	0.037350 (0.055686)	-0.020724 (0.056068)	-0.030464 (0.014284)	-0.003886 (0.234823)	0.026230 (0.347157)
CTI	0.021476 (0.031657)	0.019847 (0.030881)	0.033712 (0.031496)	-0.009746 (0.012538)	-0.033249 (0.137192)	-0.075167 (0.246778)
DG	-0.012495 (0.007971)	-0.009645 (0.007735)	-0.011713 (0.008156)	-0.000612 (0.000451)	-0.075604 (0.101213)	-0.105024 (0.178622)
GDP	0.000313 (0.000267)	0.202703 (0.098540)	0.000249 (0.000271)	-0.000717 (0.000457)	-0.000632 (0.002161)	-0.000753 (0.003059)
INFLATION	0.001989 (0.000803)	0.001614 (0.000781)	- 0.002272 (0.000803)	0.142709 (1.296145)	0.005755 (0.007273)	0.005519 (0.010223)
LLP	0.295679 (0.086404)	-0.012640 (0.021828)	0.227852 (0.077252)	-0.337719 (2.738756)	-0.012021 (0.122329)	-0.215423 (0.795991)
C	-0.017276 (0.021520)	0.007639 (0.020569)	-0.023458 (0.021703)	0.015805 (0.098618)	0.056920 (0.106845)	0.012310 (0.193463)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic						
AR(2)			0.30149	-0.268709		
Hansen statistic			0.39986	1.446726	0.704696	0.704696

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

Looking at the results presented on Table 14 , the results of the Pooled OLS indicate that the lagged value of NIM is 1.159787 . On the other hand the value of the lagged estimate using the differenced GMM estimator is 1.216927 . This result suggests that there is no significant difference in magnitudes of the two estimators. Following the previous estimations, the one step difference GMM estimator became the appropriate technique to use for NIM data.

Similar to the GMM estimation results for the bank share price dependent variable, the difference GMM results presented in table 14 reveal there is a negative relationship between the lagged Fintech and net interest margin dependent variable. The coefficient of Fintech is -0.287357 and is statistically significant at the 10% level. This result indicates that Fintech firm funding negatively predicts net interest margin and bank financial performance. The first lagged NIM variable positively predicts the current net interest margin variable. However, the second lagged NIM variable negatively predicts current net interest margin. The results suggest that past lags of NIM may not be a precise indictor of current values.

The CAP control variable has a negative coefficient but is not statistically significant. Furthermore, this result does not align with the net interest margin correlation matrix and our priori expectations. The CTI coefficient is positive and, therefore, positively predicts net interest margin, although in line with our priori expectations, the variable is statistically insignificant. GDP and LLP similarly have positive coefficients but are not statistically significant. Although in line with the literature and our priori expectations these results are not conclusive. The remaining control variables, INFL and DG, are negative and not statistically significant.

The diagnostic tests indicate that the probability of the AR (2) test is 0.30149, which is insignificant, suggesting that there is no second order serial autocorrelation in the model estimated. The diagnostic tests also indicate that the Hansen J-statistic for overidentification restrictions is 0.39986, indicating the validity of the instruments.

