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MASTERS OF BUSINESS ADMINISTRATION (MBA)
Concentration in Finance

Impact of Diversification on Bank Performance: Empirical Evidence from Ethiopian Private Commercial Banks

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Masters Thesis

June, 2024

Addis Ababa, Ethiopia

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A Masters Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of Masters of Business Administration (MBA) with Concentration in Finance

Advisor: Habtamu Berhanu (PhD)

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STATEMENT OF DECLARATION

I, Abel Betru Nedessa, hereby declare that the present masters thesis titled "Impact of Diversification on Bank Performance: Empirical Evidence from Ethiopian Private Commercial Banks" submitted in partial fulfillment of the requirements for the degree of Masters of Business Administration (MBA) with concentration in Finance to the Graduate Program of the College of Business and Economics of Addis Ababa University done with the advice and guidance of my advisor Habtamu Berhanu (PhD) is my own original work, which has not been previously submitted at this or any other university, and that all references to other authors' works have been duly acknowledged.

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STATEMENT OF CERTIFICATION

This is to certify that this present masters thesis titled "Impact of Diversification on Bank Performance: Empirical Evidence from Ethiopian Private Commercial Banks" submitted in partial fulfillment of the requirements for the degree of Masters of Business Administration (MBA) with Concentration in Finance to the Graduate Program of the College of Business and Economics of Addis Ababa University complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

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LIST OF ACRONYMS

CAPM	Capital asset pricing model
CML	Capital market line
FGLS	Feasible generalized least squares
GDP	Gross domestic product
GLS	Generalized least squares
GMM	Generalized method of moments
HHI	Herfindahl–Hirschman index
IAS	International Accounting Standard
IFRS	International Financial Reporting Standard
IMF	International Monetary Fund
LLP	Loan loss provisions
MPT	Modern portfolio theory
MPV	Market power view
NBE	National Bank of Ethiopia
NIM	Net interest margin
RBV	Resource based view
ROA	Return on assets

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ABSTRACT

The objective of this study was to examine the impact of income and loan portfolio diversification on bank performance among private commercial banks in Ethiopia. For attaining this research objective, the study followed a quantitative research approach and an explanatory research design. Thus, data was collected for both independent and dependent variables: measures of bank income and loan portfolio diversification, and measures of bank performance from 16 private commercial banks for the study period 2017 to 2022. The study used econometric models to examine the impact of income and loan portfolio diversification on banks' performance. The study found that income diversification into interest and non-interest income sources positively impacts profitability and reduces bank risk. The overall impact of income diversification on bank performance was found to be positive and statistically significant. The study also found that non-interest income diversification into fees and commissions income and other non-interest income sources has a negative impact on profitability and increases bank risk. The overall impact of non-interest income diversification on bank performance was found to be negative and statistically significant. With respect to loan portfolio diversification, the study found that naïve loan portfolio diversification was found to have a negative impact on profitability and bank risk. Similarly, loan portfolio diversification against the loan market benchmark portfolio was also found to have a negative impact on both profitability and bank risk. The overall impact of naïve loan portfolio diversification and loan portfolio diversification against the market benchmark portfolio on bank performance was found to be indeterminate without deciding what is considered an efficient trade-off between profitability and credit risk.

Keywords: Income diversification, loan portfolio diversification, bank performance, bank profitability, bank insolvency risk, bank credit risk

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

Financial institutions, commercial banks in particular, play a key role in the allocation of financial resources in an economy. Financial institutions serve as intermediaries transferring funds from surplus units (lenders) to deficit units (borrowers) who often possess greater productive opportunities or need short-term financing to help bridge the gap between their cash outflows and their expected cash inflows (Luu et al. 2021). The existence of banking institutions is linked to their ability in mitigating a host of issues that arise in the allocation and management of funds in an economy. In the absence of banks, flow of funds would be subject to problems such as informational asymmetries and greater monitoring, transaction and contracting costs between lenders and borrowers (Freixas & Rochet, 2023).

Banks help solve these problems. Banks are better monitors of borrowers than individual lenders (Heitz et al., 2022). Thus, banks take on the delegated role of monitoring the enforcement of loan contracts with borrowers, as they possess cost advantages at collecting information on creditworthiness of borrowers and monitoring the enforcement of loan contracts (Matthews et al., 2023). Without banks, the lenders (savers), which are fragmented and often largely dispersed, would need to each individually monitor the borrower and incur costs in setting up contracts with the borrower (Luu et al., 2021). This results in substantial inefficiencies as monitoring effort and transaction costs are unnecessarily duplicated. There would at least be less effective monitoring directly or in the extreme case a free-rider issue where no lender is monitoring. With bank as an intermediary, surplus units can delegate monitoring. Since banks have economies of scale advantages over small savers, the average monitoring and transaction costs are lowered.

Further, information obtained by the bank for monitoring purposes can be used in the future to reduce information asymmetries (moral hazard and adverse selection) and transaction costs are reduced. In addition, bank solve the issue of maturity and liquidity mismatch (Greenbuam et al., 2019). Banks holds assets with longer maturity than their own liabilities. Banks also avails assets more liquid to borrowers as it hold more illiquid assets itself. Overall, a banking industry allows an economy to run more efficiently, reduces the percentage of savings reserved as “unproductive liquid assets”.

In the last few decades, advances in information and communications technology, and increased competition have weighed their influence on the banking industry (Cardillo et al., 2021). As a result of these competitive pressures and technological opportunities, several banks have incorporated these new technologies and have extended the scope of their activities forming new business lines (Luu et al., 2021). These technological advances have given more emphasis to non-interest income activities at banks. This is resulting in the altering of bank production and distribution processes and bringing about large growth in the share of non-interest income besides traditional interest based income.

Among the dimensions of diversification accessible to banks are income diversification and loan portfolio diversification. In income diversification, banks expand their sources of revenue from traditional loan based interest income activities to various non-interest based income activities such as fees and commissions income (Cardillo et al., 2021). In loan portfolio diversification banks distribute their lending activities across several industries (Shim, 2019). Thus, banks end up diversifying away industry specific risks by holding portfolios of a number of loans across several industrial sectors.

Proponents of diversification point to the advantages of diversification in improving bank profitability and reducing bank risks. With respect to profitability, diversification allows firms to leverage their existing knowhow and management expertise to obtain profits from new business activities (Cardillo et al., 2021). Further, diversification can provide economies of scope benefits by leveraging excess capacity in production facilities or human capital and using it in other production processes at very small to no added cost (Datta, 2017). With respect to reducing risk, diversification can help minimize risk by avoiding investments that are highly correlated with one another such as those within the same industry and allowing firms to arrive at a set of investments with minimum risk (Western, 2020).

Although, the above proponents of bank diversification argue that diversification can improve profitability and minimize risks, critics of bank diversification emphasize the downside of diversification. For instance, Blickle et al. (2023) argue that banks that concentrate on certain economic sectors might be more efficient compared to more diversified banks that overstretch themselves in attempting to develop expertise across several economic sectors. In addition, agency theory considers diversification schemes as a means by managers to entrench themselves in firms and increase their compensation, power and prestige, while resulting in resource wastage, and reducing a firm's returns (Doğru, 2018). Consequently, with the presence of theories that support diversification and those that criticize diversification, the overall impact of diversification on bank performance is a subject of debate.

1.2. Statement of the Problem

The question of optimal allocation of resources to maximize profitability and reduce exposure to risk is a key problem facing financial institutions (Jiang et al., 2021; Mittal & Pradesh, 2020). The choice of whether to diversify limited resources or to specialize resource allocation to particular activities stands between better bank performance and increased bank risk and decreased profitability. Over the last few decades, advances in information and communications technology and increased competition present new opportunities as well challenges to the banking industry (Cardillo et al., 2021). To reap the benefits of the opportunities and neutralize the impact of challenges, banks need to solve the problem of efficient resource allocation: whether to diversify or to specialize.

In the case of Ethiopia, Ethiopian financial institutions face various risks due to the state of the global economy, with multiple macroeconomic shocks implied by the weakening of global growth along with high food, fuel and other commodity prices (National Bank of Ethiopia, 2024). Consequently, there are increased risks for financial institutions in the country. One of the solutions proposed to reduce the possibility of risk faced by banks is the diversification of loans to a variety of customers (Dean et al., 2020). This suggests that as global export and import markets face shocks (as it has in recent years with the conflict in Ukraine and the COVID-19 pandemic), banks that have a diversified loan portfolio across several sectors including domestic trade are likely to better perform than banks that are overexposed to the import/export sector. However, others argue that in times of uncertainty banks will do well if they specialize their lending to certain sectors (Blickle et al., 2023). The rationale behind is that repeated lending to a specific economic sector allows banks to be better evaluators of the business models, borrower collateral and the performance in that industry. Accordingly, having superior knowledge (i.e. an informational advantage) in a specialized sector will help boost bank profitability and reduce risk exposure by selecting better borrowers even in uncertain times. As both arguments (diversification and specialization) have merits, the problem of whether or not to diversify remains unresolved for banks.

When looking to the literature to find an answer, theories exist that suggest the positive impact of diversification (modern portfolio theory, resource based view, synergy and economies of scope view) and those that suggest the negative impact of diversification (agency theory). Similarly, empirical studies do not offer a resolution. Whereas empirical studies such as Calmès and Théoret (2021), Ferreira et al. (2019), and Shim (2019) suggest the positive impact to be gained from diversification, other empirical studies such as Kusi et al. (2020), Nguyen (2019), and Duho et al. (2020) suggest that diversification has a negative impact on bank performance. Accordingly, the problem of whether or not to diversify remains unresolved for banks.

In addition to the disagreements existing in theoretical and empirical studies, in the case of developing countries like Ethiopia, there has been very little research done on the topic of diversification such as Ketema (2020) (which found that income diversification had a positive impact on bank performance), Meressa (2017) (which found that loan advances to the manufacturing, import/export, and domestic trade/service sectors had a positive impact on bank profitability), and Meressa (2018) (which found the positive impact of loan portfolio diversification on both bank profitability and risk adjusted returns). Accordingly, the author has found only a very few studies on the impact of income and loan portfolio diversification in the Ethiopian banking industry. This is a concern since the Ethiopian banking industry has regulatory, institutional, and market differences from other study areas that are well represented in the existing empirical literature.

With multiple macroeconomic shocks, weakening of global growth and internal instability (National Bank of Ethiopia, 2024), Ethiopian banks face the problem of resource allocation, either to diversify or to focus and specialize their resources and activities, so as to successfully navigate the global and internal risks and increase their profitability. The presence of the above contradictory theories and empirical evidence and the limited studies available in the Ethiopian context indicate that the problem of whether or not to diversify remains unresolved. It is, therefore, needed to conduct further studies to shed more light on the problem. This is needed so as to add to the existing body of literature and better inform industry practitioners including bank management (who make decisions on whether or not to engage in diversification).

1.3. Research Questions

The purpose of this research is to employ econometric models to assess the impact of income and loan portfolio diversification within the Ethiopian private commercial banking industry. The main research questions are:

i. How does income diversification effect bank performance among private commercial banks in Ethiopia?
ii. How does loan portfolio diversification effect bank performance among private commercial banks in Ethiopia?

1.4. Objectives of the study

1.4.1. General Objective

The general objective of this study is to examine the effect of diversification on bank performance among private commercial banks in Ethiopia.

1.4.2. Specific Objectives

The general objective is decomposed into the following specific objectives:

- To examine the effect of income diversification on bank profitability among private commercial banks in Ethiopia
- To examine the effect of income diversification on bank risk among private commercial banks in Ethiopia
- To determine the effect of non-interest income diversification on bank profitability among private commercial banks in Ethiopia
- To determine the effect of non-interest income diversification on bank risk among private commercial banks in Ethiopia
- To examine the effect of naïve loan portfolio diversification on bank profitability among private commercial banks in Ethiopia

- To examine the effect of naïve loan portfolio diversification on bank risk among private commercial banks in Ethiopia
- To determine the effect of loan portfolio diversification against a market benchmark portfolio on bank profitability among private commercial banks in Ethiopia
- To determine the effect of loan portfolio diversification against a market benchmark portfolio on bank risk among private commercial banks in Ethiopia

1.5. Research Hypotheses

For the purposes of attaining the research objectives of the study, the following research hypotheses have been developed.

H_1: Income diversification has a positive and significant impact on bank profitability.

H_2: Income diversification has a negative and significant impact on bank risk.

H_3: Non-interest income diversification has a positive and significant impact on bank profitability.

H_4: Non-interest income diversification has a negative and significant impact on bank risk.

H_5: Naïve loan portfolio diversification has a positive and significant impact on bank profitability

H_6: Naïve loan portfolio diversification has a negative and significant impact on bank risk.

H_7: Loan portfolio diversification against market benchmark portfolio has a positive and significant impact on bank profitability.

H_8: Loan portfolio diversification against market benchmark portfolio has a negative and significant impact on bank risk.

1.6. Significance of the Study

Studies on the impact of diversification on bank performance in Ethiopia are very scarce apart for a few studies: Ketema (2020) (examined the impact of income diversification on bank performance on a sample of 17 Ethiopian commercial banks for the period 2014 – 2018 and found that income diversification had a positive impact on bank performance), Meressa (2017) (assessed the impact of bank loan distribution on bank performance for the period 2010-2016 and found that loan advances to the manufacturing, import/export, and domestic trade/service sectors had a positive impact on bank profitability), and Meressa (2018) (examined the impact of loan portfolio diversification on bank performance for the period 2012 to 2016 and found positive impact of loan portfolio diversification on both bank profitability and risk adjusted returns). This observed lack of adequate empirical literature on income and loan portfolio diversification in Ethiopia calls for more studies to be done.

Moreover, the present study, unlike previous studies, disaggregates components of non-interest income into components such as fees and commission income and other non-interest income activities to investigate the impact of non-interest income diversification (i.e. diversification across non-interest income activities). This is, in addition, to the investigation of the impact of income diversification between interest and non-interest income sources. The study uses Herfindahl-Hirschman Index to measure income and non-interest income diversification. In studying loan portfolio diversification across economic sectors, the study uses the Herfindahl-Hirschman Index as well as a distance measure (the absolute distance measure to measure diversification in bank loan portfolios against a benchmark index) to examine the impact of loan portfolio diversification on bank performance.

Furthermore, regulatory and institutional differences in the Ethiopian banking industry including the absence of foreign owned banks and the lack of active financial and capital markets makes the Ethiopian banking industry exhibit unique characteristics and distinct features. This calls to question whether existing theories in banking and finance literature and empirical evidence from developed economies and even in emerging economies in Africa can apply to the distinct landscape of Ethiopian banking.

The findings of the study can help fill the gap in existing literature on the impact of diversification in banking in the presence of unique characteristics as in the Ethiopian banking industry. Further, the findings can add to the existing body of knowledge to better inform academics (who conduct research on the banking industry), bank management (who make decisions on whether or not to engage in diversification in their pursuit of better bank performance), and to regulators (who monitor bank activities to ensure a stable financial system).

1.7. Scope of the Study

The scope of this study is set to the examination of the impact of two dimensions of diversification: income diversification and loan portfolio diversification. In addition, the study's examination of the impact of diversification is restricted to two measures of performance: profitability and insolvency risk (or credit risk for loan portfolio diversification). Further, the study assesses the impact of income and loan portfolio dimensions of diversification on bank performance solely for the Ethiopian private banking industry. The study is also restricted to examining the impact of diversification for the study period 2017 - 2022. Thus, the study is restricted to using Ethiopian private commercial banks that have been operating and have data available for the above study period.

1.8. Limitations of the Study

Although the scope of this study is set to the examination of the impact of two dimensions of diversification (i.e. income diversification and loan portfolio diversification), there are other dimensions of diversification such as geographic diversification that have not been examined in the present study.

Further, since required macroeconomic data for the fiscal year ended June 2023 was not yet published by the National Bank of Ethiopia (NBE) in its annual report until March 2024, it was not feasible to include 2023 in the study period for the present study. Additionally, the study period does not included year prior to 2017. The reason for this is that from July 1, 2018, Ethiopian banks have begun to implement IFRS9 (IMF, 2020). And according to IFRS 7:20 (c), "An entity shall disclose either in the statement of comprehensive income or in the notes, fee income and expense" (Deloitte, 2019). Consequently, annual reports of Ethiopian banks published as of year ended June, 2018 (which include comparative information of year ended 2017) disaggregate non-interest income to report fees and commissions income. Thus, for the purposes of consistency in non-interest income classifications and availability explicitly disaggregated non-interest income including fees and commissions income (which is one of the key non-interest income categories used in studies on income diversification (Bustaman et al. 2017; Nisar et al., 2018; Nguyen, 2019) and is required to test two of the study hypotheses (H_3, H_4)), the study sets the period of analysis from year ended June 2017 to year ended June 2022.

In addition, the study's analysis of the impact of diversification is restricted to accounting measures of performance: accounting data based bank performance. While other studies in developed economies and even some developing economies employ market capitalization based measures of performance, this study does not include market based measures of bank performance. The reason for this is the absence of an operating capital market for the trading of bank shares in Ethiopia at the time of the study.

1.9. Definition of Key Terms

Diversification: Diversification for the purposes of this study is defined as an increase in the number of products/services that a firm provides and/or an increase in the number of markets (sectors) served by a firm's products/services.

Income diversification: For the purpose of this study, income diversification is defined as extending bank operations to derive income from non-interest income activities.

Interest income: Interest income is the main source of income for banks generated through their lending activities.

Non-interest income: Non-interest income comprises the range of bank activities that do not rely on interest income.

Fees and commissions income: Banks earn fees and commissions income from a various range of services to their customers. Fees and commission income can include account servicing fees, letters of credit opening fees, income on CPOs (cash payment orders), letter of guarantees issued, and other financial services.

Non-interest income diversification: In this study non-interest income diversification, refers to diversification of income within the components of non-interest income sources: fees and commissions income and other non-interest income.

Loan portfolio diversification: In this study, loan portfolio diversification refers diversification of bank lending into various industries or economic sectors such as agriculture, manufacturing, domestic trade and services, export, import, building and construction, transportation, and others.

Naïve loan portfolio diversification: In this study, naïve loan portfolio diversification is diversification of a loan portfolio in such a way that each sector is allocated an equal share of total loans. It is naïve in the sense, it uses a benchmark portfolio where each sector is assumed to have equal 1/n shares (where n=total sectors) as a reference point for measuring diversification levels.

Loan portfolio diversification against market benchmark: In this study, this refers to a distance measure of loan portfolio diversification by economic sector that is used as a better measure of diversification. As opposed to the naïve portfolio diversification, the distance measure uses the aggregate private bank loan market portfolio as a benchmark of an efficiently diversified portfolio. It measures how far each bank's loan portfolio composition (across economic sectors) is from the aggregate private banking industry loan portfolio composition (i.e. the benchmark portfolio).

1.9. Organization of the Thesis

This study comprises five chapters. The first chapter introduces the study: presenting the background of the study, the problem statement, the research questions, the research objectives, the significance of the study, the scope of the study, the limitations of the study, the definitions of key terms, and the organization of the study. The second chapter deals with the review of existing literature; it proceeds by presenting the existing theoretical foundation for diversification, the existing body of empirical evidence on the topic, the gaps in the literature, and specifies the conceptual framework and the hypotheses for the present study. The third chapter provides the research methodology for the study. The forth chapter presents the summary of the descriptive statistics, correlation analysis, diagnostics tests, regression analysis and discussions. The fifth chapter presents provides conclusion for the study, discusses recommendations and implications of the research findings and suggestions of possible directions for future research.

CHAPTER TWO

2. REVIEW OF LITRATURE

This chapter reviews existing literature on the diversification and performance. The proceeds in two section: review of theoretical literature and review of empirical literature. The former provides the theoretical foundations on the advantages and disadvantages to diversification citing major theoretical perspectives and comprehensive theories on diversification, and the mechanisms through which diversification impacts a firm performance. The later provides a review of empirical studies on the impact of income and loan portfolio diversification. The chapter finishes by summarizing the review of literature, identifying existing gaps and providing the conceptual framework and the hypotheses of the study.

2.1. Theoretical Literature Review

2.1.1. Theoretical Foundations and Perspectives on Diversification

The existing literature of theories on diversification comes from a rich and diverse set of "perspectives and disciplinary paradigms." The following sections of the review of theoretical literature explore the major theoretical perspectives on diversification.

2.1.1.1. Modern Portfolio Theory (MPT)

Modern portfolio theory views diversification primarily from the perspective of the investor. According to modern portfolio theory, the rationale for diversification is risk reduction. Prior to Markowitz (1952), Williams (1938) did not consider the effect of risk when he defined the value of a security as equal to current value of future cash flows. Thus, it would follow from William's work that maximizing expected value from investments can be attained by investing in one stock alone: the one with maximum expected return (Markowitz, 1952). However, these future cash flows are uncertain. Thus, investment decision founded solely on expected return (which assume certainty of future cash flow) cannot explain real or reasonable investor behavior (Markowitz, 1991).

Since investors are concerned with both returns and risk (Markowitz, 1991), diversification comes in to focus as a mechanism for decreasing portfolio risk. Diversification's power to reduce risk comes from the correlation that exists between security returns (Markowitz, 1967). If correlation was not present, then diversification would not enable risk reduction. In reality, some security returns are negatively correlated with other security returns, residual variances among security returns do not equal zero, and even positive correlations are not perfect; this suggests that diversification can enable risk reduction (Lintner, 1965). Particularly, security returns in unrelated industries tend to be less correlated than security returns within an industry (Markowitz, 1967). Thus, better risk reduction through diversification is obtained by avoiding securities that are highly correlated with one another like those within the same industry (i.e., diversifying away from an industry).

Markowitz (1952) provided a formal way of making diversification decisions in building a portfolio by employing the "mean-variance optimization" approach (Markowitz, 1967), which uses (i) individual security returns, (ii) individual security return standard deviations, and (iii) correlations between securities returns as inputs. These inputs are used to construct an efficient frontier: the "set of Pareto optimal expected return, variance of return combinations" (Markowitz, 1991). Pareto optimality, for any point on the efficient frontier, implies that it is not possible to get a higher average return without also sustaining higher risk (standard deviation); and it is also not possible to get a lower risk (standard deviation) without having to forgo returns (Markowitz, 1967).

The works of Lintner (1965) and Sharpe (1964) on the "Capital Asset Pricing Model (CAPM)" expand on Markowitz (1952) and deal with economic equilibrium considering every investor to be a mean-variance optimizer (Markowitz, 1991). Following Tobin (1958), Lintner (1965) and Sharpe (1964) consider the investor with portfolios consisting of investments in a risk free asset and in an efficient combination of risky assets (the market portfolio). At equilibrium, efficient combinations of the risk free asset and the market portfolio be given by a straight line called the capital market line (CML): drawn from the portfolio with a risk free asset alone (no volatility) to a portfolio tangent to the efficient frontier (i.e. the set of point representing a well-diversified/market portfolio) (Sharpe, 1964). The slope of the capital market line (CML), known as the Sharpe ratio, provides the greatest ratio of portfolio return to standard deviation (volatility) (Brealey et al., 2011). The best performing portfolio is the one with highest Sharpe ratio: since it provides the highest expected return for a given level of risk (Lintner, 1965; Sharpe, 1966).

Diversification allows managers to arrive at the “most desirable portfolio”; highest value of return per unit risk (Sharpe ratio) (Lintner (1965). All best portfolios have the same Sharpe ratio and all need to lie on the capital market line; the undiversified portfolio, however, lie beyond the capital market line, reflecting inefficiency; such portfolios gain from further diversification (Lintner, 1965; Sharpe, 1966).

Overall, modern portfolio theory emphasizes the importance of diversification in building an optimal portfolio. Diversification uses the nature of correlation among securities to reduce risk enabling an investor to choose among a “set of efficient risk-return combinations” (Markowitz, 1952). Thus, managers can diversify risk through a careful selection of investments maximizing returns on their desired risk levels.

2.1.1.2. Market Power View (MPV)

This view is focused on how a firm employs diversification to gain and increase market power through anti-competitive tactics. In turn, the gained market power enables the firm to earn uncompetitively high returns. This view claims that diversified firms tend to "thrive at the expense of nondiversified firms not because they are any more efficient, but because they have access to conglomerate power” (Briglauer, 2000). For this power to be substantial the diversified firm must have a greater size than competitors in the industry. This enables a dominant firm to gain entry and expand its market power to other markets (Gribbin, 1976; Briglauer, 2000)

One of the mechanisms through which diversification enables a dominant firm to expand its market power is cross-subsidization. The higher the number of markets that a diversified firm has a leading position in, the higher the chance for the firm to leverage this dominant position to engage in anticompetitive practices. For instance, the firm, can increase prices and make monopoly profits in one market and cross-subsidize the expenses in a market with a greater competitive environment (Hutzschenreuter & Günther, 2006).

