EFFECT OF FINANCIAL TECHNOLOGY ON NON-PERFORMING LOANS AMONG COMMERCIAL BANKS IN KENYA

SAMMY NGILE NGUI

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION, FACULTY OF BUSINESS AND MANAGEMENT SCIENCES, UNIVERSITY OF NAIROBI

NOVEMBER, 2021

DECLARATION

I, the undersigned, declare that this is my original work and has not been presented to any institution or university other than the University of Nairobi for examination.

Signed: ______________________Date: _________01.12.2021_________________

SAMMY NGILE NGUI

D61/27774/2019

This research project has been submitted for examination with my approval as the University Supervisors.

Signed: ______________________Date: 1/12/2021__________________________

DR. DUNCAN ELLY OCHIENG (PhD, CIFA, CPA)

SENIOR LECTURER, DEPARTMENT OF FINANCE AND ACCOUNTING

FACULTY OF BUSINESS AND MANAGEMENT SCIENCES

UNIVERSITY OF NAIROBI

ACKNOWLEDGEMENT

This research was made possible by the help and assistance of a number of people to whom I owe a debt of gratitude. First and foremost, I want to express my thankfulness to the Almighty God for allowing me to pursue and finish my studies via his tremendous grace. I offer all respect and glory to Him.

My supervisor, Dr. Duncan Elly, deserves particular recognition for shaping my study into something important, as well as for his constant and intelligent feedback, direction, and support. My thanks is extended to my family and coworkers for their unwavering support, inspiration, and patience.

DEDICATION

This research project is dedicated to my wife, Beatrice Moraa and son, Heri Ngile for their love, support and encouragement.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
ATM	Automated Teller Machine
CBK	Central Bank of Kenya
IMF	International Monetary Fund
KCB	Kenya Commercial Bank
MFI	Micro Finance Institution
NPL	Non- Performing Loans
ROA	Return on Assets
SPSS	Statistical Package for Social Sciences
TAM	Technology Acceptance Model
VIF	Variance Inflation Factors

ABSTRACT

Financial technology continues to change and shape the banking sector in Kenya. The Kenyan banking sector has focused increasingly on fintech as a strategic instrument to achieve organization goal of reducing costs and maximizing revenues. KCB has been promoting KCB MPESA and adopted Fuliza in 2019, Equity has been using Equitel and Eazzy banking app, NCBA bank has been offering Mshwari and recently Fuliza. Other banks also have some aspect of mobile lending through their digital platforms. The big question is whether the financial performance resulting from the use of fintech has improved. This might not be a straight forward relationship as fintech comes with the risk of increased NPLs. The goal of this research was to assess the influence of fintech on Kenyan commercial banks' non-performing loan (NPL) levels. Sufficiency of bank capital and the bank's size (log total assets) served as the model's guiding factors (core capital to risk weighted assets). A descriptive approach was used to the study. There were 42 commercial banks in Kenya that were studied in this research. For the analysis, data from CBK and yearly financial statements from 2016 to 2020 was gathered. This study was conducted among 38 banks that supplied detailed data for the five years in question. Regression and correlation analysis were used to assess the study assumptions and find a connection between fintech and NPLs. NPL variation was explained by the specified independent factors with an R2 of 0.063. This meant that the non-study factors account for 93.7 percent of the fluctuations in NPLs. Findings from a one-way ANOVA indicated that the model was statistically significant. The study further found that fintech ($\beta=0.184$, $p=0.143$) had a positive but not significant effect on the level of NPLs among banks in Kenya. The study also found that bank size ($\beta=-0.358$, $p=0.016$) and capital adequacy ($\beta=0.211$, $p=0.037$) had significant effect on the level of NPLs among banks in Kenya. The research indicates that management of commercial banks should maintain issuing mobile loans since this does not raise the risk of NPLs. Policy makers such as CBK should come out with regulations and standards that would make it simple for banks to provide fintech solutions to their clientele. It also suggests that banks in Kenya should increase their asset base since bigger financial institutions are better equipped to benefit from economies of scale and have stronger systems that help them to better manage NPLs than smaller financial institutions. The paper recommends more research into the impact of fintech on other financial institutions, such as microfinance banks and SACCOs. In the future, more study might focus on the causes of NPLs in Kenyan commercial banks.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Financial technology (fintech) have greatly altered the functioning of financial firms and established the basis for banks to distinguish between their goods and their rivals (Cihak & Singh, 2013). Fintech platforms have been used by a large number of financial institutions in an effort to improve their business results (Abdulkarim & Ali, 2019). However, it is possible that the number of Non-Performing Loans (NPLs) would increase (Ugoani, 2016). Increases in gross non-performing loans (NPLs) represent a substantial danger to financial institutions, notably commercial banks, as well as the broader economy, argue Kaaya and Pastory (2013). High NPLs levels as a result of the crisis have a detrimental influence on credit availability and demand, decreasing lending to the real economy at a time when it is desperately required.

Financial intermediation theory, information asymmetry theory, and the technological adoption model were used to drive this research. Intermediation theory by Diamond (1984) said that financial institutions may build and supply tailored financial solutions to satisfy the demands of each customer by intermediating with other financial institution. By doing so, the financial intermediaries enhance credit reach but this may also contribute to increase in NPLs. The theory links fintech and NPLs. The theory of information asymmetry by Akerlof (1970) is fundamental in understanding the need for disclosure in issuing loans. Credit risk is caused by unpredicted factors in the market that influence the level of NPLs. Technology Acceptance Model (TAM) provides clarity on how customers incorporate and exploit an innovative concept (Davis, 1989). TAM will be utilized in this research to see how financial institutions in Kenya adapt to new technology.

The study focused on commercial banks in Kenya. Fintech use in Kenya has been increasing over the last decade. Several of these fintech have been enabled by working with telecommunications firms in the country such as Safaricom. The services often involve (relatively) short-term, high-interest loans. Banks utilize client cell phone information including, social media, transaction history of mobile, SMS record and calls for the evaluation of credit scores and loan amounts (Mohamed, 2018). The most common fintech services being offered by banks include M-Shwari, KCB MPESA and Fuliza (CBK, 2019). The goal of this study was to analyze how this influence the level of NPLs among commercial banks, which has been on the rise lately.

1.1.1 Financial Technology

According to Sheleg and Kohali (2011), any technical advance affecting the financial industry and its operations is referred to as financial technology. Financial technology can also refer to businesses that combine financial services with modern technology to provide user-friendly, automated, transparent, and efficient internet-based and application-oriented services (Triki & Faye, 2013). Financial technology, according to Freytag and Fricke (2017), is innovative technology that enables financial services. Banks are anticipated to provide social media platforms in the future, enabling customers to use their phones to conduct business and to access investment options made possible by financial technologies (World Bank, 2017).

A wide variety of technical choices are available for comfort, quicker response time, and operational efficiency in financial technology, (Klapper, 2016). Financial technology has affected many financial industry players. As a result, services of asset management have improved by providing retailers wealth management services via streamlined systems, algorithm proposals to assist decision-making and managed portfolios artificially through robots. The banking sector has also been affected by monitoring tax labiality, spending, credit, saving, bank service provision besides traditional banking, distribution leading technology allows for quicker transaction, mobile transfer, the usage of cryptocurrencies, and data analytics allows for cellular lending to individuals and small businesses (Yang & Liu, 2016).

In regard to operationalization, financial technologies are connection between the mobile phone and an employer's or company's bank account, as used nowadays in many financial transactions (Demirguc-Kunt et al., 2018). Fintech has already been implemented in the form of mobile banking, online banking, ATMs, agency banking, and so on. A bank's website may be used to deliver financial services through the internet banking. Peer-to-peer finance enables individuals to lend money to one another and lend money that is not utilized as a mediator by an administratively-bureaucratic banking institution. According to the present research, financial technology was conceptualized as value of mobile loans issued in a given period.

1.1.2 Non-Performing Loans

NPLs are defined by Fofack (2005) as long-term debts that have not been repaid. Late interest payments have been postponed, capitalized, or are overdue by less than 90 days with significant indications of instability in the future, according to the IMF (2015). Loans that fall into this category are termed inactive by the IMF. Also, NPLs are considered as those loans which are rolled over, where the borrower only services the interest rate while the principal amount or a fraction of it remains unpaid for duration of more than 90 days (Ezeoha, 2011). Non-performing loans (NPLs) are defined by CBK as loans for which the principal or interest has been unpaid for more than 90 days, or interest payments have been repaid or rolled over into a new loan (2019).

As a consequence of non-performing loans, banks are unable to expand lending as they once were. As a consequence, the slowdown in the development of the real sector immediately impacts banks' financial performance, enterprises in default, and the whole economy (Kithinji & Waweru 2007). Furthermore, NPLs generate difficulty in banking sectors' balance sheet asset side. NPLs also affect income statements by creating negative impacts due to provisions made for loan losses. High levels of NPLs towards banking systems endanger systemic risks that invite panic within deposits hence restricting financial intermediation, investments, together with growth. NPLs combined with external shocks together with inadequate political or legal support result in phases of greater economic cycles that are exacerbated (Brownbridge, 1998).

Several ratios are utilized in measuring NPLs. The ratios include delinquency rate which is obtained by diving total loan installments past due divided by total loan advances (Stanga, Vlahu & Haan, 2018). Saba, Kouser and Azeem (2012) operationalized NPLs as the absolute value of NPL in a given period. The most often used statistic is the ratio of non-performing loans to total loans and advances for a certain period. The greater the ratio, the more likely it is that the debtor will default. The NPL level was defined in this study as the percentage of total loans and advances that were NPL.

