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Determinants of Financial Distress: Empirical Evidence from Private Commercial Banks in Ethiopia

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Partial Fulfillment of the Requirement for the Degree of Master of
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Abstract

The major focus of this study is to investigate empirically financial distress determinants in the case of private commercial banks in Ethiopia. Fourteen private commercial banks were included in the sample that had at least six years annual report out of sixteen. Document review was used for collecting data from 2012- 2017 annual reports. In line with this objective, the study adopted quantitative methods of research approaches to test the study hypothesis. The study applied Altman's 1993 Z-score model as the proxy for financial distress and panel data model with its fixed effect estimate to test a series of hypotheses that emerge through the review of existing literature. The collected data then analyzed using descriptive statistics, correlation analysis, and panel data regression analysis. To confidently forward conclusion, normality, multicollinearity, heteroscedasticity and autocorrelation tests were conducted on the data. The data then was processed using Eviews 8 statistical package. The results show that: sampled banks were in distress zone. Specifically variables such as capital adequacy, earning ability, liquidity, bank size, and inflation has found significant influence on financial distress of private commercial banks in Ethiopia. On the other hand asset quality, management efficiency, and GDP have no influence on financial distress. Macro variables are less influence on determining financial distress compared to micro variables. In general, the research concludes that both bank specific and macroeconomic factors determine the level of financial distress of Ethiopian commercial banks. Finally, private commercial banks must take remedies and apply early warning systems to predict financial distress before bankruptcy was given as recommendation.

Keywords: *Financial Distress, Bankruptcy, Altman's z-score, CAMELS, Multiple discriminant analysis, commercial bank*

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Acronym	Full name
A	Asset quality
AIESM	Artificially intelligent expert system models
BG	Breusch and Godfrey
BI	Bank interest
BIS	Bank for international settlement
BLUE	Best linear unbiased estimator
BODs	Board of directors
BOPO	Ratio of operating expenses to operating income
CAMELS	Capital adequacy, asset quality, management efficiency, earning ability, liquidity and size
CAR	Capital adequacy ratio
CBE	Commercial Bank of Ethiopia
CBK	Central bank of Kenya
CBR	Case-based reasoning
COOP	Cooperative Bank of Oromia
CLRM	Classical linear regression model
CRIS	Composite rule induction system
CSPI	Consumer price index
DSC	Debt service coverage
DW	Durbin–Watson
EG	Economic growth
ETA	Equity capital divided by total assets
EWS	Early warning system
FD	Financial distress
FE	Fixed effect
FSIZE	Firm size
GA	Genetic algorithms
GDP	Gross domestic product
GQ	Goldfeld – Quandt
IFS	International financial statistics
IMF	International monetary fund
INF	Inflation
L	Liquidity
LM	Langrage multiplier
LNTD	Loan to total deposit ratio
M	Management efficiency
MDA	Multiple discriminant analysis
MENA	Middle east and north Africa
NAFTA	North America free trade area
NBE	National bank of Ethiopia

NBFIs	Non-bank financial institutions
NICs	Newly industrialized countries
NIM	Net interest margin
NPLTL	Nonperforming loan to total loan
OECD	Organization for economic co-operation and development
OIB	Oromia International Bank
OLS	Ordinary least square
ROA	Return on asset
ROE	Return on equity
RPA	Recursive partitioning analysis
SOL	Solvability
TBAFD	Trinity bankruptcy agents of financial distress
X²	Chi-square

CHAPTER ONE

1. Introduction

This chapter discusses the background information of the study, thus the balance of the chapter is organized as follows. The first section sets out the background of the study, then problem statement is discussed. The third section provides the research objective. The hypothesis used is presented in section four. Significance, scope, and organization of the study are presented in section five, six and seven; a structure of the study respectively.

1.1 Background of the Study

In the economic resource allocation of a country; commercial banks play a vital role; since they channel funds from depositors to investors (or from surplus unit to deficit unit) continuously. To do so and get survived in the operation, they should have to generate necessary income to cover the operational cost they incur. Beyond this, their financial performance has also a critical implication for economic growth of the county. Good financial performance rewards the shareholders for their investment. This, in turn, encourages additional investment and brings about economic growth. On the other hand, poor banking performance can lead to banking failure or distress and crisis which have negative impacts on the economic growth of the country (Vincen et al, 2013).

As an important sector in the economic role of a country, banking has a unique function of business, as well as stabilizing the state financial atmosphere. It also has some influence in company financial condition (as creditors) as disclosed in different research; that banking bankruptcy will cause a decrease in the company value asset at 4.1%, net sales decline amounting to 3.7% for companies that have a relationship as banking creditor (Verdugo, 2013) cited (Rinaldo et al, 2014). This fact illustrates the banking sector important role in the financial stability of a country.

Furthermore, they do not only facilitate saving and provide a fund for almost every investment activities of a given nation but also have a greater role in the countries' foreign trade and the whole economy. So they can be considered as the nucleus of the nations' economy. If banks fail,

it will lead to general economic crises (Demiguc et al, 1998). If it is so; knowing the meaning, cause and remedies are very important to protect banks from being financially distressed.

Surprisingly financial distress is hard to define precisely as a result of the variety of events befalling firms under financial distress, but different researchers defined it based on their own perspective. "A firm that does not generate enough cash flow to make a contractually required payment, such as principal and interest payment will experience financial distress. A firm that defaults on a required payment may be forced to liquidate its assets. More often, a defaulting firm will reorganize its financial structure" (Stephen et al, 2012). It is a period when a borrower is unable to meet its payment obligation to lenders or other creditors" Zaki, et al. (2011) cited in (Rinaldo et al, 2014). (Luciana et al, 2003); defines financial distress as a condition in which the company experienced delisted as a result of net income and book value of negative equity in a row and the company was in a merger. Generally; financial distress began when the company cannot pay the repayment schedule or when the cash flow projections indicate that the company will soon be unable to pay its obligations. And there are also several terms related to it such as failure, insolvency, and bankruptcy (Amalia Fachrud, 2008).

Analysis of financial distress is one of the predictions that is very important to determine whether a financial institution is distressed or not, especially in banking as the central element of the economy of a country. Therefore it needs an early warning system to identify initial symptoms of financial distress. Predictive models like: Logit, Altman's Z-score, Ohlson's O-score, Hazard, etc... can be used as an early warning tool for users of corporate financial ratio information, such as lenders, investors, regulators, auditors, and management, in making relevant decisions with the information of financial distress possibility in different business enterprises, including the banking sector (Rinaldo et al, 2014).

Based on several studies done in this area around the Globe; money countries experienced financial distress. Basically on their financial institutions; for example Europe, USA, and ASIA, NORDIC, Middle-East, and Sub-Saharan Africa countries. To illustrate; Research on financial distress in European banking with a commercial bank sample, interval period 2003-2007 found that European banks experienced financial distress problems (Fiordelisi and Cipollini, 2009). In sub Saharan Africa, in the year 1980s and 1990s like: banks in Kenya, Nigeria, Benin, Tanzania, Uganda, and Zambia were closed or taken over by the central bank due to insolvency and

liquidity problems caused by non-performing loans (Brownbridge, 1998). Moreover the financial crisis in Asia in the year 1997 to 1998; and, the recent financial crisis in US and Europe in the year 2007/08 were an example of this kind of financial distress and failure (Zamorski et al, 2015), (Betz et al, 2013) respectively.

The banks that experienced financial distress will be depressed if it leads towards bankruptcy by the additional costs. A number of literature states that there are two types of cost of financial distress: direct and indirect costs for firm value and performance (Heitor Almeida and Thomas Philippon, 2004). Direct costs of distress such as those entailed by litigation fees are relatively small. Indirect costs such as loss of market share and inefficient asset sales are believed to be more important, but they are also much harder to quantify (Heitor Almeida and Thomas Philippon, 2004). (Andrade and Kaplan, 1998), for example, estimate costs of the order of 10% to 20% of the firm value at the time of distress for a sample of highly leveraged firms. On the other hand loss of output and fiscal costs are costs associated with the financial system or banking failure (Heitor Almeida and Thomas Philippon, 2004). On the advanced economies as a result of the financial collapse of subprime residential mortgage market 59% of GDP was median fiscal costs and 24.8% of GDP was median output loss during the period of financial crisis 2007/08 in US (Bulow and klemper, 2013) cited in (Tadesse, 2017).

Furthermore; the cost of financial distress depends on the probability of distress and management of the distress costs (Brealey and Myers, 2000). The bankruptcy costs to the owners depend on the type of organization. In a sole proprietorship or partnership form of organization, the proprietor/ partners have to bear the costs. But in a joint stock company, where the liability of members is limited, the shareholders can walk off leaving the burden on the creditors. The loss to the shareholders depends on the value of the firm. A firm which was enjoying high market value, if suddenly turn to bankrupt, the shareholders may feel the loss heavy because of the sudden decline in the value of shares and thereby the decrease in their wealth.

Thus, to come up with these problems there are different organizations on banking area internationally; who advises regulators: to increase the resilience of the financial sector and forestall distresses. Bank for International Settlement (BIS) is one of these types of organizations. According to Basel III accord 2010 recommendation in order to minimize these costs and to manage its effect on economy, banks to increase their regulatory capital; assuming

the disturbances stem from an interaction of insufficient capitalization; excessive maturity mismatch driven by banking funding structures; and insufficient holdings of high quality liquid assets that would allow banks to independently cope with short-term funding squeeze capital (Buchholz et al, 2013). On the other hand; in an effort to reduce negative influence to the economy as a whole and costs associated with bankruptcy; regulators and corporate managers to act quickly to prevent bankruptcy or lowering the cost of failure, namely by developing early warning system (EWS) to predict potential problems that occur in the company.

In literature, it has been indicated that there is a large number of financial distress prediction techniques. But (M. Adnan Aziz and Humayon, 2006) narrowed it to three broad groups: classical statistical, artificially intelligent expert system, and theoretical models. From classical statistical models, univariate and Multiple Discriminant Analysis (MDA) are dominant techniques that used by many researchers. In the AIESM; Neural networks is widely applied. But theoretical models are often developed by employing an appropriate available statistical technique rather than by building directly on theoretical principles; they are Balance Sheet Decomposition Measurement Theory, Gambler's Ruin Theory, Cash Management Theory, and Credit Risk Theories. There are also non-financial variables that can be used in forecasting company distress; such as financial control, industry experience, management experience, staffing, product/service timing, economic timing and marketing skills, age of the company, and any changes over the past three years in the number of directors, non-executive directors, shareholders and auditors; but they are not generally accepted and is no concern of this study (Francois van der Colff and Frans Vermaak, 2015).