Such cross-subsidization can manifest in various forms like predatory pricing (Barney, 2013) Predatory pricing is taken as a lethal weapon accessible to big, diversified business in battle for market power against rivals that are small and less diversified. (Lorie & Halpern, 1970). The impact of such cross-subsidy and predatory pricing can be the driving out of rivals from the subsidized business, which enables the gaining of monopoly returns in the subsidized lines of business also (Barney, 2013). Even though predatory pricing might occur in competitive markets, it cannot be the source of long run gains without the setting up of entry barriers (Gribbin, 1976). In this way, diversification empowers a firm to extend its market power to a number of different businesses.

A second mechanism, in addition to cross-subsidization, where diversification based market power helps a firm is through mutual forbearance (Montgomery, 1994). In the case of mutual forbearance firms facing each other in more than a single market tend to take into consideration rivals' response that can go beyond market boundaries; and knowing their interdependence, businesses act less competitively (Feinberg & Sherman, 1988). Mutual forbearance might even take place for "single-product" businesses that meet each other in a several geographic locations (Bernheim & Whinston, 1990). For instance, in the case of banking, multiple contact by market leader banks in different geographic locations incentivize them to respect existing competitive standards (Solomon, 1970). For diversified firms with multi-market contact, the possible gains to launching a competitive action on a large undiversified enterprise in one market has less consequences, than launching a competitive action on a large diversified firm which can retaliate at multiple market points (Edwards, 1955). It's understood that when competition goes wrong between large diversified firms engaging in multiple markets the consequences might be disastrous. Thus, there is merit in taking a 'live and let live' approach to embrace cooperation and to respect the other firm's priorities of interest for gaining reciprocal respect. Further, Greve (2006) indicates that retaliatory ability of business varies in strength by the number of market contacts existing between the firms. Thus, diversification in to new markets (i.e. increasing the number of market contacts) can deepen the benefits of mutual forbearance

A third mechanism, where diversification based market power helps firm is the recognition of 'spheres of influence' (Bernheim & Whinston (1990). This might manifest in supportive approaches such as avoiding cutting prices in a firms home market to prices below the home market firm's prices, avoiding producing goods that a large diversified company has developed, or avoiding poaching important clients of a large diversified firm (Edwards, 1955). Thus, diversified firms meeting each other in multiple markets can each specialize in a particular subset of the markets; the combined effect being the ability to maintain high prices in multiple markets (Bernheim and Whinston (1990).

The fourth mechanism through which diversification based market power helps firm is reciprocal buying. This is where diversified multi-market firms meet each other and exchange mutual favors becoming sellers and buyers to each other (Edwards, 1955). Such an arrangement of "reciprocal buying" can occur by means of a formal contract or an informal mutual understanding.

Overall, diversification sets up the platform (i.e. the entering multiple markets for multiple contact) that enables market power based mechanisms such as cross-subsidization of underperforming business lines, mutual forbearance with competitors, respect for "spheres of influence" and reciprocal buying as a means of exchanging favors, which result in improved performance, reduced risk of price wars, and increased firm returns.

2.1.1.3. Resource Based View (RBV)

The resource based view argues that diversification is a response of rent-seeking firms to the presence of excess capacity within their factors of production or resources. (Montgomery, 1994). This focus on factors of production has roots in Ricardian economics, which views factors of production especially those in limited supply as sources of economic rent (Barney & Arikan, 2005). These productive factors are the tangible and intangible resources linked to a firm at least semi-permanently (Caves, 1992). These can include brands, technological knowhow, skilled employees, equipment, efficient processes and capital (Wernerfelt, 1984). The resource-based view makes two important assumptions with respect to these resources i) firms that are in the same industry can be heterogeneous with respect to the key resources they have; ii) these resources can be considered to not have perfect mobility to other firms(i.e. heterogeneity can be sustained).

The resource based view argues that, because of these assumptions, business resources are inelastic and are in limited supply; thus, they can serve as bases for earning economic rents (Barney & Arikan, 2005). For instance, even though labor is probably elastic in supply, the supply of very skilled employees can be inelastic. Again even though managers are probably elastic in supply, effective managers capable of leading a well-diversified business can be inelastic.

The resource based view's perspective on diversification is based on a firm's resources and their ability to create and maintain excess returns. Accordingly, the resource based view uses resources as a foundation for answering diversification question of firms. (i) When should firms diversify? Penrose, 1980) (ii) which resources diversification should be based on (Wernerfelt, 1984).

i) The prescriptive on when to diversify, according to Penrose (1980), is whenever there exist “unused productive services” from current resources (i.e.‘free’ services) that can be employed profitably and become sources of competitive advantage. Nonetheless, the possibility of a competitive advantage and excess profits from diversification is impacted by level of competition in an industry and by the cost of developing these unused resources to productive use (Mahoney & Pandian, 1992).

ii) On the question of which resources to base diversification on Barney (1991) points to those resources that have the potential for creating sustainable competitive advantages. This potential of a resource is characterized by four traits Barney (1991). It needs to be (i) valuable: allows the taking advantage of opportunities available to a firm or neutralizes a firm’s threats, (ii) rare: not present in the repertoire of firm's competitors, (iii) imperfectly imitable: not easily or perfectly copied, and (iv) non substitutable: no suitable substitutes.

Accordingly, diversification needs to be based on resources that have potential for creating sustainable competitive advantage. One such resource to base diversification on is “a high quality top management”. A firm that has high quality top management can leverage it to enter into new markets or industries. Top management houses a firm’s dominant logic that is the “learned, problem-solving behavior reinforced by economic success and stored as a shared cognitive map among the top management coalition” (Prahalad & Bettis, 1986). Quality top management and the corresponding “dominant logic” stored as a “shared cognitive map” among the top management team as a base for diversification features high levels of complexity and is not visible, and thus, is difficult for competitors to imitate (Barney & Arikan, 2005). Hence, this can allow a firm to earn sustained economic rent (high profit levels).

In addition, diversification patterns can be guided by a firm’s portfolio of core competences (Prahalad & Hamel, 2006). Core competencies are the “collective learning in the organization, especially how it coordinates diverse production skills and integrate multiple streams of technologies” (Prahalad & Hamel, 2006). In terms of imitability, such core competence are hard to imitate since they involve complex coordination of technologies and production knowhow. Competitors can attain the technologies involved in the core competence; however, it remain difficult to replicate the less tangible aspects of internal harmonization and organizational learning involved. Thus, firms can employ their existing core competencies more fully by diversifying into new ventures to increase their returns on their existing resource base.

Overall, the resource based view's perspective on diversification is that it derives from a firm's need to absorb and leverage excess capacity in its resources, particularly those resources that are "valuable rare, imperfectly imitable, lacking substitutes" as possible sources of economic rents and sustained competitive advantage (Barney, 1991; Penrose, 1980).

2.1.1.4. Synergies and Economies of Scope

According to synergies and economies of scope argument, diversification arises when firms leverage inputs that can be put to multiple uses at minimal if any incremental cost, and where these uses result in synergies. Synergy suggests that "the whole would be greater than the sum of the parts". (Carter, 1977). Hall and Lee (1999) suggest that businesses following related diversification do better than others, because of the potential for shared resources for the different business. Such input sharing can lead to "synergies" enabling a firm to take more benefit from its resources. In this sense, diversification enabled synergy is a manifestation of efficient allocation of firm resources resulting in better performance. The benefits of synergy accrue especially if firm's diversifications are in related businesses which can share production facilities, technologies and knowhow (Hall and Lee, 1999). With synergy through diversification, a firm gains cost advantages known as "economies of scope"(Briglauer, 2000).

A diversified firm can benefit from economies of scope that come from shared inputs without congestion. A firm using inputs that are imperfectly divisible can experience cases where there remains excess capacity in production facilities or human capital that is freely available for use in other production at very small to no added cost (Willig, 1979). In such cases, diversification can come in to play to capture the freely available resource and employ it to use in producing new products.

In the case of a depository institution, diversification can generate economies of scope through the use of a shared inputs such as human capital. Diversification can enable a depository institution better employ specialized labor that is underutilized (e.g. bank tellers and loan officers); it can allow the reduction of per unit cost for the fixed human capital by extending their services across several outputs (Clark, 1988). Also, a diversified depository institution could tap into economies of scope by the shared use of input such as information among a number of outputs. The attainment of information usually requires a fixed, "set-up cost"(Radner, 1970); however, as soon as information is acquired it is available for use in multiple outputs. In a bank, credit information that is acquired and analyzed for lending decisions is freely available for reuse in producing other outputs (Clark, 1988).

Diversification based on economies of scope can also be based on shared use of organizational knowhow, which can be employed in several non-competing applications (Teece, 1980). The marginal cost involved in using knowhow in another output is probably much less than the cost of production. Thus, diversification into new inputs can leverage economies of scope from existing organizational knowhow.

Overall, synergy and economies of scope argument maintains that a firms opportunity to diversify is constrained by the “flexibility, sharability and transferability” of the business' core inputs (Hill, 1985). With shared inputs that are valuable in multiple industries, a firm can benefit from economies of scope by diversifying into multiple products or industries increasing its revenue and reducing its average costs (Barney, 2013).

2.1.1.5. Efficient Internal Capital Markets

According to the internal capital markets hypothesis, diversification can create gains from the efficiency of internal capital markets (Staglianò et al., 2014). Barney (2013) notes that firms can acquire capital in two means. First, firms operating as a single business can seek out capital from external capital markets. Otherwise, a business is part of a larger diversified firm that allocates funds to it internally. The diversified firm, in turn, seeks out capital from external capital markets and allots capital to the different businesses under it. Thus, diversification forms an internal capital market, where business units compete for capital.

The diversification rational, according to Williamson (1975), is the existence of efficient internal capital markets, which feature less transaction costs and where cash flow is allocated competitively to highest return uses.

This provides diversified firms with advantages over undiversified firms with regards to the raising and allocating capital (Purkayastha et al., 2012; Staglianò et al., 2014).

In raising capital, a diversified firm's internal capital markets offers gains in transaction cost reduction (Barney, 2013). A diversified firm has access to complete and accurate information on the real performance of its business units, on their future prospects. These allows a diversified firm to make well informed capital allocations decisions. External capital markets, on the other hand, have less access to information and limited powers to carryout audits (Williamson, 1975). These constrains their ability to see the full picture of a firm's performance and future potentials (Barney, 2013). Thus, internal capital markets offer a diversified firm information with higher quantity and quality as compared to external capital markets. Accordingly, it follows that over time internal capital markets allow for better decision making.

Further, in allocating capital, a diversified firm's internal capital markets create a competitive setting for the various investment projects (Stein, 1997). In the absence of internal capital markets, information asymmetries enables managers to act opportunistically. Shareholder are also limited in their ability to take disciplinary action on management due to high transaction and monitoring costs (Purkayastha et al., 2012; Williamson, 1975).

In contrast to external capital markets, the diversified firm, which functions like an internal capital market, has detailed information on business units and has in place auditing systems which enable effective monitoring of divisional managers (Purkayastha et al.; 2012). Further, it provides the diversified firm the ability to move capital in the firm to areas where it can bring highest returns. (Stein, 1997). Specifically, the degree to which a project obtains funding in the internal capital market is subject to the firm's merits as well as its relative merits compared to other projects.

Hence, internal capital markets not only reduce transaction costs in raising capital, but also provides a diversified an efficient competitive setting for capital allocation (Purkayastha et al., 2012; Stein, 1997). Overall, a diversified firm with an internal capital market is superior to an external capital market raising and allocating capital and reducing transaction costs.

2.1.1.6. Agency Theory

Agency theory considers diversification through the lens of the agency relationship between firm managers and shareholders. This agency relationship is filled with conflicts of interests (Jensen, 1986).

Assuming that both sides of the relationship seek to maximize their personal utility, it reasonably follows that the agent might not at all times act in accordance with the principal’s best interest (Jensen & Meckling, 1976). Thus, in firms where the owners are not themselves managers there can arise deviations of interests between managers and owners. Whereas owners (shareholders) seek consistent dividend income as well as a slow capital gain in the firm’s stock, managers seek to maximize total lifetime income gain, leisure, status, and power (Monsen & Downs, 1965). This divergence causes managers to steer firms away from profit-maximization objectives.

Accordingly, Agency theory views diversification with the suspicion that it is possibly driven by managerial self-interests. Diversification is typically considered an opportunistic quest by current management seeking their own interest at the owner’s expense; if the need were to arise shareholders themselves can individually diversify their existing investment portfolio by purchasing shares in other businesses (Fox & Hamilton, 1994).

One mechanism through which diversification plays into the self-interest of managers is the through the pursuit increase in compensation, power, and prestige (Jensen, 1986). In pursuit of their own personal interest, managers strive to maximize firm growth (within certain profit constraints) extending a firm’s size further that its optimal size (Hill, 1985; Jensen, 1986). Accordingly, diversification helps attain growth objectives. Firm growth, in turn, enlarges the amount of resources under managers’ control. This often comes with greater compensation associated with managing a larger, diversified, and growing firm.

In addition to compensation, being the manager of a larger firm can come with greater power and prestige. Thus, whenever there is excess cash flow, firm managers seeking personal interest such as power and prestige employ diversification (Jensen, 1986). Managers are reluctant to give out the extra cash as dividend payouts, which reduced the assets within their control. Further, if the need for cash arose in any case – having given out excess cash as dividend – they would depend on the external capital market involving greater monitoring by creditors. Managers, thus, opt to employ excess cash flow into value reducing undertakings like diversification.

Additionally, Rose and Shepard (1994) note that diversification can increase manager compensation through entrenchment. Managers of a firm can entrench themselves in the firm through diversifying the firm into activities best suited for their abilities heightening the cost of replacing them as managers. Accordingly, diversification effectively alters the firm’s scope to align with managers specific abilities by implication entrenching current managers making them more crucial for the firm (Rose & Shepard, 1994; Shleifer & Vishny, 1989). This intern allows managers to increase their compensation and decreases their possibility of being replaced. On the other side of the agency relationship, these diversification schemes negatively impact shareholders as it results in greater management compensation, less dividend payout, and possibly less returns in the new diversified venture.

In addition to diversification into areas of a manager’s experience and ability, diversification can also reduce the compensation volatility of managers (Amihud & Lev, 1981). As compensation of is linked to current firm performance, managers seek to reduce their income risk. Thus, a manager who’s risk averse can reduce income risk, by diversifying into other products or markets to help stabilize the firm's revenue stream. Monsen and Downs (1965) add that managers likely seek out product diversification to decrease risks on individual products. And since managers (as compared to owners) tend to have greater aversion to risk with regards to firm revenue, it follows then that “manager-controlled” firms (as compared to “owner-controlled” ones) tend to exhibit greater levels of diversification (Amihud & Lev, 1981).

Overall, Agency theory argues that diversifications schemes derive from agency issues rising from the divergence of interest between owners and managers. The agency view ultimately considers diversification schemes as a means by managers to entrench themselves in firms and increase their compensation, power and prestige, while being “drains of free cash flow”, resulting in resource wastage, and reducing a firm’s returns (Jensen, 1986; Rose & Shepard, 1994).

2.1.2. Bank Profitability

Banks, as financial institutions, produce profit in great measure through managing their portfolio of assets as well as liabilities (Chambers et al., 2022). Banks also engage labor resources and employ (own) capital for their operations, besides selling bank services, which are also included in bank income statements together with income received and expenses incurred in handling their assets and liabilities. Such management of a bank's portfolio of assets and liabilities gives a key element of bank profitability. For a financial institution, income consists of interest income, fees, and commission income as well as trading income and is usually presented net of all directly allocated expenses.

For the purpose of fundamental analysis, financial ratios are used to improve the understanding and the interpretation of bank performance using the relationship between financial performance measures (Ruetschi, 2022). Financial ratios are obtained by dividing a certain financial metric by another metric. With accounting data obtained from bank financial statements, a series of key performance indicators (KPIs) are calculated. These metrics are critical for understanding bank performance through historical comparison for the particular entity or within a peer group of entities. For financial institutions, there are three major financial ratios that are most relevant in measuring financial performance and profitability: the return on assets (ROA), the return on equity (ROE), and net interest margins (NIM) (Chambers et al., 2022; Ruetschi, 2022; VanHoose, 2022). All of these measures are based on bank earnings, profit, or net income, defined as the currency amount by which the bank income from its various activities exceeds the total incurred costs (VanHoose, 2022).

The return on assets (ROA) is an accounting based measure of bank profitability which calculates bank profits as a percentage of the total value of the bank's assets (VanHoose, 2022). The return on assets is considered mainly an indicator of how bank management has been able to convert its available assets into net earnings. The second measure of bank performance, return on equity (ROE), calculates bank profits as a percentage of bank owners' equity capital. This measure is specific to measure the return on capital from the perspective of shareholders' investments in the bank. The third measure of bank performance, net interest margins, calculates profitability with respect to income earned from interest based sources alone as a percentage of the bank's total interest earning assets.

2.1.3. Bank Risk

Bank functions involve risk; banks make profit by taking on and managing risk and these risks can be categorized based on their sources (Matthews et al., 2023). Accordingly, bank risk based on their sources are given as follows: credit risk, insolvency risk, market risk, liquidity risk, and operational risk.

Credit Risk

One key risk that banks face is credit risk, i.e. the probability that a portion of bank loans will fall in value (VanHoose, 2022). It describes the risk of possible default that may occur due to borrowers failing to adhere to their required payments (Ruetschi, 2022). This can include the loss of the principal as well as interest on the principal, disruption of payment cash flows, and greater costs of collection. It is, particularly, related to the borrowers' probability of defaulting on its debt obligations. This probability of borrower default is described as the credit spread that is defined as the spread between a risky asset (with certain probability of default) and a risk-free asset (such as government backed securities which are frequently considered to not have any risk of default).

For the measurement of credit risk, the key measures include the financial ratio of nonperforming loans (which is given by loans that are past due for at least 90 days divided by the bank's total loans) and the ratios of loan loss provisions (LLP) (which is given by the bank's provision for loan loss divide by the bank total loans) (VanHoose, 2022).

Loan loss provisions (LLP) serves as a proxy for bank credit risk. Loan loss provision refer to provisions that are made for bank loans that are nonperforming (i.e. loans that have deteriorated to the point where the payment of interest and principal is in question. In Ethiopia, NBE's "Asset Classification and Provisioning (5th Replacement) Directive No. SBB/69/2018" prescribes the minimum percentage provision requirement for 5 classes of nonperforming loans: 1% and 3% provision requirement of loan amounts for stage I (pass, i.e. "less than 30 days past due date') and stage II (special mention, i.e. "30-90 days past due") respectively. Further, it prescribes provisions of 20% of loan amount for stage III-substandard loans (i.e. "90 to 180 days past due"), 50% provision of loan amount for stage III-doubtful loans (i.e."180-360 days past due") and 100% of loan amount for stage III-loss loans (i.e. "360 days past due"). Accordingly, banks allocate loan loss provisions based on the risk level of their loans.

Insolvency Risk

Insolvency risk refers to the risk of an entity being unable to meet obligations as they are due or when the entity's liabilities outweigh its assets (Ruetschi, 2022). A key concept linked with solvency is "capital adequacy". It refers to the capital base that is required in order to absorb unexpected losses that can possibly result from the risks that a bank currently faces (Robinson, 2020). Solvency problems occur due to losses exceeding capital level. A bank' capital buffer determines the bank's insolvency probability. When a financial institution runs close to insolvency, there is often greater scrutiny over the decisions made by its board of directors and management by both shareholders and stakeholders (Ruetschi, 2022). Problematic decisions, actions, and fiduciary responsibilities might lead to liabilities. A Bank in such a position may also need to be subject to independent audit on its financial situation, the enterprise value and the institution's strategic options so as to maximize the value of all of the bank's assets.

The Z-score metric is frequently employed to measure a bank's insolvency risk and is generally selected due to its simplicity, its intuitiveness, and its requirement of easily obtainable accounting data (Mercadier & Strobel, 2023). Since it only requires accounting data, it can be used whether or not the financial institutions are listed in capital markets. It is also one of the key indicators employed by the World Bank in its "Global Financial Development Database" to measure the soundness of financial institutions (Bouvatier et al., 2023). It is a well-established indicator of bank insolvency risk among academics and has been widely employed to serve as a proxy indicator for bank insolvency risk in empirical analyses (Hafeez et al., 2022).

The fundamental principle behind Z-score as measure is linked to its ability in capturing the key relationship between a bank's capital level and the variability in bank returns, such that it is possible to identify the degree of variability in bank returns that can be absorbed by bank capital without causing the bank becoming insolvent (Hafeez et al., 2022). For these purposes, bank insolvency is generally expressed as $(ROA + CAR) \leq 0$, where ROA is a bank's return on assets and CAR is a bank's equity capital to assets ratio (Bouvatier et al., 2023). If the return on assets (ROA) is assumed to be a random variable which has a "finite mean and variance", the Chebyshev inequality provides the upper bound for insolvency probability as a nonlinear function of Z-score, which is given by $Z \equiv (CAR + ROA) / ROA > 0$. The greater the value of the Z-score, the lower a bank's insolvency risk (Hafeez et al., 2022).

Market Risk

Market risk is defined as the risk of losses due to adverse market movements depressing the values of on and off balance-sheet positions (Ruetschi, 2022). The main factor that is the source of market risk for banks is exposure to changes in interest rates. The major sources of interest risk are interest rate volatility and the maturity mismatch between interest on assets and liabilities (Matthews et al., 2023). Because banks usually have long-term assets with short-term liabilities, an increase in interest rate will decrease their assets' market value more than their liabilities' market value. Accordingly, rise in interest rate will decrease banks net market value. Others factors for market risk include market price changes of foreign exchange, equities, and commodities (Matthews et al., 2023; Ruetschi, 2022). For instance of lending which involve foreign currency, the banks face the risk of foreign currency volatility.

Liquidity Risk

Liquidity risk refers to the risk of being unable to raise cash when needed to meet its ongoing obligations (Matthews et al., 2023; Ruetschi, 2022). The risk can manifest in two forms: funding liquidity and asset liquidity. Funding liquidity risk refers to the banks cash resources and the risk of being unable to borrow and raise additional cash (Ruetschi, 2022). Asset liquidity risk relates to the risk that prices of assets move against the seller including events triggered by the sellers own trades when the market is not able to absorb trades at the current price. Asset liquidity also includes the time and costs involved in transforming an asset position into cash position. This depends on the marketability of a bank's assets, the time needed for their liquidation process, and the inherent liquidity price impact of such selling. Events of extreme lack of liquidity can results in bank failure.

Operational Risk

Operational risk refers to the risk of loss that arises from inadequate or failed systems or internal processes including legal risk (Ruetschi, 2022).Operational risk can also result from malfunctions in a bank's information systems, reporting mechanisms, internal risk monitoring techniques and lack of timely corrective actions to such events. In contrast to market and credit risk, operational risks are typically not voluntarily incurred and are not driven by revenue. Further, operational risks are not diversifiable. That is given that personnel, various systems, and processes are imperfect, operational risks cannot be completely eliminated.

2.1.2. Summary of Theoretical Perspectives on Diversification

Table 1. Summary of Theoretical Perspectives on Diversification

Theoretical Perspective	Key Authors	Theory's rationale on diversification	Overall impact on firm performance
Modern Portfolio Theory (MPT)	(Markowitz, 1952; Lintner, 1965; Sharpe, 1964)	Risk reduction for a given return level Return maximization for given risk level	Results in diversifying away risk & maximizing returns at desired risk levels.
Resource Based View (RBV)	(Penrose, 1980; Wernerfelt, 1984)	Employing underutilized resources Leveraging sources of competitive advantage	Results in economic rents and sustained competitive advantage.
Synergy, Economies Of Scope	(Clark, 1988; Teece, 1980; Willig, 1979)	Sharing inputs without congestion Cost reduction through economies of scope	Results in increased revenue and reduced average costs.
Market Power View (MPV)	(Bernheim & Whinston 1990; Edwards, 1955; Gribbin, 1976; Lorie & Halpern, 1970)	Cross-subsidization Mutual forbearance Recognition of 'spheres of influence' Reciprocal buying	Results in improved performance, reduced risk of price wars, and increased firm returns.
Agency View	(Amihud & Lev, 1981; Jensen, 1986); Rose & Shepard, 1994; Shleifer & Vishny, 1989)	Non optimal expansion Managerial pursuit of power, prestige & compensation Management entrenchment Reduced management compensation volatility	Results in the draining away of free cash flow, wastage of firm resources, and reduction of total gains.
Efficient Internal Capital Markets	(Staglianò et al., 2014; Stein, 1997; Williamson, 1975)	Reduced transaction costs Avoiding information assymetries Competitive capital allocation	Results in an efficient firm with reduced costs & optimal resource allocation.

