FACTORS AFFECTING CREDIT RISK ON ETHIOPIAN COMMERCIAL BANKS: DYNAMIC PANEL DATA MODELS

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A Research Proposal submitted in Partial Fulfillment of the Requirements for the Award of the Degree of Masters in Financial Economics

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Declaration

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ACRONYMS

AFC	Asian Financial Crisis
BI	Business Intelligence
BIS	Bank for International Settlement
BOA	Bank Of Abyssinia
CAR	Capital Adequacy Ratio
CBE	Commercial Bank Ethiopia
CR	Credit Risk
DSB	Dashen Bank
GDP	Gross Domestic Product
FY	Fiscal Year
GFC	Global Financial Crisis
IMF	International Monetary Fund
LDR	Loan To Deposit Ratio
LGR	Loan Growth Rate
NBE	National Bank of Ethiopia
NPA	Non-Performing Asset
NPLs	Non-Performing Loans
PBI	Proactive Business Intelligence
PRC	People's Republic of China
SSA	Sub –Saharan Africa
ROA	Return On Asset
ROE	Return On equity
US	United States

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Abstract

Low follow up after disbursement of the loans and weakness of identifying key costumers which were arise bank- specific factors by bank's risk management team. Also, financial or economic crises may make the banking sector exposed to high credit risks, which may lead to high levels of default. Furthermore, the high level of debt burden ratio may make customers unable to pay their financial obligations, thus increasing credit risks. The current study is in line with this and aims to examine the determinants of the nonperforming loans (NPLs) in Ethiopian banking sector. To that effect, we consider internal factors that include bank-specific variables, and external factors that involve bank-specific and macroeconomic variables. We estimate a dynamic panel data model by the system Generalized Method of Moments (GMM) for a set of 13 Ethiopian commercial banks based on annual data covering the period from 2010 to 2022.

The finding revealed that for which the importance of bank-specific factors in explaining the NPLs ratio. In actual terms, there were significant and positive linkages between the one-period lagged NPLs ratio, cost efficiency ratio return on equity (bank performance) and the capital adequacy ratio on the one hand, and the NPLs ratio on the other hand, and significant and negative linkages between the bank size, loan growth rate, loan deposit ratio and the NPLs ratio.

The study provides important recommendations for bank decision makers in the Ethiopian commercial banks. Indeed, they should work on improving the operational efficiency and enhancing credit risk management and risk management in the banking sector, developing the operational framework for the monetary policy of central banks, enhancing the opportunities to benefit from the credit information industry, boosting the government's role in adopting economic policies that support investment, developing stress tests for banks, and adopting early warning systems.

Keywords: Non-performing loans; Lag variables; Dynamic Model: Dynamic Panel model; Bank specific variables and macro-economic variables; Panel data; Static panel; Estimation.

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the study

By effectively allocating capital, facilitating trade, and promoting investment, banks contribute to economic expansion. One of the most important things that financial institutions do is provide access to financing. These results from the correlation between the volumes of credit reported in the corporate income statement and the earnings of financial institutions. But during the past few decades, non-performing loans (NPLs) have emerged as one of the most significant issues facing financial institutions. Several studies have demonstrated that non-performing loans (NPLs) result in higher provisions and worse rate of return (Hakimi, 2020). Additionally, a higher NPL ratio reduces the company's credit availability, undermines stability and profitability, and limits its ability to generate cash (Boussaada, 2020).

Therefore, the country's economic progress depends heavily on the stability of the banking sector. Nonperforming loans (NPLs) are one indicator of the safety of the banking system since capitalization and credit quality play a major role in financial stability and profitability (Hajja, 2019).

By acting as intermediaries and granting loans, banks attempted to improve their financial performance; yet, banks frequently face credit risk. It was discovered that excessive credit risk is the main cause of banking industry collapses in the nation. Occasionally, it results in the collapse of the entire financial system. It is anticipated that credit risk would face if a borrower is unable to fulfill their commitment regarding future cash flows. There is unrest in the banking and financial sectors as a result of the aforementioned financial issues (Asmima et al., 2021).

According to (Rosenkranz..etl, 2019), during the post-AFC era, annual non-performing loan (NPL) ratios for the majority of economies were less than 5%. This is a significant decrease from the peak, when bad loans as a percentage of total outstanding loans reached as high as 49% for Bangladesh, Indonesia, and Thailand; 29% for the People's Republic of China (PRC); and over 10% for the Kyrgyz Republic, India, Malaysia, Pakistan, and the Philippines.

Sub-Saharan Africa (SSA) in particular has a history of having a high percentage of nonperforming loans (NPLs) in the banking sector as compared to other regions of Africa. Commodity producers and unstable states have been especially scarce in Sub-Saharan Africa. A number of factors, including macroeconomic volatility, government arrears making it difficult for domestic suppliers to repay their debts, inadequate credit risk management practices, and a backlog of troubled loans that are either unpaid or not fully written off due in part to tax legal systems, can be used to explain the structurally high level of non-performing loans in Sub-Saharan Africa (IMF, 2021).

Whatever economic crisis in the world observed in different time, the causes for these crises were different factors and one was credit risk which had its own contribution for the problem. If there were economic crisis in the world, banks were easily victimized. The major risks faced by banks were credit risk, operational market and liquidity risks. The most dangerous of all dangers is credit risk. Several scholars rated the different forms of risk according to how important they are to banks, with credit risk coming in first (Basel, 2022).

A credit risk in the banking sector pertains to the threat of a foreign bank branch or CR losing money on a loan as a result of the customer's incapacity or failure to fulfill all or part of its commitments. The risk associated with credit is the potential for the counterparty or borrower to default on their payments under the terms of the engagement (Hu and Zhag, 2021). Therefore, when one of the parties to a credit transaction is unable to pay the other parties, credit risk develops. Credit risk was measured by NPLs in banking industry.

According to (Kek et al., 2020), increases in Non-Performing Assets (NPAs), commonly referred to as Non-Performing Loans (NPLs), are a key contributor to credit risk and have a direct impact on bank performance. A bank having a high non-performing asset (NPA) ratio has a greater likelihood of experiencing credit defaults on a large scale, which will ultimately reduce the bank's net worth by depreciating its assets. As a result, the bank charges high loan rates of interest to borrowers who pose a greater credit risk in an effort to reduce credit risk. Due to the likelihood of loan default, banks become exposed to credit risk as soon as the borrower accepts the terms and conditions of the loan. In order to reduce their exposure to credit risk, banks must take proactive steps.

Evidences justified over time credit risk was a single of the crucial bank risks that influences the developments of a nation's financial system, although not much research has been done on the variables that lead to credit risk (Tehulu & Olana, 2020).

The Bank for International Settlement (BIS) states that when a borrower defaults on a loan, banks are at risk of credit loss. A recent study examined the factors that influence the development of bank-specific non-performing loans (NPLs) in Asia and discovered that both macroeconomic variables and bank-specific characteristics, like rapid credit expansion and excessive lending, play a role in the accumulation of NPLs. Additionally, there is strong evidence supporting the feedback effects of non-performing loans (NPLs) on the real economy and financial variables from the research of the macro-financial consequences of NPLs in emerging Asia. An increasing non-performing loan percentage raises the unemployment rate, slows the expansion of the economy and the credit availability. The maintenance of financial stability in an increasingly linked global financial system is depending on the national and regional processes that support non-performing loan (NPL) resolution (Rosenkranz, 2019).

An identifiable feature of financial crises is the increase of non-performing loans (NPLs). In the wake of the global financial crisis, governments and banking management have become more aware of non-performing loans (NPLs) due to their correlation with banking system failure and crises, as well as their perceived serious threat to the stability of the banking sector (Naili M., 2020).

On the other hand, the previous research on credit risk determinants in Ethiopia has produced a range of findings, indicating the complexity of this aspect in financial analysis. Several esteemed researchers, including Tole et al. (2019) and Kitila et al. (2020), have contributed valuable insights to this field within Ethiopia. However, it is important to note that certain key variables such as foreign exchange rates, profitability, and capital adequacy were not adequately addressed in these studies. Only Kitila et al. (2020) included capital adequacy as a factor to consider, and included profitability as a factor to consider.

Based on global experiences, credit risk appears to be the primary risk of a bank. In fact, the primary cause of the demise of numerous banks worldwide has been their inability to collect on loans that they have made to its clients. Banks must control both the risk associated with specific credits or transactions and the credit risk ingrained in the overall portfolio.

A banking system's solvency, safety, soundness, and profitability are heavily influenced by both macro and microeconomic conditions. The degree of asset quality is assumed to be dependent on changes in bank-specific economic situations in this study.

1.2 Statement of the Problem

There have been several empirical studies for the drivers of NPLs and on the factors influencing NPLs in the world, as per the theoretical and empirical literature review below. However, in terms of sample size, type of data, and study goals, these investigations were carried out in various ways.

Since a significant amount of commercial banks' income and profit come from providing credit, this activity is still the most important one for them. As a result, the impact of this risk might have severe adverse effects.

Risk might originate from a bank's size and its appetite for risk, or from its views on accepting risks up to a certain point. The bank is willing and able to tolerate and overcome risks up to that point. One of the arbitrary sources of credit risk is this component. Furthermore, poor customer selection and less credit officer monitoring result from unsustainable credit expansion (Cheng, 2020).

According to (Ferreira, 2021) on the loan growth rate, Credit risk may arise from many loans taken out to invest in portfolios that are vulnerable to market fluctuations or from customers intentionally misrepresenting creditworthiness. In order to avoid being supervised by major banks, companies may guarantee or permit its branches to borrow money from commercial banks using a fixed panel arrangement.

Banking is a risk-taking industry by nature, and good risk-taking is partially rewarded with profits. On the other hand, high and poorly managed risk can cause bank hardship and failure. Thus, risks are justified when they are quantifiable, comprehensible, and under control given a bank's ability to tolerate unfavorable outcomes. None of Ethiopia's banks has the depth of experience necessary to adequately apply the guidelines and manage credit risk in the banking sector.

To the best of the author's knowledge, prior research has not fully examined the factors that influence commercial banks' exposure to credit risk, with particular attention to the lending structure, ownership, and performance of individual commercial banks. Furthermore, for a comparatively shorter period of time, the majority of research concentrated primarily on credit risk management and the impact of credit risk on banking performance. Furthermore, considering how unique this case is a government-owned bank that has a dominant position and the extremely restrictive financial sector care should have been taken to use panel data to potentially add a novel finding to the current body of literature. This study is specifically intended to fill in these gaps.

Generally, from research done mentioned in above for the factors of CR in the commercial bank were measured by using fixed and random effect panel model. There were no clear mechanisms to hold endoginetiy effects within parameters so far. So, as to fill this unclear empirical findings and strict emphasis was not under consideration to Ethiopian commercial banks on this investigation for handling mechanisms about endogenity problem. The study gives contribution by utilizing dynamic panel model analysis to close the analysis gap and obtain an empirical inquiry into the impact of non-performing loans (NPLs) on Ethiopian commercial banks.

1.3 Research Questions

How the extent of credit risk in Ethiopian commercial banks affects the bank by using dynamic panel data. In this regard the study would describe the current state of situations of the bank since it did not any control over the variables, which was the situation of application of credit risk to overcome the problem using tools and measurement techniques of the bank. Therefore, the study attempts to answer the following questions.

- What are the determinant factors that affect credit risk in Ethiopian commercial banks?
- What type of measurements taken by the bank to overcome the credit risk by Ethiopian commercial banks?
- How much credit risk affects the financial systems of the bank from time to time in Ethiopia in bank industry?
- What indicates of about the extents of lags affects the present of credit risk due to endogeneity presence in the Ethiopian commercial banks?

1.4 Objective

The overall and specific objectives of the study are as follows.

1.4.1 General Objective

Using Dynamic panel data analysis, the study's primary objective is to look at the variables that influence credit risk in Ethiopian commercial banks.

1.4.2 Specific Objectives

The study aims to achieve the specific objectives listed below:-

- To explain the effect of industry specific determinants on credit risk in Ethiopian commercial banks
- Identify statistically significance time effects of macroeconomic factors on credit risk in Ethiopian commercial banks
- To show statistical significant mean difference in credit risk between Ethiopian commercial banks in the specified period

1.5 The Scope of Study

This study attempt to evaluate macroeconomic factors and bank-specific factors significantly influence non-performing loans (NPLs). So, the data used in the secondary data source which covered the period 2010-2022 only for 13 banks in the specified period.

1.6 Limitation of the Study

Financial statements of the bank were mostly confidential due to the market computation with each other. National bank did not give credit risk raw data to users, except for governmental bodies. So, the Authors force to use proxy variable i.e. NPLs. The study was also limited to access in 2023 bank’s raw data since NBE do not offer the data before its report compilation for users.

1.7 Significance of the Study

The study's conclusions and suggestions might be significant for bank management, as it might highlight certain areas that call for corrective action and provide the means for them to take those steps. Additionally, this study would provide information and a foundation for future research on relevant topics for academics, consultants, researchers, and associations.

1.8 Definitions

Non-performing loans (NPLs): - Non-performing loans (NPLs) are defined by IMF (Anon., n.d.) as default loans for which the borrowers are unable to make principal and interest payments within the specified period of time (usually more than 90 days). NPLs are therefore the essential unit for calculating loan loss. This study takes the ratio of non-performing loans (NPLs) as a measurable variable and uses it as a proxy for credit risk because it indicates the bank's asset quality and credit portfolio financial health.

Credit risk: - It's the possibility that a financial transaction won't go through exactly as expected. It is the potential for the counterparty of the asset to fail.