1.1.3 Financial Technology and Non-Performing Loans

One major debate in NPLs academic literature is factors affecting NPLs (Skarica, 2014; Louzis et al, 2012; Nkusu, 2011). The main income for banks is in the interests on loans which also increases liquidity position in banks. Hence, management of NPLs in banks serves as an addition in improving financial performance. International analysis shows that if NPLs are not managed properly, they subsequently lead to bank failures in addition to nationwide monetary fragility. Interest earnings, investment possibilities, and liquidity in the financial system are all negatively impacted by NPLs, which may lead to catastrophic consequences such as bankruptcy. Samuel (2011) notes that although banks have put measures to secure loans, mortgages and other securities, loan defaults has become part of the lending business.

Financial intermediation theory by Diamond (1984) observes that through intermediation, financial institutions may create and provide customized financial solutions to meet the needs of each client. By doing so, the financial intermediaries enhance credit reach but this may also contribute to increase in NPLs. The theory links fintech and NPLs. Merton's default risk theory by Merton (1970) also recognize that fintech can have an influence on the prevailing levels of NPLs.

The World Bank (2016) found that mobile loans and mobile money had improved financial inclusion. Nevertheless, increase in financial inclusion did not always translate to superior financial performance for commercial Banks. FinTech and financial performance have a poor relationship, according to the findings. Findings are most likely due to a rise in NPLs, which reduces the benefits of increasing financial inclusion and loan volumes.

1.1.4 Commercial Banks in Kenya

According to the CBK, a bank is defined as a corporation that participates in or intends to engage in banking activities in Kenya. There are a number of different types of commercial banking, including those that focus on accepting deposits, extending credit, and processing financial transactions. Specifically, the industry contributes significantly to the financial sector, with a special focus on the mobilization of saving and the provision of loans to businesses and consumers. The Kenyan banking sector is regulated by the CBK. 38 commercial banks and 13 microfinance firms are part of the banking sector. There are 11 of the 38 listed at the NSE (CBK, 2020).

Financial technology continues to change and shape the banking sector in Kenya. The Kenyan banking sector has focused increasingly on fintech as a strategic instrument to achieve organization goal of reducing costs and maximizing revenues. KCB has been promoting KCB MPESA and adopted fuliza in 2019, Equity has been using Equitel and Eazzy banking app, NCBA bank has been offering Mshwari and recently Fuliza. Other banks also have some aspect of mobile lending through their digital platforms (CBK, 2020). The big question is whether the financial performance resulting from the use of fintech has improved. This might not be a straight forward relationship as fintech comes with the risk of increased NPLs. CBK (2018) revealed that the level of NPLs have been on the rise over the years.

1.2 Research Problem

The introduction of fintech has enabled commercial banks reach a population that has been excluded from the traditional financial system. Theoretically, this would contribute to increased financial performance of the banks. Empirical evidence suggests otherwise though. World Bank (2016) has identified that fintech have had a positive effect on financial inclusion levels. Nevertheless, better financial success for commercial banks has not always been accompanied by an increase in financial inclusion. No connection has been shown to exist between financial well-being and the usage of fintech. It is very probable that a growth in fintech also comes with an increase in non-performing loans (NPLs), which detracts from the positives of improved financial inclusion and loan volume.

Banks in Kenya have made significant investments in fintech such as fintech to tackle issues about competition, income and cost. Non-performing loans at commercial banks have also risen sharply (NPLs). The critical question is whether the rise in NPL results from fintech. Given that fintech has already cost Kenya billions of shillings, it is critical to investigate the link between growing NPLs and fintech. It is critical to keep NPLs under control so that commercial banks' financial performance is not adversely affected. An increase in NPL among commercial banks if not checked can lead to huge losses in the banking sector and the effect would be felt in the entire economy.

A lot of empirical evidence exists on how fintech impacts financial performance of institutions like banks but very few if any have focused on fintech and NPLs. Stoica, Mehdian, and Sargu (2015) investigated how internet banking affects Romanian bank performance and E-banking, according to the study, provides affordable and efficient services that help banks operate better. India's banks' profitability has been significantly impacted by E-banking during 2006 and 2014, according to Wadhe and Saluja (2015). Results indicated that both private and public sector banks were more profitable when using e-banking. Hujud and Hashem (2017) examined the connection between Lebanon's financial technologies and profit statuses of commercial banks and found that financial technologies have a positive and significant relation to profitability.

Ndagijimana (2017) examined the impact of fintech on commercial banks in Rwanda, but did not address the country's NPL problem. King'ang'ai et al. (2016) examined financial outcome of banks' performance via agents in the Rwandan country of East Africa utilizing four Rwandan commercial bank currently functional by 31 December 2015. The results from the research showed that the regulation of bank agencies, low transaction cost via banking agencies, access to banking-related services through bank agents and general development in the market had a favorable effect on performances in terms of financial position of commercial bank. All of these investigations were conducted in a distinct setting, thus their results cannot be applied to the current situation.

Electronic banking has a positive impact on the profitability of Kenyan commercial banks, according to Mugodo (2016). A conceptual gap was revealed because of the research's focus on profitability. According to Chirah (2018), who researched how alternative banking channels impact bank productivity in Kenya, online banking has no discernible effect on the operational efficiency of Kenyan banks. Fintech and Non-Performing Loans (NPLs) are two separate concepts, hence the research has a conceptual gap. According to Abdulkadir, commercial banks in Kenya are benefiting from the use of financial technology (2019). The findings of this investigation were also backed up by Kemboi (2018). It has yet to be established how fintech affects banks' NPL. However, even though previous studies have looked at how fintech affects financial performance, there has been little study into how fintech affects non-performing loans (NPLs). The current study was based on this knowledge gap and attempts to answer the research question; how does fintech influence the level of NPLs among commercial banks in Kenya?

1.3 Research Objective

The objective of this study was determining the effect of fintech on non-performing loans of commercial banks in Kenya.

1.4 Value of the Study

The findings of this research add to the expanding body of information concerning non-performing loans in commercial banking and fintech. The findings also help in theory development as they offer insights on the shortcomings and relevance of the current theories to the variables of the study. Based on the recommendations and theories for future study, more investigations may potentially be conducted.

The government and the CBK might benefit from this study's results when crafting rules for the population in question. The study's findings help investors who are considering investing in the population under investigation by providing information on the risk-reward tradeoffs that exist in such institutions and their impact on overall performance.

The study's conclusions are meant to help commercial bank management since it provides relevant information and suggestions that may help them make better choices that reduce NPLs. Thus, they are better equipped to devise strategies and methods for their institutions to enhance non-performing loan management.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Fintech and non-performing loans (NPLs) are discussed in detail in this chapter. A conceptual framework and theories are presented to explain how the research variables are likely to interact with each other, based on past empirical investigations.

2.2 Theoretical Framework

The theories that underlie the research of fintech and non-performing loans are examined in this part. The information asymmetry and technology adoption models are discussed in the theoretical studies, as is the financial intermediation theory.

2.2.1 Financial Intermediation Theory

Diamond (1984) used the term "anchor theory" for this theory. Finance depends significantly on this theory to lessen the information imbalance between lenders and their customers. The theory's constant interaction helps lenders provide creditworthy information for their customers. Information that is provided gives creditors and loan officers a strong incentive in assessing and appraising credit to those that require it. Modern theories state that the business of financial intermediation is pegged on economic imperfections from 1970s with limited contributions (Jappelli & Pagano, 2006). The existence of the intermediaries is based on their ability to lower transaction and information costs from asymmetries (Tripe, 2003).

Criticis of financial intermediation theory argue that it overlooks the importance of lenders in reducing risk (Levine et al., 2000). Instead of focusing on the concept of participation costs, Scholtens and Van Wensveen (2000) said that credit risk management does not play a significant role in financial markets. They suggested future developments in the financial intermediation theory to understand challenges in the financial sector.

The theory is useful in examining the level of NPLs among banks as they take a number of risk measurements using modern technology in credit which involves the efficient collection of private details, treating, screening and monitoring borrowers. Financial intermediaries utilize mobile apps and other digital lending mechanisms that are useful in lowering transactional costs brought about by information asymmetry. They hence play a central role in effective functioning of financial markets. The theory is useful in understanding how fintech and NPL relate.

2.2.2 Information Asymmetry Theory

This theory was put out by Akerlof (1970), who claimed that there is an information asymmetry when borrowers and lenders interact. The assumption arises from borrowers who request for loans with no information on the possible risks associated with investment options on which the loan will be used. The lender on the other hand has no prior information on the investment by the borrower (Edward & Turnbull, 2013). Because none of them is privy to such information, adverse selection is generated thereby creating moral hazard issues (Horne, 2012).

Horne (2012) criticizes the theory stating two main reasons: signals influence information asymmetry which is not correct and investors that are heavily impacted upon by information asymmetry problems are ambiguously identified or misidentified. Stiglitz (1970) state that financial institutions write loan contractual terms seeking to attract borrowers to agree to their terms and to attract low risk credit borrowers. The effect of this is the setting of rates of interest for which loan demand exceeds loan supply. The credit amount and the collateral amount also have an impact on credit-seeker character and distribution of the credit issued, and returns to lenders (Moti et al., 2012).