2.2. Review of Empirical Literature

This section reviews empirical studies done on the impact of income and loan portfolio diversification on bank performance. This helps identify the empirically observed effect of income and loan portfolio diversification on bank performance measures. The section undertakes its review of previous empirical studies according to the following sequenced structure: (i) the relevant income diversification measures and their impact on bank performance, and (ii) the relevant loan portfolio diversification measures and their impact on bank performance. Following the review of empirical studies, the section summarizes previous studies, identifies gaps in literature, and develops the relevant hypotheses and the conceptual framework for the study.

2.2.1. Income Diversification and Its Impact on Bank Performance

2.2.1.1. Studies in the Studies in US, Europe, Asia, and Latin America

In a European study on bank income diversification, Baselga-Pascual et al. (2018) examined the impact of income diversification on return and risk on a sample of banks from 14 European countries for the period 2000 – 2012 using dynamic panel model and system-GMM estimator to address endogeneity issues. The study found evidence that income diversification has a positive and statistically significant impact on bank profitability for European banks. The study, however, did not find corresponding increase in bank risk as the profitability of these banks increased for the study period. A possible explanation for the observed positive impact in European countries could be the regulatory framework and structures in the respective economies. In addition, bank diversification has been common for longer in European countries like Germany; thus, European banks are better experienced in drawing fee based income and reaping the benefits of diversification.

A later US study by Calmès and Théoret (2021) also finds the positive impact of bank income diversification. Calmès and Théoret (2021) employ data from US Federal Deposit Insurance Corporation (FDIC) for US banks for the study period from the fourth quarter of 2001 until the second quarter of 2016. Although, fee business lines is, typically, considered to exhibit greater volatility than traditional lending business and is also considered to have unfavourable tradeoff between risk and return, the results of the study show that non-interest income activities still have a positive impact on US bank performance without causing greater insolvency risks. Using the economies of scope available to them, US Banks appear to benefit from fees based business lines increasing their profitability and reducing bank risk.

Similarly, a study in Brazil by Ferreira et al. (2019) investigated the effect of bank income diversification on the performance of Brazilian banks both in terms of bank risk and return for the study period 2003 - 2014 employing a dynamic panel model using GMM (Generalized Method of Moments) estimation technique to address potential endogeneity. The findings of the study show that non-interest income plays an important role for Brazilian bank performance showing an overall positive effect on bank return as well as risk adjusted returns for the banks studied. Nevertheless, noninterest income diversification also had a positive link with bank risk (but without statistical significance).

Like the above country level study in Brazil, another country level study by Luu et al. (2020) found the positive impact of income diversification on bank performance. Luu et al. (2020) examined the effect of income diversification on bank performance in Vietnam. The study employed data from 39 banks in Vietnam for the study period 2007 to 2017 and used fixed effects and two-step system GMM estimation techniques. The findings of the study show that in the case of Vietnamese banks income diversification has a positive and statistically significant impact on bank profitability only for state owned and foreign owned banks. Further, the result of the study show that banks tended to benefit from income diversification when they have greater level of experience in such diversification activities.

A subsequent Asian study by Hunjra et al., (2021) found similar results to Nisar et al. (2018) with respect to income diversification. Hunjra et al., (2021) examined the effect of diversification on bank risk in emerging Asian economies. The study employed generalized method of moments (GMM) estimation to investigate bank diversification over 116 listed banks in 10 emerging Asian economies for the study period 2010 to 2018. The results of the study showed that diversification, has a significant impact on bank risk. In particular, the study found that diversification into nontraditional bank activities such as those involving noninterest income tended to reduce bank insolvency risk.

Similarly, a cross country study by Wang and Lin (2021) examined the impact of income diversification on bank performance. The study by Wang and Lin (2021) used data from commercial banks from 14 Asia Pacific economies sample for the study period from 2011 to 2016 employing a dynamic panel model with a system GMM estimator. The results of the study showed that greater levels of income diversification were linked with reduced levels of banks risk. In particular for emerging economies, the study's results suggest that as the levels of income diversification got higher the degree of bank risk was lower. These results, however, do not hold true for banks in developed economies in the study sample. For the developed Asia Pacific economies, commercial bank income diversification did not have a statistically significant effect on bank risk.

A cross country study on the ASEAN-4 countries, Bustaman et al. (2017) decomposes the different components of non-interest income to investigate their impact. Bustaman et al. (2017) examined the impact of diversification on banks in the ASEAN-4 (Malaysia, Indonesia, Thailand and Philippines using random effect, System GMM estimation techniques for the period 2006-2012. The study found that diversification into non-interest income from trading can worsen the level of risk for banks. On the other hand, non-interest income from fees and commissions can have a positive impact on bank profitability and reduce levels of risk.

Similarly, Nisar et al. (2018) used cross country data to investigate the effect of income diversification in Asia. Nisar et al. (2018) examined the impact of income diversification on bank performance using data from 200 South Asian commercial banks for the period 2000 to 2014. The study finds that diversification into non-interest based income sources has a positive and significant impact on bank returns and reduces insolvency risk. Further, the study finds that income from fees and commission has a negative effect on bank returns and increases insolvency risk. These results on the impact of fees and commission income are contrary to findings by Bustaman et al. (2017).

A country level study in Vietnam by Nguyen (2019), examined the impact of income diversification on bank risk and profitability for 26 commercial banks in Vietnam for the study period 2010 to 2018 using GMM modeling technique to address endogeneity and autocorrelation issues. The study found that income diversification has a negative effect on both return on assets and return on equity. Further, the study finds that the more diversified a commercial bank, the higher its risk.

In contrast to the results by Nguyen (2019), a country level study by Buyuran and Ekşi (2020) in Turkey found the positive impact of bank income diversification on profitability. The study employed a dynamic panel model on data from 14 banks operating in Turkey for the study period 2010 to 2017 and used the Herfindahl–Hirschman Index to measure income diversification. The results of the study showed that there exists a positive and statistically significant impact between income diversification and bank performance.

Like the previous study by Nisar et al. (2018), Chandramohan et al. (2022) disaggregates non-interest income sources to test their impact on bank performance. Chandramohan et al. (2022) examined the effect of diversification on bank performance on a sample of 48 Indian banks for the study period 2007 – 2017 using dynamic GMM model. The results of the study show that non-interest income from commission based activities has a positive and significant effect on bank stability (reduction in bank insolvency risk). The findings are consistent with results by Nisar et al. (2018).

Similarly an Asian study by Uddin et al. (2022) investigated the impact of income diversification on bank profitability in Bangladesh. Uddin et al. (2022) used a dynamic panel model with system GMM estimation technique on data from 32 Bangladeshi commercial banks for the period 2007 - 2016. The study found that there exists a positive and statistically significant impact of income diversification on bank profitability. The results suggest that banks can increase their profitability by engaging in diversification strategies. The study indicates that Bangladeshi banks remain highly reliant on traditional interest for the majority of their income, the authors suggest that these banks should extend their lines of businesses to non-interest based income activities such as fee income and commission income to increase their profitability.

2.2.1.2. Studies in Africa

In a study in Tunisia, Alouane et al. (2022) examined the impact of income diversification on the performance of banks using data from Tunisian listed banks for the period 2008–2017. The study found evidence that greater levels of income diversification increased bank profitability, but this come at the cost of increased levels volatility in non-interest income revenue streams. In addition, the study found that concentrated banks ownership tended to moderate the impact of bank income diversification. Further, the study shows that banks with diversified income and concentrated ownership had less risk

A study on African banks by Sissy et al. (2017) found the positive impact of income diversification. Sissy et al. (2017) investigated the impact of income diversification on bank performance on a sample of 320 banks in 29 African countries for the period 2002 - 2013 using System GMM technique to address endogeneity. The results suggest that income diversification across and within business lines has a positive impact on risk-adjusted profitability measures. However, income diversification did not explain changes in bank risk for the sample of African banks in the study. These findings are consistent with findings from Europe by Baselga-Pascual et al. (2018), and from Asia by Nisar et al. (2018).

In contrast, a country level study in Kenya by Mulwa and Kosgei (2016) contradicts the results by Sissy et al. (2017). Mulwa and Kosgei (2016) examined the impact of diversification on data obtained from 34 Kenyan commercial banks for the period 2005 - 2013. The study found that income diversification has a negative and statistically significant impact on commercial bank returns.

Similarly, another country level study from Ghana by Duho et al. (2020) contradicts the results by Sissy et al. (2017) and confirms finds by Mulwa and Kosgei (2016). Duho et al. (2020) studied the impact of income diversification on the financial performance of 32 Ghanaian banks for the period 2000 – 2015. The study found that income diversification has a negative and significant impact on bank profitability. Further, the results of the study show that income diversification has a positive and significant impact on bank risk.

A cross country study Adesina (2021) found similar results. Adesina (2021) examined the impact of income diversification on bank performance employing sample of 400 African commercial banks in 34 African countries for the study period 2005 to 2015. The study found that greater levels of income diversification tended to decrease bank profitability and increase insolvency risk. Adesina (2021) emphasizes that the results are in line with the theoretical perspective of agency theory. Accordingly, increasing diversification and the resulting economies of scope achieve are not adequate to overcome the associated costs and diseconomies and increased risks that arise due to agency problems with bank management.

Similarly an East African cross country study by Githaiga (2021), investigated the impact of income diversification on bank performance over a sample of 53 commercial banks from six East African countries for the study period 2010 to 2018. The study found that income diversification significantly impacts bank performance. Income diversification was found to have a negative and statistically significant impact on bank profitability as measured by return on assets. The study suggests that the observed negative impact of income diversification on bank performance shows evidence for “the dark side of diversification”. As for possible reasons for this effect, Githaiga (2021) points to three possible reasons. First reason is attributed to lacking managerial expertise to effectively dealing in non-traditional bank activities. Second, Githaiga (2021) notes that the possible benefits from increased income diversification revenue could be negated by the inherent costs linked with nontraditional bank activities. And third, bank managers can also be enticed by novelty trap and neglect their conventional banking activities.

However, a cross-country study by Adem (2022) supports the findings of Sissy et al. (2017) that income diversification has a positive impact on bank performance. Adem (2022) investigated the impact of income diversification applying a dynamic model and GMM estimation technique to address concerns of endogeneity on a panel data set of banks from 45 African countries for the period 2000 – 2020. The results show that income diversification has a positive significant impact on financial stability. That is, diversification reduces the risk of insolvency of banks. Further, the results of the study suggest that income diversification both negatively and significantly impacts bank risk measures.

Similarly, a country level study on Ethiopian commercial banks by Ketema (2020) supports the findings of Sissy et al. (2017) and Adem (2022). Ketema (2020) examined the impact of income diversification on bank performance on a sample of 17 Ethiopian commercial banks for the period 2014 - 2018. The results of the study showed that income diversification into non-interest income sources had a positive and significant impact on bank performance.

2.2.2. Loan Portfolio Diversification and Its Impact on Bank Performance

2.2.2.1. Studies in US, Europe, Asia, and Latin America

In a study in the US based on loan portfolio data, Blickle et al. (2023) studied the impact of banks that choose to specialize and concentrate their loan portfolio by lending to a few sectors. For the sample period of the study, which lasted from the third quarter of 2011 to the first quarter of 2021, the study found that banks that were more specialized (banks that showed higher focus with their lending to certain sectors) tended to gain more stable income, although with slightly lower profitability. The study also found that US banks tended to specialize their loans to certain industries in times of instability and also after periods of sudden surges in deposits. The findings also show that diversification was, however, correlated with the probability of systemic crises. Thus, for US banks specialization tended to improve, performance. This specialization is in line with banks having more knowledge and expertise in certain industry sectors; this is reflected in lower rates of loan defaults. Accordingly, banks are able to attract high-quality borrowers through making generous loan conditions within the specific sector they have greater specialized industry knowledge in.

The findings by Blickle et al. (2023) suggest that a bank that specializes lending is most incentivized to employ its superior information advantage to mitigate adverse selection. Accordingly, banks are able to appeal to and retain good borrowers in their specialized sector, where they have the advantage to provide competitive loan contracts such as those that feature larger loan sizes, made at lower interest rates, as well as longer periods of maturity. For specialized banks, their industry specific knowledge makes them highly competitive. Through monitoring loans and gaining knowledge over specific industry, banks can attain greater informational advantage compared to their less informed, more diversified counterparts. Such apparent monopoly of information over a sector can be used as a sources of market power within the loan market for specialized banks that operate in the competitive industry of banking.

In a study in the US, Shim (2019) finds evidence to the contrary to the above studies. Shim (2019) examined the impact of diversification approach of bank over lending activities and the degree of market concentration that is linked with bank's financial stability performance using data on commercial bank in the US for the period 2002 to 2013. Using fixed-effect estimation to address potential concerns of endogeneity, the study showed that bank loan portfolio diversification has a positive impact on bank performance. The study found that loan portfolio diversification has a significant positive effect on bank profitability and a negative significant impact on bank insolvency risk.

In contrast, a country level study by Atahau and Cronje (2019) in Indonesia found better bank performance were linked to loan portfolio concentration and not diversification. Atahau and Cronje (2019) studied the effect of loan concentration on the performance of 109 Indonesian banks for the period 2003 to 2011 using feasible generalized least squares (FGLS) techniques. The study shows that it is loan portfolio concentration (not diversification) that leads to higher bank returns. These results are also consistent with results from the US study by Blickle et al. (2023).

A country level study by Huynh and Dang (2021) investigated the relationship between loan portfolio diversification and bank performance. Huynh and Dang (2021) employed a dynamic panel model and two-step system generalized method of moments (GMM) estimation technique on data from Vietnamese commercial banks for the study period 2008 – 2019. The results of the study show that greater levels of loan portfolio diversification across economic sectors decreases bank profitability. The impact is, however, less for banks that have business models geared towards non-interest based income activities. That is, banks that have shifted their income sources from relying heavily on traditional lending based banking activities towards a business model that incorporates greater levels of non-interest based income activities were less affected by the negative impact of loan portfolio diversification.

Another country level study by Meutia and Chalid (2021) investigated the effect of loan portfolio diversification in Indonesia. Meutia and Chalid (2021) used data from 62 Indonesian commercial banks for the study period 2010 to 2017 employing a panel data model with fixed effects estimation. The results of the study indicate that loan portfolio diversification tended to increase bank insolvency risk. The study's results also suggest that the impact on bank insolvency risk varies based on the level of market concentration.

2.2.2.2. Studies in Africa

Similar to other studies in emerging economies (Atahau and Cronje, 2019; Huynh and Dang, 2021), Adzobu et al. (2017) in a study in Ghana found that loan portfolio diversification does not necessarily imply better bank performance. Adzobu et al. (2017) examined the impact of diversification of loan portfolios into various economic sectors on bank performance for 30 Ghanaian banks for the period 2007 to 2014 using fixed effect, random effects, feasible generalized least squares (FGLS), and system GMM techniques. The results of the study show that diversification of loan portfolio has a negative and significant impact of bank returns. Further, the study finds that loan portfolio diversification has a positive and significant impact on bank risk.

Contrary to the findings of Adzobu et al. (2017), Mulwa (2018) in a study in east Africa found positive impact of diversification of loan portfolios. Mulwa (2018) examined the impact of loan portfolio diversification on bank performance using bank data from four east African countries for the period 2008 - 2015 employing Generalized Linear Models. The study found that loan portfolio diversification by sector had a positive and significant impact on bank returns. The result emphasize the importance of banks diversifying their loan portfolios into different economic sectors.

Another east African study in Kenya by Ngware et al. (2019) confirmed the findings of Mulwa (2018). Ngware et al. (2019) studied the impact of loan portfolio diversification into different economic sectors with data from 43 Kenyan commercial banks for the period form 2003 until 2017. The study found that diversification of credit provision into the four sectors had a significant and positive impact on bank returns.

Similar to the previous study in Ghana by Adzobu et al. (2017), Kusi et al. (2020) found the negative impact of loan portfolio diversification on bank performance. Kusi et al. (2020) examined the impact of loan portfolio diversification on bank performance for a sample of 30 banks in Ghana for the period 2007 to 2014 using two-step GMM and fixed effect and robust random effects models. The results show loan portfolio diversification measures had a non-linear “U-shape effect” on bank stability for Ghanaian banks. The authors argue that despite the negative short-run impact the overall long-run impact of loan portfolio diversification is positive due to increased expertise and experience in the sectors.

In an east African study in Ethiopia, Meressa (2017) examined the impact of loan portfolio distribution on bank performance for the period 2010-2016. The study found that loan advances to the manufacturing, import/export, and domestic trade/service sectors had a positive and significant impact on bank profitability. The results of the study suggest that diversifying loan portfolio towards these sectors can have positive impact on bank performance.

A subsequent study in Ethiopia by Meressa (2018) found the positive impact of diversification on bank performance. Meressa (2018) examined the impact of loan portfolio diversification on bank performance for a sample of 15 Ethiopian banks for the period 2012 to 2016. The study found positive and significant impact of loan portfolio diversification on both bank returns and risk adjusted returns. These results are consistent with other east African studies (Mulwa, 2018; Ngware et al., 2019).

2.2.3. Summary of Empirical Literature Review

Table 2. Summary of Empirical Literature Review

N	Authors (Reference)	Study Area	Study Period	Type of diversification	Empirical Findings
1	Baselga-Pascual et al. (2018)	14 European countries	2000 - 2012	Income diversification	The study found that income diversification has a positive and significant impact on profitability & no increase in bank risk for increase in profitability.
2	Calmès and Théoret (2021)	US	2001-2016	Income diversification	The study found that non-interest income activities have a positive impact on bank performance.
3	Ferreira et al. (2019)	Brazil	2003 - 2014	Income diversification	The study found that non-interest income has a positive effect on bank return risk adjusted returns.
4	Luu et al. (2020)	Vietnam	2007 - 2017	Income diversification	The study found that income diversification has a positive bank profitability for state and foreign-owned banks.
5	Hunjra et al., (2021)	10 emerging Asian economies	2010 - 2018	Income diversification	The study found that income diversification tended to reduces bank insolvency risk.
6	Wang and Lin (2021)	14 Asia Pacific economies	2011 - 2016	Income diversification	The study found that income diversification reduced levels of bank risk.
7	Bustaman et al. (2017)	ASEAN-4	2006 - 2012	Income diversification	The study found diversification to trading income increases risk & to fees and commissions income positively impacts profitability and reduces risk.
8	Nisar et al. (2018)	South Asia	2000 - 2014	Income diversification	The study finds that non-interest income diversification positively, significant impacts returns and reduces insolvency risk. Fees and commissions income diversification has a negative effect on returns and increases insolvency risk.

9	Nguyen (2019)	Vietnam	2010 - 2018	Income diversification	The study found that income diversification has a negative effect on returns.
10	Chandramohan et al. (2022)	India	2007 - 2017	Income diversification	The study found that income diversification reduce insolvency risk.
11	Uddin et al. (2022)	Bangladesh	2007 - 2016	Income diversification	The study found that income diversification increases bank profitability.
12	Alouane et al. (2022)	Tunisia	2008 - 2017	Income diversification	The study found that income diversification increased bank profitability and volatility.
13	Sissy et al. (2017)	29 African countries	2002 - 2013	Income diversification	The study found that income diversification has a positive impact on profitability.
14	Mulwa and Kosgei (2016)	Kenya	2005 - 2013	Income diversification	The study finds that income diversification has a negative significant impact on commercial bank returns.
15	Duho et al. (2020)	Ghana	2000 - 2015	Income diversification	The study found that income diversification has a negative, significant impact returns & positive impact on risk.
16	Adesina (2021)	34 African countries	2005 - 2015	Income diversification	The study found that income diversification decreases profitability and increases insolvency risk.
17	Githaiga (2021)	6 East African countries	2010 - 2018	Income diversification	The study found that income diversification has a negative on bank performance.
18	Adem (2022)	45 African countries	2000 - 2020	Income diversification	The study found that income diversification reduces insolvency risk.
19	Ketema (2020)	Ethiopia	2014 - 2018	Income diversification	The study found that non-interest income diversification has a positive, significant impact on bank performance.
20	Blickle et al. (2023)	US	2011 - 2021	Loan portfolio diversification	The study found that loan specialization has a significant positive impact on bank performance.
21	Shim (2019)	US	2002 - 2013	Loan portfolio diversification	The study found that loan diversification has a significant positive effect on profit & reduces insolvency risk.

22	Atahau and Cronje (2019)	Indonesia	2003 - 2011	Loan portfolio diversification	The study shows that it is loan portfolio concentration leads to higher bank profitability.
23	Huynh and Dang (2021)	Vietnam	2008 - 2019	Loan portfolio diversification	The study found that loan diversification decreases bank profitability.
24	Meutia and Chalid (2021)	Indonesia	2010 - 2017	Loan portfolio diversification	The study found that loan diversification increases bank insolvency risk.
25	Adzobu et al. (2017)	Ghana	2007 - 2014	Loan portfolio diversification	The study found that loan diversification has negative, significant impact on returns & a positive impact on bank risk.
26	Mulwa (2018)	4 east African countries	2008 - 2015	Loan portfolio diversification	The study found that loan diversification had a positive significant impact on returns.
27	Ngware et al. (2019)	Kenya	2003 - 2017	Loan portfolio diversification	The study found that loan diversification had a significant positive impact on returns.
28	Kusi et al. (2020)	Ghana	2007 - 2014	Loan portfolio diversification	The study found loan diversification had a negative impact on insolvency risk.
29	Meressa (2017)	Ethiopia	2010 - 2016	Loan portfolio diversification	The study found that loan advances to the manufacturing, import/export, and domestic trade/service had a positive, significant impact on profit.
30	Meressa (2018)	Ethiopia	2012 - 2016	Loan portfolio diversification	The study found positive, significant impact of loan diversification on bank returns & risk adjusted returns.

2.2.4. Summary of Review of Literature and Gaps in Literature

Theories on diversification take on various perspectives that arise from multiple disciplines from strategic management to economics to finance. These theories serve as a foundation for empirical investigations. The main comprehensive theoretical frameworks are the market power view, resource based view, synergy and economies of scope, efficient internal capital markets, agency theory and modern portfolio theory. On one hand, market power view, resource based view, synergy and economies of scope, efficient internal capital markets and modern portfolio theory all emphasize the advantages of diversification in maximizing profit, leveraging unused resources and efficient resources allocation. On the other hand, agency theory underscores how diversification rises from conflict of interest between owners and managers and is a way managers cater to their own self-interest of greater compensation, power, and prestige that associated with managing a larger diversified firm. These theoretical disagreements point to the need for empirical investigations to find evidence supporting or refuting them.

Following the growing trend in diversification in the banking industry, empirical studies have sought to establish the effect of this diversification trend on bank performance. However, the existing empirical literature on diversification provides conflicting evidence. First, studies on income diversification such as Nguyen (2019), Adesina (2021), Duho et al. (2020), and Nguyen (2019) find that income diversification has a negative impact on bank performance, whereas other studies such as Baselga-Pascual et al. (2018), Nisar et al. (2018), Sissy et al. (2017), and Uddin et al. (2022) find that income diversification positively impacts bank performance. Similarly, studies on loan portfolio diversification also find contradicting evidence. Whereas studies by Adzobu et al. (2017), Atahau and Cronje (2019), and Kusi et al. (2020) all find evidence that loan portfolio diversification has a largely negative impact, other studies by Mulwa (2018), Shim (2019) and Ngware et al. (2019) find evidence to the contrary that loan portfolio diversification does in fact improve firm performance increasing returns and reducing risk.

As can be noted in the review of empirical literature, studies on the impact of income and loan portfolio diversification in Africa are limited. Moreover, studies on the impact diversification on financial performance in Ethiopia are severely limited. Apart for a few studies Ketema (2020) on income diversification, Meressa (2017) on loan sector distribution and Meressa (2018) on loan portfolio diversification, the literature on the impact of diversification in the Ethiopian banking industry is scarce. Further, the existing studies do not, for instance, disaggregate non-interest based income diversification into its constituents such as fees and commission income. In addition, existing studies are restricted in the measures of loan portfolio diversification measures they employ in their studies. Overall, the review of literature shows the existence of gaps in the availability of studies in the Ethiopian context, which feature regulatory and institutional distinctions. The review of literature also shows the existence of gaps in the types of measures of income and loan portfolio diversification employed in the available studies.