5.5.4 Return on Asset GMM estimation

Table 15 GMM regression : ROA

Dependent Variable: ROA						
Variables	**Pooled OLS**	**Fixed effect**	**One step diff GMM**	**Two step diff GMM**	**One step sys GMM**	**Two step system GMM**
ROA(-1)	0.616928 (11.77698)	-0.061513 (1.880734)	0.773600 (0.260091)	0.977982 (1.069922)	0.733569 (0.798243)	0.678082 (1.436916)
ROA(-2)	0.000303 (0.001957)	0.030674 (0.000377)	0.074915 0.182225)	0.089395 (0.418426)	0.256281 (0.599625)	0.518288 (1.141024)
FINTECH(-1)	-0.348721 (0.148061)	-0.025892 (1.044048)	-0.146706* (0.082623)	-0.000122 (0.000320)	-0.877815 (0.445792)	-1.894871 (0.632267)
CAP	0.314668 (2.550229)	-0.022413 (0.459165)	0.014121 (0.074154)	-0.752576 (1.723620)	-0.216006 (0.484545)	0.000429 (0.001602)
CTI	0.418018 (1.880405)	-0.200743 (0.607651)	-0.086367 (0.036338)	-0.458331 (0.250294)	-0.450345 (0.320112)	-0.435708 (1.219260)
DG	0.012658 (0.056514)	-0.003496 (0.013159)	0.006606 (0.008292)	-0.075490 (0.025000)	-0.065260 (0.019228)	-0.688430 (1.221928)
GDP	-0.507344 (2.714819)	-1.942651 (3.827804)	0.000765 (0.000461)	-0.001700 (0.001579)	0.001208 (0.000934)	-0.063271 (0.033391)
INFLATION	-1.703093 (8.019677)	-0.089055 (3.826449)	- 0.000416 (0.001280)	-0.228859 (1.384161)	-0.001171 (0.001640)	0.001818 (0.002876)
LLP	-0.104225 (1.053750)	0.054898 (0.215234)	-0.155129 (0.104671)	0.000358 (0.000782)	-0.672580 (0.395362)	-0.000856 (0.002078)
C	0.007066 (0.010177)	0.056627 (0.186225)	0.048397 (0.022724)	0.002999 (0.005991)	-0.014350 (0.064288)	-0.471963 (1.092417)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic	64.56807	62.02097				
AR(2)			0.50270	0.6716	0.857193	0.847946
Hansen statistic			0.122712	0.036764	0.762271	0.839358

***** Indicate significance at the 1% level** ***Source: Author's calculations in Eviews***
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Looking at the results presented on Table 15 , the results of the Pooled OLS indicate that the lagged value of ROA is 0.616928 . On the other hand the value of the lagged estimate using the differenced GMM estimator is 0.773600. This result suggests that there is no significant difference in magnitudes of the two estimators. Following the previous estimations, the one step difference GMM estimator became the appropriate technique to use for the ROA data.

Similar to the previous bank performance dependent variables, the difference GMM results presented in table 15 suggest there is a negative relationship between the lagged Fintech and return on assets dependent variable. The coefficient of Fintech is -0.146706 and is statistically significant at the 10% level. This result suggests that Fintech firm funding negatively predicts return on asset and bank financial performance. The first and second lagged ROA variables are positively related to current ROA and have coefficients of 0.773600 and 0.074915, respectively. The lower second lag coefficient suggests that later previous values of ROA have less predictive power on current ROA values. This aligns with our priori expectations that the previous year's ROA predict current ROA although both lagged values are statistically insignificant.

The empirical evidence related to the bank performance control variables suggest that there is a positive relation between CAP, DG and the dependent ROA variable. The results for both CAP and DG align with our priori expectation. The CAP and DG coefficients are 0.014121 and 0.006606, respectively. However, neither has a statically significant predictive relationship with ROA. The coefficients of both CTI and LLP are negative and therefore have a negative relationship with the current ROA dependent variable. The CTI and LLP coefficients are -0.086367 and -0.155129, respectively. However, neither variable is statistically significant. In terms of the macroeconomic variables, the results indicate that GDP has a positive impact on bank performance. The GDP coefficient is 0.000765 and indicates that GDP positively predicts bank share prices. This is in line with our priori expectations. The INFL variable has a negative statistically insignificant coefficient of -0.000416. This result aligns with both the literature and our priori expectations.

The diagnostic tests indicate that the probability of the AR (2) test is 0.50270, which is insignificant, suggesting that there is no second order serial autocorrelation in the model estimated. The diagnostic tests also indicate that the Hansen J-statistic for overidentification restrictions is 0.122712, indicating the validity of the instruments.