This theory is essential to understanding the need of disclosing loan information in the industry. Undisclosed variables that affect bank NPLs are responsible for an increase in credit risk. The study hence seeks to examine how banks can make better appraisals using mobile APPs to lower the amount of losses and improve bank efficiency by maintaining good loans that are not declared delinquent. The theory is useful in explaining competitive market behavior. It has been utilized in many scenarios thereby confirming its credibility.

2.2.3 Technology Acceptance Model

Davis came up with the concept of technological acceptance (1989). This model focuses on consumers' adoption behavior, which is used to choose a system that is both helpful and easy to them. Moon and Kim (2015) explored the underlying essence of TAMs validity and found that TAMs core construction is not the determining factor of user acceptance—use of technology and other usability facets influence this. Davis (1989) asserted that technologies or computer system's anticipated utility is defined by the theory that it will substantially improve work performance once it is put in place. When an information system's user-friendliness is preserved, it is a sign that the user has learned how to run it and employ the new technology. The model focuses on simple use as a means of predicting system utility (Gefen, Karahanna & Straub, 2013).

When people believe electronic banking is effective, it's more likely to be used (Potaloglu & Ekin, 2015). Aspects like perceived simplicity of use and perceived usefulness are considered important in encouraging the adoption of e banking. Theory of Technology Acceptance has changed how researchers do their work. Key aspects of the current investigation is to identify the advantages and disadvantages of incorporating technology into commercial banks in Kenya and to look at how easy or difficult it is for fintech to be used within the financial sector in Kenya.

2.3 Determinants of Non-Performing Loans

A bank's NPL determinants may be identified both within and outside the firm. Internal factors are company-specific and may be controlled internally. They are fintech, asset base, interest rate, capital adequacy, ownership and liquidity. Factors outside a firm that influence NPL includes; inflation, GDP, political stability and unemployment rate (Athanasoglou et al., 2005).

2.3.1 Financial Technology

Fintech entails making investment utilizing cutting-edge technology in order to boost income and increase the system's efficiency and efficacy (Sheleg & Kohali, 2011). According to John, Fredrick and Jagongo (2014), fintech refers to new technologies that enable money transfer services and financial transactions that are regulated and carried out by financial institutions through mobile phone rather than conventional over-the-counter trades.

According to the World Bank (2016), increasing levels of financial inclusion may be attributed to the use of mobile financial services such as loans and money transfers. Even then, better financial success for commercial banks hasn't always been a byproduct of greater financial access According to the findings, there is no connection between FinTech and financial performance. It is very probable that an expansion in fintech also comes with an increase in NPLs, which detracts from the positives of expanded financial inclusion and loan volumes.

2.3.2 Bank Size

Financial and legal concerns are largely dictated by the size of a bank. The ability of a big bank to get low-cost capital and earn a high profit demonstrates that the size of the bank is inextricably linked to its ability to satisfy its financial responsibilities. Increased return on assets (ROA) may be attributed to the economies of scale associated with being a big bank (Amato & Burson, 2007). For Magweva and Marime (2016) found a correlation between bank size and NPLs, showing that the level of NPLs increases as the bank grows in size.

It is the assets of an organization that determine its size, as stated by Amato and Burson (2007). The more assets a company has, the more likely it is that it will be able to take on a big number of high-return projects than a smaller company with fewer resources. Compared to smaller businesses, larger organizations have a stronger ability to get credit facilities by pledging more collateral (Njoroge, 2014). Depending on Lee (2009), a company's NPLs might change from year to year depending on the company's assets under its control.

2.3.3 Capital Adequacy

The bank's capitalization ratio, or the proportion of equity in the bank's assets that are invested, is known as capital adequacy. It assesses a bank's ability to deal with solvency issues. Nonperforming loans were shown to have a negative correlation with the capital adequacy ratio in a study by Berger and DeYoung (1997) Capital adequacy ratios are closely linked to nonperforming loans, explain Louzis et al (2012). To reduce non-performing loans, they determined that banks with strong capital adequacy ratios may take effective measures to lessen default risks.

Accomplished banks signal to the market that they are capable of delivering above-average returns. According to Athanasoglou et al., the good financial condition of Greece's banks implies that capital is having a favorable influence on its NPLs (2005). A link between the degree of NPL in a business and the amount of capital contributed to the firm was also established by Berger et al (1987).

2.4 Empirical Review

Fintech and non-performing loans (NPLs) have been studied in both local and global contexts, and the aims, methodology, and conclusions of these earlier research have been explored here.

2.4.1 Global Studies

Studying Indian banks' profitability from 2006 to 2014, Wadhe and Saluja (2015) focused on the effects of electronic banking. Researchers used data from Indian commercial banks to conduct their investigation. According to multiple regression research, banking services and profitability are connected. Electronic banking has a positive impact on both commercial and government banks. More ATMs mean more money for the banks, according to this study. While the connections were few, however, some might be established between the financial institutions' profit and the number of branches.

Le, Ho and Mai (2019) focus on how fintech impacts income inequality in transitioning economies. Fintech's influence on income inequality was examined in 22 transitional economies between 2005 and 2015 using the two-stage least squares method and two fintech indexes. According to a research, a correlation between the GINI coefficient and the fintech index was shown to be negative. In order to minimize economic gap via the expansion of fintech, one suggestion made was that suggestions be made.

Kim et al. (2019) examined fifty four scholarly papers on the relationship among development, integration and mobile service in order to identify the critical questions and gaps in their study. Findings indicate that most of the examined literature addressed three main areas: mobile services, delivery and the environment. In the early phases of the research, the regions examined shown a prejudice to individual and institutional circumstances in the mobile banking services are being implemented, compared to real users' supply and demand and their social effect. The research techniques were selected additionally showing minimal variety and depth. This analysis enhances the knowledge of current publications on mobile financial service in regards to inclusiveness among emerging regions and identifies needs for further investigations.

2.4.2 Regional Studies

King'ang'ai et al. (2016) examined financial outcome of banks' performance via agents in the Rwandan country of East Africa utilizing four Rwandan commercial bank currently functional by 31 December 2015. The results from the research showed that the regulation of bank agencies, low transaction cost via banking agencies, access to banking-related services through bank agents and general development in the market had a favorable effect on performances in terms of financial position of commercial bank. Findings of linear regression model have created a favorable connection among agency banking effect and performances in terms of financial position of commercial bank.

Chinoda and Akande (2019) have examined Africa's mobile telephone distribution, economic development and financial inclusion. A Structural Equation Model examined mobile telephone diffusion, economic development and financial inclusion for thirty two countries in Africa between 2004 and 2016. Findings demonstrated inclusion affects economic development through mobile telephones. The implications of the study were in the management of the relevance of deploying mobile handsets for finance and growth in Africa.

Khamis (2016) has investigated impact of agent banking techniques on customer services of commercial bank in Ghana. Services provided to clients have a significant impact on such elements as decreased banking hall waits times, reduced service costs and personally tailored banking services, leading to the conclusion that the development of excellent financial services and customer service is closely related. In addition, the research showed that bank representatives substantially enhance the overall efficiency and quality of customer service in banks. As a consequence, the research deemed it essential for financial institutions to develop methods to guarantee their employees are properly motivated and to propose the usage of performance based incentives.

2.4.3 Local Studies

Financial technology was evaluated as a case study for the financial performance of Kenyan commercial banks by Wanalo (2018). Financial intermediation theory, innovation diffusion theory, and Silber's financial technology limits were the three theories employed in this study. To do this project, the methodology involved in a descriptive research was used. This study took into consideration all commercial banks. This research included a total sample size of 15 individuals and included banks from both the commercial and non-commercial sectors. Additional data was sourced from annual reports provided by commercial banks between 2012 and 2016, along with data gathered from the CBK and from the bank's website. The research utilized panel data analysis. The findings were found using the Prais Winstein regression model. Despite the increased use of ATMs and agency banking, they have little impact on a bank's overall financial health.

Ogweno (2019) aimed at finding out how financial innovations influences financial performance of Kenyan licensed MFIs. The population of the research was 13 licensed MFIs as of December 31, 2018. Five years of secondary data were collected on an annual basis (January 2014 to December 2018). A multivariate linear regression model was employed to analyze the relationships between different variables in this study. Savings accounts, mortgage accounts, and bank size are all considerations to consider. Licensed MFIs' finances were found to be unaffected by agency banking, ATMs, or a lack of capital, according to the findings of the research.

Financial channel development in Kenya from 2012 to 2017 was investigated by Sindani, Muturi, and Ngumi (2019). This study's aims are to explore how internet banking and ATM banking impact financial inclusion in Kenya. Secondary data was gathered for analysis. This research concluded that online banking has benefited Kenya's financial sector by increasing production and efficiency. Also, ATM banking has enhanced financial inclusion in Kenya.

2.5 Conceptual Framework

Figure 2.1 depicts the predicted relationship amongst the variables. As a predictor variable, researchers looked at the natural logarithm of the total amount of mobile loans issued in a particular year. There were two control variables: total assets natural log and core capital to risk-weighted assets. Non-performing loan was the response variable given by the NPLs to total loans and advances ratio.