2.2.5. Conceptual Framework

A conceptual framework describes the central elements being studied: the most important factors and variables as well as their supposed relationship (Miles, et al., 2014). Conceptual frameworks focus research to the critical variables, and their most significant relationships using literature to inform it. Accordingly, this study taking several inputs from theoretical and empirical literature on diversification and bank performance has developed the following conceptual framework.

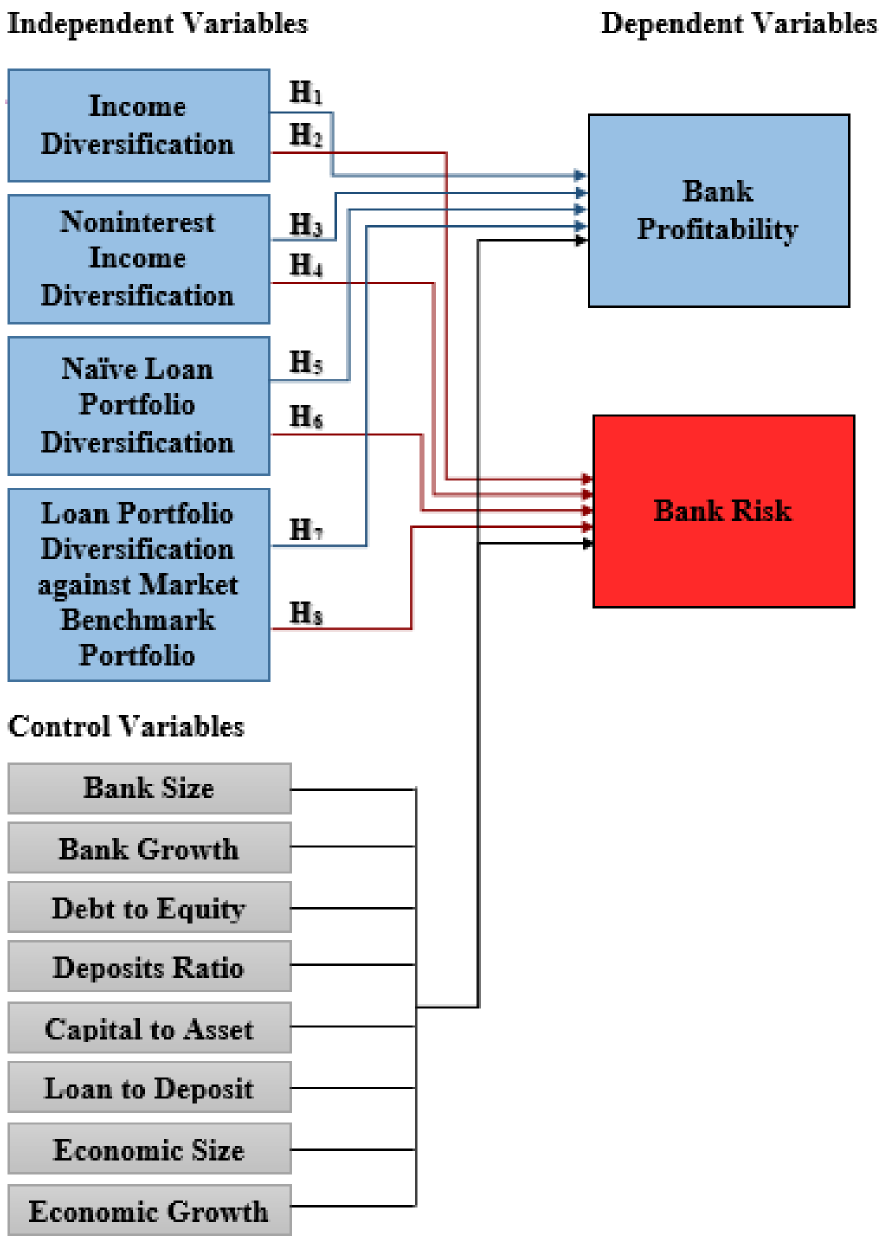

Figure 1. Conceptual Framework of the Study (Author's Compilation based on Adzobu et al. (2017), Nisar et al. (2018), Shim (2019))

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1. Research Philosophy

A research philosophy or paradigm refers to a "system of beliefs and assumptions" about the world, the "nature of research" and the "development of knowledge" with which researchers come to their study (Creswell & Creswell, 2018; Saunders et al., 2019). Research philosophy impacts the research work; thus, it needs to be specified. This, in turn, helps in explaining the choice in research approach, design, and methods.

This study takes on a positivist research philosophy. The positivist philosophy is the basis for traditional scientific research and is also known as the scientific method (Creswell & Creswell, 2018). Positivism seeks quantitative data that is precise, measures that are exact, and research that is "objective" (Neuman, 2014). Research according to the positivist proceed to test hypotheses for causal relationship by rigorously analyzing data measures.

3.2. Research Design

Research design refers to forms of inquiry within a research approach which indicate the particular directions on how the study is carried out (Creswell & Creswell, 2018). Cooper and Schindler (2014) advance a categorization of research designs: based on purpose the most important research design types are "exploratory, descriptive, and causal". Research that seeks to establish causal link among variables is referred to as explanatory research (Saunders et al., 2019). An explanatory research seeks to answer research question of 'why' or 'how' (Saunders et al., 2019). An exploratory research design is appropriate for the present study, since the present study seeks to answer the research questions of 'how':

i. How does income diversification effect bank performance among Ethiopian private commercial banks?
ii. How does loan portfolio diversification effect bank performance among Ethiopian private commercial banks?

Further, an explanatory research goes further than merely providing description and endeavors to explain the cause for the occurrence of a phenomenon employing theories and hypotheses (Cooper

& Schindler, 2014). Accordingly, an explanatory research is appropriate for the present study, since it seeks go further than description of diversification and bank performance to examine the existence of a causal relationship, and employs theories as well as hypotheses to explain the existing relationship.

3.3. Research Approach

Research approaches refer to plans and procedures meant for carrying out research encompassing the stages from general assumptions to in depth methods of “data collection, analysis, and interpretation” (Creswell and Creswell, 2018). Creswell and Creswell (2023) advance three research approaches “(i) qualitative, (ii) quantitative, and (iii) mixed methods”. The selection of research approach often proceeds from research philosophies held (Creswell and Creswell, 2018). Following the study’s research philosophy of positivism (which is largely associated with quantitative research, (Neuman, 2014), the study employs a quantitative research approach. Further, Creswell and Creswell (2018) and Saunders et al. (2019) emphasize that the assumptions of positivism remain true especially for quantitative research.

Quantitative research is seen as an approach for carrying out tests on objective theories though investigating the relationship existing between variables that are precisely, numerically measured and are statistically analyzed with systematic, statistical techniques (Creswell & Creswell, 2018; Saunders et al., 2019). Quantitative research is appropriate for the present study, since the present study seeks to test theories on the impact of diversification on firm performance by using numerical data obtained for variables measuring diversification and performance using statistical procedures.

Further, previous literature on income and loan portfolio diversification (Baselga-Pascual et al., 2018; Calmès & Théoret, 2021; Nisar et al., 2018; Nguyen, 2019; Adzobu et al., 2017; Kusi et al., 2020) have proceeded using a quantitative approach. Thus, following these key studies on this subject, the present study also proceeds with a quantitative research approach.

3.4. Research Methods

Research methods comprise the procedures of “data collection, analysis, and interpretation that researchers propose for their studies” (Creswell & Creswell, 2018).

3.4.1. Method of Data Collection

3.4.1.1. Type of Data, and Source of Data

The In the case of quantitative research approach, data is collected to be used to tests hypotheses and to either corroborate or refute theories (Creswell & Creswell, 2018). The data required to test the constructed hypotheses and theories on the impact of income and loan portfolio diversification on bank performance is objective accounting data. Further, the vast majority of previous studies on income and loan portfolio diversification (Baselga-Pascual et al., 2018; Calmès & Théoret, 2021; Nisar et al., 2018; Nguyen, 2019; Adzobu et al., 2017; Kusi et al., 2020) rely on analysis using publicly available accounting data. Accordingly, the study collects secondary panel data from bank annual reports.

The study uses panel data which takes observations on the "same 'n' entities at two or more time periods T" (Stock & Watson, 2009). The usage of panel data for carrying out research has numerous advantages compared to time-series or cross-sectional data sets (Hsiao, 2014). Panel data typically provides the researcher the following advantages: (i) access to large data set, (ii) greater number of degrees of freedom, (iii) less instances of multicollinearity among independent variables (iv) ability to control for entity specific heterogeneity and (v) possibility of detecting complicated effects not possible with time-series or cross-sectional data alone (Hsiao, 2003).

The source of data for firm specific bank variables are the respective private commercial bank annual reports, aggregated data for the Ethiopian banking industry is obtained from National Bank of Ethiopia (NBE). National macroeconomic data is also obtained from NBE annual reports.

3.4.1.2. Study Population, Sampling Method, and Sample Size

The National Bank of Ethiopia annual report for year ended June 2022 lists 22 private commercial banks in operation in Ethiopia (National Bank of Ethiopia, 2022). Thus, these 22 private commercial banks is taken as the target population of the study. From these 22 private commercial banks, only 16 banks have been operating for the study period (2017 - 2022) (Appendix 1).

Further, the choice of the study period is explained as follows. From July 1, 2018, Ethiopian banks have begun to implement IFRS9, which took the place of AS39, for the measurement and categorization of financial instruments (IMF, 2020). As per "Financial Reporting proclamation No. 847/2014", Ethiopian banks put together their financial statements for year ended June 2018 in accordance to the requirements of IFRS as well as the restatement of accompanying financial statements (i.e. comparative information) for the year ended 30 June 2017 (Awash Bank, 2018; Berhan Bank, 2018; National Bank of Ethiopia, 2018; Nib International Bank, 2018; Zemen Bank, 2018). And according to IFRS 7:20 (c), “An entity shall disclose either in the statement of comprehensive income or in the notes, fee income and expense” (Deloitte, 2019)

Consequently, annual reports of Ethiopian banks published as of year ended June, 2018 (which include comparative information of year ended 2017) disaggregate non-interest income to report fees and commissions income. Therefore, for the purposes of consistency in non-interest income classifications and availability explicitly disaggregated non-interest income including fees and commissions income (which is one of the key non-interest income categories used in studies on income diversification (Bustaman et al. 2017; Nisar et al., 2018; Nguyen, 2019) and is required to test two of the study hypotheses (H_3, H_4)), the study sets the period of analysis from year ended June 2017 to year ended June 2022.

Accordingly, the study employs a nonprobability sampling technique where members of the sample meet certain conditions – called purposive sampling (Cooper & Schindler, 2014). Employing a purposive sampling technique with the criterion of data availability for the specified study period, 16 Ethiopian private commercial banks are purposively selected for the study. Therefore, the data for the study is collected for n=16 different entities (Ethiopian private commercial banks) observed at ‘T’ different time periods (each of the years 2017, . . . , 2022, which explicitly disaggregate non-interest income including fees and commissions income according to IFRS9 required to test hypothesis H_3 and H_4) for a total of 6 * 16 = 96 observations per study variable.

3.4.2. Method of Data Analysis

In quantitative research, data analysis begins once all data collection for the study is completed and employs standardized techniques (Neuman, 2014). Data analysis typically comprises producing summaries, seeking the existence of patterns, and employing statistical techniques to evaluate study hypotheses (Cooper & Schindler, 2014). The data analysis of the study operationalizes concept and defines measurable dependent and independent variables. Further, the study specifies the econometric model and techniques to be employed in investigating the relationship between dependent and independent variables. This sets up the foundation for the following chapters of the study to provide descriptive statistics for the collected data presenting the mean values, the standard deviations, and also the range of values for the variables with respect to every dependent and independent variables employed in the study. Further, correlation analysis is used to assess the relationship existing between the dependent and independent variables of the study.

Panel Data Models

Panel data comprises both time series elements and cross-sectional elements and measures certain characteristics of the same group of individuals (entities) over time (Brooks, 2008). Panel data allows quite a rich environment enabling the development of estimation techniques as well as theoretical results (Greene, 2019). Practically, panel data enables researchers to examine problems that could not have been investigated using either cross-sectional data or time-series data alone and allow significant flexibility in modeling particular differences in behavior that exist among individuals.

In financial research, there are generally two groups of panel estimator methods that can be used: fixed effects and random effects models (Brooks, 2008). The two differ in how they treat "individual specific effects". In panel data models, the disturbance term is split into two: an individual specific effect and the "remainder disturbance". The first captures the characteristics that pertain to the specific entity and does not vary within an entity. The later captures all else that is not explained about the dependent variable and varies across entities and time.

Essentially, fixed effects regression is an approach for controlling for variables that are omitted in panel model, where such omitted variables differ across entities and not over time (Stock & Watson, 2019). Towards this end, the fixed effects regression model has 'n' different intercepts (i.e. 'n' intercept values for 'n' cross-sectional unit or entity); these intercepts are fixed parameters that are to be estimated (Baltagi, 2021).

In random effects regression, the individual effects is considered as random (Baltagi, 2021). Accordingly, the individual effects is captured using an intercept term and an error term. First, the entities has one common mean value of the intercept term (Gujarati, 2003); these intercept term is the same across all cross-sectional units as well as time (Brooks, 2008). Second, the individual differences among entities is captured by an error term (Gujarati, 2003). The error is considered a random variable that differs cross-sectionally and constant over time (Brooks, 2008). It has a constant variance and a mean value of 0 and is considered independent of the model's explanatory variables. Thus, the error term captures random deviations of an entity's intercept term from the mean value (Gujarati, 2003).

Since fixed effects regression enables arbitrary correlation between the intercept term(s) and the explanatory variables, while random effects regression does not, fixed effects regression is widely considered to be a more convincing approach to estimate ceteris paribus effects (Wooldridge, 2020). Nevertheless, random effects regression is still used in situations where the individual effect is considered such as when random randomly drawing 'n' entities from a large population and inference is made for the population as a whole (Baltagi, 2021).

Dynamic Panel Models

Panel data models can be classed as static models and dynamic models based on how they capture variable relationships over time. Static models only enable contemporaneous or instant relationship between variables such that any change in the explanatory variables at a given time 't' results in an instantaneous corresponding dependent variable change (Brooks, 2008). On the other hand, dynamic models extend to capture relationships where previous values of the dependent or explanatory variables impacts the current value of the dependent variable through the addition of lagged variables in the models (Baltagi, 2021; Brooks, 2008).

Generalized method of moments (GMM) are often used estimators for dynamic models. Since their introduction into econometric modeling by Lars Hansen in 1982, they have significantly impacted both theoretical and practical aspects of econometrics (Baltagi, 2003). Two variants of GMM have gained wide popularity: the difference GMM and system GMM estimators (Roodman, 2009a). These estimators handle critical concerns in modelling dynamic models. In dynamic panel models, the lagged dependent variable is correlated with the fixed effects component in the error term leading to "dynamic panel bias". This issue of endogeneity can be resolved in two ways (Roodman, 2009b). The difference GMM and system GMM differ in the way they proceed. Whereas the difference GMM opts to transform the data so as to remove the fixed effects, system GMM proceeds to instrument the lagged dependent variable and other endogenous variables that are considered uncorrelated with the error term.

The difference GMM (“Arellano–Bond”) estimation begins by first transforming all regressors in the model, commonly by differencing, and employs the generalized method of moments (GMM) to them (Roodman, 2009b). The system GMM (“Arellano–Bover/Blundell–Bond”) estimator enhances “Arellano–Bond” estimation by making an extra assumption: “first differences of instrument variables are uncorrelated with the fixed effects”. This assumption enables the addition of more instruments that considerably improve efficiency. It constructs a system of equations: the original and the new transformed one. Difference GMM and system GMM are normally employed as the one-step and two two-step variants (Roodman, 2009a).

Dynamic Panel Model Specification for Income Diversification

Following key studies on income diversification (Baselga-Pascual et al. 2018; Bustaman et al., 2017; Nguyen, 2019; Sissy et al., 2017), the present study employs dynamic panel model and apply generalized method of moments (GMM) estimator to examine the impact of income diversification on bank profitability and insolvency risk.

3.4.2.1. Dynamic model specification for examining impact of income diversification

Beginning with the basic dynamic panel model specification

$\mathbf{Y_{it} = \alpha Y_{it-n} + \beta_i X_{it} + \omega_{it}}$

Where: Y_{it}: dependent variable of entities i at time t

Y_{it-n}: Lag of dependent variable

X_{it}: Entities X_i in time $t - 1$

α : constant

β_i : coefficient of variable X_i

X_{it}: independent variable X_i in time t

ω_{it} : $\varepsilon_i + \mu_{it}$

Substituting the dependent, lagged dependent variables and the explanatory and control variables to examine the income diversification we get:

$$\mathbf{ROA_{it} = \alpha + \beta_1 ROA_{it-1} + \beta_2 HHI\_Inc_{it} + \beta_3 HHI\_Nn_{it} + \beta_4 SIZE_{it} + \beta_5 DEBT\_EQTY_{it} + \beta_6 DEPOSITS_{it} + \beta_7 Econ\_GRWTH_i + \omega_{it}} \quad \text{..........Model (1)}$$

$$\mathbf{Z\text{-}Score_{it} = \alpha + \beta_1 Z\text{-}Score_{it-1} + \beta_2 HHI\_Inc_{it} + \beta_3 HHI\_Nn_{it} + \beta_4 SIZE_{it} + \beta_5 DEBT\_EQTY_{it} + \beta_6 DEPOSITS_{it} + \beta_7 Econ\_SIZE_i + \omega_{it}} \quad \text{..........Model (2)}$$

Where, i refers to the i^{th} bank, t refers to the t^{th} year

$\beta_{1\text{-}7}$ represent the slope of coefficient terms for each of the independent variables

α is the intercept term

ω_{it} is the disturbance term comprising individual effects and random error term for bank i for year t

- **ROA** $_{i,t}$ is a measure of profitability as returns on assets bank i for year t
- **ROA** $_{i,t-1}$ is a measure of returns at one year lag for bank i for year t-1
- **Z-score** $_{i,t}$ is a measure of insolvency risk for bank i for year t
- **Z-score** $_{i,t-1}$ is a measure of insolvency risk at one year lag for bank i for year t
- **HHI_Inc** $_{i,t}$ measures income diversification using Herfindahl-Hirschman Index for bank i for year t
- **HHI_Nn** $_{i,t}$ measures non-interest income diversification using Herfindahl-Hirschman Index for bank i for year t
- **SIZE** $_{i,t}$ is a measure of bank size using natural logarithm of total asset for bank i for year t
- **DEBT_EQTY** $_{i,t}$ measures debt to equity ratio for bank i for year t
- **DEPOSITS** $_{i,t}$ is a measures bank deposits to assets ratio for bank i for year t
- **Econ_SIZE** $_{t}$ is a measure of economic size for country at time t
- **Econ_GRWTH** $_{t}$ is a measure of economic growth for country at time t

3.4.2.2. Static Panel Model Specification for Loan Portfolio Diversification

Following key studies on bank sectoral loan portfolio diversification (Adzobu et al., 2017; Kusi et al. 2020), the present study develops a static panel model and applies fixed effects estimation technique to examine the impact of loan portfolio diversification on bank profitability and credit risk.

Static panel model specification for examining impact of loan portfolio diversification

Beginning with the basic static panel model specification

$\mathbf{y_{it} = \alpha + X_{it}\beta + u_{it}}$

where, $\mathbf{u_{it} = \mu_i + v_{it}}$

where $\mathbf{\mu_i}$ is the unobservable individual effect and $\mathbf{v_{it}}$ is the random error term

Substituting the dependent variables and the explanatory and control variables to examine the loan portfolio diversification, we get

For examining the impact of naïve loan portfolio diversification:

$\mathbf{NIM_{it} = \alpha + \beta_1\, HHI\_Ln_{\,it} + \beta_2 BnkSIZE_{\,it} + \beta_3 Bnk\_GRWTH_{it} + \beta_4 LOAN\_DEP_{\,it} + \beta_5 CAR_{\,it} + \beta_6 DEPOSITS_{it} + \beta_7 Econ\_GRWTH_t + u_{it}}$**……….…………………………….…Model (3a)**

$\mathbf{LLP_{it} = \alpha + \beta_1\, HHI\_Ln_{\,it} + \beta_2 BnkSIZE_{\,it} + \beta_3 Bnk\_GRWTH_{it} + \beta_4 LOAN\_DEP_{\,it} + \beta_5 CAR_{\,it} + \beta_6 DEPOSITS_{it} + \beta_7 Econ\_GRWTH_t + u_{it}}$ **………….………...………………….…Model (3b)**

For examining the impact of loan portfolio diversification against market benchmark portfolio:

$\mathbf{NIM_{it} = \alpha + \beta_1\, DIST\_Ln_{\,it} + \beta_2 BnkSIZE_{\,it} + \beta_3 Bnk\_GRWTH_{it} + \beta_4 LOAN\_DEP_{\,it} + \beta_5 CAR_{\,it} + \beta_6 DEPOSITS_{it} + \beta_7 Econ\_GRWTH_t + u_{it}}$ **…………………………………………….…Model (4a)**

$\mathbf{LLP_{it} = \alpha + \beta_1\, DIST\_Ln_{\,it} + \beta_2 BnkSIZE_{\,it} + \beta_3 Bnk\_GRWTH_{it} + \beta_4 LOAN\_DEP_{\,it} + \beta_5 CAR_{\,it} + \beta_6 DEPOSITS_{it} + \beta_7 Econ\_GRWTH_t + u_{it}}$ **…………...…………………………….…Model (4b)**

Where, i refers to the i^{th} bank, t refers to the t^{th} year

$\mathbf{\beta_{1\text{-}7}}$ represent the slope of coefficient terms for each of the independent variables

$\mathbf{\alpha}$ is the intercept term

$\mathbf{u_{it}}$ is the disturbance term comprising individual effects and random error term for bank i for year t

• **NIM** $_{i,t}$ is a measure of profitability as returns on assets bank i for year t

• **LLP** $_{i,t}$ is a measure of credit risk bank i for year t

• **HHI_Ln** $_{i,t}$ measures naïve loan portfolio diversification using Herfindahl-Hirschman Index for bank i for year t

• **DIST_Ln** $_{i,t}$ measures loan portfolio diversification against market benchmark portfolio for bank i for year t

• **BnkSIZE** $_{i,t}$ is a measure of bank size using total asset for bank i for year t

• **LOAN_DEPit** $_{i,t}$ measures loan to deposit ratio for bank i for year t

• **CAR** $_{i,t}$ measures of bank capital to assets ratio for bank i for year t

• **DEPOSITS** $_{i,t}$ measures of bank deposits to assets ratio is a measure of for bank i for year t

• **Econ_GRWTH** $_{t}$ is a measure of economic growth for country at time t

3.4.2.3. Variable definition and operationalization

In order to test theories, it is necessary that study concepts (derived from review of literature) must be operationalized to form variables that are measurable and suitable for testing the hypothesized relationships (Blaikie & Priest, 2017; Cooper & Schindler, 2014).

Dependent variables

Measures of bank performance

The study makes use of two standard accounting measures of bank profitability return: return on assets (ROA), net interest margins (NIM). Further, a measure bank insolvency risk (Z-score) and credit risk measure loan loss provision (LLP) are also used. These performance are calculated for each bank and over every year in the study period.

Return on assets (ROA)

Return on assets (ROA) measures a bank's rate of return per total assets. It is given by:

$$\mathbf{ROA}_{\mathbf{i,t}} = \frac{\text{Net Income}_{\text{i,t}}}{\text{Total Asset}_{\text{i,t}}}$$

For bank i for year t.

ROA has been used as a measure of bank returns by previous studies on income and loan portfolio diversification (Nisar et al., 2018; Nguyen, 2019; Huynh & Dang, 2021).

Net Interest Margin (NIM)

Net interest margin (NIM) measures a bank's net interest income per total interest earning assets. It is given by:

$$\mathbf{NIM}_{i,\mathbf{t}} = \frac{\text{Net Interest Income}_{\text{i,t}}}{\text{Total Interest Earning Assets}_{\text{i,t}}}$$

For bank i for year t.