Bank specific factors: - are factors which are committed by bank management may influence. Factors may be mentioned either directly or indirectly in bank financial statements.

Macroeconomic factors: - These factors are elements over which are out of control from bank management. Instead, factors are linked to the nation's monetary and fiscal policies.

CHAPTER TWO

2. LITERATURE REVIWE

2.1 Theoretical Review

The theory behind this investigation was explained in this section. The agency theory and the contemporary portfolio theory are among the theories.

2.1.1 Credit Risk

The banking industry is critical to the growth of the financial market, the financial sector, and the expansion of new investment for GDP. Credit risk is among the most significant categories of risk that the bank industry must deal with. It is also referred to as the likelihood that a lending party, like Ethiopia's commercial banks or private banks, may not get paid back on a loan agreement. When a party signs a contract at a specific period, CR can also provide an explanation for why the other party is unable or refuses to return the installment of its obligations to banks as agreed upon.

According to (Safiullah, 2018) presented in their investigation and revealed that CR stands for the borrower's over 90-day late payment to banks in accordance with the terms of the contract.

Commercial banks, a significant player in the financial sector, are subject to numerous hazards as they grow. One of the biggest hazards it encounters is credit risk, which also has a significant impact on a nation's economic growth. Financial firms now understand the significance and urgency of bolstering efficient credit risk management due to the occurrence of financial crises like the US subprime mortgage crisis in 2008, the Asian financial crisis, and bank collapses (Van Biljon, 2018).

According to (Angelina et al, 2020), among the major risks that a bank faced was credit risk which has a significant effect on their profitability. That is why loans account for a sizable portion of their revenue and interest income at the same time. Thus, credit risk management is the foundation of all banking services, and the success of banking depends on one's capacity to assess credit risk and take necessary action.

2.1.2 Modern Portfolio Theory

Harry Markowitz formulated the theory in 1952.Since this theory aims to explain how diversification by commercial banks leads in a reduction in credit risk while still generating the highest possible return for their portfolio; it is pertinent to the study. In general, banks operate with both nontraditional and traditional sources of income to diversify their revenue stream. Interest from loans given to individuals and companies is one of the traditional sources of revenue, but nontraditional sources also include fees including commissions, monthly account service fees, deposit and transaction fees (Ferreira, 2018).

2.1.3 Agency Theory

The hypothesis was developed in 1976 by Michael Jensen and William Mackling. The idea states that there are two parties to a contract: the primary party and the agent. The person who makes the decision and the agent are parties to a contract. The principal will delegate authority to the agent to act on their behalf, and the principal will rely on the agent to behave in the principal's best interests by making decisions or doing other actions. The actions will be carried out by the agents in return for payment. The two sides, however, are sensible businesspeople who act in their own best interests. According to the study, the option is essential for lowering credit risk, preventing agency conflict, and defending against volatility shocks (Ramanlal, 2022). Taking into account an unfavorable selection process and the asymmetry of information are between shareholders and the executive. In this scenario, the Board of Directors (principle) chooses a manager from a pool of applicants, and the principle is responsible for ensuring that the manager (Agent) offers shareholders an optimal portfolio, that is, one that maximizes profit and minimizes risk (Ben, Gerard Mondello & Nissaf, 2020). One party is therefore in the know more than the other, leading to an informational imbalance. The agent has more information than the principal does.

2.1.4 Non-Performing Loans

Nonperforming loans (NPLs) do not have a single definition across the nation since it is acknowledged that what is appropriate in one nation could not be in another. Still, there is a consensus regarding this matter. IMF's Compilation Guide on Financial Soundness Indicators defines non-performing loans (NPLs) as follows: "A loan is non-performing when interest and/or principal payments are 90 days or more past due, or interest payments equal to 90 days or more have been capitalized, refinanced, or delayed by agreement, or payments are less than 90 days past due, but there are other good reasons such as a debtor filing for bankruptcy to doubt that payments will be made in full." (IMF, 2020).

Owing to the rate of return on bad credit, the bank will suffer losses the bigger the NPL. In order to impact the erosion of public trust if this is permitted. The formula can be used to represent non-performing loans (Anon., 2019).

Currently, BI only accepts 5% of NPL; if this amount is exceeded, the bank in question will have its rate assessed at a lower rate, meaning that its score would be worse. Worse bank credit quality leads to a greater NPL computation, which increases the total amount of NPL.

The following table lists the criteria for evaluating the NPL calculation's soundness rate:

Table 1: Criteria for NPLs Component Rating Matrix

Rating	**NPL Value**	**Predicate**
1	NPL < 2%	Risk Predicate
2	2% ≤ NPL ≤ 5%	Very healthy
3	5% ≤ NPL ≤ 8%	Healthy
4	8% ≤ NPL ≤ 11%	Pretty healthy
5	NPL ≥ 11%	Unwell

Source: Annex PBI 18/1/PBI/2019

2.2 Empirical Review

This section looks at the several studies that were done to determine how each independent variable and the dependent variable, credit risk, relate to one another.

2.2.1 Factors of Credit Risk

The quantity of credit risk, which is primarily bank-centric and the world's largest financial risk, was susceptible to a number of different factors. The components of credit risk can be divided into two groups: macro-specific and bank-specific. While macro-specific (macroeconomic) variables like GDP growth cause NPLs to decline, bank-specific factors primarily cause them to rise dramatically. Potential investors could use this information to help them choose a better investment opportunity (Shakeel Ahmed, 2021).

Macroeconomic variables recognized within the theory as key contributors to CR are GDP growth, inflation, and unemployment rates. However, factors at the bank level are those that are specific to a bank or the banking industry as a whole. These factors include things like loan growth, bank size, operating capitalization, profitability, and competitiveness. These elements would each be explained in further detail.

2.2.2 Macroeconomic Factors

Credit risk is a major factor influencing banks' profitability because loans make up a large amount of their earnings along with interest profit. A number of macroeconomic factors affect CR levels. According to a Chinese study, credit risk in the banking industry is influenced by external factors. The research finds an inverse relationship between credit risk and the pace of growth of the GDP (Twum, 2020)**.**

2.2.2.1 GDP Growth (GDP)

According to Laximi *et al* (2020), in high income countries, one macroeconomic variable that affects CR is GDP. The World Bank and the IMF made classification for 49 developed 14 countries as a sample for the study was 14. According to the study's conclusions, credit risk in high income countries was negatively correlated with GDP. According to the author, a high export share of GDP reduces trade deficits and encourages economic expansion. When the economy is functioning well, people can pay their bills and even repay their loans. This leads to a proportional decrease in non-performing loans in banks.

According to (Appiah, 2020) examined the factors determining CR in Ghana's bank sector, GDP and nonperforming loans have a very strong inverse relationship. In Ghana, 16 universal banks' panel data covering the years 2010 to 2016 was used. The results showed that high economic growth results in a reduction in NPLs and a reduction default loans in the financial industries.

GDP has no appreciable impact on CR. It has been discovered that there has been little impact on Ethiopia's commercial banks' credit risk. Over the past ten years, the main factor influencing credit risk has been GDP growth. Researchers assert that the trajectory of non-performing loans over time and between nations cannot be entirely explained by economic activity (Kefyalew Tadesse, 2019).

Credit risk became tangible in Southeast Europe's banking institutions as a result of the financial crisis, which in turn caused a slowdown in lending and investment activity, which in turn caused a slowdown in GDP development. Credit risk levels, as measured by the amount of non-performing loans (NPLs), continued to be significant despite a downward trend. GDP is the primary (macroeconomic) factor influencing credit risk, according to the size of the coefficient (Vujanović, 2022).

Numerous researches have produced empirical results that show the gross domestic product has a negative impact on credit risk (Twum et al, 2021). According to these analysts, a growing economy increases the ability of customers to repay loans, which lowers the probability of default.

2.2.2.2 Rate of Inflation (ROI)

It is the overall percentage rise in the weighted average of commodity prices, known as the Consumer Price Index (CPI). Depending on which commodities are thought to reflect a common consumption basket, different commodities make up the index. Increased opportunity costs associated with retaining money and uncertainty about future inflation can be detrimental consequences of inflation and deter investment and saving. Additionally, if inflation picks up speed, buyers can experience a shortage of products as a result of hoarding due to fear of future price increases.

According to (Million Gizaw et al., 2019), the annual change in consumer prices is utilized as the inflation gauge and is a key macroeconomic indicator of credit risk, revealed that the inflation which don’t have significant power to explain the CR posed by Ethiopian commercial banks. One alternative for external factors that influence CR is the rate of inflation. Consumers must pay more for the same goods and services when there is inflation because their purchasing power declines (San et al., 2019).

2.2.2.3 Unemployment Rate

Credit risk is greatly impacted by the unemployment rate. Credit risk and unemployment rate have a positive association. This is due to the fact that high unemployment signifies a large number of unemployed people, which raises the credit risk because those who are now jobless lack a stable income to pay their debts (Kek Swee Huan et al., 2020).

2.2.3 Bank-Specific Factors

Along with macroeconomic considerations, there are a number of factors unique to banks and the banking sector that might impact on CR. These elements include the amount of loans that banks make, their size, profitability, capitalization level, and the degree of market rivalry they encounter.

2.2.3.1 Capital Adequacy Ratio (CAR)

Toby (Anon., 2019) claims that capital sufficiency is one factor determining credit risk for commercial banks. The author emphasized the need for banks to maintain capital to absorb or mitigate risks as they arise and defined the capital adequacy ratio as the sum of shareholders' funds less total assets. According to the study's findings, capital adequacy is a potent weapon that banks can use to lower credit risk.

According to (Appiah, 2020), the characteristics that determine credit risk for Ghanaian commercial banks include capital adequacy, one of seven factors. The study's findings indicated that non-performing loans, which were used to gauge credit risk among Ghanaian commercial banks, had an inverse association with capital adequacy ratio. The author went on to say that while banks with high capital adequacy ratio may choose not to provide risky loans, which would ultimately minimize non-performing loans and credit risk, banks with low capital adequacy ratio may engage in risky lending, which could lead to a high non-performing loan rate and an increase in credit risk.

In yet another study, (Kharabsheh, 2019) on the factors influencing credit risk in Jordanian banks, bank capital and credit risk were positively and significantly correlated. The dataset from all Jordanian commercial banks from 2000 to 2017 was used in the study. They were surprised by the positive correlation as banks with limited capital are frequently drawn to profitable but risky ventures, which could lead to them taking on more risk and ultimately increasing credit risk.

Studies carried out to look into the relationships between different explanatory factors and credit risk. From 2001 to 2015, 22 commercial banks in Bangladesh were the subject of the study. The information was gathered from bank annual reports that were published. The results showed that there was a substantial and negative correlation between capital ratio and credit risk. This suggests that credit risk declines in tandem with bank capitalization (Sarker, 2018).

2.2.3.2 Bank Size (SIZE)

According to (Anon., 2020) there is a negative correlation between bank size and credit risk. According to this inverse relationship, credit risk decreases with bank size. The magnitude of the credit shrinks as the bank grows. This is due to the fact that larger banks will have greater reserves to back up the loans extended to customers. The bank will not be significantly impacted in the event of a loan default because it has higher reserves to maintain the seamless functioning of its regular banking operations. In addition, larger banks are better equipped to take on high interest rate risk since they have more money to lend to customers.

Thus, total assets of all Ethiopian commercial banks are utilized as a proxy for bank size when determining the size of Ethiopian commercial banks. The following is how the natural logarithm of the total asset is employed in this study.

$$\text{Logarithm of total Asset } = \ln(tota\ asset)$$

2.2.3.3 Bank Performance (ROE)

ROE is the amount of profit after taxes on equity. Banks exist not just to take deposits but also to provide credit services to its clients, which puts them at risk for credit. One of the ways banks make money is by charging interest on loans they make to their clients. Consequently, a bank's profitability will rise in direct proportion to the amount of loans it grants and the interest revenue it earns. Nonetheless, granting larger loans entails a larger exposure to credit risk due to the increased likelihood of loan default.

The literature indicates that returns on equity (ROE) and returns on assets (ROA) are the most widely used metrics to assess a bank's performance. Kek Swee (Anon., 2020) verified that bank performance and credit risk have an inverse connection. It suggests that the credit risk will go down as bank performance rises. The rationale for this is that improved bank performance indicates more revenue from the bank's commercial operations, which includes customer credit.

2.2.3.4 Cost Efficiency Ratio (CER)

It's unclear how cost efficiency affects non-performing loans. While it is true that banks that spend less on loan risk monitoring are more cost-effective, there is a chance that future NPL increases will result from this (Ozili, Peterson k., 2019).

According to (Shakeel Ahmed et al., 2021), the likelihood of a high NPLs ratio is decreased by a cost-efficient ratio. As a result, banks must have efficient cost management since it is necessary to reduce non-performing loans (NPLs) and increase balance sheet equity.

2.2.3.5 Loan Growth Rate (LGR)

Loan growth sometimes referred to as loan growth in credit to indicate bank credit expansions. Overly quick loan growth and abrupt drops in bank capital levels can be used as early warning signs of future trouble loans and as helpful indicators of the financial health of banks declining (Richard, 2020). The research has continuously stated that banks with lower risk-taking and robust deposit bases tend to be less unstable than those with high loan growth rates. Strong loan growth, with a lag of 2-4 years, corresponds too much higher credit losses (Anon., 2020). In actuality, one of the primary factors that led to the recent financial crisis was the surge in loans (Naili Maryem & Lahrichi Younes, 2020).