EWS consider the soundness of the whole financial sector and try to predict systemic crises; even if it is mainly concerned and focused on individual banks level (David G Mayes and Hanno Stremmel, 2012). In the account of journals, researchers used a combination of different ratios as early warning system (EWS)¹. Besides this; authors identified the determinants of the selected EWS. They stated that the strengths and vulnerabilities of deposit-takers (banks) can be analyzed under CAMELS; capital adequacy, asset quality, earnings and profitability, liquidity, and sensitivity to market risk. On the other hand, some researchers include macroeconomic

¹ Altman's Z-score, Ohoholson's O-score, Logistics, etc...

determinants like GDP, Inflation, Deposit interest rate, inflation etc... beside the aforementioned micro (firm-specific) determinants.

In Ethiopia; (Ephrem, 2015)states capital to loan ratio, net interest income to total revenue ratio have a statistically significant positive influence on the financial health of banks whereas the nonperforming loan ratio has statically a significant negative influence on the financial health of the banks. (Tadesse, 2017)describes capital adequacy, management efficiency and earning ability has a negative and significant effect on banking financial distress but bank size has to be negative and no significant influence; whereas asset quality and liquidity appeared as having a positive effect, but liquidity was only significant on banking financial distress from specific (micro) level determinants. Regarding the macroeconomic factors, economic growth and saving interest rate have significantly negative and positive effect on banking financial distress respectively; whereas inflation was not significant. Based on the inconsistency of variables on the previous researches as discussed above, this paper used CAMELS financial ratios as bank specific determinants plus macro variables (GDP and Inflation) to predict financial distress condition of private banks in Ethiopia; using Altman's 1993 Z-score model; since other traditional and early corporate failure prediction models lack the industry-specific characteristic that makes them ineffective in predicting the failure of non-manufacturing firms (John et al, 2011).

1.2 Statement of Problem

Financial distress is one of the most significant threats to many firms globally despite their size and nature². The term financial distress is used in an unenthusiastic implication to describe the financial situation of a company confronted with a temporary lack of liquidity and with the difficulties that ensue in fulfilling financial obligations on schedule and to the full extent (Outecheva, 2007) cited in (HELLEN, 2013). (Almilia, 2004) study also supports this idea; "financial distress is an early symptom of the bankruptcy of a company". It can also be a stage prior to the bankruptcy or liquidation (Luciana, 2006) cited in Nur Hasanah (2010).

Furthermore; banking crises have a negative influence on the economy as a whole and particularly the financial sectors. Therefore, when they experience financial distress,

²Crises in Europe, USA, and ASIA, NORDIC, Middle-East and Sub Saharan Africa countries

governments usually come to the rescue, offering emergency liquidity and various forms of post security programs³. For example; at least 228 of these large firm bankruptcies in the United States recorded from 1970–2005 (Edward et al, 2006). In Southeast Asia's monetary crisis has turned into an economic crisis (Rinaldo et al, 2014). In a similar way, in the year 1980s and 1990s, the sub-Saharan Africa region: Kenya, Benin, Nigeria, Tanzania, Uganda, and Zambia had also experienced banking crisis that imposes large costs to the whole economy (Brownbridge, 1998), (HELLEN, 2013), and (Daumont, 2004).

Besides the negative influence to the economy as a whole; the banks that experienced financial distress will be depressed if it leads towards bankruptcy by the additional costs. According to works of literature, there are both direct and indirect costs for firm value and performance⁴. Furthermore according to (Brealey and Myers, 2000) the primary cost is the bankruptcy or insolvency costs. When the company is declared as insolvent/bankrupt, it has to meet legal costs by way of reimbursement of expenses incurred by the receiver, his salaries, and allowances. The cost of financial distress depends on the probability of distress and management of the distress costs.

Thus, to come up with these problems there are different organizations on banking area international who advises regulators: to increase the resilience of the financial sector and forestall distress. On the other hand; in an effort to reduce negative influence to the economy as a whole and costs associated with bankruptcy; regulators and corporate managers to act quickly to prevent bankruptcy or lowering the cost of failure, namely by developing early warning system (EWS) to predict potential problems that occur in the company.

The literature on early warnings of company failure is well established, with empirical studies dating back to the early 1960s⁵. But for financial institutions, it was started since the 1970s. In literature, it has been indicated that there is a large number of financial distress prediction techniques. According to (M. Adnan Aziz and Humayon, 2006) the three broad categories are

3 (Heitor Almeida and Thomas Philippon, 2008)

4Warner, 1977, Altman, 1984, Weiss, 1990, etc Cited in (Heitor Almeida and Thomas Philippon, 2004)

⁵Altman 1968, Beaver , oholson ... etc

namely classical statistical models artificially intelligent expert system models, and theoretical models.

In the account of journals, researchers used a combination of different ratios as early warning system (EWS)⁶. Besides this; authors identified the determinants of the selected EWS. They argue that ‘the strengths and vulnerabilities of deposit-takers (banks) can be analyzed under CAMELS and macro variables.

From the work of literature reviewed; the aforementioned corporate failure prediction models are both beneficial and limited, however, no technique is consistently superior to other techniques (John et al, 2011). A major limitation to research made in relation to predicting corporate failures is the focus exclusive to the fact they can only be applied to manufacturing firms (Appiah, 2011) cited in cited in (John et al, 2011). But as a solution for this limitation, Altman developed a model in 1993⁷ to predict corporate failures for developing countries firms, emerging market companies and for non-manufacturers. After that many researchers used and verified the applicability on financial institutions and became a dominant model used in corporate failure prediction literature due to its simplicity and accuracy (John et al, 2011)

There is no financial distress management trend on financial institutions of this country; as mentioned above if FD is not properly managed or prevented using early warning systems, it leads to bankruptcy which eventually leads to bank failures. Thus it is very important for banks to be able to tell and predict if they are in financial distress so as to save them before it’s too late and avoid failure. Private commercial banks in Ethiopia are profitable, but reporting positive accounting profit and showing good progress in performance is not guarantee to the going concern of the company (Mullu, 2011); since it does not necessarily mean that profitable companies are healthy enough to fulfill their short term and long term obligations. This is due to the fact that not all of the profit can be cashed as a source of funds or be available to for covering its obligations (Pranowo, 2010).

There is two individual efforts exhausted to know the position of private commercial banks; whether they are distressed or not; using Altman’s Z-score predictive (early warning) model

⁶Altman’s Z-score, Ohoholson’s O-score, Logistics, etc...

⁷ (Altman E. , 1993)

(Ephrem, 2015) and (Tadesse, 2017). But none of them are used adequate Altman's model as a proxy of FD; (Ephrem, 2015) used Zeta-score developed for credit risk management in 2002⁸, besides this; macro variables are not got consideration in his study. Whereas (Tadesse, 2017) tried to address the limitation of Ephrem, by including both bank-specific and macro variables as determinants of FD and by using Altman's 1993 model developed for emerging market; but there is a big question on the Altman's model he used Altman's 1993, model has two version; the first one is the original z-score developed for non-manufacturing and privately owned companies, and the second one is same model but to address the emerging market⁹ problems he added a constant term +3.25. Because it is difficult to categorize private commercial banks as emerging market; a model with a constant term is not appropriate to implement. Besides the inappropriate models adopted by them; they tried to generalize the overall commercial banks only by taking less than 50% of the total population. Finally; taking very large (10-20) years or very small (1-3) years Z-scores sample to predict FD is not the best choice since on large years sample average ratios do shift over time (Altman, 2002); and small years sample is not sufficient to predict the model. Furthermore, the relative predictive ability of any model would decrease as a result of lead time increase. But on the average 5-year sample of z-score is superior predicting financial distress; Li and Rahgozar (2012) cited in (John et al, 2011).

Thus the focus of this study was to come up the above limitations by applying originally evolved 'Z' Score 'model of (Altman E. , 1993)for non-manufacturing and private companies on private commercial banks in Ethiopia. This model overcomes the manufacturing limitation of (Beaver, 1966) univarity model, (Ohlson, 1980) logit model and Altman's pioneering model¹⁰and can be used for financial institutions. Beside this the study included fourteen private commercial banks out of sixteen operating and disclosing their six years financial statement from 2012-2017. The variables used in this study predict remedy CAMELS model of financial ratios plus macro

⁸The model is developed for manufacturing company and has additional ratio X5 = sales/total assets; which is not applicable for financial institutions; since corporate failure prediction models lack the industry specific characteristic that makes them ineffective in predicting the failure of non-manufacturing firms

⁹companies issuing bonds in nonlocal currency (usually U.S. dollars) (Edward et al, 2006)

¹⁰Altman's 1968, 1983, 1993 etc . . .

variables. That enables banks to take corrective measures in due time if they find themselves in distress zone to avoid the devastating results.

1.3 Objective of the Research

1.3.1 General

The main aim of this study was to identify the determinants of financial distress of private commercial banks in Ethiopia.

1.3.2 Specific:

The specific objectives of the study are to:

1. To describe the level of financial distress of Ethiopian private commercial banks
2. To know significant determinants effect on financial distress of private commercial banks
3. To express the effect of macroeconomic factors on financial distress

1.4 Hypothesis

In order to achieve the objective of the study, a number of hypotheses are developed regarding the determinants of FD in Ethiopian private commercial banks based on different empirical and theoretical research review made. Generally, there are two testable hypotheses with their sub-hypothesis; Bank specific and macro determinants. It is formalized as follows:

Hypothesis A: Bank specific determinants (CAMELS) have significant effect on FD of banks

- **Hypothesis A₁:**Capital adequacy ratio has negative and significant effect on financial distress of banks
- **Hypothesis A₂:** Non-performing loan has significant positive effect on financial distress of banks
- **Hypothesis A₃:**Income to cost ratio has negative and significant effect on financial distress of banks
- **Hypothesis A₄:**Earning ability has negative and significant effect on financial distress of banks
- **Hypothesis A₅:**Liquidity ratio has negative and significant effect on financial distress of banks
- **Hypothesis A₆:**Bank size has negative/positive and significant effect on financial distress of banks

Hypothesis B: Macroeconomic factors determinants (GDP and Inflation have significant effect on FD of banks.

- **Hypothesis B₁:** GDP has negative and significant effect on financial distress of banks
- **Hypothesis B₂:** Inflation has positive and significant effect on financial distress of banks

1.5 Significance of the Study

The finding and recommendations enable bank stakeholders know about the causes (main determinants) of FD and to take corrective measures on those ratios; while playing their vital role in banks. It also help private commercial banks to predict their future; using different predictive models (EWSs); since the situation of being distress is not desirable and it lets gives chance to take preventive measures before happen. On the other hand this research contributes to the existing works her in Ethiopia and justifies the selection of determinants of FD and their relationship. Finally; it can serve as a reference for future studies on this area in this country.