5.5.5 Return on Equity GMM estimation

Table 16 GMM regression : ROE

Dependent Variable: ROE						
Variables	**Pooled OLS**	**Fixed effect**	**One step diff GMM**	**Two step diff GMM**	**One step sys GMM**	**Two step system GMM**
ROE(-1)	0.673663*** (0.138493)	0.517568*** (0.131715)	0.691259 (0.151341)	0.764592** (0.235013)	0.602142 (0.738430)	-4.416463 (50.03903)
ROE(-2)	-0.216606 (0.180998)	-0.302600* (0.151975)	-0.242195 (0.203070)	-0.520194 (0.755477)	0.070432 (0.933894)	10.57270 (103.3303)
FINTECH(-1)	-0.000391 (0.000456)	-0.000289 (0.000383)	-0.000615 (0.000891)	-0.001808** (0.000557)	-0.000728 (0.002576)	-0.014359 (0.137724)
CAP	1.442581*** (0.370568)	0.230887 (0.404493)	1.441598 (0.385453)	-0.550713 (0.895740)	-0.916313 (0.971194)	-34.41571 (327.3013)
CTI	-0.909954*** (0.189293)	-0.527972** (0.175316)	-0.900903 (0.198246)	0.146087 (1.161742)	-0.312517 (1.083955)	14.29273 (143.3601)
DG	0.014484 (0.041682)	-0.043970 (0.039764)	0.018862 (0.044670)	-0.204359*** (0.041658)	0.084349 (0.272895)	0.244664 (4.074705)
FIRM	0.008773*** (0.002466)	0.010293*** (0.002073)	0.000509 (0.004484)	0.014515 (0.003691)	0.019269 (0.012688)	0.070568 (0.530464)
GDP	-0.003547 (0.007066)	-0.002417 (0.005684)	0.009058 (0.002666)	0.005840 (0.023309)	-0.036417 (0.047843)	-0.369181 (3.314786)
INFLATION	-3.125492*** (0.626344)	-3.749076*** (0.546956)	-0.002790 (0.007706)	-6.685580** (1.944898)	1.100662 (2.883037)	68.29568 (657.1733)
LLP	-0.000631*** (0.000206)	-0.000609** (0.000170)	-3.112940 (0.645091)	1.146589 (0.610084)	0.525521 (0.486404)	0.011253 (0.109857)
C	0.500209*** (0.122069)	0.589257*** (0.102194)	-2.431053 (9.635594)	0.008615 (0.010289)	0.641472 (0.333822)	-3.613900 (40.96239)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic	23.45543	28.34708				
AR(2)			0.772531		0.157891	0.250074
Hansen statistic			0.499906		1.994307	2.771995

***** Indicate significance at the 1% level**
**** Indicate significance at the 5% level**
*** Indicate significance at the 10% level**

Source: Author's calculations in Eviews

Looking at the results presented on Table 16 , the results of the Pooled OLS indicate that the lagged value of ROE is 0.673663. On the other hand, the value of the lagged estimate using the differenced GMM estimator is 0.691259. Similar to the previous estimations, this result suggests that there is no significant difference in magnitudes of the two estimators. Following the previous estimations, the one step difference GMM estimator became the appropriate technique to use for the ROE data.

The difference GMM results presented in table 16 suggest there is a negative relationship between the lagged Fintech variable and the ROE bank performance variable. The Fintech variable has a negative coefficient of -0.000615 and therefore suggest that Fintech firm funding negatively predicts current ROE values. Although this result is consistent with previous GMM estimations and our priori expectations, the lagged Fintech variable is not statistically significant. The first lag of ROE variable has a positive coefficient of 0.691259 and this result suggests that the previous year's ROA positively predicts current ROA. In contrast, the second lag of ROA has a negative coefficient of -0.242195 and therefore negatively predicts current ROA. This result is similar to the ROA estimation in that neither variable is statistically significant.