2.2.3.6 Loan to Deposit Ratio (LDR)

Kashmir (Anon., 2019) justified on how to calculate LDR to determine how many credits are formed and how much money is consumed. LDR is a ratio that finds the cash source, namely by measured the loans given to outside money. The formula can be used to express LDR.

$$LDR = \frac{Total\ Loans}{Total\ Deposit} * 100\%$$

Total deposits, which comprise deposits in the banks, were calculated from the amount of loans provided. General capital revenue from the prior period, and current year's earnings are used to manage equity.

Due to the increasing amount of cash required for credit of finance, a higher LDR indicates a lesser capability for liquidity in the concerned bank. By other means, a low LDR shows a low level credit extension in relation to cash. It receives that banks were not achieved their intermediation duty to the fullest extent possible. The table below shows the bank LDR's predicate scale, ratio, and credit scores:

Table 2: LDR component Evaluation Standards Matrix

LDR	**Risk Value**	**Risk Predicate**
50% < LDR ≤ 75%	1	Very healthy
75% < LDR ≤ 85%	2	Healthy
85% < LDR ≤ 100%	3	Pretty healthy
100% < LDR ≤ 120%	4	Unwell
120% < LDR	5	Not healthy

Source: Annex PBI 18/1/PBI/2019

2.2.3.7 Return on Asset (ROA)

ROA numbers tell investors how effectively a company converts its invested capital into net income. A higher ROA number is better because a company can make more profit with less investment. Simply put, a higher ROA means a more efficient plant. By dividing a company's net profit by the entire value of its assets, ROA is computed.

Calculate it as follows. $ROA = \frac{Net\ Income}{Total\ Assts}$

Effective managers are able to alter efficiencies to lower the chance of failure. The majority of empirical data indicates that credit quality and profitability are inversely correlated. Bad debts and return on investment have a negative relationship, claims.

The fact that credit is becoming an issue is hurting banks in many ways, especially in terms of profitability. Such loans negatively affect not only the partner banks of the banking sector, but also the state budget and many other sectors (areas). One of the key factors driving down profitability is the increase in bad debts. Literature on bad debt estimates analyzed using a variety of methods is needed because of the importance of representing the solvency of borrowers, the level of risk, and the quality of banks' assets in the economy (Koten, 2021).

CHAPTER THREE

3. METHODOLOGY

A study design provides a research framework and action plan. Selecting the research approach was helpful when conducting research. This study's main goal was to find out what influences Ethiopian commercial banks' non-performing loans. It also examined statistical correlations between variables related to individual banks and the macroeconomic environment. There might be a number of factors in the interest doing so. Other factors besides the variables identified in the study can also affect non-performing loans. Therefore, an explanatory design was better solution for examining the relation within credit risk and with that of bank-specific and macroeconomic variables. The banking factors, including bank performance, CAR, CER, LDR, LGR and ROA, would be determined. Statistical significance was done by dynamic panel data analysis using fixed and random effects through STATA software and E-Views.

3.1 Data Sources

Secondary data sources were used in the investigation. Financial audited raw data was used to analysis the research which was taken from bank supervision directorate in National bank of Ethiopia.

Based on the objectives of investigating for the determinants of NPLs in Ethiopian commercial banks was assessed. The investigation was used quantitative data which was panel model analysis. It covers 12 financial years. In the sample banks were included based on the data availability in the specified years. The Ethiopian commercial banks' data were computed between 2010 and 2022 using the financial statements for each year as a guide.

3.2 Theoretical Framework for Variable

The variables employed in this study fall into two main categories: macroeconomic and bank-specific factors

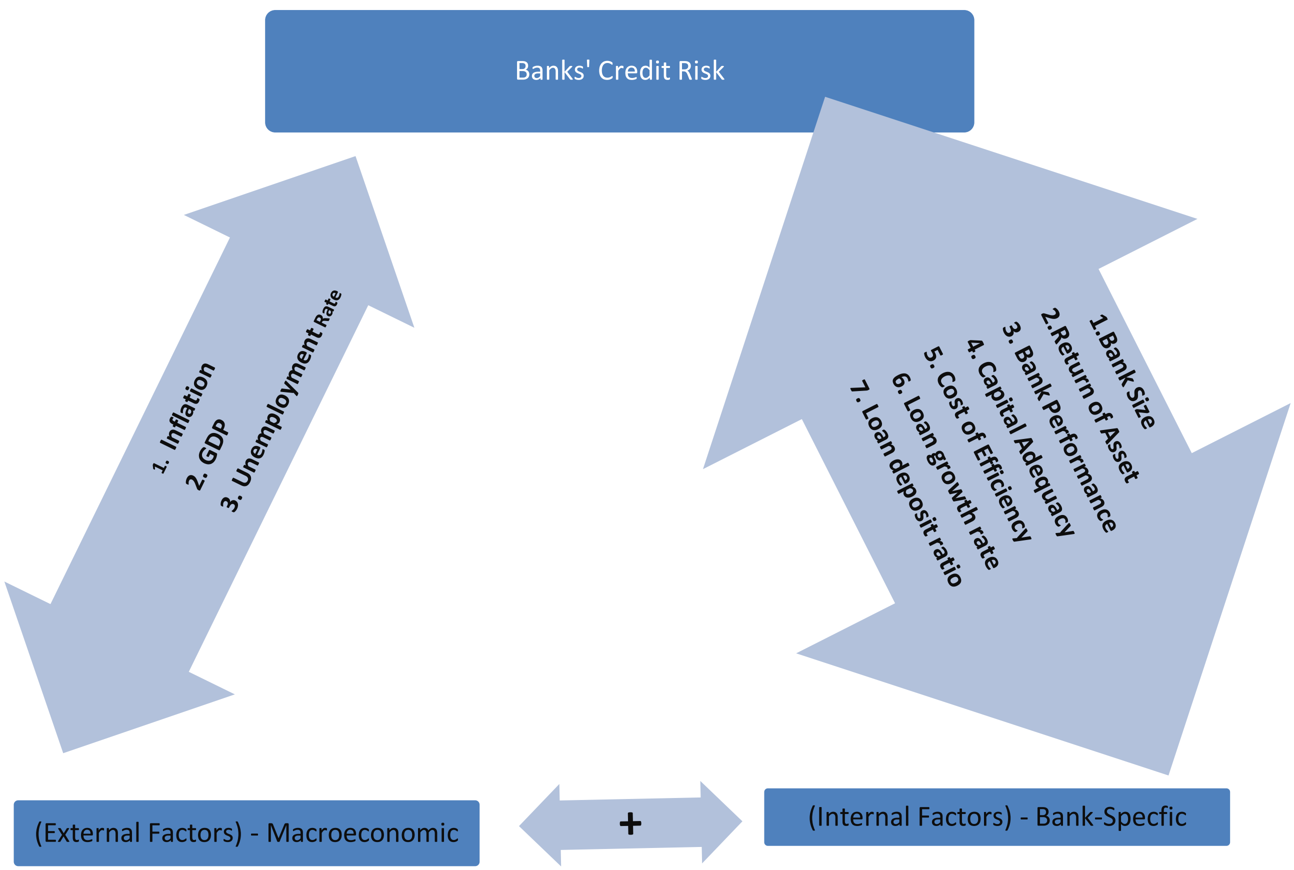


Figure 1: Theoretical Framework (sketched from the literature review, 2022)

3.3 Conceptual Framework for Variables

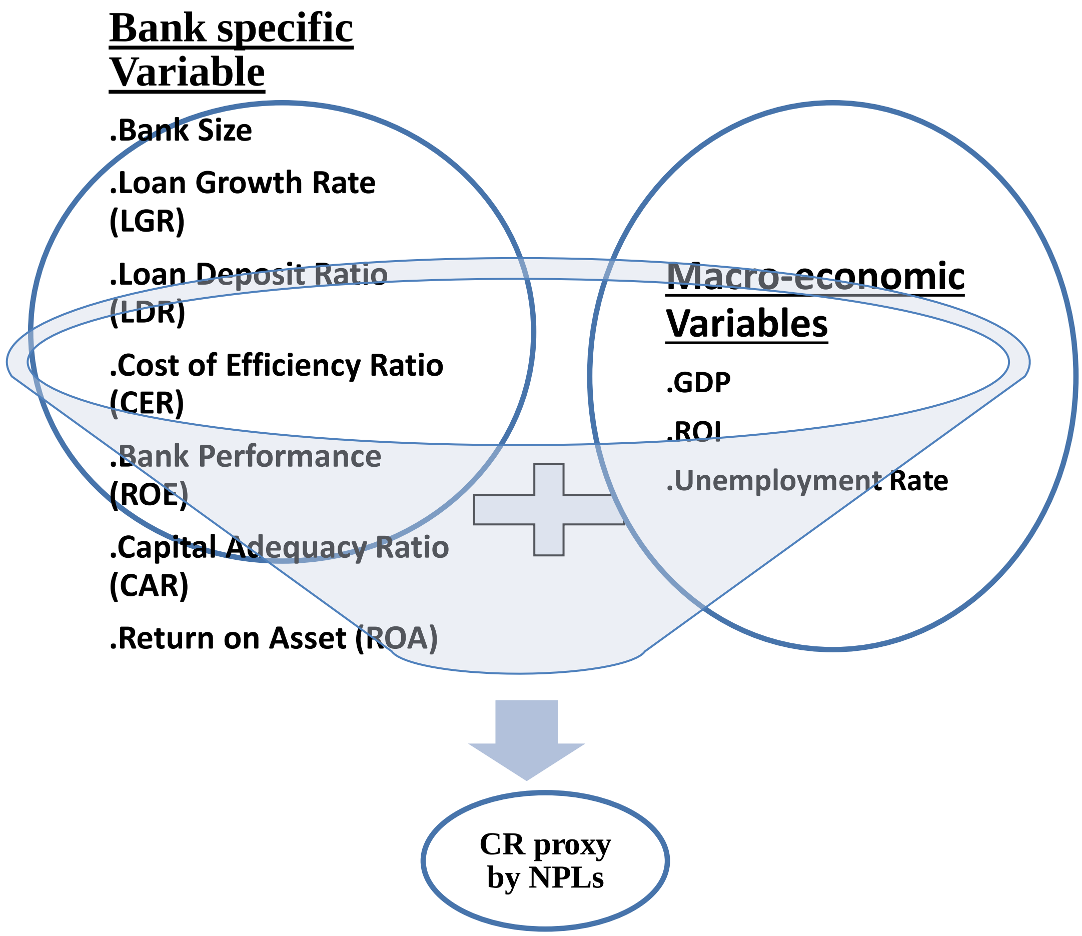


Figure 2: Conceptual Framework (sketched by Author, 2022)

This study used the non-performing loan as a proxy for the dependent variables, which was the credit risk incurred by Ethiopian commercial banks. In Figure 1, the study's theoretical framework is presented. Internal and external factors are the two basic categories into which the explanatory variables are divided. Cost of efficiency, capital adequacy, bank size, rate of return, and other bank-specific variables are examples of internal factors. In contrast, the nation's unemployment rate, GDP, and inflation are external influences. The variables impact on credit risk and the process by which they were determined using historical research are explained in the paragraphs that follow.

3.3.1 Dependent Variable

The ability of borrowers to fulfill their contractual obligations to repay loans on schedule is known as credit (Elgari, 2019). When borrowers default on their loans and the bank is unable to collect the principal and interest, the loans that have been disbursed to clients become risky for the bank. Non-performing assets (NPAs), commonly referred to as non-performance loans, were the most widely used indicator of credit risk (Beck, 2020). This was the primary driving force for the study, which uses non-performing loans as proxy for credit risk characteristics in Ethiopian commercial banks. The following formula was utilized for credit risk employed in this investigation.

$$Credit\ Risk = \frac{Non\ performing\ Loan}{Total\ Loan}$$

The amount NPLs was growing, which degrades the asset quality and efficiency of banks. If the NPLs cannot be recovered within that time frame, the income stream ceases to generate, and full principal and interest payments were not made (because of growing provision expenses hold on growing non-performing loans).These factors have a negative impact on banks' reputation, ability to mobilize resources, stability, and position as financial intermediaries; as a result, investment and associated economic growth of nations decline..

3.3.2 Explanatory Description

Table 3: Factors that determine NPLs, their proxies, symbols, and an example of how they were used in the literature.

Variables	Proxy	Notation	Expected Sign
Dependent Variable			
Credit risk	$\frac{Bad\ Loans}{Total\ Loans}$	NPLs	
Bank-Specific factors			
Bank Size	Log(total asset)	SIZE	+/-
Loan Growth Rate	$\frac{(Loan\ t+1)-(Loan\ t)}{(Loan\ t)}$	LGR	
Loan to Deposit Ratio	$\frac{Total\ Loans}{Total\ Deposits} * 100$	LDR	+
Cost Efficiency Ratio	$\frac{Operating\ Expenses}{Operating\ Income}$	CER	-/+
Bank performance	$ROE = \frac{Net\ Income}{Total\ Equity}$	ROE	-/+
Capital adequacy	$\frac{Capital}{Total\ Asset}$	CAR	-/+
Return on Asset	$\frac{Net\ income}{Total\ Asset}$	ROA	-
Macro-economic factors			
GDP	growth rate of GDP (annually)	GDP	+/-
Inflation	inflation rate (annually)	ROI	+
Unemployment	Unemployment (annually as a rate)	UNER	+

Source: assembled by the investigator from a range of literatures (2019 - 2022)

3.4 Research Design

The collection of techniques and protocols utilized in measuring and evaluating the variables listed in the research design. The dynamic panel data analysis method and descriptive explanatory design methodologies were used in this study. Descriptive research design was used to collect, analyze, and present data in order to address issues about the subject's current state during the study. Therefore, it makes the most sense to use this design to analyze the elements influencing credit risk in Ethiopian commercial banks and provide estimates as a result, ensuring that the stated objectives were fulfilled appropriately.