Z-score

Z-score serves as a proxy variable for insolvency risk. It measures the number of standard deviations a firm is from being insolvent (Bustaman et al., 2017). Z-score accounts for bank returns and equity capital in measuring insolvency risk. Z-score is calculated as follows.

$$\mathbf{Z - score}_{\mathbf{i,t}} = \frac{(\text{ROA}_{\text{i,t}} + \frac{\text{E}_{\text{i,t}}}{\text{A}_{\text{i,t}}})}{\text{sdROA}_{\text{i}}}$$

For bank i for year t,

Where $\frac{\mathbf{E}}{\mathbf{A}}$ is the capital ratio (equity capital divided by total assets, and sdROA is the standard deviation of return on assets calculated on a four year rolling window. The higher the Z-score the less the risk of insolvency. Z-score has been used as a measure of the "distance to default" for firms by previous studies on income and loan portfolio diversification (Bustaman et al., 2017; Nguyen, 2019; Shim, 2019).

Loan loss provisions (LLP)

A common method of measuring a bank's credit risk exposure is through its loan loss provision ratio (LLP) (VanHoose, 2022). Loan loss provisions (LLP) serves as a proxy for bank credit risk. Loan loss provision refer to provisions that are made for bank loans that are nonperforming (i.e. loans that have deteriorated to the point where the payment of interest and principal is in question. In Ethiopia, NBE's "Asset Classification and Provisioning (5th Replacement) Directive No. SBB/69/2018" prescribes the minimum percentage provision requirement for 5 classes of nonperforming loans: 1% and 3% provision requirement of loan amounts for stage I (pass, i.e.

"less than 30 days past due date') and stage II (special mention, i.e. "30-90 days past due") respectively. Further, it prescribes provisions of 20% of loan amount for stage III-substandard loans (i.e. "90 to 180 days past due"), 50% provision of loan amount for stage III-doubtful loans (i.e."180-360 days past due") and 100% of loan amount for stage III-loss loans (i.e. "360 days past due"). With this the above consideration, loan loss provision ratio is computed as follows.

$$\mathbf{LLP_{i,t}} = \frac{\text{Loan loss provision}_{\text{i,t}}}{\text{Total loans}_{\text{i,t}}}$$

For bank i for year t.

The greater the loan loss provision ratio, the greater the level of credit risk the bank is exposed to. Previous studies on income and loan portfolio diversification have used LLP as a proxy for bank credit risk (Bustaman et al., 2017).

Independent variables

Measures of income diversification

Herfindahl-Hirschman index of income diversification (HHI_Inc)

Following Sissy et al. (2017), Herfindahl-Hirschman Index of income diversification is computed as follows. First, relative weight of each income activity is calculated for each bank (i) for year (t).

$$\mathbf{Ne}\text{t}\ \mathbf{interest\ income}(\mathbf{NII})_{\mathbf{i,t}} = \left(\frac{\text{Net interest income}_{\text{i,t}}}{\text{Total operating income}_{\text{i,t}}}\right)$$

$$\mathbf{Non\ interest\ income}\ (\mathbf{NNI})_{\mathbf{i,t}} = \left(\frac{\text{Non} - \text{interest income}_{\text{i,t}}}{\text{Total operating income}_{\text{i,t}}}\right)$$

Then, each bank's HHI of income sources is calculated as follows.

$$\mathbf{HHI_{i,t}} = \mathbf{NII^2_{i,t}} + \mathbf{NNI^2_{i,t}}$$

The above formula calculates the degree of focus. Finally, this is converted in to a diversification measure for income.

$$\mathbf{HHI\_Inc_{i,t}} = \mathbf{1} - (\mathbf{NII^2_{i,t}} + \mathbf{NNI^2_{i,t}})$$

For bank i, on year t.

The HHI has been used to measure income diversification by previous studies such as Sissy et al., 2017; Ferreira et al., 2019; Bustaman et al., 2017).

Herfindahl-Hirschman index of non-interest income diversification (HHI_Nn)

First, relative weight of each non-interest income activity is calculated for bank 'i' for year 't'.

$$\mathbf{Fee\ and\ commission\ income}(\mathbf{FEE\_COM})_{\mathbf{i,t}} = \left(\frac{\text{Fees and commissions income}_{\text{i,t}}}{\text{Total operating income}_{\text{i,t}}}\right)$$

$$\mathbf{Other\ noninterest\ income}(\mathbf{Other\_NNI})_{\mathbf{i,t}} = \left(\frac{\text{Other non} - \text{interest income}_{\text{i,t}}}{\text{Total operating income}_{\text{i,t}}}\right)$$

Then, each bank's HHI of non-interest income sources is calculated as follows.

$$\mathbf{HHI_{i,t} = FEE\_COM_{i,t}^2 + \ Other\_NNI_{i,t}^2}$$

The above formula calculates the degree of focus. Finally, this is converted in to a diversification measure for non-interest income.

$$\mathbf{HHI\_Nn_{i,t} = 1 - (FEE\_COM_{i,t}^2 + Other\_NNI\ _{i,t}^2)}$$

For bank i, on year t

Measures of loan portfolio diversification

To measure loan portfolio diversification by industry, the study employs three concentration measures Herfindahl-Hirschman Index (HHI), and distance measures.

Herfindahl-Hirschman index of loan portfolio diversification (HHI_Ln)

The HHI is a naïve measure of loan portfolio diversification across economic sectors. It is naïve in the sense that in the absence of detailed data, a naive benchmark portfolio where each sector has 1/n shares (where n=total sectors) is used as a reference point for measuring diversification levels. For the purposes of this study, eight main economic sectors are used: agriculture, manufacturing, domestic trade, export, import, building and construction, transport and other sectors. First, relative exposure to each economic sector is calculated for each bank (i) on each year (t).

$$\mathbf{Relative\ Exposure}(\mathrm{r}\mathbf{x})\ _{\mathbf{i,t}} = \frac{\text{Loan exposure to an economic sector}\ _{\text{i,t}}}{\text{Total loan exposure}\ _{\text{i,t}}}$$

Next, each bank's HHI of loan portfolio diversification is calculated as follows.

$$\mathbf{HHI\_Ln_{i,t}} = 1 - (\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathrm{rx}_{i,t}^{2})$$

For bank i, on year t, for economic sector i: 1,.., n.

The possible range of values for HHI_Ln is between 0 and 1/n. HHI_Ln equal to 1/n is obtained when a bank's exposure is equal for every economic sector (i.e. prefect diversification). HHI_Ln equal to 0 is obtain when a bank's loans are completely concentrated to one industry (no diversification). Previous studies on diversification have used HHI to measure loan portfolio diversification by industry (Kusi et al., 2020; Shim, 2019)

Distance measure of Loan portfolio diversification (Dst_LnDiv)

The distance measure of loan portfolio diversification by economic sector can be a better measure of diversification compared to HHI when detailed data is available (Kusi et al., 2020). This is due to the fact that the aggregate private bank loan market portfolio would be a better benchmark of an efficient portfolio than the naïve portfolio that assume equal shares for all economic sectors. The distance measure is used to quantify the distance between a bank's loan portfolio and the benchmark's loan portfolio (bm). The benchmark portfolio is constructed as the average weight of the aggregate private bank loan outstanding each economic sector: agriculture, manufacturing, domestic trade, export, import, building and construction, transport and other sectors. The distance measure is used to tell how far each bank's loan portfolio share for economic sector is from the aggregate private banking industry loan portfolio. This is constructed as follows.

$$\mathbf{DIST\_Ln_{i,t}} = 1 - (\frac{1}{2}\sum_{i=1}^{n} \left|\mathrm{rx}_{i,t} - \mathrm{bm}_{t,i}\right|)$$

For bank i, on year t, for economic sector i: 1,.., n. The possible range of values for DIST_Ln is between 0 and 1. DIST_Ln equal to 1 is obtained when a bank's exposure is for every economic sector is the same as the exposure of the benchmark portfolio (bm) (i.e. prefect diversification against benchmark).

Control Variables

Bank Size (SIZE)

In the present study, bank size is proxied by the natural logarithm of total assets. The study uses bank size as a control variable to account for possible systematic differences in regards to size. This can help control for the impact of bank size on performance. Bank size is given as follows.

$$\mathbf{SIZE_{i,t}} = \ln(\text{Total assets})_{\text{i,t}}$$

For bank i for year t.

Previous studies have controlled for size in examining the impact of income and loan portfolio diversification (Adzobu et al., 2017)

Debt to Equity Ratio (DEBT_EQTY)

Debt to equity ratio is used as a control variable. Debt to equity ratio indicates the level of a bank's liabilities with respect to the banks total equity capital. The Debt to equity ratio is computed as follows.

$$\mathbf{DEBT\_EQTY_{i,t}} = \frac{\text{Total Liablities}_{\text{i,t}}}{\text{Total Equity Capital}_{\text{i,t}}}$$

For bank i for year t.

Deposits Ratio (DEPOSITS)

Deposits ratio is also used as a control variable. Deposits ratio indicates the level of a bank's deposits relative to total assets. This shows the degree to which a bank's assets are composed of deposits. The deposits ratio is calculated as follows.

$$\mathbf{DEPOSITS_{i,t}} = \frac{\text{Total Deposits}_{\text{i,t}}}{\text{Total Assets}_{\text{i,t}}}$$

For bank i for year t.

Loan to Deposits Ratio (LOAN_DEP)

Loan to deposits ratio is also used as a control variable. Loan to deposits indicates the level of a bank's outstanding loans relative to the banks deposits. The loan to deposits ratio is calculated as follows.

$$\mathbf{LOAN\_DEP_{i,t}} = \frac{\text{Total Loan Advances}_{\,i,t}}{\text{Total Deposits}_{i,t}}$$

For bank i for year t.

Capital to Asset Ratio (CAR)

Capital ratio is also used as a control variable. Capital ratio indicates the level of a bank's equity capital with respect to the banks total assets. Capital ratio also acts as a proxy variable for risk preference of bank managers, bank managers are averse to risk are more likely hold on to more capital. The capital ratio is computed as follows.

$$\mathbf{CAR_{i,t}} = \frac{\text{Equity Capital}_{\,i,t}}{\text{Total Assets}_{\,i,t}}$$

For bank i for year t.

Capital ratio has been used as a control variable in previous studies examining the impact of income and loan portfolio diversification).

Bank Size (BnkSIZE)

Bank is used as a control variable to account for possible systematic differences in regards to size. Bank size is given as follows.

$$\mathbf{BnkSIZE_{i,t}} = (\text{Total assets})_{\,i,t}$$

For bank i for year t.

Previous studies have controlled for size in examining the impact of income and loan portfolio diversification (Adzobu et al., 2017)

Bank Growth (Bnk_GRWTH)

Bank growth is also used as a control variable. It measure the year to year increase in banks size as measured by change in total assets. Bank growth is given as follows.

$$\mathbf{BnkGRWTH_{i,t}} = \frac{\text{Total Assets}_{\text{i,t}} - \text{Total Assets}_{\text{i,t-1}}}{\text{Total Assets}_{\text{i,t-1}}}$$

For bank i for year t.

Economic Growth Rate (Econ_GRWTH)

Economic growth rate is a measure of the growth of a country's total economic output. This is measured as the increase in real gross domestic product (GDP). Hence, the study control for economic growth rate. This is calculated as follows.

$$\mathbf{Econ\_GRWTH_t} = \frac{\text{real GDP}_{\text{t}} - \text{real GDP}_{\text{t-1}}}{\text{real GDP}_{\text{t-1}}}$$

For year t.

Economic Size (Econ_SIZE)

Economic size is a measure of a country's total economic output. Increase or decrease in economic output of an economy can impact bank performance. Hence, the study also control for total national economic output. This is measured as the natural logarithm of real GDP.

$$\mathbf{Econ\_SIZE_t} = \ln\ (\text{real GDP})_{\text{t}}$$

For year t.

Previous studies have controlled for GDP in studying the impact of income and loan portfolio diversification (Adzobu et al., 2017; Nisar et al., 2018).

3.4.3. Summary of empirical models and key variables to test hypotheses

Table 3: Summary of Empirical Models and Key Variables to Test Hypotheses

Explanatory variable	Measurement Variable	Dependent Variable	Measurement Variable	Hyp.	Expected Impact
Income diversification	HHI_Inc	Profitability	ROA	H1	Positive Significant
Income diversification	HHI_Inc	Insolvency Risk	Z-score	H2	Negative Significant
Non-interest income diversification	HHI_Nn	Profitability	ROA	H3	Positive Significant
Non-interest income diversification	HHI_Nn	Insolvency Risk	Z-score	H4	Negative Significant
Naïve loan portfolio diversification	HHI_Ln	Profitability	NIM	H5	Positive Significant
Naïve loan portfolio diversification	HHI_Ln	Credit Risk	LLP	H6	Negative Significant
Market BM Loan portfolio diversification	DIST_Ln	Profitability	NIM	H7	Positive Significant
Market BM Loan portfolio diversification	DIST_Ln	Credit Risk	LLP	H8	Negative Significant

CHAPTER FOUR

4. DATA ANALYSIS, PRESENTATION, AND DISCUSSION

This chapter presents the detailed analysis and discussion of the study. The first section presents the summary of the descriptive statistics of the dependent and independent variables. The next section deals with correlation analysis. The following section presents the diagnostics test for the econometric models employed in the study. The final section presents the regression results, analysis and discussions in view of the research hypotheses being tested.

4.1. Descriptive Statistics

Table 4: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Bank Performance							
ROA	96	.030	.010	.005	.058	0.285	3.505
Z-score	96	3.536	.688	1.402	5.194	-0.228	3.301
NIM	96	.059	.012	.026	.084	-0.416	3.255
LLP	96	.017	.011	.002	.064	1.977	7.313
Income Diversification							
HHI_Inc	96	.432	.075	.023	.500	-2.582	12.641
NII	96	.620	.140	.263	.988	-0.364	2.971
NNI	96	.380	.140	.012	.737	0.364	2.971
HHI_Nn	96	.164	1.331	-12.370	.500	-8.898	83.817
FEE_COM	96	.787	.294	.406	3.037	4.973	37.788
Other_NNI	96	.213	.294	-2.037	.594	-4.973	37.788
Loan Portfolio Diversification							
HHI_Ln	96	.802	.039	.606	.847	-2.309	10.221
DIST_Ln	96	.986	.012	.904	.997	-3.730	23.920
Control Variables							
SIZE	96	10.110	.895	7.633	12.119	-0.265	2.955
DEBT_EQTY	96	6.523	1.737	3.567	11.704	0.881	3.974
DEPOSITS	96	.776	.046	.642	.866	-0.760	3.214
LOAN_DEP	96	.753	.104	.506	.971	0.061	2.650
CAR	96	.140	.031	.075	.219	0.404	3.028
BnkSIZE	96	35.447	32.694	2.066	183.391	2.105	8.163
Bnk_GRWTH	96	.326	.146	.013	.829	0.569	4.030
Econ_GRWTH	96	.070	.015	.053	.095	0.585	1.847
Econ_SIZE	96	7.613	.108	7.448	7.761	-0.179	1.714

The table above provides a summary of the descriptive statistics for the dependent and independent variables in the study. The descriptive statistics includes the minimum, maximum, mean, and standard deviation of study variables as well as their skewness and kurtosis. The first group of variables are the dependent variables, which are measures of bank performance. The first variable is return on assets (ROA). ROA has a mean value of .030, minimum and maximum values are .005 and .058 respectively, and a standard deviation of .010. Since skewness for ROA (0.285) is between -0.5 and 0.5 and its kurtosis (3.505) lies close to 3, ROA follows close to a normal distribution. Thus, it can be inferred that most bank return on assets lie within one standard deviation (sd = .010) from the mean ROA of 3%. Also, it's observed that the least profitable bank for the study period had profitability of 0.50%, whereas the most profitable one had profitability of 5.8%. For the measure insolvency risk, the natural log of Z-score a mean value of 3.536, minimum and maximum values of 1.402 and 5.194 respectively, and a standard deviation of .688.

The next two dependent variables are net interest margin (NIM) and loan loss provision (LLP). Net interest margin (NIM) is found to have a mean value of .059, minimum and maximum values of .026 and .084 respectively, and a standard deviation of .012. This shows that the least profitable bank for the study period had profitability of 2.6 %: they earned net income of 2.6 cents for every birr of interest earning asset in their portfolio. The most profitable bank had a profitability of 8.4%: they earned net income of 8.4 cents for every birr of interest earning asset. As skewness for NIM (-0.416) is between -0.5 and 0.5 and its kurtosis (3.255) lies close to 3, NIM follows close to a normal distribution. Thus, it can be said that majority of bank NIMs lie within one standard deviation (sd = .012) from the mean NIM of 5.9%. For loan loss provision (LLP), the mean value is .017, whereas the minimum and maximum scores are .002 and .064 respectively with a standard deviation of .011. This indicates that the banks with the least credit risk for the study period needed to allocate 0.2 cents for every birr of loan outstanding. The riskiest bank needed to allocate 6.4 cents for every birr of loan outstanding. This is considerable difference in LLP: the riskiest bank needs to allocate 32 times more provision for their outstanding loans than the bank with least risk.

The next group of variables in the table are measures of income diversification. Income diversification into interest and non-interest income sources (HHI_Inc) is found to have a mean value of .432, minimum and maximum values of .023 and .500 respectively, and a standard deviation of .075. This shows that the highest level of income diversification into interest and non-interest income sources as measured by Herfindahl-Hirschman Index is .500; that is a perfect split between the net interest income and non-interest income sources.

Next, the table details the constituents of income as a ratio of total operating income: net interest income (NII) ratio and non-interest income (NNI) ratio. Net interest income (NII) ratio has a mean value of .620, minimum and maximum values of .263 and .988 respectively, and a standard deviation of .140. Non-interest income (NNI) ratio has a mean value of .380, minimum and maximum values of .012 and .737 respectively, and a standard deviation of .140. As skewness for NII (-0.364) and NNI (0.364) lie between -0.5 and 0.5 and their kurtosis (2.971) lies close to 3, NII and NNI follow close to a normal distribution. Therefore, it holds that for most banks the shares of net interest income and non-interest income lie within one standard deviation (sd = .140) from the mean values of 62% and 38% respectively. Overall, it is seen that on average banks' net interest income takes the greater share over non-interest income. However, it is also important to note that the share of non-interest income has at times risen to up to 73% of bank operating income.

Non-interest income diversification into fees and commissions income and other non-interest income sources (HHI_Nn) is found to have a mean value of .164, minimum and maximum values of -12.370 and .500 respectively, and a standard deviation of 1.331. The large negative minimum value of -12.370 is due to the presence of losses reported on "other non-interest income". The maximum value of .500 indicates a perfect split between the two sources of non-interest income (fees and commission income and other non-interest income).

The table, then, details the constituents of non-interest income as a ratio of total non-interest income: fees and commissions income (FEE_COM) and other non-interest income (Other_NNI). Fees and commissions income (FEE_COM) ratio is found to have a mean value of .787, minimum and maximum values of .406 and 3.037 respectively, and a standard deviation of .294. Other non-interest income (Other_NNI) ratio is found to have a mean value of .213, minimum and maximum values of -2.037 and .594 respectively, and a standard deviation of .294. The extreme minimum value for other non-interest income (-2.037) is observed due to an overall negative balance in other non-interest income. Overall, fees and commission income on average constitute the larger share of bank non-interest income with a mean value of 78.7%, while other non-interest income activities take the smaller share with a mean value of 21.3%. Therefore, fees and commissions income makes up the most revenue generating non-interest activity for private commercial banks in Ethiopia.

The following group of variables in the table are measures of loan portfolio diversification. The first is the measure of naïve loan portfolio diversification (HHI_Ln). The maximum possible level of diversification that HHI_Ln can take, where each of the eight economic sector take equal shares (i.e. 1/8), is 0.875. The minimum possible level for HHI_Ln, where all loans are given to one sector, is 0. In the present study, naïve loan portfolio diversification (HHI_Ln) is found to have a mean value of .802, minimum and maximum values of .606 and .847 respectively, and a standard deviation of .039. The next measure of loan portfolio diversification is the distance measure of loan portfolio diversification against the private banks aggregate loan market benchmark portfolio (DIST_Ln). For each bank, DIST_Ln measures how far the bank's share of loans to an economic sector is compared to the sector's share in the market benchmark portfolio. The maximum possible level of diversification against the benchmark portfolio, where a banks' loan portfolio is identical to the benchmark loan portfolio, is 1. The minimum possible level of diversification, where all loans are given to one sector, is 0. In this study, DIST_Ln is found to have a mean value of .986, minimum and maximum values of .904 and .997 respectively, and a standard deviation of .012.

The final group consists of the control variables of the study. The natural of logarithm of total assets (SIZE) has a mean value of 10.110, minimum and maximum values of 7.633 and 12.119 respectively, and a standard deviation of .895. Debt to equity ratio (DEBT_EQTY) has a mean value of 6.523, minimum and maximum values of 3.567 and 11.704 respectively, and a standard deviation of 1.737. Deposits to assets ratio (DEPOSITS) has a mean value of .776, minimum and maximum values of .642 and .866 respectively, and a standard deviation of .046. Loan to deposits ratio (LOAN_DEP) has a mean value of .753, minimum and maximum values of .506 and .971 respectively, and a standard deviation of .104. Capital to assets ratio (CAR) has a mean value of .140, minimum and maximum values of .075 and .219 respectively, and a standard deviation of .031. Since skewness for CAR (0.404) is between -0.5 and 0.5 and its kurtosis (3.028) lies close to 3, CAR follows close to a normal distribution. Thus, it can be said that majority of bank capital to assets ratios lie within one standard deviation (sd = .031) from the mean CAR value of 14.0%. Total bank assets in billions of birr (BnkSIZE) has a mean value of 35.447, minimum and maximum values of 2.066 and 183.391 respectively, and a standard deviation of 32.694. Rate of bank growth (Bnk_GRWTH) has a mean value of .326, minimum and maximum values of .013 and .829 respectively, and a standard deviation of .146. Real GDP growth rate (Econ_GRWTH) has a mean value of .070, minimum and maximum values of .053 and .095 respectively, and a standard deviation of .015. Natural log of real GDP (Econ_SIZE) has a mean value of 7.613, minimum and maximum values of 7.448 and 7.761 respectively, and a standard deviation of .108.

4.2. Correlation Analysis

The table below shows the correlation matrix for the models 1 and 2, which examine the impact of income diversification on bank profitability and insolvency risk.

Table 5: Correlation Table for Models 1 and 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) ROA	1.000										
(2) L.ROA	0.642***	1.000									
	(0.000)										
(3) Z-score			1.000								
(4) L.Z-score			0.742***	1.000							
			(0.000)								
(5) HHI_Inc	0.376***	0.311***	0.005	-0.107	1.000						
	(0.000)	(0.005)	(0.965)	(0.344)							
(6) HHI_Nn	0.257**	0.262**	0.124	0.109	0.631***	1.000					
	(0.011)	(0.019)	(0.230)	(0.335)	(0.000)						
(7) SIZE	-0.230**	-0.274**	0.136	0.116	-0.361***	-0.114	1.000				
	(0.024)	(0.014)	(0.186)	(0.306)	(0.000)	(0.267)					
(8) DEBT_EQTY	-0.502***	-0.498***	-0.187*	-0.142	-0.300***	-0.110	0.654***	1.000			
	(0.000)	(0.000)	(0.068)	(0.210)	(0.003)	(0.285)	(0.000)				
(9) DEPOSITS	-0.313***	-0.222**	-0.132	-0.101	-0.192*	-0.028	0.516***	0.568***	1.000		
	(0.002)	(0.048)	(0.201)	(0.372)	(0.060)	(0.784)	(0.000)	(0.000)			
(10)Econ_GRWTH	0.081	0.076	-0.055	0.073	0.299***	0.160	-0.438***	-0.090	-0.126	1.000	
	(0.433)	(0.505)	(0.597)	(0.518)	(0.003)	(0.120)	(0.000)	(0.383)	(0.221)		
(11) Econ_SIZE	-0.075	-0.064	0.026	-0.007	-0.329***	-0.191*	0.502***	0.088	0.126		1.000
	(0.469)	(0.571)	(0.803)	(0.950)	(0.001)	(0.062)	(0.000)	(0.395)	(0.219)		

**** p<0.01, ** p<0.05, * p<0.1; Note: Only correlation coefficients relevant to the study models are presented.*

Correlation analysis can provide insights into the existing relationships between variables that can be further explored with regression models. The first dependent variable is return on asset (ROA). As seen above, ROA is positively correlated with previous year ROA (L.ROA) with a correlation coefficient of 0.642 at 1% significance level. Similarly, Z-score is positively correlated with previous year Z-score (L.Z-score) with a correlation coefficient of 0.742 at 1% significance level. This suggests that profitability and bank insolvency risk are positively and significantly correlated to previous year profitability and bank insolvency risk respectively. Additionally, income diversification into interest income and non-interest income (HHI_Inc) is positively correlated with profitability at 1% significance level. Similarly, non-interest income diversification into fees and commission income and other non-interest income sources (HHI_Nn) is positively correlated with profitability at 1% significance level. As for correlation between independent variables, the maximum observed correlation between explanatory variables is 0.654, which is not too high to potentially cause multicollinearity issues. This is also confirmed with further testing using Variance Inflation Factor (VIF) and is presented in the following section.