1.6 Scope of the Study

The main aim of this research was to identify the determinants of FD on private commercial banks of Ethiopia. Basically it is possible to predict the possibility of FD or (bankruptcy) one year and two years before financial distress using 1993 Z” score; since it had sound prediction performance with these range than three to five years (Altman E. , 1968); but panel data requires large number of observation. To come up with this problem and to know the position of private commercial banks six years (from 2012 -2017)¹¹ data are collected from fourteen private commercial banks in the country. Finally, the study employed Altman Z-score 1993model; initially developed by him in 1983 for non-manufacturing as a proxy for dependent variable i.e. financial distress.

1.7 Limitation of the Study

Properly to implement predictive models like Altman’s z-score; obtaining accurate data from the recognized organization about their position compared to others in same industry throughout the period is very essential. Accordingly; lack of organization Ethiopia who perpetually discloses the

¹¹Li and Rahgozar (2012) cited in (John et al, 2011) on average 5-year Z-score is superior in predicting financial distress over one, two, and average of 3-year Z-scores.

position of companies was the main limitation of the research. Besides this; there is no official distress management declaration in the country; rather than the undisclosed implementation of stress testing by NBE. Because of these, the researcher limited to classify banks through distressed and not distressed; to implement and to see the predictive quality of the adopted Altman's Z-score model in sampled Ethiopian private commercial banks.

The other limitation of this study was on data collection from NBE. When comparing the financial statement data provided by NBE officials and published data by individual banks; there were tangible differences. To resolve this problem the researcher collected all financial statement from banks official website.

When collecting the secondary data; NPL data was not disclosed by banks; since it is confidential information for banks. NBE set a directive not to borrow all private commercial banks above 30% of the deposit. Accordingly, if NPL is included in this calculation the amount of loan will be reduced; i.e. the amount of income to be obtained from it will decrease. Because of this banks try to hide NPL from their financial statement. Because of this, the researcher used loan loss provision amount as a proxy of NPL. Thus there might be some difference in the actual result; since loan loss provision and NPL has some differences.

1.8 Organization of the Study

There are five chapters in this study. Chapter one provides the background to the research, statement of the problem, general and specific objective, significance and scope of the study. In the second chapter review of both theoretical and empirical literatures are discussed including determinants of FD. Based on work of literature reviewed the conceptual framework is also presented. Chapter three deal with research methodology; on which research design, model specification and hypothesis are discussed. The analysis and presentation of data are presented in the fourth chapter. It begins with presenting the descriptive statistics and correlation analysis. Testing of linear regression model assumptions for the fixed effect (FE) regression outputs comes next. It was done through the use of E-views 8 software. Finally the major findings, conclusion, recommendation and future study area, and limitation of the study are presented in chapter five.

CHAPTER TWO

2. Literature Review

2.1 Introduction

This chapter discusses the literature concerning the financial distress and its determinants. This review of literature establishes framework for the study and highlights the previous studies, which in turn, helps in clearly identifying the gap in the literature. The discussion of the literature on financial distress and its determinants has four sections; the first section considers meaning of financial distress. This is followed by the general theory of financial distress. The third section on the determinants of financial distress and the fourth is review of the empirical studies. Finally, summary on the literature review and knowledge gaps are presented in section four.

2.2 Financial Distress

Surprisingly financial distress is hard to define precisely. This is true partly because of the variety of events befalling firms under financial distress (Stephen et al, 2012). “Financial distress is a situation where a firm’s operating cash flows are not sufficient to satisfy current obligations (such as trade credits or interest expenses), and the firm is forced to take corrective action. Financial distress may lead a firm to default on a contract, and it may involve financial restructuring between the firm, its creditors, and its equity investors. Usually the firm is forced to take actions that it would not have taken if it had sufficient cash flow” (Stephen et al, 2012). Financial distress is one of the most significant threats for many firms globally despite their size and nature. The term financial distress is used in a negative connotation to describe the financial situation of a company confronted with a temporary lack of liquidity and with the difficulties that ensue in fulfilling financial obligations on schedule and to the full extent (Outecheva, 2007) cited in (HELLEN, 2013)

Almilia (2004 & 5) and (Endri, 2009) defines financial distress or problematic conditions as “a condition in which the company experienced delisted as a result of net income and book value of negative equity continuously and the company was in a merger”. Financial distress is an early symptom of the bankruptcy of a company. It can also be a stage prior to the bankruptcy or liquidation (Luciana, 2006:1) in NurHasanah (2010). A company can be said to be in financial distress or trouble condition if the company experienced a negative net income (net profit) for

several years (Whitaker, 1999) cited in (Rinaldo et al, 2014). Based on the statement of (Zaki, 2011) in the study entitled Assessing probabilities of Financial Distress of Banks in the UAE, financial distress or financial hardship can be defined to be "a period when a borrower (either individual or institutional) is unable to meet a payment obligation to lenders and other creditors" Zaki, et al. (2011) in (Rinaldo et al, 2014).

Generally, financial distress began when the company cannot pay the repayment schedule or when the cash flow projections indicate that the company will soon be unable to pay its obligations. It is also considered as a condition in which the company experiences delist as a result of net income and book value of negative equity continuously. Additionally, FD is one of the main means of the bankruptcy of the companies.

(Edward et al, 2006) Specified terms like failure, insolvency, default, and bankruptcy are sometimes used interchangeably; even if they are distinctly different in their formal usage as explained below. Failure, by economic criteria, means continues to decline in return on invested capital as compared to similar investment and risk level. Business failure includes businesses that cease operation following bankruptcy, with a loss to creditors, voluntarily withdraw, leaving unpaid obligations, or those that have been involved in court actions such as receivership, bankruptcy reorganization, or arrangement; and those that voluntarily compromise with creditors. But insolvency is an inability of the total asset to cover total liability; meaning that negative net worth. The other related term with financial distress is a default. Two types of default are there; technical and legal default. Technical defaults happen when debtors violate a condition of an agreement with a creditor. On the other hand legal default is more likely to happen when a firm fails to meet interest and principal payment. The last one is bankruptcy; it happens when either a firm becomes insolvent (negative net worth) or when a formal bankruptcy declaration is made by the court (Edward et al, 2006). Therefore, financial distress can be considered when the company cannot pay the repayment schedule or when the cash flow projections indicate that the company will soon be unable to pay its obligations.

2.3 Theoretical Literature

2.3.1 Financial Distress Agent (Cause)

Lizal (2002) in (Fachrudin, 2008) classifies the causes of the financial distress and name it as the Basic Model or Trinity Bankruptcy Agents of Financial Distress (TBAFD). There are three reasons that lead the company into bankruptcy, namely:

The first one is a neoclassical model; in this case, the bankruptcy will be if the allocation of resources is not right. It occurs when the bankruptcy restructuring has the wrong mix of assets. Estimating the difficulty is done with the balance sheet and income statement for example, profit/assets (to measure profitability), and liabilities/assets. The second reason that leads the company into bankruptcy is the financial model. This model estimates the distress with financial performance as indicators, for instance: turnover / total assets, revenues / turnover, ROA, ROE, profit margin, stock turnover, receivables turnover, cash flow / total equity, debt ratio, cash flow (liabilities-reserves), current ratio, acid test, current liquidity, gearing ratio, turnover per employee, working capital, EPS ratio and so on (Rinaldo et al, 2014). Generally in this model liquidity is a constraint for the financial structure when the mixture of the asset is not true. This means, even if the company can survive in the long run but it should also go bankrupt in the short run even if there is no explicit definition whether the bankruptcy is good or bad for re-structarization. The final one is Corporate Governance Model. On this case, he states bankruptcy has a mix of assets and proper financial structure but poorly managed. This inefficiency becomes encourage companies out of the market as a consequence of the unsolved problems in corporate governance (Fachrudin, 2008).

On the other hand based on (Luciana et al, 2003), (Rinaldo et al, 2014); There are also several indicators or sources of information regarding with the likelihood of financial distress. These are:-

- a) Cash flows analysis for the recent and future period
- b) Corporate strategies analyses that take into account potential competitors, relative cost structure, expansion plans in the industry, the ability of firms to pass on cost increases quality management and so forth.

c) Financial statements analysis of the company as well as its comparison with other companies. This analysis can be focused on a single financial variable or a combination of financial variables.

d) External variables such as return securities and bond valuation.

Meanwhile; (Edward et al, 2006)takes management inadequacy is usually the core of the problem. The ultimate reason (cause) of failure is usually simply running out of cash. They also stated other variety of means related reasons such as:

- Chronically sick industries (e.g., agriculture, textiles, department stores).
- Deregulation of key industries (i.e., airlines, financial services, healthcare, and energy).
- High real interest rates in certain periods.
- International competition.
- Overcapacity within an industry.
- Increased leveraging of corporate America.
- Relatively high new business formation rates in certain periods.

Bankruptcy is the worst condition of the financial distress. According to Darsono and Ashari (2005) cited in (Daul at Sihombing, 2008), as outlines some similar arguments which support (Edward et al, 2006) that the agency (causes) of bankruptcy can be divided into two: internal factors and external factors. Internal factors are factors that originate from the internal management of the company, while external factors can come from external factors that relate directly to operations or macroeconomic factors (Rinaldo et al, 2014). Thus internal factors that can lead to the bankruptcy of the company include: First, inefficient management causes continuous losses that ultimately induce the company not able to pay its obligations. This inefficiency is caused by the wastage in the cost, lack of skills and management expertise; and an imbalance in the number of owned capital with a number of receivable –payable, owned. Second, extremely debts that lead to huge interest expense so far will create minimum earnings then could even cause harm. Receivables that are too big to detrimental because too many idle assets that do not generate revenue; and third, the moral hazard by management. Fraud by company management could lead to bankruptcy. The fraud resulted in losses for the company that eventually bankrupted the company. Cheating can be corrupt management or providing incorrect information to shareholders or investors (Daul at Sihombing, 2008).

From a different perspective, different authors revealed a number of reasons that lead firms to bankruptcy. Such as: (Arnab, Bhattacharjee and Jie Han, 2010) reveal the causes of bankruptcy are divided into two factors means macroeconomic factors (exchange rates, interest rates, etc.) and microeconomic factors (profitability, capital structure, cash flow, and the individual characteristics of other companies).Kunt and Detragiache (1996) define banking crisis as a situation where any of the following conditions holds: (i) non-performing loans is greater than 10%; (ii) the cost of bank rescue is at least 2% of GDP; (iii) banking problems result to large-scale nationalization of banks; and (iv) extensive bank runs lead to emergency measures (Cyn-Young et al, 2013).

2.3.2 Financial Distress Prediction

The first useful information when a company experiences financial distress is to accelerate action to prevent problems before the bankruptcy. Then the second is the management can take merger action/ take over the model. The third, the company is more capable to pay the debt and run itself better; and the fourth is giving an initial sign in bankruptcy existence (Brigham and Huston, 2005). The prediction of company's survival is essential for management and company owners to anticipate the possibility of potential bankruptcy. Predicting bankruptcy is a difficult exercise and many challenges have to be faced. The first challenge starts with the selection of the technique to be used.