3.4.1 Data Collection Instruments

The investigation selected a sample of 13 functionally operating banks, comprising Ethiopian commercial banks. Based on the data accessibility, these banks were selected. The time period, which consists of 13 financial years, runs from 2010 to 2022. Nonperforming loans were used to quantify credit risk; return to equity, return on asset, loan growth, loan to deposit, CAR, CER and unemployment rate, GDP and inflation were chosen as the control variables.

In this study, dynamic panel data were utilized. Because dynamic panel data provides for individual-specific variables, which can account for variance among different units over time, the author preferred to use dynamic panel data.

Table 4: Ethiopian Commercial Banks Included for Investigation

No.	Name of the Bank	Year of Establishment
1.	Commercial bank of Ethiopia	1963
2.	Awash	1994
3.	Dashen	1995
4.	Abyssinia	1996
5.	Wegagen	1997
6.	Hibret	1998
7.	Nib	1999
8.	Oromia Cooperative	2005
9.	Lion	2006
10.	Oromia	2008
11.	Zemen	2009
12.	Bunna	2009
13.	Birhan	2010

Note: Aberration used for purpose of simplicity for analysis in STATA commands

3.5 Data Analysis

The first step in this study was to obtain the essential data from the previously mentioned sources. The data are then rearranged, changed, and calculated to get the whole set of data needed for this investigation. E-views, SPSS, and STATA were applied to analyze the research. The NPLs was the dependent variable in the study. Averages and measures of dispersion were employed in the variables in descriptive analysis. It was assessed utilizing NPLs. The study's explanatory variables also include Bank-specific indicators include bank size, growth of loan, loan deposit, CER ratio and CAR, return on asset, ROE, GDP, the unemployment rate, and rate of inflation were examined. This is Non-performing loan ratio. This is only the dependent variables.

For the inferential analysis, a one-tailed test using Pearson's correlation was used. The analysis indicated earlier was based on the study's goals, which included figuring out how closely each independent variable was related to the dependent variable and examining the direction of effect between the two variables. The dynamic panel model was also used to investigate the issue's primary bank-specific components as well as the effects of independent variables on the dependent variable. Tables displaying the statistical results were then supplied with the study results.

3.5.1 Model Specification

Examining the factors that influence NPLs at Ethiopian commercial banks were the goal of this study. The nonperforming loans ratio was used in this study as a dependent variable, while credit risk measured by proxy NPLs over total loan, bank size measured, loan growth, rate of return, LDR, CER, CAR, ROA, GDP, rate of inflation, annual inflation growth, unemployment rate were used as explanatory variables. The Ethiopian commercial bank commonly utilizes these variables, thus they were picked. In order to assess the variables influencing NPLs at Ethiopian commercial banks, this study utilized statistical analysis that was prevalent in the majority of the literature. The most prevalent regression model in the literature frequently takes the following format;

The model is econometrically having the general setup form of the following type:

$Y_{it} = a_i + bx_{it} + u_{it}$ -- (1)

Y_{it} = represent the dependent variable for Ethiopian commercial bank i for time period t.

ai = represent the intercept term.

b = represent the parameter to be estimated for independent variable that

xit = represent independent variables.

uit =represent the error term.

When analyzing the impact of factors on credit risk, the link between the dependent and explanatory variables in this study is represented as follows:

NPLs (CRit) = f (SIZE, LGD, LDR, CER, ROE, CAR, ROA, GDP, ROI, UNER) ---------------------- (2)

f = Functional relationship

From the above equation (2) the model constructed as the econometric form of the form;

$$NPLs\ (CR_{it}) = \beta_0 + \beta_1 SIZE_{it} + \beta_2\, LGR_{it} + \beta_3\, LDR_{it} + \beta_4 CER_{it} + \beta_5\, ROE_{it} + \beta_6\, CAR_{it} + \beta_7 ROA_{it} + \beta_8\, GDP_{it} + \beta_9\, ROI_{it} + B_{10}\, UNER_{it} + \varepsilon_{it} \quad (3)$$

Where; i (i=1, 2…13) = Ethiopian commercial bank

t = Year (t = 2010-2022)

CR = Credit risk measured (NPLs)

SIZE = log (total asset)

LGR = Loan growth rate

LDR = Loan deposit ratio

CER = Cost efficiency Ratio

ROE = return on equity

CAR = Capital adequacy

ROA = Return on Asset

GDP = Growth rate of the economy

ROI = Rate of inflation

UNER = unemployment rate, $\boldsymbol{B_0}$ = Constant **term, B_1 to B_{10} = coefficients and ε_{it} = error term**

In the model's sub-indices, 'i' stands for horizontal cross-sections, or banks, and “t” stands for time dimension, or years. The coefficients B_0 and B_1 to B_{10} depict the independent variable slope coefficients and the ε_{it} error term.

3.6 Tests for the Assumption

The standard tests of normality, heteroscedasticity, multi-collinearity, and the autocorrelations assumption are used to evaluate the pooled OLS estimate.

3.6.1 Average Value of Error term Assumption

The standard tests for normality, heteroscedasticity, and multi-collinearity and autocorrelation assumptions were applied to the pooled OLS estimate.

3.6.2 Test for Normality Assumption

Most statistical techniques require the assumption of normalcy because it was necessary for the validity of correlation, regression, and parametric tests. One of the most important quality criteria for statistical analysis in this context is normalcy. In particular, regression analysis and parametric tests need the presence of normality conditions. For modest sample sizes, these statistical tests for normalcy were very helpful. Hopefully, a rigorous examination of normalcy will lead to more significant research whose findings and interpretations will eventually be given top priority for approval and publishing (Ajay S., 2021).

3.6.3 Heteroscedasticity Test

The Modified Wald test would be used to determine whether the fixed effect estimates are heteroscedastic. In the event that heteroscedasticity is present in the fixed effect model, the coefficient standard errors and corresponding t-values will almost certainly yield an incorrect result. In that instance, the results indicate rejecting the null hypothesis because the p-value is less than 0.05, indicating that the residuals do not meet the homoscedasticity assumption (Saom S.A , Nishat T. et al, 2022).

3.6.4 Multi-collinearity Test

Multi-collinearity in the multiple regression equation occurs when two or more explanatory variables have a substantial association with one another. When there is a multi-collinearity issue, the independent variable's significance is diminished since a higher standard error results in lower regression coefficient significance (Adusei, 2018). Furthermore, since multi-collinearity dataset cannot reliably evaluate the involvement of explanatory variables in explaining the variation in the dependent variable's value, severe multi-collinearity of independent variables is unsatisfactory. Following the pooled OLS regression, various test methods would be used to assess the multi-collinearity among the determinants.

3.6.5 Autocorrelation Test

Many tests to ascertain whether serial error correlation is present in a pooled OLS model have been proposed in the literature. Finding serial correlation is a simple process once pooled OLS has been estimated. One rationale for testing for serial correlation is that it should be absent if the model is assumed to be dynamically complete in the conditional mean.

CHAPTER FOUR

4. RESULT AND DISCUSSION

Important works that were related to the subject were examined in the earlier chapters in order to provide background information and to identify areas of knowledge gaps. The previous chapter also covered the research methodology utilized in this study, which allowed for the achievement of sufficiently broad research objectives and the analysis of the output under it. This chapter included an overview of the acquired data as well as a discussion of a significant correlation and regression analysis finding. There are four parts in this chapter. According to the first section, section 4.1 covered the descriptive statistics of the variables. Summery statistics was presented under section 4.2. Econometric/Quantitative analysis was presented and analyzed, under section 4.2. Presented the result of regression analysis and. Finally; under section 4.3 dynamic panel model analyses was presented.

4.1 Descriptive Statistics

Instead of measuring the variables in their converted form, the statistical descriptions of variables are measured at the level of the series or data. In quantitative research, the term "qualitative statistics" refers to a summary statistic that uses and analyzes statistics to quantitatively describe or summarize aspects from a set of data. Thus the simple and detailed qualitative statistics for the explained and explanatory variables were presented in detail analysis. The exogenous variable as discussed in the previous section was credit risk measured by a proxy form of NPLs and the independent variables were SIZE, LGR, LDR, CER, ROA, ROE, CRA with macro-economic factors; GDP, rate of inflation and unemployment rate were applied to see the impacts of CR in Ethiopian commercial banks.

4.1.1 Summary of Statistics

Compare the averages, standard deviation, maximum and lowest values, and number of observations of specific variables across the 13 Ethiopian commercial banks that were the subject of a study from 2010 to 2022 using the tables and figures in this section. When calculating descriptive statistics, series or data levels were used rather than modified forms.

A balanced panel data set with non-missing points in the chosen sample without transformation was employed in the investigation, as demonstrated by Table 4's identical number of observations (N) (169) for all the variables under consideration. With a standard deviation of 1.56%, our data indicates that Ethiopian commercial banks had an average of 2.26% non-performing loans. Between 2010 and 2022, the NPLs had minimal and maximum values of 0.022% and 1.06%, respectively.

The mean of bank size and loan growth rate equals 10.24% and 28.90% and the standard deviations of these variables were 0.64 and 15.88. In additions to the minimum values were 8.58 and -10.88 and maximum values were 12.06 and 82.73 respectively. The mean of loan to deposit ratio in selected Ethiopian commercial banks from 2010 up to 2022 counted 64.54% with the standard deviation 12.89. The minimum and maximum values were 37.34 and 97.97 respectively.

Statistical mean for CER and ROE as return of equity ratio equals 94.00 and 22.99 where as the standard deviation of these determinate variables were 53.71 and 11.16 respectively. The minimum values of these determinant variables were 1.39 and 0.04 on the other round the maximum values were 283.08 and 77.71 respectively.

4.2 Summary Statistics

As seen from the above table the descriptive statistics of variables in the regression model for Ethiopian commercial banks. Since, there are 169 observations for all dependent and independent variable. The overall statistics include many features of the data that were analyzed. The standard deviation displays the degree of variation from the mean value. A high standard deviation suggests that the data point is dispersed throughout a wide range of values, whereas a low standard deviation suggests that the data point tends to be extremely close to the mean. All have comparatively low standard deviations, with the exception of the loan growth rate and cost efficiency ratio, as can be seen in the summary data. This indicates that the link between credit risk and the independent variables was stable over the long term.

During the period under review based on the table of the dependent variable non-performing loan, the mean of NPLs was 2.26 % shows the average NPLs in Ethiopian commercial banks in all 13 years in 13 selected Ethiopian commercial banks. NPL ranged from 1.060% to 0.22 % the deviation has small values (i.e. 1.56%). This value revealed that NPLs was easily measureable among Ethiopian commercial banks, as NPLs was not in static manners.

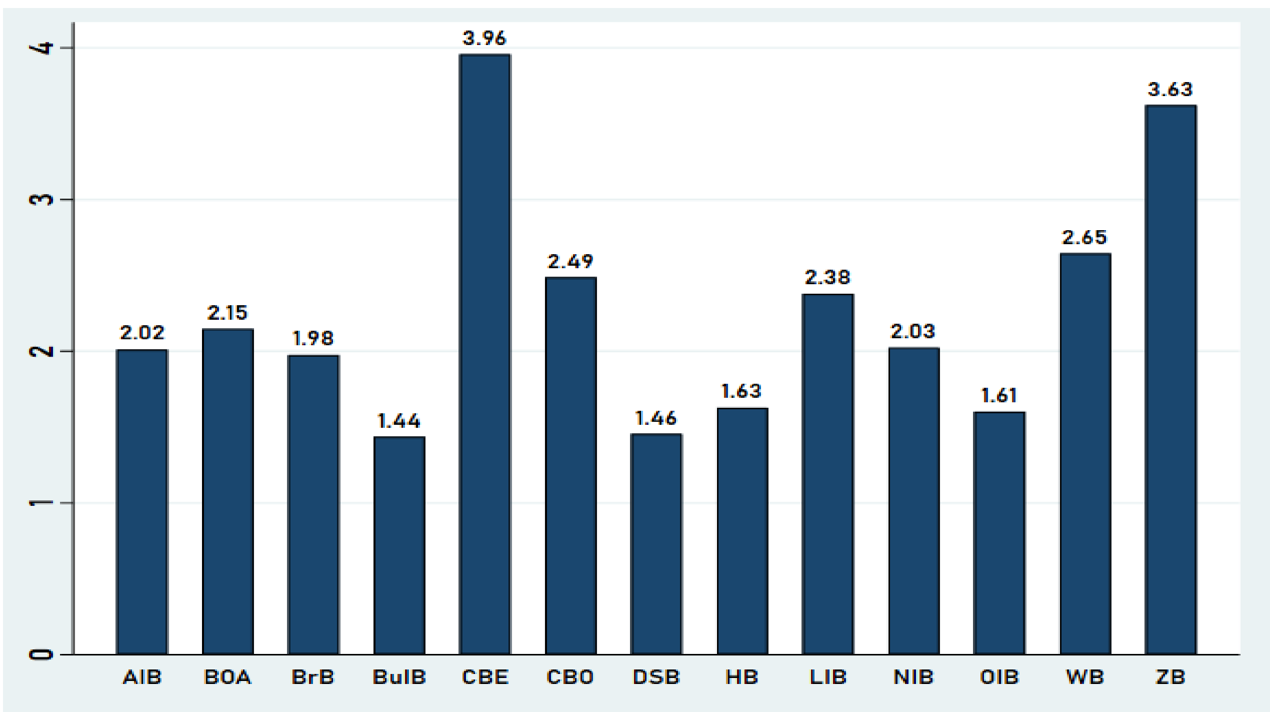
Table 5: Descriptive statistics of Ethiopian Commercial Bank Variables