The table below shows the correlation matrix for models 3 and 4, which examine the impact of loan portfolio diversification on bank profitability and credit risk.

Table 6: Correlation Table for Models 3 Through 4

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) NIM	1.000									
(2) LLP		1.000								
(3) HHI_Ln	0.004	-0.197*	1.000							
	(0.965)	(0.055)								
(4) DIST_Ln	0.107	-0.344***		1.000						
	(0.298)	(0.001)								
(5) BnkSIZE	0.363***	-0.080	0.260**	0.331***	1.000					
	(0.000)	(0.441)	(0.011)	(0.001)						
(6) Bnk_GRWTH	-0.247**	-0.156	-0.372***	-0.265***	0.048	1.000				
	(0.015)	(0.130)	(0.000)	(0.009)	(0.639)					
(7) LOAN_DEP	0.533***	0.040	0.021	0.148	0.477***	-0.250**	1.000			
	(0.000)	(0.702)	(0.842)	(0.149)	(0.000)	(0.014)				
(8) CAR	-0.334***	-0.247**	-0.216**	-0.123	-0.556***	-0.115	-0.174*	1.000		
	(0.001)	(0.015)	(0.034)	(0.232)	(0.000)	(0.264)	(0.090)			
(9) DEPOSITS	0.174*	0.136	0.221**	0.142	0.370***	0.065	-0.144	-0.627***	1.000	
	(0.091)	(0.187)	(0.031)	(0.167)	(0.000)	(0.530)	(0.161)	(0.000)		
(10) Econ_GRWTH	-0.449***	-0.041	-0.093	-0.217**	-0.406***	0.249**	-0.658***	0.115	-0.126	1.000
	(0.000)	(0.690)	(0.365)	(0.034)	(0.000)	(0.015)	(0.000)	(0.263)	(0.221)	

**** p<0.01, ** p<0.05, * p<0.1; Note: Only correlations coefficients relevant to the study models are presented.*

The first dependent variable, which is a measure of profitability, is net interest margin (NIM). Net interest margin (NIM) is observed to be positively and significantly correlated with bank size (BnkSIZE), loan to deposit ratio (LOAN_DEP), and deposits to assets ratio (DEPOSITS). Net interest margin (NIM) is, however, negatively and significantly correlated with bank growth rate (Bnk_GRWTH), capital to asset ratio (CAR) and economic growth rate (Econ_GRWTH). The second dependent variable, which is a measure of credit risk, is loan loss provision ratio (LLP). Loan loss provision ratio (LLP) is negatively and significantly correlated with naive loan portfolio diversification measure (HHI_Ln) with a correlation coefficient of -0.197at 10% significance level. Similarly, loan loss provision ratio (LLP) is negatively and significantly correlated with loan portfolio diversification against the private banks aggregate loan market benchmark portfolio measure (DIST_Ln) with a correlation coefficient of -0.344 at 1% significance level. Loan loss provision ratio (LLP) is also negatively and significantly correlated with bank capital to asset ratio (CAR) with a coefficient of -0.247 at 5% significance level. With respect to correlation between independent variables, the maximum observed correlation between explanatory variables is -0.658. This is not too high to potentially cause issues of multicollinearity. This is also confirmed with further testing using Variance Inflation Factor (VIF) and is presented in the following section.

4.3. Econometric Model Diagnostic Tests

This section covers the conducting of diagnostic tests on the econometric models of the study. The section proceeds by performing diagnostic tests for classical linear regression model (CLRM) assumptions and discusses approaches to 'solving' issues associated with using models in which one or more of the assumptions do not hold. These solutions usually proceed in such a way that either the assumptions in question are no longer violated or that the issues are side-stepped, so alternative techniques are employed which remain valid (Brooks, 2008). These assumptions are necessary to demonstrate that the estimation techniques have desirable characteristics, and that hypothesis testing performed based on the coefficient estimates is done validly.

4.3.1. Zero mean value of error term

The first assumption that is considered is whether the expected value of error terms in a regression model is equal to zero (Brooks, 2008). The error term consists of all factors that impact the value of the regression model's dependent variable outside the effects of the independent variables (Kohler & Kreuter, 2012). Thus, $E(u_t) = 0$ indicates that average impact of all of such factors is equal to zero, when the model is tested over several trials, or that all such influences not included in the model will tend to cancel each other out over the long run.

Brooks (2008) points to the fact that if a constant term happens to be included as part of the regression model, this first assumption will not be violated. Since all models in the study include constant terms, following Brooks (2008) it can be asserted that the assumption that the average value of the error terms equals zero holds true.

4.3.2. Homoscedasticity

The second assumption that is tested for is homosckedasticy: $Var(u_t) = \sigma^2$. The assumption necessitates that for all the values of the independent variables the variance of the error terms needs to be the same (Brooks 2008; Kohler & Kreuter, 2012). The case that the error terms are without constant variance is called heteroscedasticity, or "unequal spread, or variance" (Gujarati, 2003). If the assumption of homoscedasticity does not hold in a regression model, then the estimated coefficients will not be efficient (Kohler & Kreuter, 2012). When estimation is not efficient, there is a growing probability that the estimated regression coefficient will move away from the population true value.

4.3.2.1. Breusch-Pagan test for heteroskedasticity

Breusch-Pagan test for heteroskedasticity is a test for heteroscedastic disturbances for a linear regression model based on the Lagrangian multiplier test framework (Breusch & Pagan, 1979; Wooldridge, 2020). In Stata, estat hettest command performs the Breusch Pagan (1979) and Cook Weisberg (1983) test for heteroskedasticity. The null hypothesis for the test is:

H_o: there is homosckedasticy of error terms.

The null hypothesis is rejected if the test yields a p-value that is smaller than 0.05, and it is concluded that heteroskedasticity is present. The following table presents results for the Breusch-Pagan (1979) and Cook-Weisberg (1983) test for heteroskedasticity for models 1 through 4.

Table 7: Results for the Breusch-Pagan and Cook-Weisberg Test for Heteroskedasticity for Models 1 through 4

Model 1	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of ROA	chi2(1) = 2.98 Prob > chi2 = 0.0842
Model 2	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of Z-score	chi2(1) = 3.15 Prob > chi2 = 0.0760
Model 3a	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of NIM	chi2(1) = 0.09 Prob > chi2 = 0.7657
Model 3b	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of NIM	chi2(1) = 0.01 Prob > chi2 = 0.9317
Model 4a	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of LLP	chi2(1) = 11.47 Prob > chi2 = 0.0007
Model 4b	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of LLP	chi2(1) = 16.11 Prob > chi2 = 0.0001

Based on the above table, for model 1 we fail to reject the null hypothesis at a p-value of 0.0842 and conclude the homosckedasticy of error terms. Similarly for model 2, we fail to reject the null hypothesis at a p-value of 0.0760 and conclude the homosckedasticy of error terms. In model 3a, we fail to reject the null hypothesis at a p-value of 0.7657and conclude homosckedasticy of error terms. Also in model 3b, we fail to reject the null hypothesis at a p-value of 0.9317 and conclude homosckedasticy of error terms. However in models 4a and 4b, we reject the null hypothesis at p-values of 0.0007 and 0.0001 respectively and conclude the presence of heteroskedasticity of error terms. Thus, the study finds evidence for the presence of heteroskedasticity in models 4a, and 4b.

4.3.2.2. Dealing with Heteroskedasticity

Having the assumption of homosckedasticy when, in fact, disturbances are heteroskedastic will still yield regression coefficient estimates that are consistent; the estimates will, however, be biased (Baltagi, 2005). Further, the estimates' standard errors will not be efficient. This issue can be corrected and prevented by regularly employing "heteroskedaticity robust standard errors" (Cameron & Trivedi, 2009). A regression model estimator is called "robust" when it is not sensitive to departures away from the model's base assumptions (Greene, 2019). When both the "homoskedasticity-only" and "heteroskedasticity-robust standard errors" happen to be the same, there is no loss by employing "heteroskedasticity-robust standard errors"; nonetheless if the two are different, then heteroskedasticity robust ones (which are more reliable) need to be used (Stock & Watson, 2019). Thus, the simple solution would be to always employ "heteroskedasticity-robust standard errors". For practical econometric purposes, robust estimators will maintain their desirable characteristics despite violations of certain assumptions of the model. In Stata, "heteroscedasticity robust standard errors" can be employed by using the vce(robust) option and are available with most estimation commands (reg, xtreg, xtabond2) (Hoechle, 2007; Roodman, 2009b). Accordingly, the study employs "heteroskedasticity-robust standard errors" for static models 3 and 4 and dynamic models 1 and 2.

4.3.3. No autocorrelation

The third assumption that is tested is the assumption of no autocorrelation; that is covariance between error terms over time needs to equal zero (Brooks, 2008). This means that the errors terms are assumed to be uncorrelated with each other. If this assumption fails to be true, then the error terms are said to exhibit serial correlation, or autocorrelation, since they are correlated over time (Wooldridge, 2020). Similar to heteroscedasticity, it is needed to test for autocorrelation and take action to correct for it or seek alternative procedures which will yield BLUE estimators (Gujarati, 2011). The result of ignoring autocorrelation while it exists is similar to ignoring heteroscedasticity (Brooks, 2008). That is, the coefficient estimates obtained through OLS are inefficient.

The diagnostic tests for autocorrelation proceed by first running tests for dynamic models 1 and 2 using Arellano – Bond test and continue with running tests for autocorrelation for static models 3 through 4 using Wooldridge test for autocorrelation in panel data .

4.3.3.1. Arellano – Bond Autocorrelation Test for Dynamic Models 1 & 2

The "Arellano–Bond test for autocorrelation" has a null hypothesis that there is no autocorrelation; and it is run over the differenced residuals (Mileva, 2007). Arellano–Bond test tests for first-order and second- order autocorrelation. The first test for AR (1) in first differences often rejects the null hypothesis, since the existence of a lagged dependent variable in dynamic models often results in autocorrelation (Mileva, 2007). The more important test for AR (2) in first differences will test for autocorrelation in levels. When serial second-order autocorrelation error terms is present, it shows that the instrument employed is not consistent (Lillo & Torrecillas, 2018). In Stata, xtabond2 command also includes results for Arellano–Bond test for autocorrelation of error terms: AR (1) and AR (2). The null hypothesis for Arellano and Bond autocorrelation test is:

Ho: There is no autocorrelation.

Typically, it is expected that the result for AR(1) will be significant at 5%; and it is expected that the probability of AR(2) (pr > z) will not be significant at 5% (Lillo & Torrecillas, 2018). This will show that there is no serial autocorrelation in the error terms. Thus, AR(2) will be used to test the null hypothesis. The following table presents the results for the Arellano-Bond test for autocorrelation in dynamic models 1 and 2.

Table 8: Results for Arellano – Bond Autocorrelation Test for Dynamic Models 1 & 2

Model 1 SYS GMM Two-Step	Arellano-Bond test for AR(1) in first differences	z = -1.97 Pr > z = 0.049
	Arellano-Bond test for AR(2) in first differences	z = 1.14 Pr > z = 0.254
Model 1 SYS GMM One-Step	Arellano-Bond test for AR(1) in first differences	z = -2.10 Pr > z = 0.036
	Arellano-Bond test for AR(2) in first differences	z = 1.27 Pr > z = 0.203
Model 2 SYS GMM Two-Step	Arellano-Bond test for AR(1) in first differences	z = -1.55 Pr > z = 0.122
	Arellano-Bond test for AR(2) in first differences	z = -1.07 Pr > z = 0.285
Model 2 SYS GMM One-Step	Arellano-Bond test for AR(1) in first differences	z = -1.31 Pr > z = 0.191
	Arellano-Bond test for AR(2) in first differences	z = -1.31 Pr > z = 0.190

Based on the above table, for AR(1) in model 1, as anticipated, we reject the null hypothesis at p-values of 0.049 and 0.036 for the two-step and one-step GMM estimations respectively and conclude the presence of first-order autocorrelation of error terms. In contrast, for AR(1) for model 2, we fail to reject the null hypothesis at a p-values of 0.122 and 0.191 for the two-step and one-step GMM estimations respectively and conclude the absence of first-order autocorrelation of error terms. The presence of first-order autocorrelation in the differenced residuals does not imply that the estimates are inconsistent (Liu et al., 2013). However, it is required that second-order autocorrelation is absent, so that the estimates are consistent.

Accordingly, for AR(2) in model 1, we fail to reject the null hypothesis at p-values of 0.254 and 0.203 for the two-step and one-step GMM estimations respectively and conclude the absence of second-order autocorrelation of error terms. Similarly in model 2, we fail to reject the null hypothesis at p-values of 0.285 and 0.190 for the two-step and one-step GMM estimations respectively and conclude the absence of second-order autocorrelation of error terms.

4.3.3.2. Wooldridge Autocorrelation Test for Static Models 3 through 4

In Stata, **xtserial** command performs Wooldridge (2002) test for autocorrelation of errors terms of a linear panel model.

For the Wooldridge Autocorrelation Test, the null hypothesis is:

H_o: there is no first-order autocorrelation.

We reject the null hypothesis if the test yields a p-value that is smaller than 0.05, and conclude the presence of autocorrelation. The following table presents the results for the Wooldridge test for autocorrelation in panel data for static models 3 through 4.

Table 9: Results for Wooldridge Autocorrelation Test for Static Models 3 through 4

Model 3a	Wooldridge test for autocorrelation in panel data Ho: no first-order autocorrelation	F(1, 15) = 19.185 Prob > F = 0.0005
Model 3b	Wooldridge test for autocorrelation in panel data Ho: no first-order autocorrelation	F(1, 15) = 21.211 Prob > F = 0.0003
Model 4a	Wooldridge test for autocorrelation in panel data Ho: no first-order autocorrelation	F(1, 15) = 31.890 Prob > F = 0.0000
Model 4b	Wooldridge test for autocorrelation in panel data Ho: no first-order autocorrelation	F(1, 15) = 27.640 Prob > F = 0.0001

Based on the above table, for model 3a, we reject the null hypothesis at a p-value of 0.0005 and conclude the presence of first-order autocorrelation of error terms. Similarly in model 3b, we reject the null hypothesis at a p-value of 0.0003 and conclude the presence of first-order autocorrelation of error terms. In model 4a, we reject the null hypothesis at a p-value of 0.0000 and conclude the presence of first-order autocorrelation of error terms. Also in model 4b, we reject the null hypothesis at a p-value of 0.0001 and conclude the presence of first-order autocorrelation of error terms. Thus, the study finds evidence for the presence of first-order autocorrelation in models 3 through 4.

4.3.3.3. Dealing with autocorrelation

Similar to heteroskedasticity when error terms are serially autocorrelated, the predicted standard errors are "wrong" and result in statistical inferences that are misleading (Stock & Watson, 2019). In the case where the regression error terms are autocorrelated, the typical "heteroskedasticity-robust standard errors" are not valid, since they were obtained with the assumption of no serial autocorrelation. (Stock & Watson, 2019). The solution to this issue is to employ standard errors which are robust to the cases of heteroskedasticity and serial autocorrelation. One type of these "heteroskedasticity-and autocorrelation-robust standard errors" are clustered standard errors. In the case of panel data, the cluster would comprise an entity. Accordingly, clustered standard errors would allow for both heteroskedasticity and autocorrelation within the entity.

These standard errors will be valid "whether or not there is heteroskedasticity, autocorrelation, or both" (Stock & Watson, 2019). In Stata, estimation commands that are used with the option vce(cluster) enable the use of clustered standard errors (Cameron & Miller, 2015; Hoechle, 2007). In dynamic GMM estimations, xtabond2's robust option is similar to cluster() option available in many other estimation commands, yielding standard errors which are robust to both heteroskedasticity and autocorrelation present within entities (Roodman, 2009b). Accordingly, the present study employs clustered standard errors in Stata using cluster() option for static models and robust option in dynamic GMM models.

4.3.4. Normality

The next assumption considered is the normality assumption. According to this assumption, the disturbances are normally distributed, with zero mean and constant variance (Greene, 2019).This assumption will need to hold in order to perform single or joint hypothesis tests on a model's parameters (Brooks, 2008). This is enabled due to the property of a normal distribution: "that any linear function of normally distributed variables is itself normally distributed" (Gujarati, 2003). And since our model estimators are linear functions of the normally distributed error terms, the model estimators will also be normally distributed. This makes the task of hypothesis testing very straightforward.

4.3.4.1. Shapiro-Wilk test for normality

The Shapiro–Wilk test is basically a goodness-of-fit test: it determines how well the sample data can fit to a normal distribution (King & Eckersley, 2019). In Stata, swilk command performs the Shapiro-Wilk test for normality.

For the Shapiro–Wilk test, the null hypothesis is:

Ho: "Sample comes from a normal distribution."

We reject the null hypothesis if the test yields a p-value that is smaller than 0.05, and conclude that the sample does not come from a normal distribution. The following table presents the results for the Shapiro–Wilk test for normality for models 1 through 4.

Table 10: Results for Shapiro-Wilk Test for Normality for Models 1 through 4

Model 1 SYS GMM Two-Step	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M1a	80	0.978	1.535	0.939	0.174
Model 1 SYS GMM One-Step	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M1b	80	0.978	1.536	0.940	0.174
Model 2 SYS GMM Two-Step	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M2a	80	0.984	1.068	0.143	0.443
Model 2 SYS GMM One-Step	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M2b	80	0.987	0.923	-0.176	0.570
Model 3a	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M3a	96	0.985	1.178	0.364	0.358
Model 3b	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M3b	96	0.982	1.452	0.826	0.205
Model 4a	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M4a	96	0.990	0.803	-0.484	0.686
Model 4b	Shapiro-Wilk W test for normal data					
	Variable	Obs	W	V	z	Prob>z
	residual_M4b	96	0.984	1.250	0.494	0.310

Based on the above table, for model 1 we fail to reject the null hypothesis at a p-value of 0.174 for the two-step and one-step GMM estimations and conclude that the error terms do indeed follow a normal distribution. In model 2, we again fail to reject the null hypothesis at p-values of 0.443 and 0.570 for the two-step and one-step GMM estimations respectively and conclude that the error terms follow a normal distribution. For model 3a, we fail to reject the null hypothesis at a p-value of 0.358 and conclude that the error terms follow a normal distribution. Also in model 3b, we fail to reject the null hypothesis at a p-value of 0.205 and conclude that the error terms follow a normal distribution. Similarly in model 4a, we fail to reject the null hypothesis at a p-value of 0.686 and conclude that the error terms follow a normal distribution. Finally in model 4b, we also fail to reject the null hypothesis at a p-value of 0.310 and conclude that the error terms follow a normal distribution. Thus, the study finds that the error terms for all models from 1 through 4 do indeed follow a normal distribution.

4.3.5. No multicollinearity

The following assumption that is tested for is that there is no multicollinearity among the regressors in the econometric model. That is, that the explanatory variables in the model are uncorrelated with each other (Brooks, 2008). In the extreme case, where explanatory variables have no relationship between each other they would be called orthogonal and the adding or removing of one such variable does not affect coefficients of other variables. In the opposite end, where the explanatory variables have perfect multicollinearity, the resulting regression coefficients will be indeterminate with standard errors that are not defined (Gujarati, 2003). In the case where multicollinearity is not perfect but high, regression coefficients estimation will be possible but the respective standard errors will tend to be large. Consequently, precise estimation of the coefficients is not possible. Practically, when there are two competing explanatory variables that are highly correlated, the result would be that neither of their coefficients would be statistically significant, whereas taken separately each would be significant (Brooks, 2008).

4.3.5.1. Variance-Inflating Factor (VIF)

One technique of checking for multicollinearity is the variance-inflating factor (VIF) value. VIF values can be used to check for the presence of multicollinearity; they indicate the extent to which linear relationships (i.e. multicollinearity) among regressors impact the standard error estimates of the regression parameter estimates (Kleinbaum et al., 2013). As the level of multicollinearity increases, the value of VIF increases, and "in the limit" this can be infinite (Gujarati, 2003). Conversely, when there is no multicollinearity among the regressors, then the value of VIF will be 1. The inverse of VIF values (1/VIF) is known as tolerance (TOL). Accordingly, for perfect multcollinearity, TOL would equal 0 and for no multicollinearity TOL equals to 1. VIF and TOL can be used interchangeably. In Stata, estat vif command calculates variance inflating factor (VIF) for the regressors in a model. In general, when VIF values are greater than 10, it is an indication of the presence of high multicollinearity issues among explanatory variables that is severe enough to require corrective action (Gujarati, 2003; Kleinbaum et al., 2013).

The following table presents variance-inflating factor (VIF) for the regressors in model 1.

Table 11: Results for Variance Inflation Factor Test for Multicollinearity for Model 1

	Variance inflation factor		
		VIF	1/VIF
Model 1	DEBT_EQTY	2.896	.345
	SIZE	2.627	.381
	HHI_Inc	2.026	.494
	HHI_Nn	1.776	.563
	DEPOSITS	1.579	.633
	L.ROA	1.454	.688
	Econ_GRWTH	1.216	.822
	Mean VIF	1.939	.

In the above table, for model 1, the study finds that the VIF values are low compared to the threshold of 10 for high collinearity suggested by (Gujarati, 2003; Kleinbaum et al., 2013). In fact, the maximum observed VIF value is 2.896 and the mean VIF value is 1.939. Based on the above results, we conclude that there is a low level of collinearity among the regressors in model 1.

The following table presents variance-inflating factor (VIF) for the regressors in model 2.

Table 12: Results for Variance Inflation Factor Test for Multicollinearity for Model 2

	Variance inflation factor		
		VIF	1/VIF
Model 2	SIZE	3.506	.285
	DEBT_EQTY	2.887	.346
	HHI_Inc	2.148	.466
	HHI_Nn	1.847	.541
	DEPOSITS	1.613	.620
	Econ_SIZE	1.565	.639
	L.Z-score	1.285	.778
	Mean VIF	2.122	.

From the above table, for model 2, we also find that the VIF values are again low compared to the threshold of 10 for high collinearity (Gujarati, 2003; Kleinbaum et al., 2013). For model 2, the maximum observed VIF value is 3.506, and the mean VIF value is 2.122. From the above results, we conclude that there is a low level of collinearity among the regressors in model 2.

The following table presents variance-inflating factor (VIF) for the regressors in models 3a & 4a.

Table 13: Results for Variance Inflation Factor Test for Multicollinearity for Models 3a & 4a

	Variance inflation factor		
		VIF	1/VIF
Models 3a & 4a	LOAN_DEP	2.900	.345
	CAR	2.329	.429
	DEPOSITS	2.285	.438
	BnkSIZE	2.182	.458
	Econ_GRWTH	2.127	.47
	Bnk_GRWTH	1.465	.682
	HHI_Ln	1.406	.711
	Mean VIF	2.099	.

From the above table, for models 3a and 4a, we also find that the VIF values are low compared to the threshold of 10 for high collinearity (Gujarati, 2003; Kleinbaum et al., 2013). For models 3a and 4a, the maximum observed VIF value is 2.900, while the mean VIF value is 2.099. Thus, we conclude that there is a low level of collinearity among the regressors in models 3a & 4a.

The following table presents variance-inflating factor (VIF) for the regressors in models 3b & 4b.

Table 14: Results for Variance Inflation Factor Test for Multicollinearity for Models 3b & 4b

	Variance inflation factor		
		VIF	1/VIF
Models 3b & 4b	LOAN_DEP	2.818	.355
	CAR	2.311	.433
	DEPOSITS	2.285	.438
	BnkSIZE	2.242	.446
	Econ_GRWTH	2.138	.468
	Bnk_GRWTH	1.264	.791
	DIST_Ln	1.262	.793
	Mean VIF	2.046	.