The CAP and DG control variables both have a positive relationship with ROE. The CAP and DG coefficients are 1.441598 and 0.018862 respectively, suggesting that both variables positively predict ROA. However, neither variable is statistically significant. The CTI and LLPP control variables both have a negative relationship with ROE. The CTI and LLP coefficient variables are -0.900903 and -3.112940 and this result suggests that both variables negatively predict current ROE values. Additionally, neither variable is statistically significant. In terms of the macroeconomic variables, the results indicate that GDP has a positive impact on bank performance. The GDP coefficient is 0.002790 and indicates that GDP positively predicts bank share prices. This is in line with our priori expectations. The INFL variable has a negative statistically insignificant coefficient of -0.002790. This result aligns with both the literature and our priori expectations.

The diagnostic tests indicate that the probability of the AR (2) test is 0.772531, which is insignificant, suggesting that there is no second order serial autocorrelation in the model estimated. The diagnostic tests also indicate that the Hansen J-statistic for overidentification restrictions is 0.499906, indicating the validity of the instruments.

5.6 Chapter Summary

Various sources in the literature present contrasting empirical evidence of the relationship between the growth of the Fintech sector and bank financial performance. This section summarizes the results of the descriptive statistics, correlation matrixes, the OLS, FE, and GMM estimations of the bank financial performance dependent variables and the Fintech independent variables. Overall, the evidence suggests a negative and significant relationship between the growth of the Fintech payment segment and bank financial performance. This result is in line with the hypothesis set out in Chapter 4, that Fintech firm growth had a negative relationship with Bank financial performance.

The descriptive statistics presented in Table 4 highlighted the upward trend and growth in the value of the Fintech payments segment within South Africa. Similarly, the robustness check Fintech proxy (Fintech firm funding) had growth throughout the period, excluding two years with no funding values. The correlation matrixes between the bank financial performances presented contrasting results. The results of the bank share price and net interest margin correlation matrixes showed evidence of a positive relationship between the Fintech Index variable and both dependent variables. This result aligns with empirical evidence by (Haddad and Hornuf, 2021, Low and Wong, 2021). The relationship between net interest margin and the Fintech Index was also statistically significant at the 10% level, suggesting that both variables being correlated. In contrast, the correlation between bank share prices and the Fintech Index was insignificant. The correlation matrixes for the same variables in the robustness check presented similar results, with bank share prices and net interest margin positively correlated to the Fintech firm funding proxy.

The return on equity correlation matrix showed evidence of a negative relationship between the Fintech index variable and ROE. This result is consistent with empirical evidence by (Almulla and Aljughaiman, 2021, Nikita Sari, 2020, Phan et al., 2020). The relationship between ROE and the Fintech index variable was, however, not statistically significant. The empirical evidence from the correlation matrix suggests a relationship between Fintech firm growth and ROE. The ROA correlation matrix showed a positive relationship between the Fintech Index and ROA, which does not align with the literature.

Furthermore, the relationship was not statistically significant, and no further conclusions could be drawn from the results. In contrast, the correlation matrix results for the same variables in our robustness check were both negative, with the Fintech firm funding variable being statistically significant at the 5% level for ROE. Given both sets of correlation matrix results, this study can conclude that there is a relationship between Fintech firm growth and ROA and ROE.

Tables 9 to 12 represent the results of the OLS and FE estimations of all four bank financial performance variables against the Fintech Index. The estimation results follow the corresponding correlation matrix results. Both bank share price and net interest matrix have a positive relationship with the Fintech Index variable. The relationship is statistically significant at the 10% level for net interest margin and the index. These results are in line with empirical evidence from (Haddad and Hornuf, 2021, Low and Wong, 2021). The ROA and ROE regression results were also consistently negative, with the Fintech index being statistically significant at the 10% level for the ROA FE regression. The results are in line with the results of the correlation matrixes and align with our priori expectations as well as the literature. Various studies, such as (Almulla and Aljughaiman, 2021, Nikita Sari, 2020, Phan et al., 2020), have similar results.