Year	NPLR	SIZE	LGR	LDR	CER	ROE	CAR	ROA
2010	2.810396	9.513909	27.99443	57.0621	145.5989	22.78348	49.38658	3.058521
2011	2.414888	9.672813	36.78738	51.64057	171.6585	26.85062	45.38737	4.006283
2012	1.958894	9.788079	27.05441	57.7117	151.2235	28.54789	33.44972	4.06426
2013	2.423305	9.910393	20.62955	57.48044	118.7228	25.75975	29.15762	3.996102
2014	2.305759	9.998924	35.58837	57.17939	114.9765	25.92592	27.1714	4.36584
2015	1.956616	10.12125	21.79025	63.43263	94.99722	24.55439	21.52448	4.434
2016	2.292157	10.2256	32.06388	63.71719	79.17479	21.93525	19.75284	4.087756
2017	2.162997	10.36459	28.1598	65.2459	77.72032	20.52078	18.86595	3.672573
2018	1.780931	10.48788	30.58516	62.8597	59.94443	20.79311	19.21217	3.74478
2019	1.782684	10.58988	25.08445	68.71364	60.54219	22.1007	14.71889	3.911655
2020	1.807874	10.68618	34.93377	72.94423	52.03437	21.21088	15.14277	3.575269
2021	2.500414	10.8036	25.05459	79.47607	44.66234	17.86757	14.00992	3.375512
2022	3.175806	10.90232	29.995	81.55109	50.75215	20.05156	14.54314	3.688516
Total	2.25944	10.2358	28.90162	64.53959	94.00061	22.99246	24.79407	3.844697

Keep in mind that the factors employed in the sample, descriptive statistics of each determinants of year-wise were provided in Table 6, 2022, 2021, and 2010 have mean NPLs of 3.18, 2.50 and 2.81, respectively, which were higher. Furthermore, in 2018 had minimum NPLs of 1.78 and a highest loan deposit rate in 2022 as the mean LDR counts at 81.55%, it could account for the low percentage of loans that are impaired in comparison to the previous years. In the chosen years, the banks' loan growth and profitability both remained strong. Additionally, the banks in the sample have a sufficient degree of capital adequacy, which is typically employed as a safeguard against hazards.

4.2.1 Graphical Description of NPLs Ratio

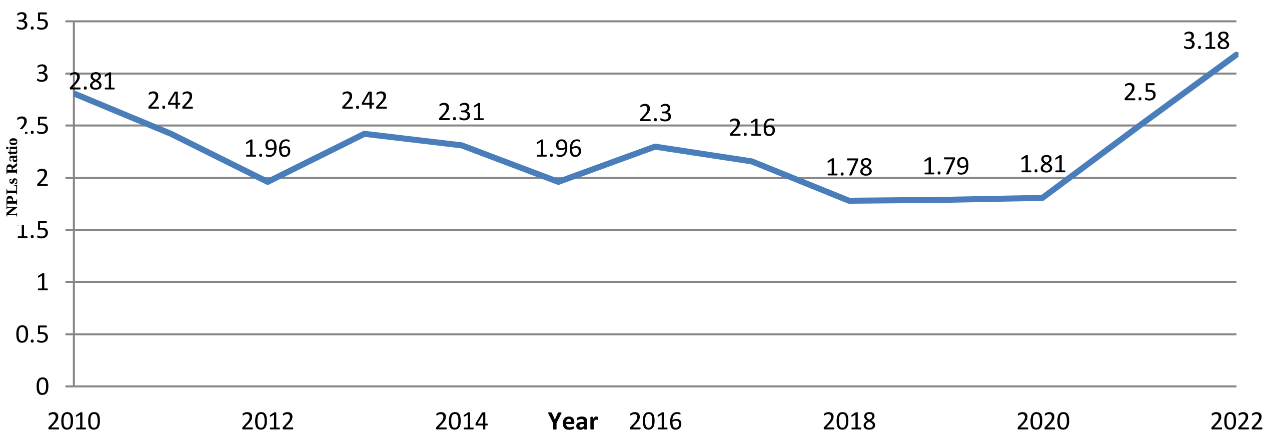
Figure 3: NPL Ratios by Banks (percent, individual mean 2010-2022)



NPL volatility in CBE is thus comparatively elevated. The magnitude of NPL ratios appears to be higher in CBE, where the distribution was the greatest across all banks from 2010 to 2022, on average among banks. The average variability of CBE is more than twice that of other banks and around twice that of BrB, HB, OIB, and AIB. Nonetheless, CBE and ZB record a few extreme values or outliers, suggesting that overall bank volatility remains higher in those two banks.

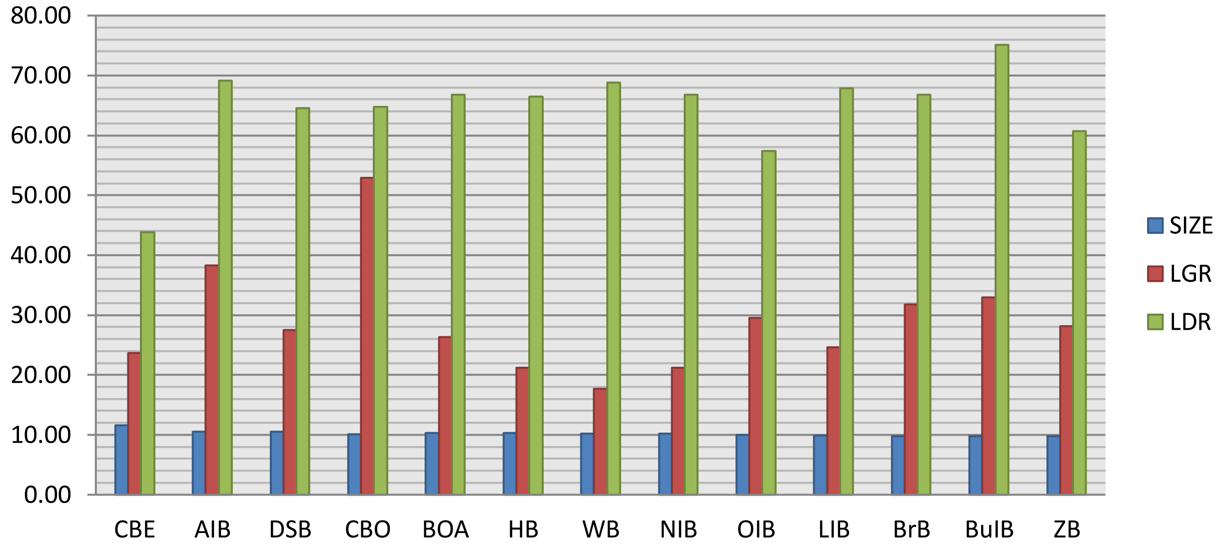
Red flags are raised when the percentage of non-performing loans (NPLs) rises, as it did in 2022, to 3.18. Over the course of the investigation, Figure 2 shows how NPLs changed. In the current paper, the researcher took under consideration of dynamic panel of 13 Ethiopian commercial banks from 2010- 2022. Figure 3 below showed the statistical description of NPLs for 13 Ethiopian commercial banks. The NPLs ratio was turned downwards by an average of 1.79 rates at 2020 from the rest fiscal years. We understood from figure 3 that the NPLs ratio in Ethiopian commercial banks were lined 2≤ NPLs ≤5% which indicates very health. This outcome aligned with PBI (2019), which identified standards for evaluating the NPL computation's soundness rate.

Figure 4: Trend of NPLs Ration year wise for Ethiopian commercial banks



4.2.2 SIZE, LGR and LDR

The graphical representation showed the of average Bank size, loan growth rate and loan to deposit ratio in Ethiopian commercial banks from 2010 to 2022.



Source: Authors' calculations using information from NBE, 2024

Figure 5: Average of SIZE, LGD and LDR in banks from 2010-2022

As seen in above figure 4 highest LDR was noted in BuIB whereas the lowest loan to deposit ratio was recorded at CBE for the period under review in period 2010 up to 2022. Lots of Ethiopian commercial banks figure out at the range of 25% to 75% of LDR which implied very health condition that described in IPB (2019). This was not the aim of this research. Whatever there was little fluctuation of loan growth rate for all Ethiopian commercial banks? Else, the figure lined out bank size was at moderate cases in all Ethiopian commercial banks from 2010 to 2022.

4.3 Econometric/Quantitative Analysis

4.3.1. Pearson Correlation Analysis

Furthermore, correlational analysis needs to be covered prior to delving into the empirical process and performing statistical analysis on the data we have. In this way, the Pearson's pair-wise coefficient matrix was generated in order to evaluate the correlation and multicollinearity among variables. **Table 6** displays the pair-wise correlation matrix, which shown that there was not much pairwise association between any of the explanatory variables.

Table 6: Summary of Pearson correlation analysis

	NPLR	SIZE	LGR	LDR	CER	ROE	CAR	ROA	GDP	ROI	UNER
NPLR	1.0000										
SIZE	0.1727	1.0000									
LGR	-0.2677	-0.1071	1.0000								
LDR	-0.2318	0.1402	-0.0043	1.0000							
CER	0.1504	-0.4012	0.0098	-0.5278	1.0000						
ROE	0.0622	0.3260	0.0125	-0.3603	0.5243	1.0000					
CAR	0.0693	-0.7508	0.1069	-0.4651	0.6551	-0.0096	1.0000				
ROA	-0.1499	-0.2027	0.0422	0.1628	0.0641	0.0217	-0.0104	1.0000			
GDP	-0.0032	-0.5478	-0.0191	-0.5657	0.5907	0.1742	0.6130	0.0316	1.0000		
ROI	0.0683	0.3417	0.0980	0.3710	-0.2001	-0.0845	-0.2213	-0.0193	-0.4984	1.0000	
UNER	0.0177	0.6162	0.0337	0.6332	-0.6483	-0.2128	-0.6416	-0.0391	-0.8700	0.6162	1.0000

Source: STATA- 15 output, Ethiopian commercial banks data, 2024

From the results of Pearson correlation analysis table 8 was figure out in matrix form. Investigation calculated correlation of the exogenous with endogenous bank-specific and macro-economic factors. The result revealed that non-performing loan (NPLs) was positively correlated with bank size, cost of efficiency ratio, and ROE, CAR, rate of inflation and unemployment rate at cv (correlation coefficient) of 0.1727, 0.1504, 0.0622, 0.0693, 0.0683 and 0.0177 respectively. On the other hand, loan growth rate, loan deposit ratio, return of asset and GDP are negatively correlated with credit risk (proxy by NPL) at cv(correlation coefficient) of -0.2677, -0.2318, -0.1499 and -0.0032 respectively. Besides, the result showed that there was a high correlation (0.6551) between CAR and CER. All of the independent variables were not significantly associated, as table 7 demonstrates, with none having a correlation value less than 0.7. As a result, the analysis looks at each of the 10 independent factors. In this Pearson correlation matrix describes about there was no multi-colinarity and authocrilation test for pooled OLS test.

4.4 Empirical Result for Model Test

The empirical findings are shown in this section. Using panel data, the primary factors influencing credit risk in a subset of Ethiopian commercial banks were determined. Three types of effect models were used in this empirical analysis: fixed, random, and dynamic.

4.4.1 Pooled OLS Estimation

As a first step, we used the following model to fit our data, resulted as shown below.

$$NPLs\ (CR_{it}) = \beta_0 + \beta_1 SIZE_{it} + \beta_2\ LGR_{\ it} + \beta_3\ LDR_{\ it} + \beta_4 CER_{\ it} + \beta_5\ ROE_{\ it} + \beta_6\ CAR_{\ it} + \beta_7\ ROA_{\ it} +$$

$$+\ \beta_8 GDP_{it} + \beta_9\ ROI_{\ it} + B_{10}\ UNER_{\ it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(1)}$$

As observed that from Table 8 below the adjusted estimated R-squared was 32.12, that described the 32.12% of variability in non-performing loans was lined with the variability of exogenous factors, or the 32.12% variability was outlined in the model. The model was weak for valuable for this research. At least 50% the output variable was explained by the response factors. So, no further manipulation other statistical tests like most common OLS assumption tests for the presence of Normality, Autocorrelation, and Multi-collinearity assumption. Even though, if there were statistically significant variables in the panel model.

Table 7: Pooled OLS Estimation

Source	SS	df	MS			
				Number of obs	=	166
				F(10, 155)	=	7.33
Model	130.455439	10	13.0455439	Prob > F	=	0.0000
Residual	275.693676	155	1.77866888	R-squared	=	0.3212
				Adj R-squared	=	0.2774
Total	406.149115	165	2.46150979	Root MSE	=	1.3337

NPLR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SIZE	1.052084	.4044194	2.60	0.010	.2531989	1.850969
lnLGR	-.9235231	.1897345	-4.87	0.000	-1.298322	-.5487241
LDR	-.0313386	.0133281	-2.35	0.020	-.0576668	-.0050104
CER	.0111197	.0038902	2.86	0.005	.003435	.0188044
ROE	-.0461847	.0162044	-2.85	0.005	-.0781946	-.0141748
CAR	.0245774	.0170904	1.44	0.152	-.0091827	.0583375
ROA	.0027178	.0280417	0.10	0.923	-.0526755	.058111
GDP	-.0094756	.1233662	-0.08	0.939	-.2531716	.2342205
lnROI	-.1255493	.2888945	-0.43	0.664	-.6962277	.4451292
UNER	.5883499	.4417444	1.33	0.185	-.2842662	1.460966
_cons	-5.41498	4.528999	-1.20	0.234	-14.36151	3.531547

Source: Authors Computation with STATA-15 using NBE data, 2024

4.4.1.1. Tests for Pooled OLS Regression Model Assumption

4.4.1.1.1 Error term Zero Assumption

Pooled PLS assumption needed to fulfill in ordinary least square regression was the error term average value should equals zero. The regression equation boldly made the assumption that the constant term value would never be broken. As a result, the regression equation contains the constant term which was excepted zero.