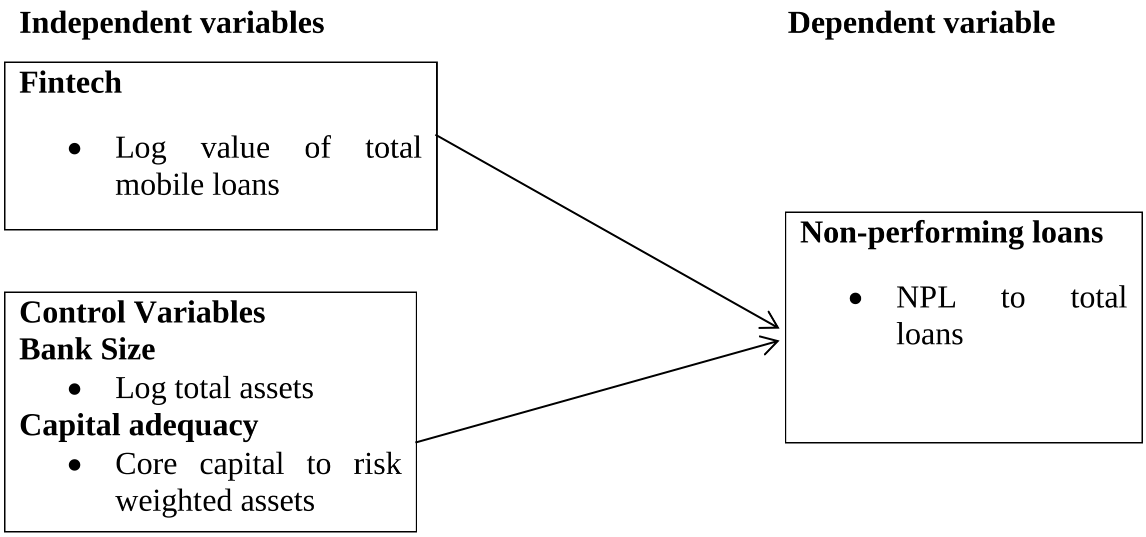

Figure 2.1: The Conceptual Model

Source: Researcher (2021)

2.6 Summary of the Literature Review and Research Gaps

The examined researches revealed a knowledge gap that requires scholarly attention. First, the findings on fintech and performance are mixed. The differences from the studies can be explained on the basis of different operationalization of fintech by different researchers thereby indicating that findings are dependent on operationalization model. In previous research, the focus was on how fintech impacts performance, but NPLs were neglected, which is why this study sought to fill that hole. Table 2.1 summarizes research gaps.

Table 2.1: Summary of Relevant studies and Gaps

Author and year	Focus of study	Methodology	Findings	Research gaps	Current study
Ogweno (2019)	To investigate how performance of licensed MFIs financially is influenced by financial technologies in Kenya.	Multiple linear regression model	Agency banking, number of ATMs and capital adequacy has a statistical insignificant impact on performance of licensed MFIs in terms of their financial position.	Research did not take into account effect of fintech on NPLs	Effect of fintech on NPLs
Sindani et al. (2019)	Impact of financial channels of distribution evolution on financial inclusion in Kenya	Ordinary least square	Financial inclusion is positively correlated with ATMs and Internet banking	The effect of financial technology on NPL was not established	The current study will investigate the effect of fintech on NPL
Abdulkadir (2019)	Explored how performances in terms of financial position of commercial bank is affected by financial technology	Ordinary regression analysis	Financial technology substantially affected performances in terms of financial position of commercial bank.	Ordinary regression analyses has its shortcomings when dealing with ordinary data. A fixed or random effects model would have been more appropriate	The current study will apply either random or fixed effects model
Kamande (2018)	To explore how performances in terms of financial position of commercial bank is impacted by electronic banking	Multiple regression analyses	Mobile and internet banking are statistical insignificant determinants of performances in terms of financial position of commercial bank.	Did not consider effect of fintech on NPLs	Effect of mobile loan volumes on NPLs

Chirah (2018)	Explore how operational efficiency of commercial bank is impacted by alternative banking channel	Ordinary least square	Mobile banking, ATMs, internet banking, capital structure, agent banking and firm size are statistical negligible determinants of operational efficiency of commercial banks	The study used OLS which has its own limitations	The current study will apply either random or fixed effects model
Muli (2018)	To find out how electronic banking affects the efficiency of commercial banks in Kenya.	Descriptive, correlation and regression analysis	Commercial banks' efficiency was favorably influenced by factors such as capital adequacy, liquidity, mobile banking, ATMs, and bank size.	Did not consider mobile loans as one of the variables	Measures fintech in terms of mobile loans
Wanalo (2018)	To explore how performances in terms of financial position of commercial bank is affected financial technology.	Panel data analysis	Agency banking and ATMs had optimistic but minimal effect on performances in terms of financial position of commercial bank.	Study operationalized financial technology as just ATMs and agency banking leaving a gap on other types of financial technology	Measures fintech in terms of mobile loans

Source: Author (2021

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains how the study's goal of examining the impact of fintech on commercial banks' non-performing loans (NPLs) was achieved. Design, data collection, and analysis all feature prominently in this chapter.

3.2 Research Design

Fintech in regards NPLs in commercial banks were studied using a descriptive design approach. The researcher was very interested in the phenomenon's nature, therefore this approach seemed theoryl (Khan, 2008). It was also sufficient in defining the interrelationships of the phenomena. This design also accurately and legally showed the variables, therefore it was possible to answer the study questions (Cooper & Schindler, 2008).

3.3 Population

The population of a research is the total number of observations made on a given set of occurrences (Burns & Burns, 2008). All 42 commercial banks in Kenya as of December 31, 2020, were included in this study's population (see appendix I). It wasn't necessary to sample the population since it was small.

3.4 Data Collection

For this research, data from the banks' yearly financial statements from 2016 through 2020 was compiled into data-collection forms. CBK financial publications of specific banks were used for the reports. Loan and advance totals, mobile loan totals and non-performing loan totals, risk weighted assets and core capitals were data of interest that was collected in the study.

3.5 Data Analysis

The data was analyzed using SPSS version 24. Statistical data was presented in the form of tables and graphs. Descriptive statistics were used to compute the standard deviation and central tendency for each variable. Inferential statistics made use of correlation and regression. In order to determine the correlation between study variables, correlation was used, and regression was used to determine the cause and effect between factors. Multivariate regression linearly calculated the correlation between dependent and independent variables.

3.5.1 Diagnostic Tests

Tests for model viability were conducted using diagnostics such as normality, multicolinearity and homogeneity. The assumption of normality was that the distribution of the dependent variable's residuals was normal and close to the mean. Shapiro-Wilk or Kolmogorov-Smirnov tests were used. If a variable had no normal distribution, it was adjusted using the logarithmic adjustment methodology. Stationarity test was utilized in determining if the statistical properties such as variance, mean, as well as autocorrelation change with the passage of time. The Dickey Fuller test was used to determine this characteristic. The robust standard errors were used if the data did not fulfill this characteristic (Khan, 2008).

Autocorrelation is a measure of how similar one time series is when compared to its lagged value across successive timings. It was determined by utilizing the Wooldridge method and the robust standard errors were applied when a presumption was broken. Multiple independent variables may be found to have a perfect or nearly perfect linear connection when they are all taken into account. VIFs and tolerance thresholds were employed. If any multicolinear variables were present, they were eliminated and a new measurement was used instead. If the variance errors in a regression are distributed among the independent variables, heteroskedasticity confirms this. This was tested using the Breuch Pagan test and if data does not meet the homogeneity of variances assumption, robust standard errors were employed (Burns & Burns, 2008).

3.5.2 Analytical Model

The following equation was applicable:

$$Y= \beta_0 + \beta_1X_1+ \beta_2X_2+ \beta_3X_3 +\varepsilon$$

Where: Y = Non-performing loans given as the ratio of NPLs to total loans on an annual basis

β_0 =y regression equation intercept.

β_1, β_2, β_3 =are coefficient of regression

X_1 = Fintech as measured by the natural logarithm of total mobile loans on an annual basis

X_2 = Bank size as assessed via the natural logarithm of total assets on an annual basis

X_3 = Capital adequacy as given by the ratio of total core capital to risk weighted assets

ε =error term

3.5.3 Tests of Significance

The overall model and the significance of the variables were determined by parametric testing. ANOVA and the t-test were used in this research to assess the model's relevance and the significance of each variable.

CHAPTER FOUR: DATA ANALYSIS, RESULTS AND FINDINGS

4.1 Introduction

This chapters looks into CBK data to see how fintech affects the NPLs of banks in Kenya. Correlation and regression data were represented in tables utilizing descriptive statistics, as indicated in the segments below.

4.2 Descriptive Analysis

This research includes the average, the maximum, the lowest values, and the standard deviation. Table 4.1 displays the variable statistics. For all 42 banks whose data was gathered, SPSS was utilized in the analysis from 2016 to 2020. The figures are listed below.

Table 4.1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
NPLs	190	.0008	38.5539	.350286	2.7909380
Fintech	190	8.4730	17.2928	14.328772	1.5842653
Bank size	190	14.7750	20.6163	17.713741	1.3487735
Capital adequacy	190	.0280	2.1258	.236362	.2086072
Valid N (listwise)	190				

Source: Research Findings (2021)

4.3 Diagnostic Tests

Based on the information gathered, diagnostic tests were carried out. Using a 95 percent confidence interval or a 5% significance threshold, we were able to gather a wide range of data. Diagnostic tests were helpful in determining if the data was false or true. The closer the confidence interval is to 100%, the more accurate the data used is deemed to be. Normality, multicollinearity, heteroskedasticity, and autocorrelation were all tested in this case.