Based on the above table, for models 3b and 4b, the study finds that the VIF values are again low compared to the threshold of 10 for high collinearity (Gujarati, 2003; Kleinbaum et al., 2013). For models 3b and 4b, the maximum observed VIF value is 2.818, whereas the mean VIF value is 2.046. Based on the above results, we conclude that there is low level of collinearity among the regressors in models 3b & 4b. Overall, the results show that there is a low level of collinearity among the regressors for models 1 through 4.

4.4. Specification test for static models 3 through 4

4.4.1. Deciding between fixed effects and random effects

Researchers usually run random effects and fixed effects estimations, and test whether there is statistically significant differences between the resulting coefficients of the explanatory variables (Wooldridge, 2020). Hausman (1978) was the first to propose one such test. The null hypothesis is that there are random individual effects and the estimators would be similar since both are consistent (Cameron & Trivedi, 2009). In the alternative hypothesis, these estimators would diverge. When the Hausman test rejects the above null hypothesis, then fixed effects estimates are used. Otherwise, the random effects estimates are used. Practically, the failure to reject the null hypothesis indicates that either that the random effects and fixed effects estimates are close enough that there is no material difference, or that sampling variation is large enough in the fixed effects estimate that it will not be possible to conclude statistically significant differences. (Wooldridge, 2020). Wooldridge (2020) also emphasizes that fixed effects nearly always will be much more convincing compared to random effects for policy analysis with aggregate data. Overall, fixed effects is widely considered more convincing in estimating ceteris paribus effects.

However, in cases where the standard errors used are robust to heteroskedasticity and serial autocorrelation (i.e. cluster robust standard errors), instead of the “nonrobust Hausman test”, a modified Hausman test should be used (Cameron & Miller, 2015; Cameron & Trivedi, 2022; Papke & Wooldridge, 2023; Wooldridge, 2010). This test would need to account for both serial autocorrelation and heteroskedasticity (Wooldridge, 2002). Wooldridge (2010) proposes one such test: a “regression-based cluster-robust version of the Hausman test” for determining whether to reject random effects in favor of fixed effects. In Stata, the xtoverid command implements this test (Baltagi, 2021; Cameron & Miller, 2015; Cameron & Trivedi, 2022).

The null hypothesis for cluster-robust version of the Hausman test (Woldrdige, 2010) is:

Ho: The random effects model is appropriate.

If the null hypothesis is rejected, then the fixed effects model is appropriate (Cameron & Miller, 2015; Cameron & Trivedi, 2022).

The following table presents the results for the cluster-robust version of the Hausman test (Wooldridge, 2010) for models 3 through 4.

Table 15: Cluster-Robust Hausman Test (Wooldridge, 2010) for Models 3 through 4

Model 3a	Test of overidentifying restrictions: fixed vs random effects Cross-section time-series model: xtreg re robust cluster(Bankid)	Sargan-Hansen statistic 88.666 Chi-sq(7) P-value = 0.0000
Model 3b	Test of overidentifying restrictions: fixed vs random effects Cross-section time-series model: xtreg re robust cluster(Bankid)	Sargan-Hansen statistic 95.247 Chi-sq(7) P-value = 0.0000
Model 4a	Test of overidentifying restrictions: fixed vs random effects Cross-section time-series model: xtreg re robust cluster(Bankid)	Sargan-Hansen statistic 29.221 Chi-sq(7) P-value = 0.0001
Model 4b	Test of overidentifying restrictions: fixed vs random effects Cross-section time-series model: xtreg re robust cluster(Bankid)	Sargan-Hansen statistic 14.080 Chi-sq(7) P-value = 0.0498

Based on the above table, for model 3a and model 3b, we reject the null hypothesis at a p-value of 0.0000 and conclude that the fixed effects model is appropriate. For model 4a, we reject the null hypothesis at a p-value of 0.0001 and conclude that the fixed effects model is appropriate. Finally for model 4b, we also reject the null hypothesis at a p-value of 0.0498 and conclude that the fixed effects model is appropriate.

4.5. Specification tests for dynamic models 1 and 2

4.5.1. Deciding between Difference GMM and System GMM

In deciding between difference GMM and system GMM, Blundell and Bond (2023) place importance on recognizing that for the coefficient of a lagged dependent variable, the OLS estimate tends to be upwards biased, and the fixed effects (within groups) estimate tends to be downwards biased. Accordingly, a consistent and unbiased estimate of the coefficient of the lagged dependent variable is "expected to lie in between the OLS levels estimate and the within groups estimate" (Bond et al., 2001). In the case that the estimate of the first difference GMM is near or below the fixed effects (within groups) estimate, it is likely that the obtained difference GMM estimate is also downwards biased, potentially owing to weak instruments. In such cases, it can be important to consider alternative estimators like the system GMM estimator, which allows significant decrease in finite sample bias and an increase in precision by taking advantage of additional moment conditions.

Accordingly, this study tests to check if the first difference GMM estimates are close to or below the fixed effects (within groups) estimates, if so the study proceeds with the system GMM estimator. The table below summarizes the coefficients obtained for the lag dependent variables for dynamic models 1 and 2.

Table 16: Testing for Consistent and Unbiased Estimate of the Coefficient of the Lagged Dependent Variable for Dynamic Models 1 and 2

Model 1	**Coef. for Lag ROA**	**Model 2**	**Coef. for Lag Z-score**
Pooled OLS	0.499	Pooled OLS	0.737
Fixed Effects (FE)	0.180	Fixed Effects (FE)	0.328
DIFF_1 GMM	0.156	DIFF_1 GMM	0.229
DIFF_2 GMM	-0.044	DIFF_2 GMM	0.211
SYS_1 GMM	0.462	SYS_1 GMM	0.579
SYS_2 GMM	0.420	SYS_2 GMM	0.649

Based on the above table, for model 1, the coefficients for the lagged dependent variable (L.ROA) for the first and second difference GMM are 0.156 and -0.044 respectively. Both these values lie below the fixed effect estimate of 0.180; thus, following Bond et al. (2001) it is likely that these difference GMM estimates are downwards biased. In the case of the system GMM estimates, the results show that the one-step and two-step system GMM estimates are 0.462 and 0.420

respectively, whereas the pooled OLS result is 0.499. Both the one-step and two-step system GMM estimates lie below the pooled OLS estimate and above the fixed effects estimate. Bond et al. (2001) notes that consistent and unbiased estimate of the lag dependent variable is "expected to lie between the OLS levels estimate and the Within groups estimate". As seen in the table above, both system GMM estimates lie between the pooled OLS and fixed effect estimates. Accordingly, for model 1 the study proceeds to employ system GMM estimates.

Similarly, for model 2, the coefficients for the lagged dependent variable (L.Z-score) for the first and second difference GMM are 0.229 and 0.211 respectively. Both these values lie under the fixed effect estimate of 0.328 and are likely to be downwards biased (Bond et al., 2001). For the system GMM estimates, the results show that the one-step and two-step system GMM estimates are 0.579 and 0.649 respectively, which are below the pooled OLS estimates of 0.737 and above the fixed effects estimate of 0.328. Thus, both the one-step and two-step system GMM estimates lie between the pooled OLS and fixed effect estimates. Following Bond et al. (2001), for model 2 the study also proceeds to employ system GMM estimates.

4.5.2. Deciding between One Step and Two Step GMM

Generally, researchers report the results of the one-step GMM along with the two-step results due to the downward bias in the standard errors obtained in two-step GMM (Roodman, 2009b). However, Windmeijer (2005) developed a small-sample correction for the standard errors of the two-step GMM. These corrected two-step standard errors are rather accurate and the two-step GMM estimation with these corrected standard errors appears to be modestly superior to the one-step GMM estimation with cluster-robust standard errors (Roodman, 2009b). These standard errors with Windmeijer correction are available in Stata using xtabond2 command with the robust option in the two-step GMM estimation. Accordingly, this study employs the Windmeijer-corrected standard errors with the two-step system GMM estimation. In this study, the one-step system GMM estimation results are also presented for reference.

4.5.3. Tests for Overidentification

Sargan/Hansen test of overidentifying restrictions (J test) is considered the basic model specification test for the GMM estimators (Blundell & Bond, 2023). An important assumption for the validity of the GMM estimators is that the instruments used are exogenous (Roodman, 2009b).

In cases where, the model is “exactly identified” (i.e. the number of regressors equal the number of instruments), determining invalid instruments is considered impossible. However, when the model is overidentified, (which mostly holds for difference and system GMM models), it is possible to obtain a test statistic to check the “joint validity of the moment conditions (identifying restrictions)” (Roodman, 2009a; Roodman, 2009b). If there are more instruments than are needed to identify an equation, then it is possible to test whether the included additional instruments are valid or not. (i.e. “Are they uncorrelated with the error term?”) (Wooldridge, 2002). Accordingly, the Sargan/Hansen test of overidentifying restrictions (J test) is commonly and reasonably considered a test of instrument validity (Roodman, 2009a). In Stata, xtabond2 command also includes results for Sargan and Hansen test of overidentification.

4.5.3.1. Sargan Test of Overidentification

The null hypothesis for the Sargan test of overidentification is that “All the overidentifcation restrictions are valid.”

Ho: “All the overidentifcation restrictions are valid.”

The Sargan test’s results will be interpreted as follows. If the resulting probability (Prob>chi2) is equal to or greater than 0.05, we cannot reject the null hypothesis. Thus, the overidentifcation restrictions are valid. Conversely, if the probability (Prob>chi2) is less than 0.05, there is no evidence indicating the overidentifcation restrictions are valid. Thus, we would reject the null hypothesis and conclude the overidentifcation restrictions are not valid.

Table 17: Sargan Test of Overidentification for Dynamic Models 1 & 2

Model 1	Sargan test of overid. Restrictions: (Not robust, but not weakened by many instruments.)	chi2(2) = 4.52 Prob > chi2 = 0.104
Model 2	Sargan test of overid. Restrictions: (Not robust, but not weakened by many instruments.)	chi2(3) = 6.20 Prob > chi2 = 0.102

Based on the above table, for model 1, we fail to reject the null hypothesis at a p-value of 0.104 and conclude that the overidentifcation restrictions are valid. Similarly, for model 2, we fail to reject the null hypothesis at a p-value of 0.102 and conclude that the overidentifcation restrictions are valid.

4.5.3.2. Hansen Test of Overidentification

The null hypothesis for the Hansen test is the same as the one for the Sargan test.

Ho: "All the overidentifcation restrictions are valid."

The Hansen test's results will be interpreted as follows. If the resulting probability (Prob>chi2) is equal to or greater than 0.05, we reject the null hypothesis. Further, p-values that are close to 1 (i.e. "implausibly perfect") are also reasons for concern (Lillo & Torrecillas, 2018; Roodman, 2009a). It is recommended that the p-value for the Hansen test be within the range of 0.05 ≤ (Prob>chi2) < 0.8 and optimally in the range 0.1 ≤ (Prob>chi2) < 0.25 (Lillo & Torrecillas, 2018; Roodman, 2009a).

Table 18: Hansen Test of Overidentification for Dynamic Models 1 & 2

Model 1	Hansen test of overid. Restrictions: (Robust, but weakened by many instruments.)	chi2(2) = 3.27 Prob > chi2 = 0.195
Model 2	Hansen test of overid. Restrictions: (Robust, but weakened by many instruments.)	chi2(3) = 3.15 Prob > chi2 = 0.369

Based on the above table, for model 1, we fail to reject the null hypothesis at a p-value of 0.195 and conclude that the overidentifcation restrictions are valid. Similarly, for model 2, we fail to reject the null hypothesis at a p-value of 0.369 and conclude that the overidentifcation restrictions are valid. Since Hansen test p-values for models 1 and 2 are between 0.10 and 0.40, it indicates that the overidentifcation restrictions are valid (Lillo & Torrecillas, 2018; Roodman, 2009a).

4.5.4. Difference-in-Hansen's J test of exogeneity

Further, the system GMM estimator also makes the additional assumption of exogeneity to achieve the validity of the additional instruments used in level equations (Roodman, 2009a; Wintoki et al., 2012). According to this assumption, the "covariance between an explanatory variable and the time-invariant error component is not zero but is constant over time, then first-differences of that explanatory variable are uncorrelated with that error component" (Blundell & Bond, 2023).

With this assumption the appropriately lagged first-differences of explanatory variables can be included as instruments for the equations in levels (Blundell & Bond, 2023; Roodman, 2009a).

The Difference-in-Hansen (J test) tests for this assumption over a subset of instruments (Roodman, 2009a). The Difference-in-Hansen test is an extension of Hansen test of overidentifying restrictions (J test) "to test nested hypotheses, where (only) a subset of the moment conditions that are valid under the null hypothesis remain valid under a less restrictive alternative hypothesis" (Blundell & Bond, 2023). This is accomplished by calculating the increase in the J statistic that occurs due to the addition of a given subset to the estimation (Roodman, 2009a).

The null hypothesis for this test is that the subset of instruments used in the levels equations remain exogenous (Wintoki et al., 2012).

Ho: "The subset of instruments used in the levels equations are exogenous."

Table 19: Difference-In-Hansen's J Test of Exogeneity for Dynamic Models 1 & 2

Model 1	**Difference-in-Hansen tests of exogeneity of instrument subsets**
	GMM instruments for levels Hansen test excluding group: chi2(1) = 1.26 Prob > chi2 = 0.261 Difference (null H = exogenous): chi2(1) = 2.00 Prob > chi2 = 0.157
Model 2	**Difference-in-Hansen tests of exogeneity of instrument subsets**
	GMM instruments for levels Hansen test excluding group: chi2(2) = 1.90 Prob > chi2 = 0.386 Difference (null H = exogenous): chi2(1) = 1.24 Prob > chi2 = 0.265

Based on the above table, for model 1, we fail to reject the null hypothesis for the difference-in-Hansen tests of exogeneity of instrument subsets at p-values of 0.261 and 0.157 and conclude that the instruments subset used in the levels equations are exogenous. Thus, the subset of instruments used in levels equations are valid. Similarly, for model 2, we fail to reject the null hypothesis at p-values of 0.386, and 0.265 and conclude that the instruments subset used in the levels equations are exogenous. Thus, the subset of instruments used in levels equations are valid.

4.6. Regression Results

4.6.1. Model 1: Income diversification and bank profitability

Table 20: Regression Results - Income Diversification and Bank Profitability (Model 1)

	Two-Step GMM Estimation			One-Step GMM Estimation		
ROA	Coefficient	Corrected Std. Error	p-value	Coefficient	Corrected Std. Error	p-value
L.ROA	0.4202***	0.1220	0.001	0.4617***	0.0921	0.000
HHI_Inc	0.0418***	0.0144	0.004	0.0308**	0.0128	0.016
HHI_Nn	-0.0006***	0.0002	0.007	-0.0003	0.0003	0.204
SIZE	0.0070***	0.0023	0.002	0.0060**	0.0026	0.019
DEBT_EQTY	-0.0045**	0.0018	0.011	-0.0039**	0.0020	0.048
DEPOSITS	-0.0114	0.0370	0.758	-0.0314	0.0337	0.351
Econ_GRWTH	0.1469**	0.0627	0.019	0.1842***	0.0584	0.002
Constant	-0.0423	0.0290	0.144	-0.0196	0.0370	0.596
Number of observations			80			80
Number of groups			16			16
Number of instruments			10			10
Wald chi2(7)			770.79			1009.28
Prob > chi2			0.000			0.000

**** p<.01, ** p<.05, * p<.1*

This section proceeds by first presenting the overall regression results and continues with a discussion with focus on the main variables of interest for the study: income diversification variables (HHI_Inc & HHI_Nn). As seen in the above table, the lag variable of ROA is found to have a positive and statistically significant impact on current year ROA. Both the two-step and one-step results confirm this with coefficients of 0.4202 and 0.4617 respectively at 1% significance level. This shows that previous year profitability has a positively and statistically significant impact on current year profitability; that is, bank performance will tend to persist from a given year to the next.

As for control variables, the study finds that bank size is found to have a positive and statistically significant impact on profitability with coefficient of 0.0070 and 0.0060 for the two-step and one-step GMM estimations respectively at 1% significance level. This shows that larger banks tend to be more profitable than banks of smaller size. It is likely that large banks are able to leverage their economies of scale together with their costly risk management techniques to generate increased profitability. Also, the study finds that bank debt to equity ratio (DEBT_EQTY) impacts bank profitability negatively with coefficients of -0.0045 and -0.0039 for the two-step and one-step GMM estimations respectively at 5% significance level.

With respect to the main variables of interest, the study finds that income diversification into interest and non-interest income sources (HHI_Inc) has a positive and statistically significant impact on profitability with coefficients of 0.0418 and 0.0308 for the two-step and one-step GMM estimations respectively at a 1% significance level. In contrast, with respect to our second variable of interest, the study finds that non-interest income diversification into fees and commissions income and other non-interest income sources (HHI_Nn) is found to have a slight negative impact on bank profitability with coefficients of -0.0006 and -0.0003 for the two-step and one-step GMM estimations respectively at 1% significance level for the two-step estimation only.

The result that income diversification into interest income sources and non-interest income sources (HHI_Inc) has a positive impact on bank performance are consistent with studies such as Calmès and Théoret (2021), Baselga-Pascual et al. (2018), and Nisar et al. (2018). These benefits can possibly come from increased income generating capabilities, decreased operating costs due to operating synergies or from a combination of the two (He et al., 2021). With respect to increased income generation, diversification can be beneficial to banks if there is a net positive gain from diversifying into different ventures. This can happen when current capabilities enable the efficient delivery of other financial services. With regards to operating synergies, diversification would be beneficial if there is a net reduction in cost owing to shared input costs and economies of scope from sharing of inputs such as human capital, technology and information systems across several product lines.

This is a sound inference from the theoretical perspective of synergy and economies of scope argument, which maintains that a firms opportunity to diversify is constrained by the “flexibility, sharability and transferability” of the business' core inputs (Hill, 1985). With shared inputs that are valuable across multiple activities, a bank can benefit from economies of scope by diversifying into multiple products increasing its revenue and reducing its average costs (Barney, 2013). For instance, the attainment of credit information for lending decisions usually requires a fixed, "set-up cost"(Clark, 1988; Radner, 1970); however, as soon as information is acquired it is available freely (or at less average cost) for producing other outputs (Clark, 1988). Thus, this enables banks to increase their overall profitability through diversification.

Overall, in the case of Ethiopian private banks greater levels of income diversification can increase bank profitability. *Thus, with this finding, the first hypothesis of the study that income diversification has a positive and significant impact on bank profitability is supported.*

With respect to the second variable of interest in model 1, the result that non-interest income diversification between fees and commissions income and other non-interest income sources (HHI_Nn) has a slight negative impact on bank profitability contradict This results are consistent with the findings of Bustaman et al. (2017). Bustaman et al. (2017) which is notes that a possible reason for banks performing negatively in “other non-interest income” sources is the lack of high expertise in performing higher risk activities such as trade transactions, compared to their capacities in selling fees and commissions income products.

The findings of this study show that in the case of Ethiopian private banks diversification of non-interest income activities (HHI_Nn) away from fees and commissions income into other non-interest income sources negatively affects bank profitability. Accordingly, it is concentration in fees and commission based activities and not diversification away from it into “other non-interest income” activities that tends to improve bank profitability. *Thus, with these findings, the third hypothesis of the study that non-interest income diversification has a positive and significant impact on bank profitability is not supported.*

4.6.2. Model 2: Income diversification and bank insolvency risk

Table 21: Regression Results - Income Diversification and Insolvency Risk (Model 2)

	Two-Step GMM Estimation			One-Step GMM Estimation		
Z-score	Coefficient	Corrected Std. Error	p-value	Coefficient	Corrected Std. Error	p-value
L.Z-score	0.6487***	0.2291	0.005	0.5787***	0.2038	0.005
HHI_Inc	2.1300**	1.0505	0.043	2.2155**	0.9917	0.025
HHI_Nn	-0.0662**	0.0304	0.030	-0.0615**	0.0282	0.029
SIZE	0.9158	0.6910	0.185	1.0623*	0.5482	0.053
DEBT_EQTY	-0.2282	0.1997	0.253	-0.2644	0.1664	0.112
DEPOSITS	-3.2192	2.0975	0.125	-4.4670**	1.9930	0.025
Econ_SIZE	-3.1439	2.7106	0.246	-3.6810*	2.1566	0.088
Constant	19.0549	16.3592	0.244	23.0588*	13.2407	0.082
Number of observations			80			80
Number of groups			16			16
Number of instruments			11			11
Wald chi2(7)			4031.77			2270.52
Prob > chi2			0.000			0.000

*** *p<.01*, ** *p<.05*, * *p<.1*

This section first presents the overall regression results and continues with a discussion with focus on the main variables of interest. The above table shows that the lag variable of Z-score is found to have a positive and statistically significant impact on current year Z-score. Both the two-step and one-step results confirm this with coefficients of 0.6487 and 0.5787 respectively at 1% significance level. This indicates that the previous year bank stability has a positive and statistically significant impact on the stability of the bank for the current year. With regards to control variables, the study finds that bank size is found to have a positive and statistically significant impact on bank stability with coefficient of 1.0623 for the one-step estimation at 10% significance level. This indicates that the larger a bank size the greater its stability. Also, the study finds that deposits ratio (DEPOSITS) and Economic size (Econ_SIZE) tend to negatively impact bank stability with coefficients of -4.4670 and -3.6810 respectively for the one-step estimation at 5% and 10% significance levels respectively.

For the main variables of interest for the study, the study finds that income diversification between interest and non-interest income sources (HHI_Inc) has a positive and statistically significant impact on bank stability (reduces insolvency risk) with coefficients of 2.1300 and 2.2155 for the two-step and one-step GMM estimations respectively at a 5% significance level. In contrast, for the second variable of interest, the study finds that non-interest income diversification into fees and commissions income and other non-interest income sources (HHI_Nn) has a negative and statistically significant impact on bank stability (increases insolvency risk) with coefficients of -0.0662 and -0.0615 for the two-step and one-step GMM estimations respectively at 5% significance level.

The results of the study show that in the case of Ethiopian private banks greater levels of diversification into non-interest based income activities can reduce insolvency risk (increase bank stability). Thus, as banks shift from traditional interest earning banking activities into nontraditional banking activities that generate non-interest income, insolvency risk is reduced.

The findings of the study that income diversification between interest based sources and non-interest based income sources (HHI_Inc) has a positive and statistically significant impact on bank stability (i.e. reduces insolvency risk) is consistent with findings by Nisar et al. (2018), Adem (2022) and Chandramohan et al. (2022). Potential reasons for this findings, as suggested by Bustaman et al. (2017) is that bank income diversification into non-traditional products can act to cross-subsidize losses caused by unfavorable performance of bank interest income. Banking income that is derived from the sale of non-traditional products can be used to effectively cushion against the risk of bank failures, act to stabilize bank profits, and help neutralize risks of greater competitive environments.

In addition to cross-subsidization, income diversification into non-interest income sources is also beneficial from the risk reduction perspective. From the perspective of risk reduction, the revenue of diversified firms is less riskier than the revenue of undiversified firms (Barney, 2013). As long as income from a bank‘s different product lines’ are not perfectly and positively correlated, income diversification will reduce bank risk to some degree. Accordingly, banks can effectively diversify away much of the risk associated with depending on traditional interest income sources alone. Modern portfolio theory is consistent with these findings. It emphasizes the importance of diversification in reducing risk by choosing among a “set of efficient risk-return combinations”

(Markowitz, 1952). In the case of banks, since non-interest income such as fees and commission income are relatively less correlated with interest income sources, the impact of including both income sources is likely to reduce the overall risk position of a bank's revenue streams.

Overall, results of the study show that in the case of Ethiopian private banks greater income diversification into non-interest based income activities can reduce insolvency risk. *Therefore, with this finding, the second hypothesis of the study that income diversification has a negative and significant impact on bank insolvency risk is supported.*

With respect to the second variable of interest in model 2, non-interest income diversification between fees and commissions income and other non-interest income sources (HHI_Nn) is found to have a negative and significant impact on bank stability (increases insolvency risk). This is consistent with the findings of Bustaman et al. (2017). However these results contradict results from Sissy et al. (2017) and Nisar et al. (2018). Potential reasons for this findings as suggested by Calmès and Théoret (2021) is that the new portfolio components (other non-interest activities) have greater variance than the old ones (fees and commissions activities), this might act to increase bank risk levels. Further, lack of high expertise in performing higher risk activities such as trade transactions involved "other non-interest income activities" compared to bank capacities in selling fees and commissions income products can cause the observed negative impact of non-interest income diversification into "other non-interest income activities" (Bustaman et al., 2017). These findings of this study show that, in the case of Ethiopian private banks, non-interest income diversification (HHI_Nn) away from fees and commissions income into "other non-interest income sources" negatively affects bank stability (i.e. increases insolvency risk).