4.4.1.1.2. Test for Normality Assumption

The majority of statistical methods require an expectation of normality. One of the most important quality criteria for statistical analysis in this context is normality. In particular, regression analysis and parametric tests need the presence of normality conditions. For modest sample sizes, these statistical tests for normalcy were very helpful. Hopefully, a thorough examination of normalcy would lead to more significant research whose findings and interpretations will eventually be given top priority for approval and publishing (Ajay S., 2021). The skewness normality test was used for this test, and all p-values were ≤ 5% at the significance level (see table **18** in the **appendix**).

4.4.1.2 Heteroskedasticity Test

When the variance of the error component in a dynamic panel model is not constant across all data, it is referred to as heteroskedasticity. This can lead to biased and inconsistent estimates of the model parameters, and also affects the validity of statistical inferences. So as describe below table 8 heteroskedasticity test statistics is significant for all variables (p-value ≤ 5% level). This means there is constant variance in the model.

Table 8: Heteroskedasticity test result

```
. estat hettest SIZE lnLGR LDR CER ROE CAR ROA GDP ROI UNER

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: SIZE lnLGR LDR CER ROE CAR ROA GDP ROI UNER

         chi2(10)      =    55.64
         Prob > chi2   =   0.0000
```

4.4.1.3 Multi-collinearity Test

Multi-collinearity in dynamic panel model can be measured using various statistical techniques. One popular method is to figure out each independent variable in the model's variance inflation factor (VIF). The VIF calculates the amount that multi-collinearity contributes to an estimated regression coefficient's increased variance. Generally speaking, multi-collinearity that is problematic is indicated by a VIF number larger than 10. There was no issue with multi-collinearity in the model, as can be shown in table 9 below, where all independent variables have VIF values less than 10.

Table 9: Multi-collinearity Test Result

```
. estat vif
```

Variable	VIF	1/VIF
UNER	8.72	0.114650
SIZE	6.62	0.150959
CAR	6.03	0.165963
CER	4.53	0.220904
GDP	3.99	0.250577
ROE	3.23	0.309199
LDR	3.12	0.321014
ROI	2.57	0.388774
ROA	1.22	0.817041
lnLGR	1.11	0.899260
Mean VIF	4.11	

4.4.2 The Fixed Effect Model

As stated in chapter three research design and methodology section fixed-effect model is one of known model in panel data analysis .since moved to this model after conducting Hausman test our attention to fixed effect model.

Fixed effects regression model is given by:

$$NPLs\ (CR_{it}) = \beta_0 + \beta_1 SIZE_{it} + \beta_2\, LGR_{\ it} + \beta_3\, LDR_{\ it} + \beta_4 CER_{\ it} + \beta_5\, ROE_{it} + \beta_6\, CAR_{it} + \beta_7\, ROA_{it} +$$

$$+ \beta_8\, GDP_{it} + \beta_9\, ROI_{it} + B_{10}\, UNER_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\mathbf{(2)}$$

Where; i (i = 1, 2, 3…, 13) = Ethiopian commercial bank

t = years (years = 2010-2022)

$\boldsymbol{B_0}$ **= is a** Constant **term, B_1 to B_{10} = coefficients and ε_{it} = error term/residuals**

Table 10: Fixed Effect Model Estimation

Fixed-effects (within) regression		Number of obs =	169
Group variable: BankCode		Number of groups =	13
R-sq:		Obs per group:	
within = 0.9815		min =	13
between = .		avg =	13.0
overall = 0.7434		max =	13
		F(10,146) =	773.60
corr(u_i, Xb) = -0.4925		Prob > F =	0.0000

Year	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SIZE	4.311418	.3130498	13.77	0.000	3.692723	4.930113
LGR	.0065642	.0033563	1.96	0.052	-.000069	.0131975
LDR	-.0024525	.00734	-0.33	0.739	-.0169588	.0120539
CER	-.0159576	.002107	-7.57	0.000	-.0201217	-.0117935
ROE	-.0028784	.007654	-0.38	0.707	-.0180053	.0122484
CAR	-.0337365	.0081462	-4.14	0.000	-.0498362	-.0176369
ROA	-.0025998	.0290374	-0.09	0.929	-.0599878	.0547881
GDP	.0200335	.0502519	0.40	0.691	-.0792816	.1193485
ROI	.0256281	.0082203	3.12	0.002	.0093819	.0418743
UNER	1.29063	.2292005	5.63	0.000	.83765	1.743609
_cons	1969.87	3.083239	638.90	0.000	1963.777	1975.964
sigma_u	2.1833069					
sigma_e	.54788555					
rho	.94075821	(fraction of variance due to u_i)				

F test that all u_i=0: F(12, 146) = 29.71 Prob > F = 0.0000

Source: Authors Computation with STATA-15 using NBE data, 2024

From the fixed effect estimation model we had seen that five explanatory variables are a significant effect. From the output bank size, rate of inflation and unemployment rate have a positive impact on NPLs on the other hand cost efficiency rate (CER) and (CAR) have a negative impact on credit risk measured as a proxy for NPLs. The panel data's overall, within, and between R-square values are highly significant, suggesting that about all of the variation in the dependent variable can be explained by the factors in the fixed effect model. The fixed effect shows large positive autocorrelation in which case indicates considering the first differencing model has an advantage, for processes with large positive autocorrelation 'rho'. The Fixed effect model was a suitable model for estimating in comparison to the pool OLS, as shown by the F-test's p-value of greater than zero in this case.

4.4.3 The Random Effect Model

The random effect model is predicated on the assumption that *i's* are random; this implies that individual error components are not auto-correlated across time-series units and cross-sections, nor with each other. The following is how the random effect model is stated:

$$NPLs\ (CR_{it}) = \beta_0 + \beta_1 SIZE_{it} + \beta_2\ LGR_{it} + \beta_3\ LDR_{it} + \beta_4 CER_{it} + \beta_5\ ROE_{it} + \beta_6\ CAR_{it} + \beta_7\ ROA_{it} +$$

$$+ \beta_8 GDP_{it} + \beta_9\ ROI_{it} + B_{10} UNER_{it} + u_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(3)}$$

Table 11: Random effect model estimation

```
Random-effects GLS regression                   Number of obs     =        166
Group variable: BankCode                        Number of groups  =         13

R-sq:                                           Obs per group:
     within  = 0.3310                                         min =         12
     between = 0.2838                                         avg =       12.8
     overall = 0.3090                                         max =         13

                                                Wald chi2(10)     =      72.69
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

NPLR	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
SIZE	1.449235	.4624255	3.13	0.002	.5428974	2.355572
lnLGR	-1.03264	.1902609	-5.43	0.000	-1.405545	-.6597358
LDR	-.0166081	.0143801	-1.15	0.248	-.0447925	.0115763
CER	.0106913	.0041351	2.59	0.010	.0025866	.0187959
ROE	-.0571326	.0158102	-3.61	0.000	-.08812	-.0261452
CAR	.0307168	.0167615	1.83	0.067	-.0021352	.0635688
ROA	-.0052642	.0358213	-0.15	0.883	-.0754727	.0649443
GDP	.0011326	.1142752	0.01	0.992	-.2228426	.2251078
lnROI	-.0862918	.2708549	-0.32	0.750	-.6171577	.4445741
UNER	.1881487	.4465035	0.42	0.673	-.6869821	1.063279
_cons	-8.925658	4.970601	-1.80	0.073	-18.66786	.8165417
sigma_u	.43583325					
sigma_e	1.1967056					
rho	.11710492	(fraction of variance due to u_i)				

Source: Authors Computation with STATA-15 using NBE data, 2024

The random effect model told us again only four explanatory variables were significant effect on credit risk .So, loan growth (lags) and ROE had a positive impact on the credit risk whereas bank size and cost efficiency rate had a negative impact on economic growth. The random effect model's variables may not have fully explained the variation in the dependent variable, as indicated by the overall, between- and within-group R-squared values, which are almost less and less significant than the fixed effect model.

4.4.4 The Dynamic Pane Effect Model (GMM-Type)

Dynamic panel model is panel type which considers the putting the output variables as the lag to serve as a response variables.

The dynamic panel model was calculated as shown below:

$$NPLs\ (CR_{it}) = \beta_0 + \delta NPLsi\ (t-1) + \beta_1 SIZE_{it} + \beta_2\ LGR_{\ it} + \beta_3\ LDR_{\ it} + \beta_4 CER_{it} + \beta_5 ROE_{it} + \beta_6 CAR_{it} + \beta_7 ROA_{it} + \beta_8 GDP_{it} + \beta_9 ROI_{it} + \beta_{10} UNER_{it} + u_{it} \quad \textbf{(4)}$$

Where: NPLs: The output variable

δ: intercept

β: constant vector

u_{it}: error component

The Arellano-Bond GMM estimation approach yields efficient, unbiased, and consistent parameter estimations in dynamic panel data regression. The estimation outcomes of the GMM Arellano-Bond one-step estimator are as follows.

Furthermore, the specification test is performed on the dynamic model. The first test is the Sargan test, to determine the validity of the use of instrument variables whose number exceeds the number of expected parameters (over identifying conditions); the hypothesis is as follows:

Table 12: Dynamic Panel Model Estimation

```
Arellano-Bond dynamic panel-data estimation     Number of obs      =        112
Group variable: BankCode                        Number of groups   =         13
Time variable: Year
                                                Obs per group:
                                                              min =          7
                                                              avg =   8.615385
                                                              max =          9

Number of instruments =     65                  Wald chi2(12)      =      46.03
                                                Prob > chi2        =     0.0000
Two-step results
                                 (Std. Err. adjusted for clustering on BankCode)
```

L.NPLR	Coef.	WC-Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
NPLR						
L2.	12.3102	5.276911	2.33	0.020	1.96764	22.65275
L3.	-33.42899	16.20887	-2.06	0.039	-65.19778	-1.660194
SIZE	-73.7877	35.51382	-2.08	0.038	-143.3935	-4.181893
lnLGR	-43.9078	21.63069	-2.03	0.042	-86.30317	-1.512438
LDR	-2.384076	1.177614	-2.02	0.043	-4.692157	-.0759951
CER	.5439353	.2625724	2.07	0.038	.029303	1.058568
ROE	-.7887305	.3869169	-2.04	0.041	-1.547074	-.0303872
CAR	.3511335	.1713715	2.05	0.040	.0152517	.6870154
ROA	1.096126	.5716217	1.92	0.055	-.024232	2.216484
GDP	-1.598728	.8696759	-1.84	0.066	-3.303261	.1058058
ROI	4.43733	2.135415	2.08	0.038	.2519932	8.622666
UNER	15.45297	7.233911	2.14	0.033	1.274767	29.63118
_cons	979.5318	477.0133	2.05	0.040	44.60292	1914.461