Based on an extensive literature review, (M. Adnan Aziz and Humayon, 2006) have narrowed the multitude of financial distress prediction techniques down to three broad categories, namely classical statistical models, artificially intelligent expert system models, and theoretical models (Francois van der Colff and Frans Vermaak, 2015). The discussion below is based on these three categories.

A. Classical statistical models

I. Univariate Model:

(Beaver, 1966)was the pioneer in building a corporate failure prediction model with financial ratios and to apply a univariate discriminate analysis model on a number of financial ratios of a paired sample of failing and non-failing companies in order to predict company failure. Beaver's

study dichotomous classification test is applied in order to identify those ratios that were the best in classifying the companies as failing or non-failing. Based on this he classified a company as failed when any one of the following events occurred: bankruptcy, bond default, an overdrawn bank account or nonpayment of a preferred stock dividend. He found that there are three valid financial ratios to forecast financial failure and they are: Cash Flow / Total Debt, Net Income / Total Assets (returns on assets) and Total Debt / Total Assets (debt ratio) (HELLEN, 2013). The results indicate that failing companies have limited cash flow and smaller amounts of liquid assets than healthy companies. Beaver was able to classify 78% of the sample companies accurately five years before failure (Francois van der Colff and Frans Vermaak, 2015).

II. Risk Index Model:

Tamari (1966) refuted Beavers theory by coming up with a model to eliminate the negative effects of using univariate model. Unlike Beavers method of classification, he used the easy handheld point system based on several financial sets to predict precisely. Each firm was attributed a certain number of points, between 0 and 100, according to the values of the ratios for the firm. A higher total of points indicated a better financial situation. The risk index takes account of the fact that some ratios are more important than others. The index system, however is just a sum up of the univariate ratio which means they simplify the relationship between individual ratios or the correlation coefficient. Secondly, the weight of each variable is allocated by the subjective assumption that causes the model unreliable. He also did not consider the multi-collinearity between selected ratios. That may cause some factors to be exaggerated for double counting the related financial ratios. These are the reasons why he introduced a risk index. It is a simple point system which includes different ratios, generally accepted as measures of financial health (HELLEN, 2013).

III. Multiple Discriminant Analysis:

(Altman E. , 1968); was the first researcher to apply the Multiple Discriminant Analysis (MDA) approach to the financial distress prediction domain. In an effort to address the question of the predictive accuracy of univariate analysis, he converted a univariate analysis to a multiple discriminant analysis (MDA). The MDA's strength lies in its ability to measure a company's financial attributes by analyzing several ratios simultaneously, as well as the interaction between

these ratios. To do so; he used a sample of 33 solvent companies and 33 distressed companies. He developed a Z-score bankruptcy prediction model and determined a cut point of Z-score (2.675) to classify healthy and distressed firms. The results showed that the Z-score model had sound prediction performance one year and two years before financial distress, but did not indicate good prediction utility three to five years before financial distress. His Z-Score model has become a popular and widely accepted measure of financial distress. He concluded that if the discriminant model was used correctly and periodically, it would be able to predict company financial distress early enough to enable management to realize the extent of the distress in time and consider corrective action to avoid failure (HELLEN, 2013).

IV. Logit and probit analysis

Ohlson's 1980 research on MDA was extended by (Harrison, 2005), who employed logit and probit analysis. Logit analysis refers to logistic regression, which is a type of regression analysis for predicting the outcome of categorical dependent variables based on one or more predictor variables (Judy et al, 2015). Probit analysis refers to a specialized regression model of binomial response variables. The Harrison analysis surmounted constraints associated with MDA. As cited in (Francois van der Colff and Frans Vermaak, 2015); one of the constraints was that certain statistical requirements were imposed on the distributional properties of the predictors. Secondly, the output of the application of the MDA model had limited intuitive interpretation. Lastly, there was a constraint related to the matching procedures used in the MDA. Using variables for predictors was better than using them for matching purposes (Francois van der Colff and Frans Vermaak, 2015).

(Ohlson's, 2002) study reported on logit analysis, which was an improvement on the prediction reliability and accuracy of the MDA model (Judy et al, 2015).

Beside this Koh (1991) cited in (Francois van der Colff and Frans Vermaak, 2015) used probit analysis based on six financial ratios to compare the prediction of assessment of auditors on the going concern status of sample companies. Then they concluded that prohibit model was an effective prediction model that outperformed auditors' going concern assessments. This model was, however, limited by the use of only six financial ratios, which laid it open to the risk of misclassification costs.

B. Artificially Intelligent Expert System Models (AIESM)

i. Recursive partitioning analysis

Recursive partitioning analysis (RPA) is a non-parametric procedure that estimates a classification rule as a sequence of binary partitions of independent variables. At each set, this technique splits a subset of the sample into two groups by selecting and partitioning the independent variable that most improves the homogeneity of category assignments applied to the two resulting groups (Harrison, 2005).

According to (Harrison, 2005), RPA has attributes that make it similar to both the univariate approach to classification and multivariate procedures. While both RPA and MDA techniques lead to accurate classification results on a data set of failed and healthy companies, RPA was usually superior to MDA. The RPA models performed better than the MDA models in terms of actual cross-validated bootstrapped results. However, Harrison (2005:46) admitted that RPA did not exhibit the same continuous scoring system qualities that MDA displayed.

The other researcher's who used this model are (Steyn-Bruwer and Hamman, 2006) to classify financially distressed companies in South Africa. They concluded that the prediction accuracies in their study were not what they expected, because of two phenomena. Firstly, the complete population of industrial companies was modeled; hence the researchers attributed their average results to a 'grey area' in contrast to the extreme input data used in other studies. Secondly, they argued that most of the previous research did not use a hold-out sample, and therefore did not report validation results (Francois van der Colff and Frans Vermaak, 2015)

ii. Case-based reasoning (CBR)

CBR solves a new classification problem with the help of similar previously solved cases CBR programs can be applied directly to bankruptcy prediction by application of its typical four-stage procedure of (1) identification of a new problem, (2) retrieval of solved cases from a "case library", (3) adaptation of solved cases to provide a solution to the new problem, and (4) evaluation of the suggested solution and storage in the case library for future use ... (M. Adnan Aziz and Humayon, 2006).

iii. Neural networks

Neural networks perform classification tasks in a way intended to imitate brain processes. The “neurons” are nodes with weighted interconnections that are organized in layers. Each node in the input layer is a processing element that receives a variety of input signals from source objects (information about firms, in the case of bankruptcy prediction) and converts them in to a single output signal. The latter is either: accepted as a classifying decision; or re-transmitted as an input signal to other nodes (possibly including itself) Signal processing continues until a classifying decision is reached (with some probability, the firm will fail) that satisfies pre-specified criteria (M. Adnan Aziz and Humayon, 2006).

iv. Genetic algorithms (GA)

Based on the idea of genetic inheritance and Darwinian theory of natural evolution (survival of the fittest), GAs work as a stochastic search technique to find an optimal solution to a given problem from a large number of solutions. GAs executes this search process in three phases: genetic representation and initialization, selection, and genetic operation (crossover and mutation). The process continues until the actual population converges towards increasingly homogeneous strings. In order to solve a classification problem like bankruptcy, researchers extract a set of rules or conditions using GAs. These conditions are associated with certain cut-off points. Based on these conditions, the model would predict whether or not a firm is likely to go bankrupt (M. Adnan Aziz and Humayon, 2006). Consequently, Liang 1992 proposed a composite rule induction system (CRIS) to overcome these drawbacks and applied CRIS to a bankruptcy data set containing 50 cases. Each case included four nominal and five non-nominal attributes. Twelve experiments were conducted and the data set was randomly divided into a training sample and a holdout sample. The results indicated that CRIS had the highest accuracy (80.8%) followed by ANN (78.3%) in bankruptcy prediction. Both CRIS and ANN outperformed MDA (75.8%).

v. Rough sets model

The aim of rough sets theory is to classify objects using imprecise information. In this model, knowledge about the objects is presented in an information table that, in effect, works like a decision table containing sets of condition and decision attributes that is used to derive the

decision rules of the model by inductive learning principles. Every new object (for example, a firm) can then be classified (healthy or in financial distress) by matching their characteristics with the set of derived rules

C. Theoretical models

According to (M. Adnan Aziz and Humayon, 2006), theoretical models are often developed by employing an appropriate available statistical technique rather than by building directly on theoretical principles. Unlike the statistical and artificial intelligence expert system models, which focus on the symptoms of company failure, theoretical models attempt to determine the causes of failure. Some of these models are the Balance Sheet Decomposition Measurement Theory, Gambler's Ruin Theory, the Cash Management Theory, and the Credit Risk Theories (Francois van der Colff and Frans Vermaak, 2015).

These models predict financial distress in firms by looking at distress conditions present in firms. Another way of looking at this problem is by looking at the factors that lead to distress. As (Tadesse and Yohannes) stated the health assessment can be generated in various ways, such as Trade-off theory, agency theory, distress theory, Entropy theory, etc....

One model under this category is **Trade-off theory**: This theory underlines that although the tax benefit of debt will cause the value of a firm to increase as leverage is increased, this will only be true to a point since leverage increases, so too does the likelihood of default. The cost of financial distress eventually becomes so great that it erodes the benefits of the tax shield, and firm value begins to decline since there is an optimal debt level. The second one is the balance sheet decomposition (**Entropy theory**); firm's financial statements in this case 'the balance sheet' is used to signal if there are major changes in the composition of assets and liabilities over a certain period of time. If the statements reflect significant changes in the composition of the balance sheet, it is likely that the firm is incapable of maintaining a healthy financial position resulting to distress. The other model under theoretical model is **Gambler's Ruin Theory**. In this theory the firm takes place as the gambler playing with a certain sum of money with probabilities of gain or loss. In regard to financial distress, a firm will continue to operate until its net worth is zero or until it goes bankrupt. The assumption is that the firm has some given amount of money comes to or exits the firm randomly thus experiencing positive or negative cash flows. If the cash flow is continually negative and the firm declares bankruptcy but

continues operation as long as the net worth is greater than zero. The fourth one is cash **management theory**; which is similar to the gamblers ruin theory as it looks at short-term management of firm's cash. The cash inflows and cash outflows extended imbalance leads to financial distress (HELLEN, 2013). Finally; the **credit risk theory** is mainly based on economic theories of corporate finance. It is the risk that any borrower/counterparty will default, for any (whatever) reason (M. Adnan Aziz and Humayon, 2006).