Tables 13 to 16 presented the results of the GMM estimations of all four bank financial performance variables against Fintech firm funding. All four models based on the approach by Bond et al. (2001) and Presbitero (2006) took on the one-step difference GMM model specification. Furthermore, all four estimations presented a negative relationship between the bank financial performance variables and the lagged Fintech firm funding variable. Three of the four models were statistically significant. Bank share prices, NIM and ROA were statistically significant at 5%, 10% and 10%, respectively. These results suggest that Fintech firm funding negatively predicted bank financial performance.

Although there was some variance in our model results in relation to the OLS and FE regressions of our bank share and net interest margin dependent variables, this study concluded that interactions between the different independent variables may have attributed to the variance in the multivariable estimations. In conclusion, given the GMM regression results as well as the evidence from the correlation matrixes this study finds that the empirical evidence suggests that Fintech firm growth within the payments segment does have a negative and significant relationship with bank financial performance.

CHAPTER 6: CONCULSIONS AND RECOMMNEDATIONS

The primary objective of this research was to determine the relationship between the growth of Fintech firms in the payments segment and the performance of the South African banking sector. A measure for Fintech firm growth was required to achieve this goal. Therefore, the secondary objective of this research was to create a Fintech firm growth index to achieve our primary goal.

Various studies in the literature have investigated the nature of the relationship between Fintech firm growth and Bank financial performance. Several studies found empirical evidence suggesting that the sector's growth positively influenced the financial performance and financial stability of the banking sector. In contrast, other studies found conflicting evidence suggesting that the growth of the Fintech sector negatively impacted financial performance and stability. Furthermore, these studies used various proxies to measure the growth of the Fintech sector indicating a lack of a consistent measurement proxy for the growth of the Fintech sector. Although the relationship between Fintech firm growth and bank financial performance has been widely reviewed in the literature, there is a gap in the literature regarding this relationship within the South African context. Furthermore, there is currently a lack of a measurement proxy for Fintech firm growth within South Africa. This research merely provided a starting point in addressing this gap while establishing a measure for the growth of Fintech firms in South Africa

6.1 Literature Review and Methods

The literature review presented in Chapter 2 began by attempting to define the term Fintech. However, as noted in the chapter, there is a lack of a consensus on a definition of the term. Bettinger (1972) first described Fintech as the combination of bank and information technology expertise. Other definitions of the term refer to Fintech as a new and unique sector or segment of the financial industry; Micu (2016) defined Fintech as a new segment incorporating a wide range of technologies to facilitate trade, business between corporations and services in the retail sector. Furthermore, in other sources in the literature, Fintech is defined from the business model point of view. Dorfleitner et al. (2016) define Fintech as the innovative business models that transform the finance industry. The varying definitions and lack of consensus on a definition can be partly attributed to the sector's rapid growth.

The rate of growth of Fintech within the developed and emerging markets has been high since the end of the global financial crisis. Globally, the rate of Fintech adoption is 64%, with South

Africa having an adoption rate of 82%, the highest in the African emerging markets segment (EY, 2019). This rapid growth of Fintech can be attributed to various attributes within respective domestic markets. Within South Africa, the retail sector has been the primary driver of Fintech firms as producers and retailers partner up with Fintech firms to provide consumers with a broader range of checkout options. Globally, a change in user demographics in the financial services sector, mobile phone penetration and increases in internet access have driven the adoption of Fintech firms. Millennials are increasingly averse to in-person interactions. Furthermore, Gen Z consumers operate in an environment with high remote access. Fintech firms have been able to address these changes in consumer expectations better more rapidly than the traditional banking sector. Increased internet penetration and mobile phone access growth rates in emerging markets in Africa have also been attributed to the growth of the Fintech firm payment subsegment. South Africa has the highest mobile phone penetration rate on the continent at 89% (Poushter and Oates, 2015).