```
Instruments for differenced equation
        GMM-type: L(2/.).L.NPLR
        Standard: D.SIZE D.lnLGR D.LDR D.CER D.ROE D.CAR D.ROA D.GDP D.ROI
                  D.UNER
Instruments for level equation
        Standard: _cons
```

Source: Authors Computation with STATA-15 using NBE data, 2024

Here for the heteroscedasticity test, one can use the Sargan test; for the autocorrelation test, one can use the Arrelano-Bond test.

Three of the four assumptions tested in table 11 are found to be met, while the autocorrelation assumption is not. Because of the impact of the dependent variable data lag, this condition frequently arises in models involving time series data. Therefore, dynamic panel data regression analysis—which incorporates the lag factor from the dependent variable data known as the Arello Bond Model—is used to address this autocorrelation problem. The regression model comparison for static panel data and dynamic panel data is as follows:

4.5 Model Selection

Table 12 presents the outcomes of the three distinct techniques for estimating static panel data, and table 12 provides the outcomes of the three distinct techniques for estimating dynamic panel data. The results hold true for all models taken into consideration.

Table 13: Results from the Panel model; 2010–2022 (unbalanced): NPLs

	Pooled OLS estimation		Fixed Effects		Random Effects	
Repressor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	-5.414	0.234	1969.87***	0.000	-8.925658	0.073
NPLs(y_{t-1})	-	-	-	-	-	-
SIZE	1.0520	0.010	4.311	0.000	1.449235	0.002
lnLGR	-0.923	0.000	0.006	0.052	-1.03264	0.000
LDR	-0.0313	0.020	-0.002	0.739	.0166081	0.248
CER	0.011	0.005	-0.01	0.000	.0106913	0.010
ROE	-0.046	0.005	-0.003	0.707	-.0571326	0.000
CAR	0.024	0.152	-0.034***	0.000	.0307168	0.067
ROA	0.002	0.923	-0.003	0.929	-.0052642	0.883
GDP	-0.009	0.939	0.020	0.691	.0011326	0.992
lnROI	-0.125	0.664	0.025***	0.002	-.0862918	0.750
UNER	-0.588	0.185	1.290***	0.000	.1881487	0.673
R-square	32.12%		98.15%		33.10%	
Wald chi2(12)	7.33		773.60		72.69	
F-statistic	0.0000		0.0000		0. 0000	

Note: ***, **, * shows significance on 1%, 5% and 10%, respectively.

Source: Computed by the author based on NBE data computation, 2024

Every model has qualities that are satisfactory. R-squared ranges in value from 32.12% for the pooled OLS estimation model to 98.15% for the fixed effect estimation model. As demonstrated in table 13 for the static model estimate, fixed effect estimation yields the highest R-squared value, accounting for 98.15% of the variation in the independent variable.

The three models—three static models (pooled, fixed, and random) and three dynamic models—show that at least one independent variable influences the dependent variable, and all simultaneous tests are significant, indicating that the model was fit. Two important variables are present in the independent variables that have a significant impact on both the pooled and dynamic models when evaluated from the journal. On the other hand, the dynamic model is the best model with the biggest r-square value when seen from the adjusted R square side. Moreover, the heteroscedasticity assumption autocorrelation test on lag data for the test of serial correlation was conducted using the autocorrelation residuals test, specifically the **estat hettest** test, on the dynamic panel model to determine whether the model is fit.

The two methods were primarily used to highlight the variations and parallels between the models. Calculating these two panel models would improve the significance and correlation robustness of study findings. Furthermore, a dynamic approach would be more comfortable given the cyclical presence of the credit risk structure and the significance of delays of dependent variables in the model.

Every model has qualities that are acceptable. R-squared counts from 98.15% for fixed effect model, to 99% for dynamic fixed effect model. Also, Wald chi(2) test which is the static panel counts as 35.15 with p-value (0.000) whereas the dynamic panel was 46.03, Wald chi(2), implied that dynamic panel was the best for fit model in this research.

Table 14: Results from the Panel (2010–2022) Dependent Variable: NPLs (%)

	Fixed Effects		Dynamic effects (GMM-Type)	
Repressor	Coefficient	p-value	Coefficient	p-value
Constant	1969.87***	0.000	979.531	0.040
NPLs(y_{t-1})	-	-	12.310	0.020
SIZE	4.311***	0.000	-73.788	0.038
lnLGR	0.006*	0.052	-43.907	0.042
LDR	-0.002	0.739	-2.384	0.043
CER	-0.015***	0.000	0.543	0.038
ROE	-0.003	0.707	-0.788	0.041
CAR	-0.034***	0.000	0.351	0.040
ROA	-0.003	0.929	1.096	0.055
GDP	0.020	0.691	-1.598	0.066
ROI	0.025***	0.002	4.437	0.038
UNER	1.290***	0.000	15.452	0.033
R-square	98.15%		99%	
Wald chi2(12)	35.25		46.03	
F-statistic	0.0000		0.0000	
			estat bond test	**0.7380**

Note: ***, **, * indicate significance on 1%, 5% and 10%, respectively.

Source: Author's calculations using STATA 15 output, NBE, 2024

Based on the regression table 16 mentioned above, the model can be represented mathematically as follows:

$$NPLs\ (CR_{it}) = \beta_0 + \delta NPLsi\ (t-1) + \beta_1 SIZE_{it} + \beta_2\ LGR_{it} + \beta_3\ LDR_{it} + \beta_4 CER_{it} + \beta_5 ROE_{it} + \beta_6 CAR_{it} + \beta_7 ROA_{it} + \beta_8 GDP_{IT} + \beta_9 ROI_{it} + \beta_{10} UNER_{it} + u_{it}$$

$$NPLs\ (CR_{it}) = 979.531 + 12.310 NPLsi\ (t-1) - 73.788 SIZE - 43.907 LGR - 2.384 LDR + 0.543 CER - 0.788 ROE + 0.351 CAR + 4.437 ROI + 15.452 UNER$$

Table 16 presented the result of credit risk proxy by NPLs as output variable and SIZE, LGR, LDR, CER, ROE, CAR, ROA, GDP, inflation rate and unemployment rate were as factor variables for selected 13 Ethiopian commercial banks for period from 2010 up to 2022.

The dynamic panel effect estimation result indicates that the null hypothesis, according to Wald-chi (2)-statistics tests, is that all slope parameters (Bi) were jointly zero. The test statistics in the aforementioned situation indicate that the null hypothesis should be rejected even at the 5% level of significance, as indicated by the p-value of zero. This means that credit risk, which is quantified in terms of non-performing loans, was jointly influenced by all the independent factors, including bank size, loan growth rate, loan to deposit ratio, cost efficiency rate, return on equity, capital adequacy ratio, rate of inflation, and unemployment rate.

In a sample of 13 Ethiopian commercial banks, the following factors were statistically significant in relation to credit risk: bank size, loan growth rate, loan to deposit ratio, cost efficiency ratio, return on equity, capital adequacy ratio, rate of inflation, and unemployment rate. In selected Ethiopian commercial banks, bank size, loan growth rate, loan to deposit ratio, and return on equity had statistically significant but negative effects on credit risk, while the output, holding other variables constant, showed that the cost efficiency ratio, capital adequacy ratio, rate of inflation, and unemployment rate had a statistically significant and positive effect on credit risk. In Table 3, the loan to deposit ratio (LDR) coefficient defied previous expectations compiled from various literature sources. Furthermore, in 13 chosen Ethiopian commercial banks between 2010 and 2022, GDP and return on asset did not show a statistically significant relationship with credit risk at 5% level of significance.

4.6 Discussion on Results and Findings

4.6.1 Bank Specific-Factors with Credit

Credit risk was proxy by NPLs ratio which revealed in Tables 14; determinants on the NPLs ratio from the full dynamic panel of 13 Ethiopian commercial banks over the 2010-2022. CER, CAR ROI and unemployment rate indicated that the NPLs ratio reacted positively and significantly to its past own values at the 5% significance. Remind the independent variables, the findings reveal that cost efficiency ratio, rate of inflation, unemployment rate and the capital adequacy ratio are relevant drivers of the NPLs ratio for the Ethiopian commercial banks since the related coefficients were statistically significant at 5% level positively. Indeed, an increase of one unit in cost of efficiency ratio, inflation rate, and unemployment rate and capital adequacy ratio tends to increase the NPLs ratio by 0.543, 4.437, 15.452 and 0.351 units, respectively. Else, a unit change in bank size, loan growth rate, loan deposit ratio and return on equity (bank performance) tends to decrease the NPLs by 73.788, 43.907, 2.384, 0.788 units respectively.

Additionally, the study found a strong and positive correlation between the rate of inflation and non-performing loans (NPLs). This finding suggests that inflation has a beneficial effect on the asset quality of a subset of Ethiopian commercial banks. This data suggests that the effects of rising interest rates brought on by inflation and the generally decreasing economic conditions that accompany rising inflation outweigh any potential benefits for borrowers' ability to service their debt. Therefore, the researcher's finding was consistent with Nikola Radivojevic (2017) but not consistent with Jovovic (2014). The rate of inflation and non-performing loans (NPLs) showed a positive but minor link, according to her findings. Additionally, the rate of NPLs and NPLs (yt-1) showed a strong positive correlation. The result was consistent with the earlier findings. The explanation could be that the debtors' creditworthiness declined during the observed period, but they were able to borrow money only at higher lending rates, which added to the rise in NPLs and the NPLs rate; in all specifications, there was a positive and significant correlation between the NPLs (yt-1) and the NPLs rate. The literature supports this result, emphasizing the dynamic persistence of NPLs across the examined period.

Ethiopian commercial banks return of asset indicator had positive relation with NPLs but not statistically significant with credit risk. The ROA ratio was positive with insignificant at the 5% significance level, suggesting a correlation between the bank's declining performance and rising credit risk. This demonstrates that Ethiopian commercial banks prioritize income diversification above responding to income generation. This finding was in line with and supported in the previous study by Mohammed Adem (2022) in credit risk factors in commercial banks of Ethiopia.

4.6.2 Macro-Economic Factors with Credit

The results showed that the amount of non-performing loans (NPLs) is influenced by macroeconomic variables, specifically the rate of unemployment and inflation. One important metric for identifying non-performing loans (NPLs) in the consumer lending portfolio is the inflation coefficient. Regarding the research conducted by Lobna Abid et al. (2019) and Mohammed Adem (2022), this discovery aligns with earlier findings. This is explained by the fact that, in Ethiopian commercial banks, a decline in the inflation rate has a favorable effect on debtors' financial circumstances and ultimately leads to loan payback, explaining the positive correlation between inflation and non-performing loans which inflation have time effect on NPLs.

As the unemployment rate's p-value is 0.033, below the 5% significant level, it is determined that the rate has a substantial impact on credit risk in the at time effect in Ethiopian commercial banks. The coefficient further strengthens the relationship between credit risk and unemployment rate. This suggests that credit risk would rise along with the unemployment rate. This conclusion was confirmed by the Kek S. et al. (2020) study on Malaysian credit risk drivers.

Lastly, GDP and NPLs have negative relationship showed by the result. As there was down turn in economic growth NPLs would have high inflated results. This finding suggests that an inclined in NPL ratio would decreases GDP growth from time period 2010 – 2022 in Ethiopian commercial banks. A unit change increase in NPLs counts to decrease an effect by 1.598 % had effect on GDP. But GDP is statistically insignificant with NPLs at 5% value level. The result reveals that GDP has no time effect on NPLs IN Ethiopian commercial banks. So, this finding is compatible with the last few years' investigation done by Junkyu L. and Peter R. (2019) on NPLs in Asia.

CHAPTER FIVE

5. CONCLUSION AND RECOMENDATION

This chapter concludes with conclusions and suggestions derived from the factual results. Three subsections were mentioned by the author. The study's conclusion was covered in the first section, recommendations were considered in the second, and additional research was discussed in the third section, which concluded with sections based on the research paper's findings.

5.1 Conclusion

With a sample of 13 Ethiopian commercial banks, we used dynamic panel model analysis to investigate the factors influencing the NPL ratio in this research. The panel data approach is used to investigate the factors that lead to non-performing loans (NPLs) between 2010 and 2022. The majority of the research's findings are consistent with those of numerous other authors' studies.

Every variable that was taken into account for our experiments was split into two groups. Macroeconomic factors were included in the first group, and bank-specific variables were included in the second. Among the macroeconomic factor factors, the impact of GDP, inflation rate, and employment rate were examined. The impact of bank size, loan growth rate, loan to deposit ratio, cost-efficiency ratio, capital adequacy ratio, return on equity, and return on asset were among the factors that were tested for their particular banks.

It appears that bank-specific factors are more significant in determining credit risk, with six of the seven variables deemed statistically significant. The model's findings imply that credit activity has a negative effect on the quantity of NPLs. The study's findings show that, with 5% of level, there is a positive and statistically significant correlation between credit risk and the capital adequacy ratio (CAR). According to this finding, the credit risk would rise by 0.351 for every unit that the capital adequacy ratios of a certain Ethiopian commercial bank were raised. The findings also demonstrate that, at the 95% confidence level, the coefficient of cost efficiency ratio (CER) variable in credit risk has a positive and statistically significant impact. Accordingly, there would be a 0.543 rise in credit risk for every unit increase in the operating expense to operating income variable.

Bank size and credit risk showed a negative link, and there was a strong relationship between 95% confidence levels and credit risk. The findings indicate that a one unit change in the GDP would result in a 73.788 reduction in credit risk. This demonstrates that there was a negative correlation between credit risk and bank size. According to this inverse relationship, credit risk decreases with bank size. This outcome is consistent with the research conducted by Kek S. et al. (2020), who also discovered a negative correlation between bank size and credit risk. Larger banks are more exposed to default risk than smaller banks, according to Bardhan and Mukherjee (2019). In addition, larger banks than smaller ones will have greater capital to cushion the credit risk.

The study unequivocally demonstrates that macroeconomic factors, specifically the unemployment and inflation rates, have a significant beneficial impact on the amount of non-performing loans. Additionally, the results of this study indicate that the rate of inflation (ROI) has a significant deterministic function for the percentage of non-performing loans (NPLs), demonstrating a clear correlation between the non-performing loans of particular Ethiopian commercial banks and the quality of bank assets. This result is consistent with the findings of Drs. Jamel et al (2022). Considering this, inflation should generally make the NPLs worse. Elevated inflation raises interest rates and reduces borrowers' ability to repay. These findings align with previous research, including those of Koju et al. (2019), Lee et al. (2019), and Ali Burhan et al. (2021).

Lastly, unemployment was the second macroeconomic factor that was employed to assess credit risk. The dynamic effect model research revealed that the credit risk is impacted by the statistically significant unemployment rate. The unemployment rate and credit risk were positively correlated. This is due to the fact that high unemployment indicates that there are more people without jobs, which raises the credit risk because these individuals lack a steady source of income to pay their debts. This showed that there was time effect in Ethiopian commercial banks between unemployment rate and credit risk. These results were also reported by Kek S., et al. (2020), who discovered that a high unemployment rate statistically significantly distorts credit risk.

This study presents macroeconomic and bank-specific factors that affect the credit risk of a subset of commercial banks in Ethiopia. The study is distinct from others since it used the dynamic panel model technique; the findings indicate that the lagged NPLs ratio, which attempted to reduce the presence of lags by using the dynamic panel model, has a highly significant and favorable effect.

5.2 Recommendations

The following outlets have been recommended by the study based on its findings:

Author recommends that National Bank should focus on minimizing rate of inflation as main homework since high inflation would aggravate NPLs ratio for Ethiopian commercial banks. Ethiopian commercial banks do have deep pervious financial statement information on borrowers about credit history by credit risk management team take as advantage to minimize the NPLs ratio. So, minimizing the ratio of NPLs, especially as credit information gives a database that identifies the bank to overlook accurate selection of customers before granting credit.

Ethiopian commercial banks should adopting strategies mechanism teams to settle credit risk concede with the country's economic status like GDP, unemployment rate, inflation rate which were increase the NPLs ratio. By putting well internal risk rating system to credit rating the Ethiopian commercial banks must specify innovative mechanism for bank's target for repayment. In addition, banks better focusing on well-established procedure for taking on new credit as well as for modifying, renewing, and re-financing current credit. Adopting system that shows flagging warning that consider the factors affecting the NPLs ratio.

5.3 Additional Research

Finally, more research on the variables influencing credit risk on Ethiopian commercial banks is required. This study just looks into the previously listed parameters; however, there might be more elements that affect credit risk, such as management and policy studies in the region with more advanced economical modeling systems based on primary data sources from individual banks. Furthermore, there can be unreported information on credit risk from stakeholders and borrowers on the client side.

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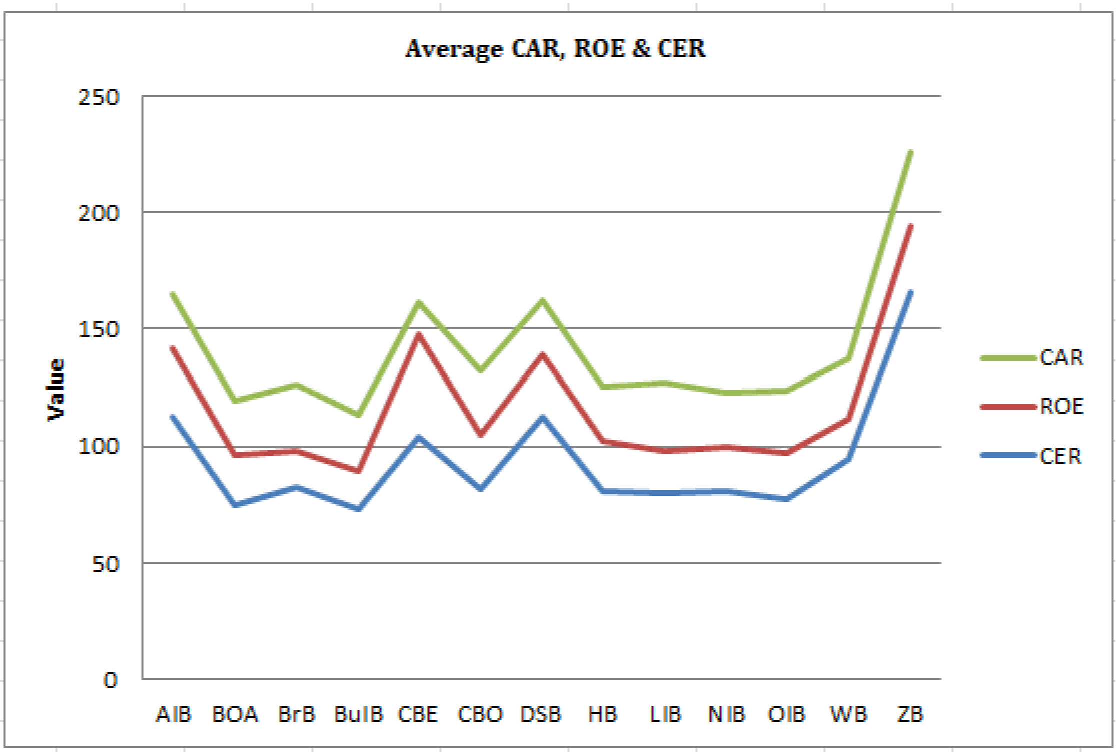
Appendix

1. **Table 15:** Simple Descriptive Summary Statistics of STATA-15 output for Macro-Economic Variables

Year	GDP	ROI	UNER
2010	10.6	6.821932	2.34
2011	11.4	27.55937	2.31
2012	8.7	17.2269	2.29
2013	9.9	6.881769	2.25
2014	10.3	7.803627	2.41
2015	10.4	9.458352	2.57
2016	8	14.15815	2.73
2017	10.1	14.36448	2.9
2018	7.7	13.25492	3.06
2019	9	17.7309	3.22
2020	6.1	19.76212	4.13
2021	6.3	25.39249	3.93
2022	6.4	29.78	4.02
Total	8.838462	16.16885	2.935385

2. **Figure 6:** Average summary of capital adequacy, return on equity and cost efficiency ratio of Ethiopian commercial banks from 2010 - 2022



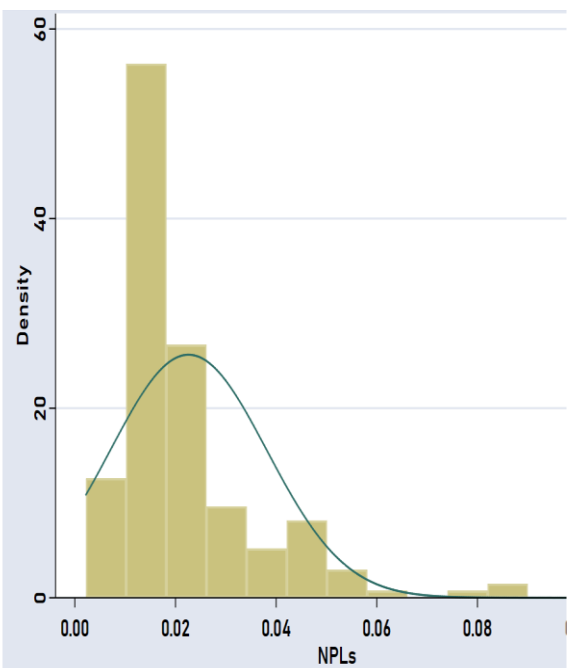
3. **Table 16:** Summary Statistics the Dependent Variables and Independent Variables of Ethiopian Commercial Banks from 2010 - 2022