2.3.3 Summary of Predictive Models

A variety of models have been developed in the academic literature to predict financial distress using techniques such as univariate model, risk index model, multiple discriminant analysis (MDA), logit, probit, recursive partitioning, and using univariate model, risk index model, recursive partitioning analysis, case-based reasoning (CBR), neural networks, genetic algorithms (GA) and rough sets model. Despite the number of models available, both the business community and researchers often rely on the models developed by (Beaver, 1966) univariate model, Ohlson's (1980) logit model and Altman's pioneering model, (HELLEN, 2013)

William H. Beaver. (Beaver, 1966) Carried out univariate analysis; comparing the financial ratios of 79 failed firms and 79 non-failing firms. He examined the predictive power of thirty accounting ratios for five consecutive years leading up to the bankruptcy of the tested firms. He found the 'cash flow to debt ratio' resulted in being the best predictor of corporate failure with a 78%. The second best indicator was 'net income to total assets' ratio with misclassification rate of 13% for first year before failure and misclassification rate of 28% for the 5th year before failure. The 3rd, 4th, 5th, and 6th ranks belonged to 'total debt to total assets', 'working capital to total assets', current ratio, and no credit interval ratios respectively. A limitation of Beaver's work is based primarily on the univariate nature of the model he developed. It only allows for one ratio used at a time, this can give inconsistent results for a firm should other ratios be utilized. Not only this; but the financial complexity of a firm cannot be captured by one single ratio. Lastly, the cut-off point determined is chosen post failure of a company which means that, in reality; the failure status of a company must be predicted resulting in inaccurate classifications (Rose, 2013).

In 1968 Edward Altman advanced upon Beaver's work by incorporating four more variables into the model to give an overall more precise prediction of manufacturing corporate failure. Altman's multi-discriminant analysis (MDA) model differed to Beavers model in relation to the ratios chosen of highest prediction such as liquidity, profitability, financial leverage, solvency, and sales activity¹² (sales to total assets). The application of the Z-score model involves a group of healthy and bankrupt companies and classifies those companies with a Z-Score value; distressed (highly risky and likely to go bankrupt); the healthy and grey area with uncertain results (Altman et al, 2010). He also developed a model in Altman 1995 to predict corporate failures for developing countries firms (Mexican companies), emerging market companies and for non-manufacturers. Generally; 'Z score' is a highly accurate corporate failure predictor however it does have its limitations. Even if his early model: Altman 1968, Altman 1983; was industry specific, as it was formulated for operating manufacturing companies cited in (Rose, 2013).

Ohlson (1980) wanted to offset the limitations of the discriminant analysis model and he employed logit analysis or a logistic regression model into corporate failure prediction studies. Logit uses data averages where a healthy company is given a value of 0 and a distressed company is given a value of 1. Ohlson analyzed 105 bankrupt companies and 2058 non-bankrupt companies from 1970 to 1976. The results showed that size, financial structure (total liabilities to total assets), performance and current liquidity were important determinants of bankruptcy (Abdullah et al, 2008) cited in (Rose, 2013). The studies by (Chen et al, 2009) stated that: "Logit Regression would have a better theoretical jurisdiction and more diversity and breadth for the independent variables selected." These variables included; Retained Earnings/Total Asset, Net Income/Net Sale, OPBAT/ Shareholder's Fund and the Quick ratio (Siew Bee et al. 2011). However; Ohlson's model also has its limitations. Which has two econometric problems with the single period logit model pointed out by Hillegeist (2004) cited in (Rose, 2013). The first is the sample selection bias that arises from using only one, non-randomly selected observation for each bankrupt company, and second, the model fails to include time-varying changes to reflect the underlying risk of bankruptcy. These problems demonstrated that the results would be biased, inefficient and inconsistent coefficient estimates.

¹²in order to filter the function from the possible distortion related to the sector; Altman 1995 excluded sales/total assets activity ratio

Generally; there are majorly five different types of bankruptcy prediction model. Univariate analysis progressed to Multiple Discriminant Analysis. Logit/Probit analysis came next. Recursive Partitioning Algorithm followed. Finally, Neural Networks is the latest bankruptcy prediction model. Practically most of the bankruptcy studies had used multiple discriminant analysis (MDA) statistical techniques to develop models and have included large and small firms, as well as private & publicly held firms. Multiple discriminant analysis is the heart of this research paper. Thus this study uses only Altman's (1993) i.e.; one of the models in MDA; as a result of the model overcomes the industry limitation of other models and its simplicity as well as accuracy and follow credit risk and entropy theory to identify the factors that lead to distress.

2.4 Determinants of Financial Distress

2.4.1 Inducement Factors of Banking Crisis

On the account of the journal of the Determinants of Banking Crises in Developing and Developed Countries; (Rant et al, 2014) described the factors that determine the occurrence of banking crises (Rinaldo et al, 2014)

Using data from the years 1980 - 1994 of the economic crisis in several countries, then choosing as the samples are countries included in the International Financial Statistics (IFS) of the IMF. To identify these factors do estimate multi-variant logit models. The determining factors include macroeconomic, financial, and institutional (Rinaldo et al, 2014). The first determinant is the macroeconomic factors such as Lower GDP growth, aggregate output shocks, Inflation, Nominal interest rates and monetary policy. The second element is the financial factor: high real interest rates also caused by other things, such as financial liberalization. The third part is an institutional factor: on this existence of deposit insurance schemes tends to increase the likelihood of systemic banking problems (Rant et al, 2014).

2.4.2 Determinants of Financial Distress

A. Bank Specific Factors

The EWS mainly focused on individual banks level and were concerned with individual banking failures, but there are other EWS that consider the soundness of the whole banking or financial sector and try to predict systemic crises (David G Mayes and Hanno Stremmel, 2012)

According to works of literature; the strengths and vulnerabilities of deposit-takers (banks) can be analyzed under the headings of capital adequacy, asset quality, earnings and profitability, liquidity, and sensitivity to market risk. This is commonly known as the CAMELS framework.

CAMELS; is a ratio that describes the relationship or a ratio between certain numbers to the other amounts included in the financial statements of a financial institution (Rinaldo et al, 2014). In some studies, researchers omit the sensitivity to market risk factor from CAMELS¹³. This omission can be explained by difficulties in capturing this relationship with accounting and financial data. Therefore, some researchers use the size of the bank as an approximation. However, this proxy neglects the fact that business size is not strictly accompanied by market exposure¹⁴. Other researchers such as Männasoo and Mayes (2005, 2009) or Whalen (1991) used deposits ratios to capture this effect. Others think that it is more appropriate to measure the sensitivity as the bank's holding with volatile liabilities. Thus; based on the above argument; this study focus on all elements of CAMELS: using 'S' as Size of the Bank; as bank-specific factors that affect financial distress.

The original CAMELS model focuses on accounting and financial data for banks. Some authors also added macroeconomic data to capture economic pressures and shocks that could trigger a banking failure or to cover disagreement in cross country studies. Variables such as GDP growth, inflation, inter-bank saving interest rates, exchange rates, and government policies are included to capture those effects (David G Mayes and Hanno Stremmel, 2012). Thus; in this study, the researcher also included GDP and Inflation; since these variables are macro factors that have been published and publicly available data. Other macro variables like, inter-bank saving interest rates, exchange rates, and government policies are not included in the study. This is because, saving interest rate has no effect on the dependent variable since SIR remained constant 5% within the study period 2012-2017, whereas foreign exchange was changed but it is highly correlated with inflation, but government policy is difficult to measure.

¹³ (Tadesse, 2017),

¹⁴For example, a small savings bank has a low sensitivity and small specialized trading bank high market sensitivity. Of course, it is important to consider the size, but it is not satisfactory to replace the sensitivity component with the size indicator.

1. Capital Adequacy

Capital adequacy and availability ultimately determine the robustness of financial institutions to withstand shocks to their balance sheets. Not only does capital adequacy come first on the list but it is the key variable considered important in the Basel framework for ensuring healthy banks. Bank's capital serves as lesson to absorb losses and shocks (David G Mayes and Hanno Stremmel, 2012). For large corporations such as banks and firms, capital or equity play an important role in order to maintain the stability or the solvency of these organizations. In order to evaluate capital adequacy, the current study used the ratio of equity capital divided by total Assets (ETA) which is able to divide banks ranging from critically undercapitalized to well-capitalized although this ratio does not have fine gradations (Rinaldo et al, 2014).

Capital adequacy is the financial ratio that Altman founded to be the most valuable variable to predict bankruptcies with. The ratio describes the relationship between working capital and total assets. Working capital itself is a measurement that describes the assets of a company that is meant to be put into practice often within less than three years and is calculated as current assets minus current liabilities¹⁵. According to Altman, a typical reaction for a company going through an economically difficult time with constant operating losses is decreasing the current assets. (Al-Rawi, Kiani, and Vedd (2008) cited in (Oscar Taurell and Viktor Augustsson, 2012).

According to Ephrem (2015); Capital adequacy is ultimately determines how well banks can cope with shocks to their balance sheet and he added it would be best measured through the ratio of capital to total loan provided by the bank (IBD). (Tadesse, 2017), also defined it in term of capital to deposit ratio because the primary risk is depository risk derived from the sudden and considerably large scale of deposit withdrawals. Altman's research finds this ratio to be more helpful than other liquidity ratios, such as the current ratio or the quick ratio. (Altman, 2000; Chuvakhin& Germana, 2003) cited in (Sanobar, 2012). In general, having sufficient capital allows a bank to absorb losses and still keeps running its daily business operations, even under higher financial distress condition. Thus this study uses ETA ratio of private commercial banks to measure capital adequacy, because of it shows the pictures of the company ability to handle

¹⁵But most of the time it takes the period less than 12 months.

unexpected insolvency; and it is found to be significant in most researchers as determinants of financial distress in financial as well as non-financial institutions¹⁶.

2. Assets and Their Quality

The condition and quality of individual asset categories can trigger financial problems and act as an important accelerator of bank fragility (David G Mayes and Hanno Stremmel, 2012). Other researchers argue that risks to the solvency of financial institutions most often derive from an impairment of assets, which in turn can arise from deterioration in the financial health and profitability of the institutions'

To get the measure for asset quality the ratio of nonperforming loans (NPLs) to total loans is often used (Rashidah et al, 2014), (Carpeto, et al. 2010). As a first step, loans are often considered to be nonperforming when principal or interest on them is due and left unpaid for 90 days or more beyond the maturity date¹⁷. Loan classifying and provisioning requires much more than simply looking at amounts overdue (John, 2016). (Bridge 1998), asserted that high level of nonperforming loans had been the major cause of bank failure in Kenya, Nigeria, Uganda and Zambia cited in (Ephrem, 2015). Thus for asset quality, this study uses the ratio of nonperforming loans divided by total loans (NPLTL). The main reason is because nonperforming loans are those risk assets not generating income and/or non-performing loans are closely related to the exposure of credit risk and though this is a useful numerator, it is also able to portray on how well banks are coping with their financial challenges and the prediction of distress (Sahut&Mili, 2011) cited in (Rashidah et al, 2014)

3. Management Efficiency

Management quality is the third element in CAMELS ratings. The ability and skill of the bank management play a crucial role in the performance and success of the institution. The higher the management competence, the lower is the vulnerability of the bank and the likelihood of making wrong decisions. Previous literatures by (Rashidah et al, 2014), (Sahut and Mili, 2011), (Ephrem, 2015) , (David G Mayes and Hanno Stremmel, 2012) and Sahinbas (2011) stated that measurement for management quality is treated as a qualitative aspect and considered as the

¹⁶Altmans (2008), 1968, 2000, 2005, (Yohannes, 2014), (Tadesse, 2017), (Ephrem, 2015), etc ...