The global financial crisis and the resulting regulatory gaps have been widely attributed to the global boom in the growth of the Fintech sector in the literature. The crisis created a credit crunch, reduced the supply of mortgages and small business credit and lending was frozen. Traditional banking institutions were unable to lend credit or invest in IT infrastructure. The resulting lack of client confidence, unstable financial and regulatory period provided an opportunity for novel, innovative offerings from FinTech's to bridge the gap. Additionally, these Fintech firms did not need to overcome the growing mistrust and risk aversion by consumers of traditional financial services (Haddad and Hornuf, 2021). These gaps in the regulation and perceived failures of the traditional banking sector have allowed for the boom of the Fintech sector, by allowing Fintech firms to leapfrog the banking, financial compliance, and payment regulations of traditional banks. However, Brandle and Hornuf (2020) found that Fintech firms often do not fully comply with financial regulations and take advantage of regulatory arbitrage. This can potentially undermine the financial markets through the associated regulatory risk. Although these regulatory gaps have been acknowledged within the South African context by the South African Reserve Bank, the sector's growth remains positive.

Various theoretical frameworks have been applied to exploring the adoption of Financial Technologies across literature. Studies such as Haddad and Hornuf (2021), Li et al. (2017), and Phat et al. (2020) attribute the growth of the sector to consumer theory. The Consumer theory explains how new service and product offerings, such as those offered by Fintech firms, act as either a compliment when used with existing incumbent offerings or a substitute if they can replace the incumbents' offerings. Fintech firms would, therefore, have a negative effect on the demand and profitability of traditional banking services if perceived as a substitute for traditional bank offerings. The disruptive innovation theory follows from consumer theory and tastes that new market entrants offering successful substitutes for traditional incumbent services and target overlooked markets disrupt traditional retail banks by offering more affordable services and goods to consumers. The theory makes a distinction between sustaining innovation and disruptive innovation.

A further applicable model to the growth of Fintech is the Diffusion of Innovation theory. Diffusion of innovation is a process in which innovation is spread through various channels over a period of time through society. The theory further states that the adoption of innovation is dependent on taking a client-orientated approach to communicate the advantages of the innovation to adopters. Various studies, such as those by Coetzee (2019) and Alwi et al. (2019), have applied the innovation of Fintech to the diffusion of innovation theory. Studies, such as those by Hamdan et al. (2021) and Hubert et al. (2019), find the Diffusion of Innovation theory similar and complementary to the Technology Acceptance Model in terms of explaining the adoption of information technology. These studies argue that the Technology Acceptance Model employs constructs that are a subset of the perceived innovation characteristics. The main objective of the Technology Acceptance model is to understand the primary impact of external variables on consumers' internal beliefs, attitudes, and intentions.

The Fintech sectors is South Africa is the most matured in the continent, closely followed by Nigeria's own Fintech sector. The South African Fintech sector is home to 217 Fintech Firms (SARB, 2019). Various studies within the literature point to the money transfers and mobile payments segment as being the driver of Fintech firm growth within South Africa. Underpinning this growth in the payments segment is the increasing mobile phone and internet penetration, and as the global prices of smartphones drop, this growth is likely only to increase. However, the growth of the sector is limited in South Africa by the regulatory framework which has proven to be both an enabler and deterrent to the entrance of new Fintech markets entrants. The Payments Fintech subsegment is the largest and most mature in South Africa, accounting for 30% of all Fintech firms (SARB, 2019). The subsegment accounts for 6% of the total addressable transactional volume being addressed by traditional banking firms.

Internationally, regulatory frameworks in the payments segment have enabled the growth of the sectors as incumbent banks are required to share data with FinTech firms. However, these policy changes have yet to be reflected in the South African banking framework. Although the payments segment is expected to grow, fintech firms in the payments segment are limited due to the regulatory requirements that these firms partner with incumbent banks (SARB, 2019).