4.3.1 Normality Test

This study included the Shapiro-Wilk and Kolmogorov-Smirnov tests. This criteria stated that data was considered normal if the probability was higher than 0.05.

Table 4.2: Normality Test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	Df	Sig.
NPLs	.161	190	.300	.869	190	.853
Fintech	.173	190	.300	.918	190	.822
Bank size	.178	190	.300	.881	190	.723
Capital adequacy	.175	190	.300	.874	190	.812

a. Lilliefors Significance Correction

Source: Research Findings (2021)

The p-values are above 0.05, which indicates that the data was evenly distributed, as stated above. It was accepted as a consequence of this, showing that the researcher was unable to reject the hypothesis of normal distributions.

4.3.2 Multicollinearity Test

William et al (2013) expressed this characteristic as correlations between the predictor variables. This attribute was tested using VIF. Field (2009) says that VIF values over 10 suggest that this feature exists.

Table 4.3: Multicollinearity Test

Variable	**VIF**	**1/VIF**
Fintech	3.418	0.293
Bank size	2.836	0.353
Capital adequacy	3.291	0.304

Source: Research Findings (2021)

Table 4.3 shows the VIF values that were discovered to be less than ten, indicating that Multicollinearity was not present, as per Field (2009).

4.3.3 Heteroskedasticity Test

The error process in cross-sectional units may be homoscedastic, yet vary across units called groupwise Heteroskedasticity. Breuch Pagan is calculated for each group using the hettest program. Heteroskedasticity is a term used to describe the heteroskedasticity of residuals. According to the null hypothesis; $\sigma^2_i = \sigma^2$ for i =1...Ng, where Ng is the cross-sectional units.

Table 4.4: Heteroskedasticity Test

Modified Wald test for group wise heteroskedasticity in regression model
H0: sigma(i)^2 = sigma^2 for all i
chi2 (190) = 231.38
Prob>chi2 = 0.2476
Source: Research Findings (2021)

There is insufficient evidence to reject the null hypothesis of Homoskedastic error terms, based on the data in Table 4.4.

4.3.4 Autocorrelation Test

The Breusch-Godfrey autocorrelations test was employed to detect serial correlations in a model's idiosyncratic term since typical serial correlation biases make the results more efficient.

Table 4.5: Autocorrelation Test

Wooldridge test for autocorrelation in panel data H0: no first-order autocorrelation
F(1, 190) = 0.365
Prob> F = 0.3924
Source: Research Findings (2021)

It is clear from Table 4.5 that the null hypothesis of no serial connection is not rejected, since the p-value of 0.3924 is significant.

4.3.5 Stationarity Test

Results for the Levin-Lin Chu unit root are provided in Table 4.6. P-values were less than 0.05, thus panels with unit roots were excluded. The panel data for all the variables were stationary as a result of this.

Table 4.6: Levin-Lin Chu unit-root test

Levin-Lin Chu unit-root test			
Variable	**Hypothesis**	**p value**	**Verdict**
NPLs	Ho: Panels contain unit roots	0.0000	Reject Ho
Fintech	Ho: Panels contain unit roots	0.0000	Reject Ho
Bank size	Ho: Panels contain unit roots	0.0000	Reject Ho
Capital adequacy	Ho: Panels contain unit roots	0.0000	Reject Ho

Source: Research Findings (2021)

4.4 Correlation Results

Correlation analysis was used to determine the correlation between each predictor variable and the response variable. Table 4.7 shows the size and direction of the correlations between the research variables.

Table 4.7: Correlation Results

		NPLs	Fintech	Bank size	Capital adequacy
NPLs	Pearson Correlation	1			
	Sig. (2-tailed)				
Fintech	Pearson Correlation	.097	1		
	Sig. (2-tailed)	.185			
Bank size	Pearson Correlation	-.174*	-.043	1	
	Sig. (2-tailed)	.017	.553		
Capital adequacy	Pearson Correlation	.155*	.002	.033	1
	Sig. (2-tailed)	.033	.973	.655	

*. Correlation is significant at the 0.05 level (2-tailed).

b. Listwise N=190

Source: Research Findings (2021)

The results in Table 4.7 reveal that fintech and NPLs are positively but not significantly correlated (r=0.097) at 5% significance level. This implies that fintech and NPLs change in the same direction but the association is not significant statistically. In addition, the results show that bank size and NPLs are negatively and significantly correlated (r=-0.174) at 5 % significance level. Further, results show that capital adequacy and NPLs are positively and significantly correlated (r=0.155) at 5 % significance level.

4.5 Regression Results

To find out how much of NPLs can be accounted for by the selected variables, a regression analysis was performed. Tables 4.8 to 4.10 show the regression findings.

Table 4.8: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.252[a]	.063	.048	2.7228701

a. Predictors: (Constant), Capital adequacy, Fintech, Bank size

Source: Research Findings (2021)

The independent factors analyzed explained 6.3 percent of the variance in NPLs across commercial banks in Kenya, according to the adjusted R^2. This suggests that just 6.3 percent of the difference in NPLs across commercial banks in Kenya can be attributed to these three variables, whereas other factors that were not addressed in this study account for 93.7 percent.

Table 4.9: ANOVA Analysis

Model		Sum of Squares	Df	Mean Square	F	Sig.
	Regression	93.176	3	31.059	4.189	.007[b]
1	Residual	1379.008	186	7.414		
	Total	1472.184	189			

a. Dependent Variable: NPLs

b. Predictors: (Constant), Capital adequacy, Fintech, Bank size

Source: Research Findings (2021)

Table 4.9's ANOVA results reveal that the data has a 0.007 level of significance, which implies that the data may be used to draw inferences about the variables.

Table 4.10: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
	(Constant)	.591	.119		3.151	.000
	Fintech	.184	.125	.104	1.469	.143
1	Bank size	-.358	.147	-.173	-2.437	.016
	Capital adequacy	.211	.058	.150	2.106	.037

a. Dependent Variable: NPLs

Source: Research Findings (2021)

The coefficient of regression model was as below;

$$\mathbf{Y = 0.591 + 0.184X_1 - 0.358X_2 + 0.211X_3}$$

Where:

Y = NPLs; X_1 = Fintech; X_2 = Bank size; X_3= Capital adequacy

4.6 Discussion of Research Findings

The objective of this research was to examine the effect of financial technology on non-performing loans (NPL). Descriptive research was used to analyze 42 commercial banks in Kenya. It relied on data from CBK and individual bank annual reports for this investigation. The natural logarithm of the value of all mobile loans in a particular year was used to measure Fintech. The control variables in this research were bank size and capital adequacy. Descriptive and inferential statistics were used to analyse the data. The results are discussed in this section.

The results of correlation analysis revealed that fintech did not have a significant association with NPLs among banks in Kenya. Although the association was positive, the magnitude was not significant. An increasing bank's NPL levels tend to decrease as the institution's size increases in a strong negative association with the NPLs of the institution. According to the data, banks with superior capital adequacy had a substantially higher rate of non-performing loans (NPLs).

The three variables selected for regression account for 6.3% of variance in NPLs among Kenyan banks, according to the data. The p value for this study's explanatory power, which was less than 0.05, was also significant. As a result, the model seemed to have accurately predicted how variables interacted. Even while fintech has little effect on NPLs, the scale of a bank does have a major negative impact on this problem. NPL levels were shown to be significantly influenced positively by a firm's capital adequacy level.

The results are in tandem with Kamande (2018) who found that Kenyan commercial banks' financial performance was influenced by electronic banking. All 42 of Kenya's commercial banks were sampled. The research utilized the value of mobile, internet, agency, and ATM transactions as a predictor variable. Return on assets, the study's response variable, was used to gauge financial performance. Secondary data was gathered from January 2013 to December 2017 across a five-year timeframe. In the study, it was shown that bank size and ATM availability had a substantial influence on capital adequacy, liquidity, and ATM availability. Mobile banking and internet banking seem to have little effect on the financial health of commercial banks, according to the research.

The results also concur with Chirah (2018), who studied the influence of alternative banking channels on the efficiency of Kenyan commercial banks, these findings are also consistent. This study's population includes 42 commercial banks from Kenya. It was discovered that the values assigned to various mobile banking, internet banking, ATM, and bank agent transactions varied. According to this ratio, operational efficiency may be determined. Every year from January 2013 to December 2017, a total of five years of secondary data was collected. In the conclusions of this research, liquidity has a considerable and positive value. At ATMs, agencies, mobile banking, online banking, and the size and structure of companies are statistically inconsequential factors of commercial bank operational performance according the research.

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter summarizes the findings of the preceding chapter, draws additional conclusions, and discusses the limits of the research that were discovered over the course of the investigation. In addition, it makes policy recommendations and makes ideas for areas where more research should be conducted, among other things.

5.2 Summary of Findings

The study's objective was to assess what effect fintech was having on the non-performing loan (NPL) levels at Kenyan banks. The use of financial technology, the size of the bank, and the availability of capital adequacy were all factors considered. The study was conducted using a descriptive approach. SPSS was used to analyze secondary data from CBK. Annual reports from 38 banks for the five-year period from 2016 to 2020 were used to gather data.