¹⁷Asset classification and provisioning directive no SBB/43/2008/4.9.1

hardest one to measure as compared to other components in CAMELS ratings. Because it was difficult to measure management quality with accounting data and they assumed that the results for the ratios describe the different strategies used by the decision makers (Rashidah et al, 2014).

However, Lane, Looney, and Wansley (1986) and Wheelock and Wilson (2000) cited in (David G Mayes and Hanno Stremmel, 2012) incorporate measures of management efficiency that are also frequently used in practice. The FDIC provides also an efficiency ratio to assess the management quality. This efficiency ratio reflects expenses as a percentage of revenue. According to (Sahut and Mill 2011) cited in (Ephrem, 2015) and (Andualem, 2015); “the management efficiency is measured in terms of its asset turnover, average collection period and average payment period. Because it indicate the firm’s viability as well as speed of turning over its assets within the year, which determines the firm’s financial distress. Non distressed banks have higher efficiency score” finally they found the result have no significant influence (Ephrem, 2015) but positive and significant influences found by (Andualem, 2015) and (Tadesse, 2017) on Zeta score, Debt Service Coverage (DSC) and z-score are used as a proxy of financial distress respectively. Therefore, this study also uses the same formula to measure the efficiency of bank managers to know the effect on financial distress.

4. Earnings and Profitability

This category reflects the sustainability of earnings and profits. Recent research has applied a wide variety of earnings indicators, but the common choice is profitability or accounting measures such as ROA or ROE (David G Mayes and Hanno Stremmel, 2012). (Melaku, 2016), on his study stated that common operating ratios used to assess bank profitability or earning ability (ROA) and (ROE). Same measure was provided by (Sarker, 2006), on which he dictated the best and widely used indicators are (ROA) and (ROE). Whereas (Tadesse, 2017) clarified that the indicators for earning ability of financial institution is commonly judged by ROE¹⁸. Following these and other studies used ROE as measure of earning ability¹⁹; Because it is more deterministic than ROA; this study also use only ROE as determinants financial distress of private

¹⁸“It capture the bank’s ability of earnings for performing the activities like funding dividends, maintaining adequate capital levels, providing for opportunities of investment for bank to grow and maintaining the competitive outlook while managing distress” (Tadesse, 2017).

¹⁹ (Ephrem, 2015), (Oscar Taurell and Viktor Augustsson, 2012), (Yohannes, 2014)

banks in Ethiopia. Earning power constitutes a fundamental incentive to operate a firm and the ratio is therefore interesting to study as an explainable variable to bankruptcy. In general, there is a negative relationship between earning ability and the likelihood of distress since higher levels of profitability should allow banks to improve their capital and economic performance (Ephrem, 2015), (Oscar Taurell and Viktor Augustsson, 2012).

5. Liquidity

Liquidity is essential for a bank's ability to meet and repay its short-term obligations and unexpected withdrawals of depositors and creditors (David G Mayes and Hanno Stremmel, 2012). On the other hand the level of liquidity influences the ability of a banking system to survive shocks. For instance, a large shock, contributing to credit or market losses, could cause a loss of confidence in the banking sector by market participants or depositors. In turn, this could result in a liquidity crisis that has the potential to push solvent banks into insolvency, because if they lose access to funding, they could be forced to sell assets at depressed prices to obtain liquidity. As a result of these bank managers should and must take full consideration about it; especially related to the process of deposits and loans (Rashidah et al, 2014). About measures; different studies have tried various ways of capturing these effects based on their perspective. But the well-used (known) idea (measure) is the loan-to-deposit (LNTD) ratio. Thus in order to strengthen up the results for liquidity, this study also used the ratio of loan-to-deposit (LNTD).

6. Size of Banks

Although the sixth CAMELS component is risk of markets sensitivity and its concern is with the impact on banks from shifts and fluctuations in the financial market. This study use size of the bank as an approximation²⁰ since Ethiopia has no financial market to trade equity securities and other derivatives.

The boundary between bankrupt and non-bankrupt firms is different for small and larger firms, which decreases the performance of the model estimation when data from one size category are applied to another size category. Altman models also regarded the suitability of the original Z-

²⁰“Abrams and Huang (1987), Avkiran and Cai (2012), Kolari, Glennon, Shin, and Caputo (2002), and Wheelock and Wilson (2000) used the size to approximate the sensitivity to market risk.” (David G Mayes and Hanno Stremmel, 2012)

Score model (for manufacturing firms) for all firms as debatable because of the size difference. But the benchmark Z''-Score for liquidity risk –model (Zeta-score) is estimated for data from many size categories, from very small to very large firms. On this issue researchers argue that large firms are better managing their cash flow and/or more diversified and less exposed to liquidity shocks, and also it is a proxy for volatility of firms asset, therefore; difficult to fail or distressed (Shumway (2012) cited in (Ahmad et al, 2017)). To the contrary “too big to fail” argument states that when the size of the firm increases the likelihood of distress also increase because of assurance from the government at the time of solvency. By considering this banks become risk taker which leads them to distress (Iannotta, et al., 2007) cited in (Tadesse, 2017). The researcher added the natural logarithm of total assets is best to measure size of the firm since the size of total assets should be sensitive to the probability of financial distress (Hotchkiss 1995)cited in (Yohannes, 2014).

B. Macroeconomic Determinants

1.Economic Growth (GDP):

Gross Domestic Product (GDP) is one of the macroeconomic factors that affect financial distress of banks²¹. The economic growth is measured by change in the real GDP growth rate and it is hypothesized to affect financial institutions distress negatively (Yohannes, 2014). During the declining GDP growth the demand for credit falls which in turn negatively affect the profitability of banks. On the contrary, in a growing economy as expressed by positive GDP growth, the demand for credit is high due to the nature of business cycle. During boom the demand for credit is high compared to recession (Athanasoglou et al., 2005). (Melaku, 2016); Also states that during periods of strong economic growth, loan demand tends to be higher, allowing banks to provide more loans. Strong economic conditions are also characterized by high demand for financial services, thereby increasing the bank’s cash flows, profits and non-interest earnings. Accordingly, fewer loans would be defaulted during strong economic conditions.

²¹ (Tadesse, 2017), (Yohannes, 2014), (Melaku, 2016), etc ...

2. Inflation (INF):

Inflation reflects a situation where the demand for goods and services exceeds their supply in the economy. High inflation rate is associated with higher costs as well as higher income. Inflation is expected to exert a positive effect on financial distress. On the other hand, a negative coefficient is expected when its costs increase faster than its income (Kevin et al 2001) cited in (Yohannes, 2014). Generally researchers recommended that having low and stable inflation is significant for viability of financial activities.

2.5 Empirical literatures

2.5.1 Financial Distress Global Experience

(Rashidah et al, 2014), conducted research on the effectiveness of CAMELS model in detecting FD in Islamic banks in Malaysia using neural networks; the data collected from 17 Islamic banks for four year from the period of 2006-2010. Based on their finding all Islamic banks have higher ETA ratios which portray a good performance of capital adequacy and are less likely to face distress. As for asset quality all banks did not have a possibility of FD as they are able to handle their non performing loans throughout the year. Meanwhile for management quality all Islamic banks show lower ratios in paying salaries to their employees. Earning ability shows better performance and will be less likely to face FD in terms of ROA but not ROE. Liquidity indicates the banks have a large number of loans but they have sufficient liquid assets in order to cover their liabilities and commitments.

(Muhammad et al, 2011) On their study titled ‘the influences of micro and macro variables toward financial distress condition on manufacture companies listed in Indonesia stock exchange’ in 2009; said “Financial distress occurs because companies are not able to manage and maintain the stability of the company's financial performance”. Micro variables are from financial ratios and macro variables are from sensitivity of corporate toward macroeconomics factors are identified as independent variables. While financial distress condition is identified as dependent variable. This is determined by doing a dummy variable in the financial statements of companies with value of “1” to the financial statements affected by financial distress and “0” for non-financial distress. Giving those values are based on 3 indicators of financial distress: Cash Flow, Net Operating Income and Earnings per Share. The secondary data are collected from 38

companies and the sample that used is 78 financial reports of manufacturing companies. The results show that micro variables and macro variables simultaneously influence toward financial distress condition. Then partially variable liquidity ratio, leverage ratio, and profit margin ratio are significantly influence toward financial distress condition. While variable inventory turnover ratio and variables macro that come from sensitivity company towards BI rate, inflation, CSPI are not significantly influence toward financial distress condition.

According to (Yauriet al, 2012), who investigated the effect of recapitalization on Nigerian banking distress, concluded that increasing minimum capital requirement had only accounted for a short-term improvement in the liquidity position of banks and improvement in their asset quality but were not have long-term effect on forestalling distress. Therefore, they had recommended improving bank corporate governance to prevent future occurrence of the threat of distress in the banking sector, which is also consistent with the findings of (Baklouti et al, 2016).

Most recently, (Kinyariro, 2016) investigated the contribution of Basel III accord in preventing distress of Kenyan commercial banks. They used Altman's Z-score as a measure of bank distress for 43 banks for the period 2013-2014 and identified, liquidity requirement of the accord, as having a significantly positive effect on distress; however, leverage and capital requirements were appeared insignificant.

(zhichao et al, 2014); conducted a research with the title of "Determinants of Financial Distress in U.S. large bank holding companies". From 860 whose total asset exceeds 1 billion dollars for the period from 2003-2012 as listed in the FR Y-9C form²². Private companies or miss important data are deleted, to finally obtain a total of 354 BHCs with 2288 observations i.e. firm-years and using distance-to-default (DD) as a measure of the probability of distress.