The lending sector makes up 12% of the sector and is responsible for 1.49% of the total addressable lending sector; the sector growth has been attributed to the increased demand due to previously underserved consumers not being served by incumbent lending providers. Similarly to the payments segment, lending FinTech firms must register as credit service providers with the NCR (SARB,2019).

The saving and deposit subsegment is also closely related to the traditional banking sector and is the most regulated segment. The subsegment is comprised of 14 Fintech firms, four of which are digital challenger banks. These include TymeBank, Discovery, BankZero and Hello Paisa.. Although Digital banks are required to obtain banking licenses and are subject to liquidity and capital reserve requirements by the Reserve Bank of South Africa, the subsegment addressed 1% of the 28.7 million banked South Africans and is set to outgrow the deposit sector by 7% (SARB, 2019). The regulatory pressures in the investment and capital raising subsegments have meant there is little or no growth. Fintech firms in the investment subsegment executed 1.392% of the 68 million trades at the JSE and alternative exchanges. The growth in the segment has been dampened by regulatory changes restricting the use of cryptocurrency as legal tender.

The South African banking sector is highly regarded as world-class in its efficiency and regulation within the literature. Various papers, such as Moyo (2018) and Schwab (2016), found that the sector is one of the most developed globally. Although highly concentrated, with the 5 largest banks controlling over 90% of the market share, the sector shows evidence of high financial stability (Coetzee, 2019). The South African Banking sector follows stringent regulatory laws applied by the Reserve Bank, resulting in banks adopting risk-averse nature in their financial operation. Banks in the sector are required to fully comply with the Basel Committee on Banking supervision standards and are required by the FSRA to move toward the Twin-peaks framework. The South African banking sectors are regulated by both the Prudential Authority and the FSCA. Various studies have argued that this strict regulation has had a negative effect on the growth of the Fintech sector.

Furthermore, the Payment Association of South Africa regulates banks and third-party payment providers and requires these parties to register as payment service providers or third-party payment providers. This requirement suggests that non-bank Fintech Firms that participate in the national payments system via a sponsorship agreement with an established licensed incumbent bank. This regulatory requirement effectively enforces partnerships between non-licensed, non-banking Fintech firms and incumbent banks.

Studies on the empirical evidence of the nature of the relationship between Fintech firm growth and bank financial performance have produced varied findings. Various studies in the literature found a positive relationship between Fintech firm growth and bank financial performance; however, in contrast, other studies found a negative relationship. These various studies employed varied Fintech Firm proxies, bank financial performance variables and methodologies. The various proxies and methodologies in the literature informed the proxies and methodology used in this study.

Empirical evidence by Haddad and Hornuf (2021) found a positive relationship between Fintech Firm growth and Bank financial performance. This study employed OLS and FE regression analysis to come to this result. This paper used the growth rate of Fintech startups as the proxy for Fintech firm development. Similarly, studies by (Li et al., 2017 Low and Wong, 2021 Safiullah et al., 2022) provided evidence of a positive relationship between the development of Fintech Firms and Bank financial performance.

Although the studies by Li et al (2017) and Low and Wong (2021) made use of the five-factor asset pricing model methodology to come to this conclusion, the results were consistent. Furthermore, Safiullah et al. (2022) employed a dynamic panel GMM regression and arrived at the same conclusion.In contrast, Phan et al. (2020) and Almulla and Aljughaiman (2021) found the relationship between fintech firm growth and bank financial performance to be negative. Interestingly, the study by Phan et al .(2020) was undertaken in Indonesia, a developing nation, whereas the study by Alumulla and Aljughaiman ,(2021) studied the relationship in respect to conventional and Islamic banks. Both papers employed the use of OLS, FE and GMM regressions to come to this conclusion. Bank financial performance variables were consistent with various other sources and included NIM, ROE, ROA. Furthermore, the methodology employed was consistent with Haddad and Hornuf (2021) and Safiullah. The OLS and FE methodology were widely used within the literature and formed the basis of our research methodology. However, due to the various Fintech proxies employed within the literature, this study incorporated multiple proxies to better capture the growth of the Fintech firm payment segment in South Africa.