```
summarize NPLR SIZE lnLGR LDR CER ROE CAR ROA GDP lnROI UNER
```

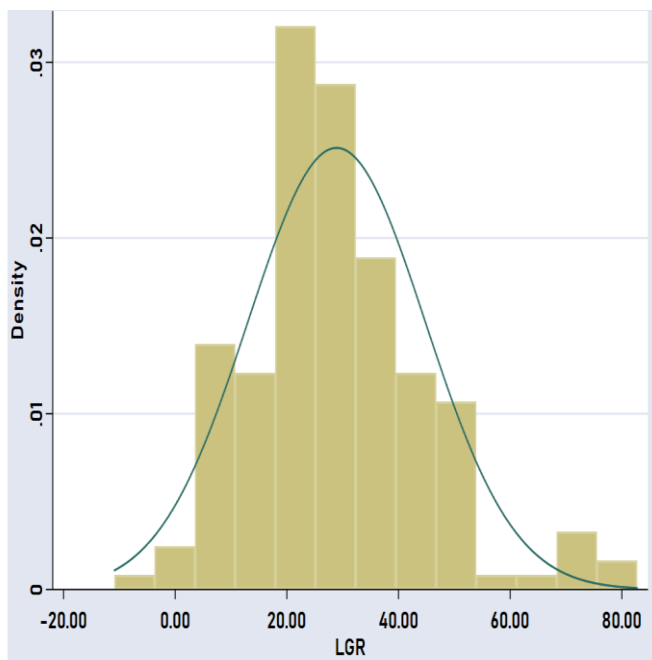
Variable	Obs	Mean	Std. Dev.	Min	Max
NPLR	169	2.25944	1.555965	.2213853	10.59816
SIZE	169	10.2358	.6416879	8.57924	12.06355
lnLGR	166	3.239321	.572286	1.237705	4.415533
LDR	169	64.53959	12.89086	37.33804	97.96808
CER	169	94.00061	53.71258	1.392272	283.0768
ROE	169	22.99246	11.1638	.0413951	77.70858
CAR	169	24.79407	12.96243	4.362479	57.89314
ROA	169	3.844697	4.035797	.0413951	22.87688
GDP	169	8.838462	1.734764	6.1	11.4
lnROI	169	2.669239	.4904939	1.920143	3.393837
UNER	169	2.935385	.6684363	2.25	4.13

4. **Figure 7:** Distribution Figure for each Variables (2010-2022)

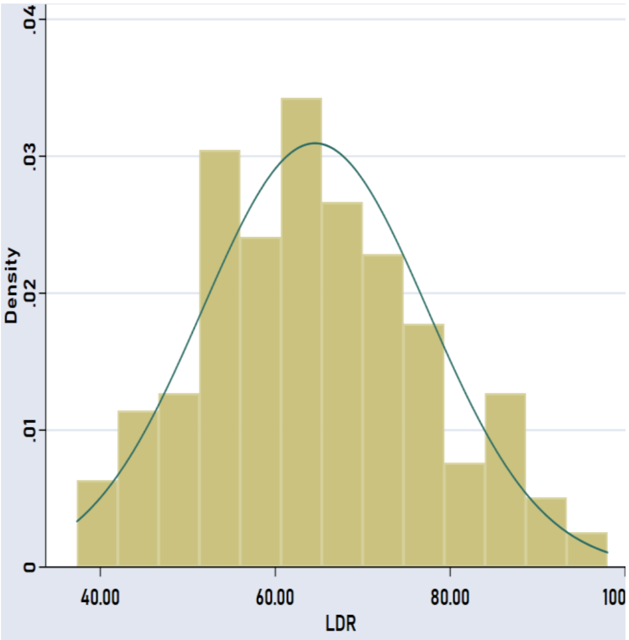
A. Distribution of NPLs (2010-2022)



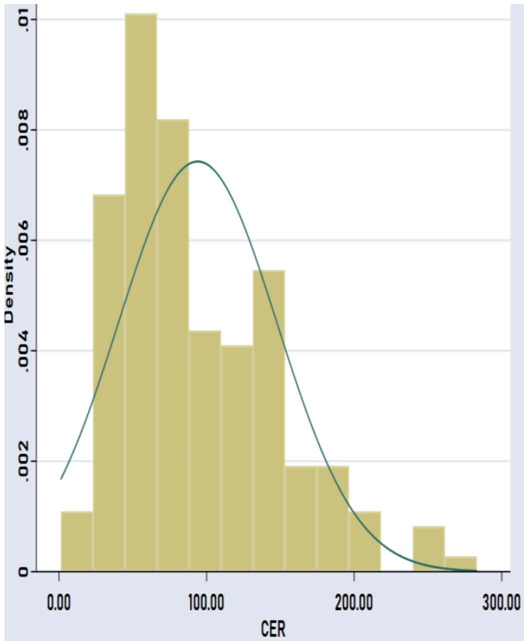
B. Distribution of LGR (2010-2022)



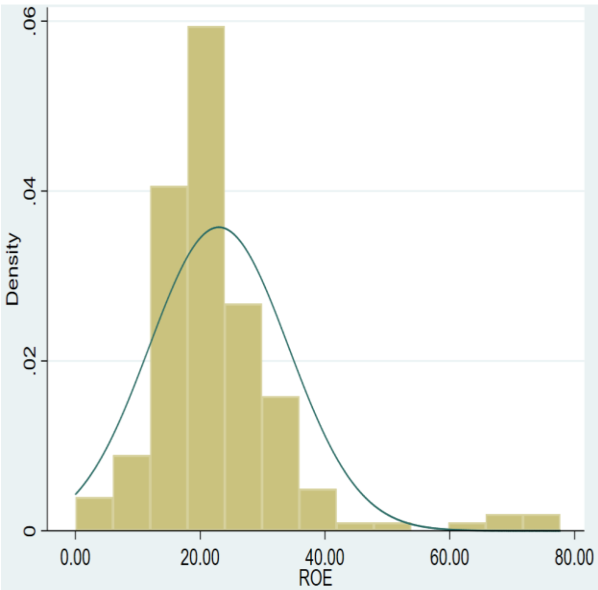
C. Distribution of LDR (2010-2022)



D. Distribution of CER (2010-2022)



E. Distribution of ROE (2010-2022)



F. Distribution of CAR (2010-2022)

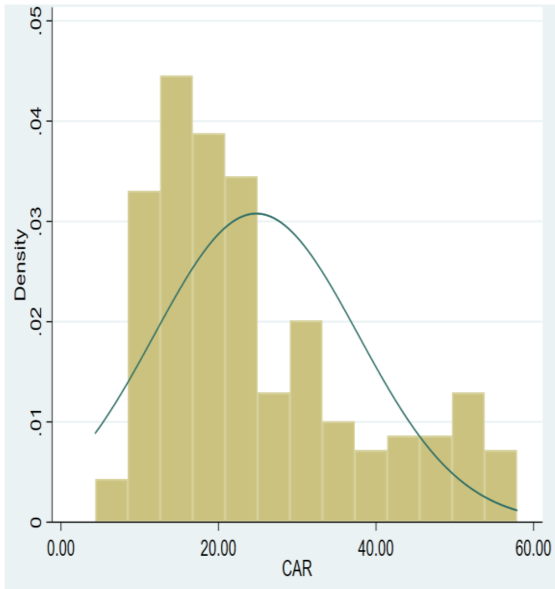


Table 18. Normality Test for Pooled OLS estimation

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	
NPLR	169	0.0000	0.0000	10
SIZE	169	0.1747	0.1525	
LGR	169	0.0001	0.0121	2
LDR	169	0.1821	0.2172	
CER	169	0.0000	0.1003	2
ROE	169	0.0000	0.0000	9
CAR	169	0.0000	0.9865	2
ROA	169	0.0000	0.0000	14
GDP	169	0.0906	0.0000	10
ROI	169	0.0231	0.0000	3
UNER	169	0.0003	0.0000	3