The first objective was to find out how fintech was affecting non-performing loans (NPLs) in Kenyan banks. According to the correlation data, Fintech has a positive connection with NPLs at the 5% significance level. A relationship between the two could not be established. According to regression results ($\beta=0.184$, $p=0.143$), there was a positive but not statistically significant effect of fintech on the level of NPLs in Kenyan banks.

The second objective was to find out whether the size of a bank in Kenya affected its NPLs. This study found that the size of the bank was negatively associated with NPLs at a threshold of significance of 5 percent. As can be shown from regression findings (β=-0.358, p0.016), bank size in Kenya has an adverse influence on non-performing loans.

The third objective was to look at how capital adequacy affected Kenyan banks' non-performing loans, or NPLs. Using a 5 percent significance threshold, data reveal that capital adequacy is linked to NPLs. According to regression findings (β=0.211, p=0.037) from the research, capital adequacy has a positive and substantial influence on Kenyan banks' NPLs.

5.3 Conclusions

The study's goal was to discover if fintech and NPLs go hand in hand. In the research, fintech had a small but beneficial impact on non-performing loans.There's a chance this means banks with a lot of mobile loans don't have a lot of non - performing loan. The study concludes that fintech is not a significant determiner of NPLs among banks.

According to this study, NPLs were also affected by the size of the bank. This suggests bigger banks may be better able to handle their NPLs. Larger financial institutions have superior organizational structures, which means they're more likely to keep track of loans. The study concludes that bank size is a significant determiner of NPLs.

There was a considerable and favorable impact on NPLs when it came to capital adequacy, according to the research findings. As risk-weighted assets rise, it is possible that non-performing loans may also rise (NPLs). By lending more, banks with greater core capital are more likely to take on more risk, which might lead to a rise in NPLs. According to the findings, NPLs are strongly influenced by a firm's capital adequacy.

The results of this research are consistent with those of Wanalo (2018), who analyzed the financial performance of commercial banks in Kenya to determine if the deployment of technical financial technology had a substantial influence on financial performance. Panel data analysis was employed in this study. These findings were based on the Prais Winstein regression model. Despite the increased use of ATMs and agency banking, they have little impact on a bank's overall financial health.

Wadhe and Saluja (2015) studied the profitability of Indian banks from 2006 to 2014, focusing on the influence of electronic banking. The study's data was gathered from commercial banks in India. Banking services and profitability were examined using a multiple regression analysis. Private and public sector banks' profitability has been demonstrated to be improved via e-banking. According to the conclusions of this research, increasing the number of ATMs leads to increased earnings. Despite the lack of linkages, it is possible that the profitability of financial institutions is linked to the number of branches they have.

5.4 Recommendations for Policy and Practice

Fintech does not lead to a rise in NPLs, according to the findings of the research. Because mobile loans do not raise the likelihood of delinquency, the research suggests that commercial bank managers continue to provide them. Banks should be able to provide mobile loans to their customers more easily thanks to regulations and standards developed by policymakers like CBK.

The size of the bank has also been demonstrated to have an effect on the level of NPL. In order for Kenyan banks to reap the benefits of economies of scale and stronger systems that help them in decreasing and monitoring non-performing loans, they should thus concentrate on strengthening their asset base.

Capital adequacy has a considerable impact on NPLs, according to the research results. Because banks with greater capital have been shown to have higher levels of NPL, the research suggests that the CBK on its mission to regulate commercial banks monitor and establish guidelines for the maximum amount of core capital a bank may have and what proportion of that can be provided as loans.

5.5 Limitations of the Study

In Kenya, banks' non-performing loans (NPLs) are regarded to be influenced by a number of factors. The research focused on three characteristics in particular. It is possible that banks' NPLs will be influenced by other variables, as well. Some are controlled by the company, such as corporate governance and liquidity while others are outside the control of management such us unemployment rate and political instability.

The research used a scientifically sound analytical technique. Furthermore, the research omitted qualitative data, which may have shed light on the link between fintech and NPLs. More precise results may be achieved via the use of qualitative approaches such as focus groups or open-ended questionnaires. The research was limited to a five-year time frame (2016 to 2020). It's still not known whether the effects will endure for much longer. In addition, it's not obvious whether the same outcomes will be obtained until 2020. Major economic events should have been taken into consideration by conducting the study over a longer time period.

The data was analyzed using an OLS regression model. Due to limitations in regression models, such as erroneous and misleading results that might alter the value of a given variable, research findings couldn't be generalized properly. If the regression was run on additional data, the outcome may have been much different. Consequently, the model utilized posed still another obstacle.

5.6 Suggestions for Further Research

According to the results, the R square was found to be 6.3%. As a result, it's possible that the study didn't cover all the possible causes of NPLs in Kenyan banks. Other researches ought thus to focus on other factors for example; corporate governance, liquidity, ownership structure, management efficiency among other factors that affect NPLs among banks.

The study was limited to banks in Kenya. Additional research on other financial institutions such as microfinance banks and SACCOs should be conducted, according to the study's suggestions. Future research should look into how fintech affect other factors besides the NPLs, such as company value, efficiency, and growth, to name a few.

Because of the readily available data, the focus of this research was drawn to the last five years. Past studies may span a longer time period, such as ten or twenty years, and might have a significant impact on this study by either complementing or contradicting its conclusions. Examining business cycles over a longer period of time reveals the impact of boom and bust cycles.

This research also used a regression model, which has its own set of problems, such as misleading and erroneous findings when a variable is altered. Fintech and the amount of NPLs are connected in various ways, and future study should concentrate on models like the Vector Error Correction Model.

REFERENCES

Berger, A.N., Hancock, D.& Humphrey, D.B. (1987). Bank efficiency derived from profit function. *Journal of Banking and Finance,17*(2);317-347

Brownbridge, M. (1998). The causes of Financial Distress in Local Banks in Africa Causes and Remedies. *African Journal of Accounting, Economics, Finance and Banking Research*, 5, (2), 12-33

Burns, N. & Burns, S. (2008). *The Practice of Nursing Research: Conduct, Critique and Utilization*: 5th Edition: St Louis, Elsevier Saunders

Central Bank of Kenya (2019). *Statistical bulletin*. Nairobi: Government press.

Central Bank of Kenya (2020). *Statistical bulletin*. Nairobi: Government press.

Chinoda, T. & Akande, J. (2019). Financial inclusion, mobile phone diffusion and economic growth, evidence from Africa. *International Journal of Economics and Finance Issues,9*(5);104-110

Chirah, A. (2018). *Effect of alternative banking channels on operational efficiency of commercial banks in Kenya*, Unpublished MBA research project, University of Nairobi

Cooper, R., & Schindler, S. (2008). *Business research methods.* New York: Mc Grawhill

Cytonn. (2019). Cytonn markets outlook report

Dawood, T., Pratama, H. & Raja, M. (2019). Does financial inclusion alleviate household poverty? Empirical evidence from Indonesia. *Economics and Sociology,12*(2);235-252

Diamond, W. (1984). Financial intermediation and delegated monitoring, *Review of Economic Studies, 51*(3), 393-414

Ezeoha, E. (2011). Banking consolidation, credit crisis and asset quality in a fragile banking system: Some evidence from Nigerian data, *Journal of Financial Regulation and Compliance*, 19:1, 33 – 44

Ghosh, S. (2019). Financial inclusion, economic growth and mobile telephony in India. *Innovation and Development10*(3);1-23

Fofack, H. (2005). *Non-performing loans in sub-Saharan Africa: Causal Analysis and Macroeconomic Implications*. IMF Working Paper No 05/69, Washington DC.

Francis, E., Blumenstock, J. & Robbinson, J. (2017*). Digital credit. A snapshot of the current landscape and open research questions*. Sociology and Business.

Horne, A. (2012) 'Interception of Communications' Standard Note SN/HA/6332. London: House of Commons

Jappelli, T. & Pagano M. (2006). *Role and Effects of Credit Information Sharing: In the Economics of Consumer Credit*, edited by G. Bertola, R. Disney and C. Grant, MIT Press: Cambridge, Massachusetts, 347-371

John, K.M., Fredrick, S.N.& JagongoA. (2014). Factors affecting pricing of loanable funds by commercial banks in Kenya. *International Journal of Business and Social Science,1*(1);139-154

Jorion, P. (2014). Risk management. *Annual Review of Financial Economics, 2*(9);347-365

Kaaya, A. & Pastory, D. (2013). Credit Risk and Commercial Banks Performance in Tanzania: a Panel Data Analysis. *Research Journal of Finance and Accounting, 4(*16), 44-57.

Kamande, J. (2018). *Effect of electronic banking on financial performance of commercial banks in Kenya*, Unpublished MBA project, University of Nairobi

Kemboi, B. (2018). *Effect of financial technology on profitabilityof commercial banks in Kenya,* Unpublished MBA Research Project, University of Nairobi

Khan, J. A. (2008). *Research Methodology*. New Delhi. APH Publishing Corporation

Khan, W. A., & Sattar, A. (2014). Impact of Interest Rate Changes on the Profitability of four Major Commercial Banks in Pakistan. *International Journal of Accounting and Financial Reporting*, *4*(1), 142-147

Kigen, K.P. (2010) *The Impact of Mobile Banking on Transaction Costs of Microfinance Institutions*. Unpublished MBA Thesis, University of Nairobi, Nairobi

Kim, D. W., Yu, J. S., & Hassan, M. K. (2019). Financial inclusion and economic growth in OIC countries. Research in International Business and Finance, 43, 1e14.