6.2 Key Findings

The findings of our statistical analysis suggest a negative relationship between Fintech Firm growth in the payments segment and Bank financial performance in the South African context. These results are consistent with findings from by Phan et al. (2020) and Almulla and Aljughaiman (2021) . The results of the correlation matrices between the FinTech growth index and NIM, ROE, ROA and Bank share price were varied and non-conclusive. The correlation matrices for Bank share, NIM and ROE were all positive, with only NIM having a statically significant result. ROA had a negative but non-statistically significant result.

The OLS and FE regression results between the multivariate regression and the Fintech firm index show similar contrasting results. The OLS and FE regressions for the bank share price and net interest matrix have a positive relationship with the Fintech Index variable. However, the relationship is statistically significant at the 10% level for net interest margin and the Fintech firm Growth Index. The results of the return on assets and return on equity OLS and FE regression were negative, with the relationship being statistically significant at the 10% level for return on asset.

The results of the GMM robustness check with Fintech firm funding in relation to our primary OLS and FE regressions suggest a negative relationship between Fintech firm growth and bank financial performance. The Bank share price, NIM and ROA GMM results were negative and statistically significant, these results are consistent with Phan et al. (2020). These results, given the context of the regulatory pressures faced by payment Fintech firms in South Africa, are not surprising. Furthermore, South Africa has one of the most developed bank sectors in Africa, financial inclusion and access to bank branches are high. The results from our findings suggest Fintech firm growth in the segment has increased the availability of services that substitute or directly compete with incumbent bank financial services or that banks to not offer such as Crypto payments wallets .This result supports the study by (Coetzee, 2019) that suggests that Fintech firms may disrupt and erode the banks client relationship therefore affecting bank performance. Furthermore, these findings indicate an opportunity for Fintech firms and banks to form partnerships.

6.3 Delimitations and Further Research

The relationship between Fintech firms and bank financial performance in South Africa has been under-researched within the literature. Furthermore, the lack of a consistent Fintech firm measurement proxy suggests there is potential for more research to be undertaken. This thesis attempted to analyse the impact of the Fintech firm payment subsegment on bank financial performance in South Africa.

Due to the lack of a comprehensive Fintech data source for South Africa, multiple proxies were required to attempt to determine the nature of the relationship between Fintech firms and bank financial performance. Given a more robust data source and time, a further similar study investigating the relationships between each proxy and bank financial performance variables would possibly produce more comprehensive results on the topic. Additionally, further studies focusing on Fintech firm influence on bank performance of smaller vs larger banks could determine if the size of the banking institutions have an influence on the relationship. Finally, employing the use of not only supply side but also demand-side Fintech firm data would be helpful in further establishing more detail regarding the growth of the sector.

6.4 Recommendations

The study recommends that the South African Reserve Banks and Policymakers push for less stringent regulations on Fintech Firms in South Africa to encourage partnerships and competition within the financial sector. The study found that the growth of the sector in other regions has improved financial inclusion and served as a complementary sector to the traditional banking sector. The addition of more Fintech firms in the financial sector has the potential to increase the liquidity within the sector by serving previously underserved South African consumers. Fintech firms are able issue out credit and banking services to consumers who may prove to be too risky to serve through AI driven credit modelling and cheaper cost of operation.

The partnerships of Fintech Firms and established banks has the likelihood of improving the stability of the financial sector and improving the positions of incumbent banks, through the introduction of new business models and financial products. Fintech Inventors also benefit from the improved support of policymakers, allowing for the growth of entrepreneurial pursuits in the sector. Lastly, the growth of the sector has positive implications for South African consumers as this improves their access to financial services but also reduces the cost of these services.

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