And they found house price index is consistently significant and positively; associated with the Distance-to-Default (DD) measure in the U.S. banking market; the three major banking risk characteristics i.e. non-performing loans, short-term wholesale funding, and the credit-risk indicator are reliable factors behind DD determination. For the two alternative measures of BHC activity diversification, non-interest income is positively related with BHCs' DD whereas off-

²² "FR Y-9C is a regulatory report showing Consolidated Financial Statements of Bank Holding Companies. Our BHC database based on FR Y-9C is downloaded from the website of the Federal Reserve Bank of Chicago" (zhanget al, 2014)

balance-sheet activity is negatively associated with the financial distress measure; and finally relevant capital requirements indicators including Tier-I Risk-Based Capital Ratio, Total Risk-Based Capital Ratio, and Tier-I Leverage Ratio should be taken in regulatory assessment of BHCs' financial distress (zhichao et al, 2014).

The other study done in USA was “(Sinkey, Treza and Dince 2012), they applied a ZETA model which is revised model of Z score analysis for predicting the bank failure. The purpose of their study was to test the cross-industry validity of the ZETA model. They used the test sample consisting of commercial banks that failed in the United States during the early 1980s. They found that although it is not as accurate as the original ZETA model, this version of the ZETA model is successful in identifying bank failure in about 3 out of 4 cases. According to the researchers the possible reasons of the model being not as accurate as its original version is inability of bank accounting data to reflect market values, the presence of criminal misconduct as a major contributing factor in bank failures, and the process by which banks are declared insolvent” cited in (Ephrem, 2015).

Because of insolvency and illiquidity caused by non-performing loans many of the local banks set up in Kenya, Nigeria, Uganda and Zambia have been closed down or taken over by their Central Banks. The severity of bad debt problems was attributable to problems of moral hazard and adverse selection; according to Martin (Martin, 1998); The causes of financial distress in local banks in Africa and implications for prudential policy mainly addressing Nigeria, Kenya, Uganda, and Zambia who have gained a significant share of banking and financial markets in four sub-Saharan African (SSA) countries since the mid-1980s. Finally, the study discussed four biggest contributors to bad loans of many of the failed banks in those countries such as Insider lending, Lending to high-risk borrowers, Macroeconomic instability, and Liquidity support and prudential regulation.

(SAMIRA, 2013); assessed the utility of statistical technique mostly termed as multiple discriminant analysis (MDA) in bankruptcy prediction of firms listed in Nairobi Stock Exchange (NSE) in Kenya during the period of 2008 to 2012 and also delisted firms from NSE from the period of 1996 to 2012 by divided into five different sectors. She used Altman's (1993) Z''-score multi discriminant financial analysis model which provides the framework for measuring the financial performance of the firms. Then she concluded that Altman's (1993) Z'' score model is

efficient in predicting bankruptcy prediction but NSE used model to differentiate failed and non-failed firms in the study was insufficient to predict bankruptcy prediction because of failed firms clearly stated that the model was intended for non-manufacturing firms since most of the failed firms that were classified in distress zone have scores of safe zone or grey zone.

2.5.2 Cross Country Studies

According to (ZHEN, 2014); Bank failures affect owners, employees, and customers, possibly causing large-scale economic distress. Thus, banks must evaluate operational risks and develop early warning systems. In this study (ZHEN, 2014) investigated bank failures in the Organization for Economic Co-operation and Development (OECD), the North America Free Trade Area (NAFTA), the Association of Southeast Asian Nations (ASEAN), the European Union (EU), newly industrialized countries (NICs), the G20, and the G8 countries. Using financial ratios to analyze and explore the appropriateness of prediction models (logistic model). Their study encompassed 772 banks to analyze the factors that influence financial early warning systems; the data period from 2002 to 2012 of NAFTA countries.

The results suggested that nonperforming loans have a significantly positive correlation with bank distress in the OECD, whereas provisions for loan losses, return of equity, interest income to interest expenses, and non-interest income to non-interest expenses have a significantly negative correlation. The loan ratio and non-performing loans have a significantly positive correlation with bank distress in the NAFTA. Capital ratio has a significantly negative correlation with bank distress in the ASEAN, whereas the loan ratio, non-performing loans, and fixed assets have a significantly positive correlation. The loan ratio and non-performing loans have a significantly positive correlation with bank distress in the EU, whereas provisions for loan losses have a significantly negative correlation. Capital ratio and provisions for loan losses have a significantly negative correlation with bank distress in the NIC, whereas loan ratio, non-performing loans, and fixed assets have a significantly positive correlation. Capital ratio, provisions for loan losses, interest income to interest expenses, and non-interest income to non-interest expenses have a significantly negative correlation with bank distress in the G20. Capital ratio, provisions for loan losses, interest income to interest expenses, and non-interest income to non-interest expenses have a significantly negative correlation with bank distress in the G8, whereas fixed assets have a significantly positive correlation (Yvonne, 2011)

Since banking distress is a very rare event in a single country (Poghosyan and Cihak, 2009), Pesola (2005) cited in (Tadesse, 2017), used the ratio of banks' loan losses to lending as a measure of financial distress and fragility when investigating the Nordic countries macroeconomic determinants of banking fragility and distress. It is assumed that a significant increase in banks' loan losses does not emerge out of the blue. Loan losses have a rather long gestation period when the borrowers' vulnerability to negative shocks like change in interest rate gradually increases. Therefore, it was concluded that high customer indebtedness combined with adverse macroeconomic surprise shocks, such as change in income as measured by GDP and change in real interest rate, contributed to the financial distress in banking sector. Loan losses were also display strong autoregressive behavior which might indicate a feedback effect from loan losses back to macroeconomic level in deep recessions (Tadesse, 2017)

Similar to Bou-Said and saucier (2003), Poghosyan and Cihak (2009) had also reported that some of distressed banks had had good cost to income ratios; however, management efficiency was not appeared significant. But Konstandina N.V. (2006), Poghosyan and Cihak(2009) were identified liquidity as insignificant in affecting EU banking distress.

2.5.3 Studies in Ethiopia

(Ephrem, 2015); conducted a research having similar title 'determinants of Banks financial distress her in Ethiopia' of this study. As a pioneer he estimated determinants of financial distress using data starting from 2002/03 to 2011/12 and six private commercial banks in Ethiopia using panel data regression. In the study, the revised Altman's Z-score (2000) model: which can be applied for non-manufacturing firms was used as proxy for financial distress and independent variables like: Non –performing loan, capital adequacy, interest income to total revenue, efficiency, and size are used. And the study has no macro factors like: GDP, Inflation, deposit interest rate, etc. But finally he come up with conclusion that capital adequacy ratio, net interest income to total revenue ratio have statistically significant positive influence on the financial health of banks whereas the non-performing loan ratio has statically significant negative influence on the financial health of the banks. Whereas bank size and efficiency has no statistically significant influence on the Zeta score of the selected private commercial banks. The selection of explanatory variables are not sufficient and don't have any convenience justification.

Later on (Tadesse, 2017) conducted research in this area; In this study, he tried to include some unique determinants of financial distress in Ethiopia which was not addressed by (Ephrem, 2015) such as; CAMEL + Size as specific explanatory variables and GDP, inflation rate and saving interest rate as macro factors. And Altman (Z-score, 1993) model developed for emerging market (there is a constant term of +3.25) was used as a proxy for the dependent variable: financial distress.

To achieve the objective of the research he used secondary data which was collected for eight banks for sample period covering from 2006 to 2015 and analyzed using descriptive statistics and fixed effect (FE) regression model; during that time there are 18 (eighteen) banks in operation but selected 8 (eight) banks having at least 10 (ten) years financial statement was the benchmark.

Finally, he concluded the findings in two dimensions. Each of these two is contradicting each other. The first one is the descriptive statistics; based in this concluded that sampled banks were under distress but the FE regression model shows that those banks are not distressed. Farther identified capital adequacy, management efficiency, earning ability and bank size as having a negative effect on banking financial distress and except size, all of them appeared significant; whereas asset quality and liquidity appeared as having a positive effect, but liquidity was only significant. Regarding the macroeconomic factors, economic growth and saving interest rate have significantly negative and positive effect on banking financial distress respectively; whereas inflation was not significant.

There are a number of individuals conducted researches on financial distress in different organizations in Ethiopia other than financial institutions. (Yohannes, 2014), in his study he investigated empirically financial distress determinants in the case of manufacturing share companies in Addis Ababa. Data were obtained from annual report of 12 companies who had at least five years report from the period of 2009 up to 2013. The study applied panel data model with its random effect estimate to test a series of hypotheses that emerge through the review of existing literature. Whereas he adopted quantitative methods of research approaches to test the study hypothesis and descriptive statistics, and panel data regression analysis is used to analyze. Based on these; solvability (SOL), firm size (FSIZE), economic growth (EG) and liquidity (LI) have positive and significant influences to Debt Service Coverage (DSC) as a

proxy of financial distress. On the other hand, leverage (Lev) has a negative and significant relation with DSC. Other variables such as profitability, efficiency and inflation have no significant impact on the status of firm's financial distress in manufacturing share companies in Addis Ababa-Ethiopia

Beside (Yohannes, 2014); (ANDUALEM, 2011) also conducted a research on "the determinants of financial distress of selected firms in beverage and metal industry of Ethiopia". His study estimated determinants of financial distress using panel data starting from 1999 to 2005. He used sample of 68 companies selected out of 116 share companies in the beverage and metal industry of Ethiopia. The results show that profitability, firm age, liquidity and efficiency have positive and significant influences to Debt Service Coverage (DSC) as a proxy of financial distress. On the other hand, leverage has a negative and significant relation with DSC. On the other day; he also tried to see overall manufacturing firm's situation in Ethiopia for the period from 1999 to 2005 by taking debt service coverage ratio as main proxy in addressing financial distress. Based on panel data General Least Square (GLS) regression method used: liquidity, profitability, and efficiency had positive and significant influences on debt service coverage. On contrary, leverage has negative and significant influence on Debt Service coverage.

2.6 Summary of Literature Review

As evidenced in the literatures discussed so far financial distress, in general, is determined by both bank-specific and macroeconomic indicators. Based on the research findings, as discussed above, capital adequacy, asset quality, management efficiency, earning ability, liquidity and size (CAMELS) have effect on banking financial distress. In addition to these bank-specific factors, macroeconomic indicators like GDP, inflation, deposit interest rate, exchange rate etc... have also effect on the distress of manufacturing and financial institutions including commercial banks. But the findings were not consistent across studies²³.

For example, Mulyaningrum (2008) states that BOPO is not influenced significantly. But the ratio of loan to deposit ratio (LDR) has a significant influence on a bank's bankruptcy prediction. In Almilia study (2005) describes that LDR has no significant effect. In addition to these ratios, net interest margin (NIM), Return on Equity (ROE) and the Non-Performing Loan (NPL) has

²³(Ephrem, 2015; Tadess, 2016 and Sahut and Mili, 2011), Mulyaningrum (2008), Almilia study (2005, (Kurniasari, 2013), Sahut and Mili (2011) etc....

declared no significant effect for predicting bankruptcy of a bank in both studies. In another study (Kurniasari, 2013), indicates that the CAR, NPL, ROA, and ROE do not significantly affect the probability of financial distress of banks. While the LDR and ROA significantly influence the probability of financial distress Indonesian banks.