Kithinji, A & Waweru, N. (2007). Merger and restructuring and Financial Performance of Commercial Banks in Kenya, *Economic, Management and Financial Market Journal 2* (4), 9-39

Koki,K. (2018).Effect of mobile credit on bank performance. Evidence from commercial banks in Kenya.*DBA Dissertation, United States International University-Africa*

Le, Q., Ho, H., & Mai, N. (2019) The impact of financial inclusion on income inequality in transition economies. *Manag. Sci. Lett. 20*(9); 661–672

Lee, J. (2009). Does the size matter in firm performance? Evidence from US public firms, *Internal Journal of the Economic of Business*, 16(2), 199- 203

Levine, Loayza & Beck (2000). Financial Intermediation and Growth: Causality and Causes, *Journal of monetary economics* 46, 31-77

Louzis, D. & Angelo, V. & Vasilios, M. (2012). Macroeconomic and Bank-Specific Determinants of Non-Performing Loans in Greece: A Comparative Study of Mortgage, Business, and Consumer Loan Portfolios. *Journal of Banking & Finance*,*36* (10), 21-33

Magweva, R., & Marime, N. (2016). Bank specific factors and bank performance in the multi-currency era in Zimbabwe. *African Journal of Business Management*, *10*(15), 373-392

Moti H.O, Masinde J.S, Mugenda N.G & Sindani M.N(2012), Effectiveness of credit Management System on Loan Performance; Empirical Evidence from Microfinance Sector in Kenya, *International Journal of Business, Humanities and Technology* 2(6) 99 –108

Mugodo, E.A. (2016) Effect of electronic banking on financial performance of commercial bank in Kenya. Unpublished MSc project, University of Nairobi.

Ndagijimana, A.N. (2017). *Effect of fintech on the financial performance of commercial banks in Kenya*. MBA project, University of Nairobi

Njoroge, A. (2014). *Relationship between capital structure and financial performance*. An unpublished masters project from the University of Nairobi

Nkusu M (2011), Nonperforming Loans and Macro financial Vulnerabilities in Advanced Economies, IMF Working Paper No 11/161.

Ogweno, W. (2019). *Effect of financial innovations on financial performance of licensed microfinance institutions*, Unpublished MBA Project, University of Nairobi

Pagano, M., & Jappelli, T. (1993). Information sharing in credit markets. *The Journal of Finance*, 43(5), 1693- 1718.

Saba, I., Kouser, R., & Azeem, M. (2012). Determinants of Non-Performing Loans: Case of US Banking Sector. *The Romanian Economic Journal, 44*(5), 567-574

Samuel, D. (2011). Non-Performing Loans and Terms of Credit, *RBI Occasional Papers, Winter,* 24, (3), 81-121

Scholtens, B.& van Wensveen, D. (2000). A critique on the theory of financial intermediation,. *Journal of Banking & Finance, Elsevier, 24*(8);1243-1251,

Sheleg, O., & Kohali, A. (2015). The impact of internet banking on the performance of Romanian banks: DEA and PCA approach. *Procedia Economics and Finance,* 20, 610-622.

Skarica, B. (2014). Determinants of non-performing loans in central and Eastern European countries. *Financial Theory and Practice38*(1);37-59

Sindani, W. M., Muturi, W., Ngumi, P. (2019). *Effect of financial distribution channels evolution on financial inclusion in Kenya*, Nairobi, Kenya

Stanga, I., Vlahu, R., & Haan, J. (2018). Mortgage delinquency rates: A cross-country perspective. *CEPR Policy Portal. 1* (1);1231-1273

Stiglitz, E.J. (1970). The structure of investor preferences and asset returns and separability in portfolio allocation. *Journal of Economic Theory,2*(2);122-160

Tripe, D. (2003). An exploration of the relationship between bank capital levels and return on equity. Proceeding of the 16th Australasian Finance and Banking Conference, December 2003, Palmerston North, pp: 1-15.

Ugoani, J. N. N. (2016). *Nonperforming Loans Portfolio and its effect on Bank Profitability in Nigeria*: College of Management and Social Sciences, Rhema University, e-ISSN 2236- 269X

Wadhe, T. &Saluja, M.S. & (2015). Impact of e- banking on profitability of commercial banks in India. *International Journal in Management and Social Science, 3*(2);121-132

Wanalo, E. (2018). *Effect of technological financial innovations on financial performance of firms of commercial banks in Kenya*, Unpublished MBA Research Project, University of Nairobi

World Bank (2016). Information and Communications for Development 2016: Maximizing Mobile. Washington, DC: World Bank.

APPENDICES

Appendix I: Commercial Banks in Kenya

1	ABSA Bank Kenya	1916
2	Access Bank Kenya	8th January 1985
3	African Banking Corporation Limited	8th December 1994
4	Bank of Africa Kenya Limited	30th April 2004
5	Bank of Baroda (K) Limited	1st July 1953
6	Bank of India	5th June 1953
7	Citibank N.A Kenya	1st July 1974
8	Consolidated Bank of Kenya Limited	18th December 1989
9	Co-operative Bank of Kenya Limited	1st July 1968
10	Credit Bank Limited	30th November 1994
11	Development Bank of Kenya Limited	20th September 1996
12	Diamond Trust Bank Kenya Limited	15th November 1994
13	DIB Bank Kenya Limited	13th April 2017
14	Ecobank Kenya Limited	16th June 2008
15	Equity Bank Kenya Limited	28th December 2004
16	Family Bank Limited	1st May 2007
17	First Community Bank Limited	29th April 2008
18	Guaranty Trust Bank (K) Ltd	13th January 1995
19	Guardian Bank Limited	20th December 1995
20	Gulf African Bank Limited	1st November 2007
21	Habib Bank A.G Zurich	1st July 1978
22	I&M Bank Limited	27th March 1996
23	Kingdom Bank Limited	2nd March 2010
24	KCB Bank Kenya Limited	1st January 1896
25	Mayfair CIB Bank Limited	20th June 2017
26	Middle East Bank (K) Limited	28th November 1980
27	M-Oriental Bank Limited	8th February 1991
28	National Bank of Kenya Limited	1st January 1968
29	NCBA Bank Kenya PLC	5th November 2019
30	Paramount Bank Limited	5th July 1995
31	Prime Bank Limited	3rd September 1992
32	SBM Bank Kenya Limited	1st April 1996
33	Sidian Bank Limited	23rd March 1999
34	Spire Bank Ltd	23rd June 1995
35	Stanbic Bank Kenya Limited	1st June 2008
36	Standard Chartered Bank Kenya Limited	1910
37	UBA Kenya Bank Limited	25th September 2009
38	Victoria Commercial Bank Limited	11th January 1996

Source: CBK (2020)

Appendix II: Research Data

Bank	Year	NPLs	Fintech	Bank size	Capital adequacy
1	2016	0.1426	13.4492	16.9342	0.1645
1	2017	0.1566	14.5950	16.9451	0.1528
1	2018	0.1829	14.6453	17.0576	0.1560
1	2019	0.1989	14.8834	17.1451	0.1844
1	2020	0.1490	15.0790	17.1964	0.1538
2	2016	0.2325	14.6052	18.0537	0.1639
2	2017	0.2606	15.9889	17.8408	0.1616
2	2018	0.2816	15.9219	17.8080	0.1578
2	2019	0.3383	15.8584	17.7090	0.1602
2	2020	0.4139	15.7852	17.5996	0.1083
3	2016	0.0754	13.7599	18.0376	1.9617
3	2017	0.0846	14.5768	18.2332	0.3053
3	2018	0.0586	14.9398	18.3812	0.3229
3	2019	0.0882	14.7218	18.6278	0.3466
3	2020	0.0828	15.1152	18.7805	0.3274
4	2016	0.0420	15.3316	19.2998	0.1840
4	2017	0.0521	13.5734	19.3751	0.1786
4	2018	0.0556	14.2855	19.4197	0.1803
4	2019	0.0610	14.4647	19.6003	0.1638
4	2020	0.0560	14.9982	19.7397	0.1667
5	2016	0.0202	11.1449	17.5571	0.4230
5	2017	0.0139	12.7982	17.6829	0.4574
5	2018	0.0207	12.5000	17.8521	0.5397
5	2019	0.0713	12.9661	17.9537	0.4392
5	2020	0.0936	14.0891	17.9514	0.4842
6	2016	0.0580	13.2541	18.2945	0.2832
6	2017	0.0192	14.2506	18.4534	0.2637
6	2018	0.0368	13.1748	18.4028	0.2555
6	2019	0.0162	14.1294	18.2656	0.2764
6	2020	0.0257	12.9685	18.3858	0.2715
7	2016	0.1059	15.6607	19.1891	0.1792
7	2017	0.0745	16.2099	19.2507	0.1845
7	2018	0.0831	15.9346	19.3199	0.1732
7	2019	0.0797	16.0608	19.3172	0.1573
7	2020	0.0553	16.0866	16.4642	0.0939
8	2016	0.1176	13.9119	16.4487	0.0790