Accordingly, for Ethiopian private commercial banks non-interest income diversification into sources other than fees and commissions income increases insolvency risk. A possible reason could be lack of high expertise in these "other non-interest income" activities. *Therefore, with this finding of the study, the forth hypothesis of the study that non-interest income diversification has a negative and significant impact on bank insolvency risk is not supported.*

Overall, drawing on the results for both measures of performance (profitability, model 1, and insolvency risk, model 2) the study finds that bank income diversification has an overall positive impact on bank performance, where as non-interest income diversification has an overall negative impact on bank performance.

4.6.3. Models 3a and 3b: Loan portfolio diversification and bank profitability

Table 22: Regression Results - Loan Portfolio Diversification and Profitability (Models 3a & 3b)

	Fixed-Effects (FE) Estimation Naïve Diversification Model (3a)			Fixed-Effects (FE) Estimation Market BM Diversification Model (3b)		
NIM	Coefficient	Robust Std. Error	p-value	Coefficient	Robust Std. Error	p-value
DIST_Ln				-0.1900***	0.0516	0.002
HHI_Ln	-0.0765***	0.0178	0.001			
BnkSIZE	0.0000	0.0001	0.842	0.0000	0.0001	0.975
Bnk_GRWTH	-0.0093	0.0076	0.240	-0.0085	0.0081	0.307
LOAN_DEP	0.0235*	0.0123	0.074	0.0275*	0.0136	0.062
CAR	0.0927	0.0779	0.253	0.1084	0.0863	0.229
DEPOSITS	0.0492	0.0445	0.286	0.0460	0.0447	0.320
Econ_GRWTH	-0.2414***	0.0375	0.000	-0.2536***	0.0397	0.000
Constant	0.0713	0.0435	0.122	0.1956**	0.0672	0.011
F(7,15)			24.980			33.967
Prob > F			0.000			0.000
Number of observations			96			96
Number of groups			16			16
R-squared			0.596			0.595

**** p<.01, ** p<.05, * p<.1*

The above table shows the results for the fixed effects estimation for models 3a and 3b with separate columns based on the diversification measures employed. The first three columns show the results for the naïve loan portfolio diversification (model 3a) as measured by Herfindahl-Hirschman Index (HHI_Ln). The next three columns show results for the loan portfolio diversification against a benchmark portfolio (the private banks aggregate loan market benchmark portfolio) (model 3b) measured by a distance measure (DIST_Ln).

Beginning with the results for naïve loan portfolio diversification (model 3a), the results show that the measure of naïve loan portfolio diversification (HHI_Ln) is found to have a negative and statistically significant impact on profitability as measured by net interest margin (NIM). As shown above, HHI_Ln has a coefficient of -0.0765 at 1% significance level. The result indicates that unit increase in naïve loan portfolio diversification (HHI_Ln) will cause profitability to decrease by a factor of -0.0765. With regards to control variables, the study finds that bank loan to deposits ratio (LOAN_DEP) ratio is found to have a positive and statistically significant impact on profitability with coefficient of 0.0235 at 10% significance level. Also, the study finds that economic growth (Econ_GRWTH) tends to negatively impact net interest margins with a coefficient of -0.2414 at a 1% significance level.

On the right column, we have results for the impact of loan portfolio diversification against the benchmark portfolio measured by DIST_Ln (model 3b). Loan portfolio diversification against the market benchmark portfolio (DIST_Ln) is found to have a negative and statistically significant impact on profitability as measured by net interest margin (NIM). The results show that DIST_Ln has a coefficient of -0.1900 at 1% significance level. The result indicates that unit increase in loan portfolio diversification against the market benchmark portfolio (DIST_Ln) will cause profitability to decrease by a factor of -0.1900. For control variables, the study finds that bank loan to deposits ratio (LOAN_DEP) is found to have a positive and statistically significant impact on NIM with coefficient of 0.0275 for at 10% significance level. Further, the study finds that economic growth (Econ_GRWTH) tends to negatively impact NIM with a coefficient of -0.2536 at a 1% significance level.

The results above show that, for both measures of loan portfolio diversification (HHI_Ln and DIST_Ln), loan portfolio diversification has a negative and statistically significant impact on bank profitability as measured by net interest margins (NIM). These results are consistent with findings of Adzobu et al. (2017). The results are not, however, consistent with findings by Mulwa (2018), and Shim (2019). There are potential reasons that help explain this effect. Kusi et al. (2020) notes that the presence of diseconomies of scale in the course of diversification of loan portfolios into new economic sectors could lead to decreasing bank profitability. These can arise due to greater degree of competition in certain economic sectors by existing market players. Accordingly, the best opportunities to offer loans are highly competed for. High competition in combination with the lack of adequate expertise in the new economic sector can result in adverse selection (i.e. attracting firms that incumbent banks with much more experience would not provide loans to) (He et al., 2023). These factors can result in lower bank profitability.

In addition, Blickle et al. (2023) points that expertise in an economic sector goes together with superior monitoring capabilities due to informational advantage. Accordingly, banks that specialize in loan origination and monitoring to only certain economic sectors might prove to perform better to banks that engage in greater loan diversification. Banks that concentrate on certain economic sectors might be more efficient at loan monitoring compared to more diversified banks that overstretch themselves in attempting to develop expertise across several economic sectors.

The findings of this study show that in the case of Ethiopian private banks for the study period loan portfolio diversification across economic sectors negatively affects bank profitability. This findings are not consistent with the theoretical perspective of synergies and economies of scope. From the theoretical perspective of synergies and economies of scope, banks extending their lending to different sectors would be expected to leverage their existing knowhow and credit information in loan origination and monitoring in to non-competing applications (Radner, 1970; Teece, 1980). The marginal cost involved in using loan origination and monitoring knowhow and credit information already obtained for another credit activity is expected to be lower than the cost of production (i.e. less average cost). Thus, it would follow from the theoretical argument of synergies and economies of scope that banks that diversify into other economic sectors would be expected to exhibit greater profitability. However, for Ethiopian private commercial banks, synergistic and economies of scope advantages have not materialized enough to positively impact bank profitability.

Accordingly, with these findings, the fifth hypothesis of the study that naïve loan portfolio diversification has a positive and significant impact on bank profitability is not supported. In addition, the seventh hypothesis of the study that loan portfolio diversification against the market benchmark portfolio has a positive and significant impact on bank profitability is also not supported.

4.6.4. Models 4a and 4b: Loan portfolio diversification and bank credit risk

Table 23: Regression Results - Loan Portfolio Diversification and Credit Risk (Models 4a & 4b)

	Fixed-Effects (FE) Estimation Naïve Diversification Model (4a)			Fixed-Effects (FE) Estimation Market BM Diversification Model (4b)		
LLP	Coefficient	Robust Std. Error	p-value	Coefficient	Robust Std. Error	p-value
DIST_Ln				-0.2373***	0.0486	0.000
HHI_Ln	-0.0830***	0.0196	0.001			
BnkSIZE	0.0000	0.0001	0.536	0.0000	0.0001	0.634
Bnk_GRWTH	-0.0284**	0.0110	0.021	-0.0281**	0.0104	0.016
LOAN_DEP	-0.0099	0.0205	0.637	-0.0064	0.0215	0.771
CAR	-0.3786**	0.1293	0.010	-0.3587**	0.1218	0.010
DEPOSITS	-0.0906	0.0574	0.136	-0.0943	0.0565	0.116
Econ_GRWTH	0.0597	0.0639	0.365	0.0404	0.0669	0.555
Constant	0.2179***	0.0581	0.002	0.3844***	0.0728	0.000
F(7,15)			4.803			6.333
Prob > F			0.005			0.001
Number of observations			96			96
Number of groups			16			16
R-squared			0.347			0.365

**** p<.01, ** p<.05, * p<.1*

Similar to the previous table, the above table shows the results for the fixed effects estimation for models 4a and 4b with separate columns based on the diversification measures employed. The first three columns show the results for the naïve loan portfolio diversification (Model 4a) as measured by Herfindahl-Hirschman Index (HHI_Ln). The next three columns show results for the loan portfolio diversification against a benchmark portfolio (private banks aggregate loan market benchmark portfolio) (Model 4b) measured by a distance measure (DIST_Ln).

The results of the study show that the measure of naïve loan portfolio diversification (HHI_Ln) is found to have a negative and statistically significant impact on credit risk as measured by loan loss provision ratio (LLP). As shown above, HHI_Ln has a coefficient of -0.0830 at 1% significance level. The result indicates that unit increase in naïve loan portfolio diversification (HHI_Ln) will cause credit risk as measured by loan loss provisions ratio (LLP) to decrease by a factor of -0.0830.

As for the control variables, the study finds that bank growth rate (Bnk_GRWTH) is found to have a negative and statistically significant impact on credit risk with coefficient of -0.0284 at 5% significance level. Further, capital to assets ratio (CAR) is shown to also negatively impact credit risk with a coefficient of -0.3786 at 5% significance level.

On the right column, we have the results for the impact of loan portfolio diversification against the benchmark portfolio (private banks aggregate loan market benchmark portfolio) measured by DIST_Ln. The study finds that loan portfolio diversification against the market benchmark portfolio (DIST_Ln) is found to have a negative and statistically significant impact on credit risk as measured by loan loss provision ratio (LLP). The results show that DIST_Ln has a coefficient of -0.2373 at 1% significance level. Accordingly, this indicates that unit increase in loan portfolio diversification against the benchmark portfolio (DIST_Ln) will cause credit risk as measured by loan loss provision ratio (LLP) to decrease by a factor of -0.2373.

With regards to control variables, the study finds that bank growth rate (Bnk_GRWTH) is found to have a negative and statistically significant impact on credit risk with coefficient of -0.0281 at 5% significance level. Additionally, the study finds that bank capital to assets ratio (CAR) tends to negatively and significantly impact credit risk with a coefficient of -0.3587 also at 5% significance level.

Accordingly, for both measures of loan portfolio diversification (naive loan portfolio diversification, HHI_Ln, and loan portfolio diversification against the benchmark portfolio, DIST_Ln), the results of the study confirm that loan portfolio diversification has a negative and statistically significant impact on bank credit risk as measured by loan loss provisions ratio (LLP). The results are consistent with findings by Shim (2019). These findings are also consistent with modern portfolio theory, which notes that the riskiness of the income flows of a more diversified portfolio is lower than the riskiness of the income from a less diversified portfolio (Barney, 2013). In the case of loan portfolios, it would follow that banks with more diversified loan portfolios will tend to have less risk than banks with less diversified loan portfolios. This risk reduction benefit according to Lintner (1965) comes from the correlation in returns from different income streams due to the existence of negatively and non-perfectly positively correlated income streams. For banks, loan performance across different economic sectors is likely to be less than perfectly-positively correlated and potentially negatively correlated. Thus, the overall risk of a more diversified loan portfolio would be less than a less diversified loan portfolio. Consistent with this theory, in the case of Ethiopian private commercial banks, higher loan portfolio diversification (both naïve loan portfolio diversification and loan portfolio diversification against the benchmark portfolio) is found to negatively and significantly impact credit risk.

Accordingly, with these findings, the sixth hypothesis that naïve loan portfolio diversification has a negative and significant impact on bank credit risk is supported. Similarly, the eighth hypothesis that loan portfolio diversification against the market benchmark portfolio has a negative and significant impact on bank credit risk is also supported.

In determining the overall impact of loan portfolio diversification on bank performance, Acharya et al. (2006) suggests that if bank return and bank risk "either both increase or both decrease, the overall effects on bank performance are ambiguous and cannot be determined without taking a stand on what constitutes an 'efficient' risk-return trade-off". In the present study, the result of models 3a and 3b suggest that loan portfolio diversification across economic sectors negatively affects bank profitability. On the other hand, the results from models 4a and 4b suggest that loan portfolio diversification negatively impacts bank credit risk. With the contradicting results on profitability and credit risk, following Acharya et al. (2006), the overall impact of loan portfolio diversification on Ethiopian private bank performance is indeterminate without deciding what is considered an efficient trade-off between profitability and credit risk.

4.7. Summary of empirical results

Table 24: Summary of Regression Results according to Research Objectives

Specific Research Objectives	Research Findings
• To examine the effect of income diversification on bank profitability among private commercial banks in Ethiopia	• Income diversification has a positive and significant impact on bank profitability.
• To examine the effect of income diversification on bank risk among private commercial banks in Ethiopia	• Income diversification has a negative and significant impact on bank risk.
• To determine the effect of non-interest income diversification on bank profitability among private commercial banks in Ethiopia	• Non-interest income diversification has a negative and significant impact on bank profitability.
• To determine the effect of non-interest income diversification on bank risk among private commercial banks in Ethiopia	• Non-interest income diversification has a positive and significant impact on bank risk.
• To examine the effect of naïve loan portfolio diversification on bank profitability among private commercial banks in Ethiopia	• Naïve loan portfolio diversification has a negative and significant impact on bank profitability
• To examine the effect of naïve loan portfolio diversification on bank risk among private commercial banks in Ethiopia	• Naïve loan portfolio diversification has a negative and significant impact on bank risk.
• To determine the effect of loan portfolio diversification against a market benchmark portfolio on bank profitability among private commercial banks in Ethiopia	• Loan portfolio diversification against market benchmark portfolio has a negative and significant impact on bank profitability.
• To determine the effect of loan portfolio diversification against a market benchmark portfolio on bank risk among private commercial banks in Ethiopia	• Loan portfolio diversification against market benchmark portfolio has a negative and significant impact on bank risk.

CHAPTER FIVE

5. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

This chapter presents a summary of the empirical results of the study in light of the specific research objectives and provides conclusion for the study in view of the research questions of the study. The chapter also discusses the practical recommendations and implications of the research findings and presents suggestions for possible directions for future research.

5.1. Introduction

The present study empirically investigated the impact of income diversification and loan portfolio diversification by economic sector on bank performance. These investigation seeks to answer two key research questions: i) how does income diversification effect bank performance among Ethiopian private commercial banks? And ii) how does loan portfolio diversification effect bank performance among Ethiopian private commercial banks?

In seeking to answer the above research questions, the study explores the income and loan portfolio diversification landscape of the Ethiopian private banking industry and provides evidence on the nature of impact diversification has on Ethiopian private banks.

5.2. Summary of findings

The present study examined the impact of income and loan portfolio diversification on bank performance among Ethiopian private commercial banks. The results of the study are summarized as follows according to the respective specific research objectives.

First for the first research objective: to examine the effect of income diversification on bank profitability among private commercial banks in Ethiopia, the study found that income diversification into interest and non-interest income has a positive and statistically significant impact on profitability with coefficients of 0.0418 and 0.0308 for the two-step and one-step GMM estimations respectively at 1% significance level. For the second research objective, to examine the effect of income diversification on bank risk among private commercial banks in Ethiopia, the study found that income diversification into interest and non-interest income has a positive and statistically significant impact on bank stability (reduces insolvency risk) with coefficients of 2.1300 and 2.2155 for the two-step and one-step GMM estimations at 5% significance level.

For the third research objective, to determine the effect of non-interest income diversification on bank profitability among private commercial banks in Ethiopia, the study found that non-interest income diversification into fees and commissions income and other non-interest income sources has a slight negative impact on profitability with coefficients of -0.0006 and -0.0003 for the two-step and one-step GMM estimations at 1% significance level for the two-step estimation only.

For the fourth research objective, to determine the effect of non-interest income diversification on bank risk among private commercial banks in Ethiopia, non-interest income diversification between fees and commissions income and other non-interest income sources was found to have a negative and statistically significant impact on bank stability (increases bank insolvency risk) with coefficients of -0.0662 and -0.0615 for the two-step and one-step GMM estimations respectively at 5% significance level.

For the fifth research objective, to examine the effect of naïve loan portfolio diversification on bank profitability among private commercial banks in Ethiopia, naïve loan portfolio diversification is found to have a negative and statistically significant impact on profitability as measured by net interest margins with a coefficient of -0.0765 at 1% significance level. For the sixth research objective, to examine the effect of naïve loan portfolio diversification on bank risk among private commercial banks in Ethiopia, naïve loan portfolio diversification is found to have a negative and statistically significant impact on bank credit risk as measured by loan loss provision ratio with a coefficient of -0.0830 at 1% significance level.

For the seventh research objective, to determine the effect of loan portfolio diversification against a market benchmark portfolio on bank profitability among private commercial banks in Ethiopia, diversification against the aggregate loan market benchmark portfolio is found to also have a negative and statistically significant impact on profitability as measured by net interest margins.

For the eighth research objective, the study found that loan portfolio diversification against the aggregate loan market benchmark portfolio is found to have a negative and statistically significant impact on credit risk as measured by loan loss provision ratio with a coefficient of -0.2373 at 1% significance level.

5.3. Conclusions

Based on the results found, conclusions for the study are drawn in view of the research questions. The two key research questions that are the starting point for this research are: i) how does income diversification effect bank performance among Ethiopian private commercial banks? And ii) how does loan portfolio diversification effect bank performance among Ethiopian private commercial banks?

The first research question is answered as follows. The study found that income diversification into interest and non-interest income has a positive and statistically significant impact on both profitability and bank stability (reduces insolvency risk). On the other hand, non-interest income diversification into fees and commissions income and other non-interest income sources is found to have a slight negative impact on bank profitability and a negative impact on bank stability (increases bank insolvency risk).

Therefore, it can be concluded that the overall impact of income diversification into interest and non-interest income on bank performance is positive. These conclusions are consistent with modern portfolio theory, which notes that the riskiness of the revenue of diversified firms is less than the riskiness of the revenue of undiversified firms as long as the income flows are not perfectly and positively correlated (Barney, 2013). Since bank income flows from net interest income and non-interest income sources is relatively less correlated, the study results confirm that income diversification into interest and non-interest income sources reduces insolvency risk (increases stability). Additionally, this conclusion is consistent with synergy and economies of scope argument. Banks are able to employ “flexibility, sharability and transferability” of the business' core inputs such as human capital, information systems, technological infrastructure, and loyal customer base to sell more non-interest income based products. This engages the economies of scope available to banks to increase their profitability.

In addition, it is also concluded that the overall impact of non-interest income diversification between fees and commissions income and other non-interest income sources is negative. It can be inferred that it is concentration in fees and commission based non-interest income activities and not diversification away from them into “other non-interest income sources” that tends to improve bank profitability. A possible reason could be the lack of high expertise in these “other non-interest income” activities compared to bank capabilities in selling fees and commission income products.

In order to answer the second research question, the study employs two measures of loan portfolio diversification: naïve loan portfolio diversification as measured by Herfindahl-Hirschman Index and loan portfolio diversification against a benchmark portfolio (the private banks aggregate loan market benchmark portfolio) measured by a distance measure. Again, the study examines impact on bank performance on both profitability and credit risk so as to draw conclusions on the overall impact of diversification on bank performance. The second research question is answered as follows. Naïve loan portfolio diversification is found to have a negative and statistically significant impact on both bank profitability and credit risk. Similarly, diversification against the benchmark portfolio is found to have a negative and statistically significant impact on both bank profitability and credit risk.

Therefore, it can be concluded that the overall impact of loan portfolio diversification (both naïve loan portfolio diversification and diversification against the benchmark portfolio) on bank performance is ambiguous. The overall impact of loan portfolio diversification can be described as a tradeoff between bank profitability and credit risk. Thus, the overall impact cannot be determined without having to decide what is considered an "efficient" tradeoff between profitability and credit risk.

Altogether, it can be concluded that the overall impact of income diversification on bank performance is positive when considering income diversification into interest and non-interest income and negative when considering non-interest income diversification into fees and commissions income and other non-interest income sources. In the case of loan portfolio diversification, it can be concluded that the overall impact of both naïve loan portfolio diversification and loan portfolio diversification against the benchmark portfolio on bank performance constitutes a trade-off between profitability and credit risk and is overall indeterminate without deciding what is considered an efficient tradeoff between profitability and credit risk.

5.4. Recommendations

Based on the findings of the study, the following recommendations are made on bank income and loan portfolio diversification.

Since the result of the study show that income diversification has a positive and significant impact on bank profitability, it is recommended that banks consider ways to increase their diversification into non-interest based banking activities by providing more fees and commissions services such as by engaging with new clients who need letters of credit, letter of guarantees, and cash payment order (CPO) services. Further, this will also help reduce insolvency risk and improve bank stability.

Overall, in view of increasing competition in the banking industry, banks can leverage their current information systems, human capital, technological infrastructure, and loyal customer base to sell more non-interest income based products. This engages the economies of scope available to them to increase their profitability and reduce their income volatility.

However, banks should not regard all income diversification in the same way. Particularly, diversification within non-interest income sources (away from fees and commissions income) can negatively impact their bank profitability and increase their insolvency risk. Thus, before engaging in "other non-interest income activities", it is recommended that banks conduct careful and through due diligence to examine the potential market returns and their internal capabilities and expertise in these ventures. When banks try to expand their operations in hope of diversifying revenue, they may be moving beyond their areas of comparative advantage and entering new activities in which they struggle to be competitive. Such low performance can possibly be attributed to the fact that banks lack the capabilities and core-capabilities in these new activities. Towards this end, if banks deem the potential benefits from such ventures as beneficial, it is recommended that banks engage in strategic activities that build internal capabilities and core competencies both in terms of human capital, technological infrastructure, and information systems so that they can attain the desired levels of profitability in the long run in these newly entered activities.

It is also recommended that banks reduce their credit risk by engaging in loan portfolio diversification both in the form of naïve loan portfolio diversification and loan portfolio diversification against the loan market benchmark portfolio. However, this must be done with caution as this will also result in reduced profitability. Thus, it will be important for banks to decide on what they consider is an "efficient trade-off between risk-and return".

Banks that choose to diversify into new economic sectors in order to reduce their credit risk will also need to prudently evaluate and improve their capabilities in loan origination and loan monitoring in the new sectors, while guarding against adverse selection in accepting new customers. Banks will also need to continue to make required investments in their risk management systems. This will help banks to increase their gain from loan portfolio diversification, while reducing the possible risk associated with diversifying loan portfolios.

5.5. Suggestions on Possible Directions for Future Research

Banks' response to diversification might vary based on their current risk levels. Banks with high risk can respond differently to diversification than banks with moderate and low risk. Hence, future studies that disaggregate the bank data based on current risk level (high, low and moderate) can yield interesting insights on the impact of diversification in view of such risk characteristics.

Another possible direction for future research is whether there exists a threshold beyond which greater levels of diversification impact banks negatively (i.e. the "U-shaped, nonlinear, relationship" suggested by Kusi et al. (2020)) for the Ethiopian banking industry.

In addition, future research can explore the impact of loan portfolio diversification against a bench mark portfolio comprising the respective economic sectors' contribution to national GDP as suggested. This might provide key insights on the potential advantages of basing diversification decisions based on this benchmark portfolio, which might be a possible alternative path of pursuing bank loan portfolio diversification.

Since microfinance institutions play a key role in allocating funds in developing countries such as Ethiopia, it makes them relevant for studies of diversification. The significant economies of scale advantages present in large banks might be lacking in microfinance institutions. This characteristics of microfinance institutions makes the examination of the impact of diversification on microfinance institutions important and likely to produce key insights.

The start of capital markets in Ethiopia will introduce market valuation based measures of bank performance. Market capitalization data from banks listed on the capital market will open up possibilities of research into whether diversification leads to a premium (higher valuation) or a discount (lower valuation) in the market value of banks that choose to pursue it.

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Appendix 1: List of Private Commercial Banks in Ethiopia as of June 2022

No.	Name of Bank	Year Established
1	Awash Bank*	1994
2	Dashen Bank*	1995
3	Bank of Abyssinia*	1996
4	Wegagen Bank*	1997
5	Hibret Bank*	1998
6	Nib International Bank*	1999
7	Cooperative Bank of Oromia*	2004
8	Lion Interenational Bank*	2006
9	Oromia Bank*	2008
10	Zemen Bank*	2008
11	Berhan Bank*	2009
12	Bunna International Bank*	2009
13	Abay Bank *	2010
14	Addis International Bank*	2011
15	Debub Global Bank*	2012
16	Enat Bank*	2011
17	Zamzam Bank	2020
18	Hijra Bank	2021
19	Goh Betoch Bank	2021
20	Shebelle Bank S.C	2021
21	Siinqee Bank S.C	2021
22	Tseday Bank S.C	2022

* Indicates the bank has been operating for the study period 2017- 2022

Source: National Bank of Ethiopia (NBE) Annual Report (2022)