Bank	Year	NPLs	Fintech	Bank size	Capital adequacy
8	2017	0.1527	13.1426	16.4149	0.0509
8	2018	0.1533	13.8898	16.3718	0.0280
8	2019	0.2568	14.0673	16.2888	0.1352
8	2020	0.0638	14.0719	16.1464	0.1551
9	2016	0.0722	13.0293	16.3200	0.2285
9	2017	0.0754	13.0224	16.4904	0.1477
9	2018	0.0724	13.2537	16.7006	0.1451
9	2019	0.0870	13.5020	16.8910	0.1496
9	2020	0.0342	13.7576	19.6518	2.1258
10	2016	0.0390	15.0340	19.6787	0.2277
10	2017	0.0620	15.0109	19.7736	0.2268
10	2018	0.1009	15.5781	19.8406	0.1618
10	2019	0.0979	16.1124	19.9402	0.1505
10	2020	0.2601	16.1330	16.6135	0.2508
11	2016	0.2098	14.3190	16.6072	0.2355
11	2017	0.2981	14.3780	16.5449	0.2323
11	2018	0.3695	14.6360	16.5472	0.3147
11	2019	0.0241	14.4732	19.4199	0.1463
11	2020	0.0325	14.2760	19.6087	0.1850
12	2016	0.0666	14.2875	19.7107	0.1901
12	2017	0.0629	15.2683	19.7497	0.2111
12	2018	0.0683	15.6160	19.7719	0.2091
12	2019	38.5539	16.3843	14.7750	0.7005
12	2020	0.0037	16.3125	15.4739	0.2990
13	2016	0.0095	8.6540	16.0114	0.1486
13	2017	0.0622	8.4730	17.7749	0.2496
13	2018	0.1628	8.7650	17.6683	0.1944
13	2019	0.3770	8.9370	17.7944	0.1599
13	2020	0.1735	8.9819	17.8130	0.1659
14	2016	0.1448	14.5097	18.1380	0.1622
14	2017	0.0272	14.4261	19.8748	0.2017
14	2018	0.0628	15.1980	19.9761	0.1966
14	2019	0.0553	15.6354	20.0779	0.2041
14	2020	0.0710	14.6307	20.1671	0.1593
15	2016	0.0873	15.8102	20.3283	0.1979
15	2017	0.0367	15.8072	18.2134	0.1441
15	2018	0.1197	16.6319	18.0567	0.2078
15	2019	0.1923	16.5526	18.0516	0.1986
15	2020	0.1618	16.4875	18.0204	0.1952
16	2016	0.1409	13.9028	18.1831	0.1869

Bank	Year	NPLs	Fintech	Bank size	Capital adequacy
16	2017	0.2346	14.1470	16.4941	0.1145
16	2018	0.3195	15.6077	16.5190	0.1399
16	2019	0.4078	15.9390	16.6697	0.1534
16	2020	0.4882	15.7806	16.6992	0.0911
17	2016	0.4145	14.2011	16.7474	0.0810
17	2017	0.0916	14.7579	17.5282	0.2649
17	2018	0.1108	15.0670	17.2864	0.2547
17	2019	0.1088	15.1934	17.2774	0.2387
17	2020	0.1467	15.2987	17.4516	0.2597
18	2016	0.1090	14.7349	17.1856	0.2428
18	2017	0.0304	14.4013	16.4972	0.1763
18	2018	0.0169	14.5828	16.5037	0.1904
18	2019	0.0453	14.6201	16.5757	0.2022
18	2020	0.0757	14.8757	16.5997	0.2275
19	2016	0.0689	11.6827	16.6120	0.2220
19	2017	0.0842	12.5462	17.0226	0.1577
19	2018	0.0923	11.9296	17.1171	0.1872
19	2019	0.0929	12.9837	17.2596	0.1620
19	2020	0.1064	13.0078	17.3218	0.1866
20	2016	0.1534	13.7061	17.3744	0.1711
20	2017	0.0792	14.0772	16.1408	0.3213
20	2018	0.1871	14.2170	16.3419	0.3911
20	2019	0.0745	14.4033	16.8845	0.2463
20	2020	0.0922	13.6780	17.0273	0.2729
21	2016	0.0437	12.4380	18.0874	0.1813
21	2017	0.0692	12.6520	18.0912	0.1769
21	2018	0.1081	13.4776	18.0282	0.1700
21	2019	0.2494	12.3870	17.9190	0.1534
21	2020	0.2356	13.4740	17.8490	0.1456
22	2016	0.0248	14.8357	19.0716	0.2020
22	2017	0.0289	14.6567	19.1652	0.1815
22	2018	0.0870	15.1431	19.2966	0.1858
22	2019	0.1079	15.4955	19.3315	0.1792
22	2020	0.0979	16.1981	19.4287	0.2156
23	2016	0.0517	13.9230	16.6358	0.1625
23	2017	0.1720	14.9697	16.5742	0.2008
23	2018	0.1331	15.1743	16.3714	0.1933
23	2019	0.0446	16.4039	20.1400	0.1536
23	2020	0.0705	16.3720	20.2045	0.1801
24	2016	0.0766	13.1488	20.2873	0.1663

Bank	Year	NPLs	Fintech	Bank size	Capital adequacy
24	2017	0.0627	13.1722	20.3868	0.1955
24	2018	0.1016	14.2912	20.6163	0.1903
24	2019	0.1590	13.9164	15.4706	0.3933
24	2020	0.1807	13.7920	15.4489	0.5708
25	2016	0.3825	15.9989	15.4946	0.4494
25	2017	0.1374	16.5515	15.9516	0.3119
25	2018	0.0821	17.1188	16.1101	0.3869
25	2019	0.0718	17.2928	16.1741	0.3316
25	2020	0.0940	17.1680	16.1683	0.3093
26	2016	0.1931	13.1120	16.3327	0.3442
26	2017	0.1116	13.4730	18.6473	0.1399
26	2018	0.1749	13.2621	18.5348	0.0715
26	2019	0.3001	13.1230	18.5148	0.0542
26	2020	0.3913	13.7946	18.5591	0.0370
27	2016	0.3564	13.1780	18.5343	0.1150
27	2017	0.0912	13.2730	18.9262	0.2059
27	2018	0.1126	13.2089	18.9481	0.2304
27	2019	0.1089	13.1657	19.1442	0.2227
27	2020	0.1224	13.4661	19.1550	0.1869
28	2016	0.0519	15.8709	16.1693	0.2412
28	2017	0.0828	15.8396	16.0592	0.2741
28	2018	0.1056	16.0799	16.0711	0.2946
28	2019	0.1318	16.5700	16.1067	0.2853
28	2020	0.1211	16.7438	16.1615	0.2450
29	2016	0.0170	14.1168	17.9899	0.1729
29	2017	0.0362	16.1623	17.9950	0.2216
29	2018	0.0486	16.3715	18.1721	0.2248
29	2019	0.0606	16.3834	18.4220	0.3729
29	2020	0.1018	16.4759	18.5049	0.4136
30	2016	0.1025	12.5908	18.7977	0.1509
30	2017	0.8832	12.6277	16.0873	0.1281
30	2018	0.7290	13.0815	16.2608	0.1644
30	2019	1.2528	13.3428	18.0733	0.2425
30	2020	0.8521	13.5197	18.0994	0.2312
31	2016	0.1284	13.0425	16.7655	0.2468
31	2017	0.2383	13.4555	16.8541	0.2325
31	2018	0.2780	14.1686	16.7757	0.1646
31	2019	0.2035	14.4548	17.0467	0.1440
31	2020	0.1968	14.6174	17.0908	0.1793
32	2016	0.0411	13.5625	19.1552	0.1870

Bank	Year	NPLs	Fintech	Bank size	Capital adequacy
32	2017	0.0505	14.2903	19.1847	0.1812
32	2018	0.0666	14.9790	19.3319	0.1684
32	2019	0.0945	14.9697	19.4537	0.1740
32	2020	0.0998	14.7987	19.4947	0.1834
33	2016	0.1015	14.3780	19.2707	0.2116
33	2017	0.0829	14.7036	19.3389	0.2091
33	2018	0.0896	14.9574	19.4705	0.1852
33	2019	0.1169	14.8312	19.4694	0.1947
33	2020	0.0953	14.5404	19.5264	0.1773
34	2016	0.3332	16.0002	16.4876	0.1745
34	2017	0.1677	16.2735	16.4404	0.1627
34	2018	0.4271	16.1346	16.2268	0.1265
34	2019	0.5598	16.2419	16.0372	0.2201
34	2020	0.7111	16.4453	15.7413	0.2060
35	2016	0.1103	14.7419	16.1624	0.2164
35	2017	0.1156	14.8352	16.1547	0.2230
35	2018	0.2416	14.0358	16.1419	0.2908
35	2019	0.2211	14.6208	16.1414	0.2111
35	2020	0.2857	14.7272	16.0475	0.2015
36	2016	0.0180	13.1792	15.8672	0.2379
36	2017	0.0186	13.5055	15.5385	0.3868
36	2018	0.0436	13.5092	15.6880	0.3878
36	2019	0.1276	14.2825	16.5455	0.3316
36	2020	0.2432	14.3957	16.5936	0.2537
37	2016	0.0329	10.7413	16.8122	0.1930
37	2017	0.0255	10.8024	16.9247	0.2545
37	2018	0.0008	10.9464	17.0730	0.2274
37	2019	0.0308	11.8670	17.2917	0.1909
37	2020	0.0506	12.9946	17.4010	0.2015
38	2016	0.1750	14.2878	17.2703	0.2003
38	2017	0.1731	14.2873	17.2654	0.1999
38	2018	0.1712	14.2869	17.2605	0.1995
38	2019	0.1692	14.2864	17.2556	0.1991
38	2020	0.1673	14.2860	17.2507	0.1987