Sahut and Mili (2011) concluded that management efficiency has a negative and significant effect on financial distress of MENA banking sector. Besides, in line with Konstandina (2006) for Russian banks, this study disproved the significant and positive effect of asset quality.

In Ethiopia; (Ephrem, 2015) states capital to loan ratio, net interest income to total revenue ratio have a statistically significant positive influence on the financial health of banks whereas the nonperforming loan ratio has a statically significant negative influence on the financial health of the banks. (Tadesse, 2017) describes capital adequacy, management efficiency and earning ability has a negative and significant effect on banking financial distress but bank size has to be negative and no significant influence; whereas asset quality and liquidity appeared as having a positive effect, but liquidity was only significant on banking financial distress from specific (micro) level determinants. Regarding the macroeconomic factors, economic growth and saving interest rate have significantly negative and positive effect on banking financial distress respectively; whereas inflation was not significant.

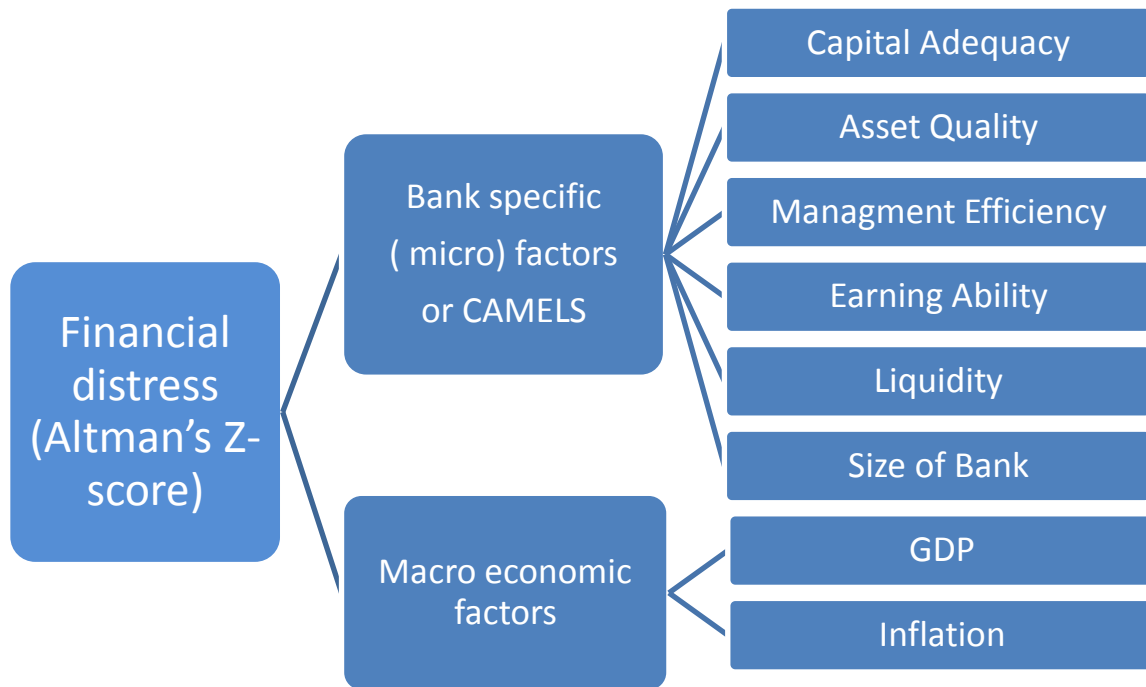
However, apart from considerable researches that have been done in the area of financial distress of manufacturing firms, there are only two financial sector concerned researches done in Ethiopia: Ephrem (2015) and Tadesse (2017). Therefore, this study aimed to tackle and tries to fill the gap observed in the previous study while contributing to the body of knowledge. More specifically, the research was different in the following dimensions (**Gap**):

A large (10-20) years sample is not the best choice since average ratios do shift over time (Altman, 2002). Li and Rahgozar (2012) cited in (John et al, 2011) also found that “on average 5-year Z-score is superior in predicting financial distress over very large or short years Z-scores”. Beside this previous researchers are only limited to long listed banks and tried to generalize to all. Whereas the study data of this research are collected from all private commercial banks operating for at least six years (2012 up to 2017); based on this 87.5% of banks currently operating in Ethiopia are included in the study the remaining 12.5% banks are left out of the study: they are Enat bank and Debu Global bank; this is because these banks are established in

2012 and don't have complete financial statement report on that year. Beside this the study examines the effect micro (bank specific) and macroeconomic factors by making some adjustments, which were tested (used) by (Taddese, 2017); and, Finally, the study employed an appropriate Altman et al. (1993) model; initially developed by him in 1983 for non-manufacturing used by (Ephrem, 2015)²⁴ as a proxy for dependent variable i.e. financial distress. But Taddese used a model only for emerging market scoring (EMS) having a constant term +3.25.

Conceptual Frame Work

Based on above empirical work of literature reviews the researcher adopt the following conceptual frame-work;



Zones	Score
Safe	$Z > 2.6$
Grey	$1.1 < Z < 2.6$
Distress	$Z < 1.1$

Source: (Altman E. , 1993)

²⁴ But he used and sited Altman's 2000 and the measure was Net operating profit/ Total asset used

CHAPTER THREE

3. Research Methodology

3.1 Introduction

The third chapter of this study briefly discusses about the research methodology. On which the chapter first describes the research design, target population and sample of the study, the data collection as well as the data analysis techniques to be used to achieve the objective of the study. Then model specification and finally research hypotheses are presented on the second and third part respectively.

3.1.1 Research Design

“A research design is the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to the research purpose with economy in procedure. In fact, the research design is the conceptual structure within which research is conducted; it constitutes the blueprint for the collection, measurement and analysis of data” (Kothari, 2004). That is why, it is a paramount to properly define and evaluate the research design before even conducting the research.

There are three basic research approaches; these are quantitative, qualitative and mixed research approaches. The quantitative research relies on the measurement and analysis of statistical data to produce quantifiable conclusions. (Creswell, 2009) states that, it is one means to test objective theories by examining the relationship among variables. Generally the problem is best addressed using quantitative research through understanding the variables influence on the outcome since it is made using scientific methods, which include: the generation of models, theories & hypotheses, the development of instruments and methods for measurement, Experimental control and manipulation of variables, collection of empirical data and modeling, and analysis of data. Therefore, for this study quantitative research approach was used to see the relationship between

the financial distress (Z'' – score of Altman’s 1993 model)²⁵ of private commercial banks through specific and macroeconomic determinants.

The study also adopted an explanatory research approach by using balanced panel research design to meet the research objective. As explained by (Bhattacharjee, 2012), explanatory research attempts to identify causal factors and outcomes of the target phenomenon.

A panel data is stand for information across both time and space, and it measures some quantity about them over time (Brooks, 2014). One of the merits of using panel data is addressing a broader range of the subject and tackles more complex problems that would be possible with either of pure time-series or pure cross-sectional data. Giving more informative data as it consists of both the cross-sectional information, which captures individual variability, and the time series information, which captures dynamic adjustment is the other advantage (Brooks, 2014).

3.1.2 Target Population and Sample

The target population of this study are; all private commercial banks that are operating in the country during the study period i.e. 2012-2017. In Ethiopia, currently there are sixteen privately owned commercial banks. Fourteen of them have more than six years of operation and has a financial statement on the study period stated above.

The sampling technique used in this research to select banks having a longer period so as to get sufficient information was purposive sampling from non-probabilistic sampling methods. As stated by (Kothari, 2004), purposive sampling is more desirable when the total population is small and a known characteristic of them is to be studied. The numbers of banks in the country are few; however, adopted balanced panel data needs a large number of observations; thus fourteen private commercial banks were selected due to the availability of full data for the selected time period. These banks are; NIB International Bank, Awash International Bank, Dashen Bank, Wegagen Bank, Zemen Bank, United Bank, Lion Bank, Oromia International Bank, Bank of Abyssinia, Buna International Bank, Birehan International Bank, Addis International Bank, Cooperative Bank of Oromia and Abay Bank. But the remaining two banks: Debu Global Bank and Enat Bank are not selected as a sample; because they were less than six

²⁵Despite the various techniques for bankruptcy predictions, Altman’s Z-Score model remains to be the most extensively used and researched method.

years in operation. Thus; it is possible to draw a relationship among variables using 84 observations (14banks x 6 year's data).

3.1.3 Data Collection Instrument

The secondary source of data for this research was from each banks annual report for micro (bank specific) factors whereas macroeconomic factors are from NBE. The past (2012-2017 G.C) financial statement data i.e. balances sheet²⁶ and income statement²⁷ are collected from NBE and each banks website. For the data of macroeconomic variables like GDP and Inflation are also be obtained from NBE dataset. In order to increase the credibility and reliability of the research findings, the study used audited financial statements.

3.1.4 Data Analysis Techniques

Data analysis is a systematic process which applies statistical techniques to evaluate data through inspecting, transforming and modeling data to draw useful information or decision making. This research adopted Altman's 1993 z-score model as a proxy for financial distress; z-score were developed through the use of MDA. MDA's strength lies in its ability to measure a company's financial distress attributes by analyzing several ratios simultaneously, as well as the interaction between these ratios.

Thus ratios are calculated for financial distress (z-score) and explanatory variables of fourteen banks using six years period from 2012 to 2017 with the aid of Microsoft Excel. Then these data were analyzed using descriptive statistics, correlations coefficient and FE regression analysis to see the relationship of explanatory or independent variables on the dependent variable. The descriptive statistics of both dependent and independent variables were calculated over the sampled periods. This helps to convert the raw data into a more meaning full form which enables the researcher to understand the ideas clearly. And then interpret with a statistical description including standard deviation, mean, minimum & maximum. Then, correlation analyses between dependent and independent variables were made to see the degree of linear association between them. Multiple linear regression analysis was used at the end to determine the relative importance of each independent variable in influencing the dependent variable (financial distress) of

²⁶ Or Statement of financial position (for IFRS reports)

²⁷ Or Statement of profit or loss and other comprehensive income (for IFRS reports)

Ethiopian private commercial banks. To conduct this, the researcher used statistical tools E-views8 software. The study has also performed diagnostic tests to ensure whether the OLS assumptions are violated or not and other related tests²⁸.

3.2 Model Specification

The following regression model is adopted from (Tadesse, 2017) for the testing hypothesis:

$$FD_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + \beta_7 x_{7it} + \beta_8 x_{8it} + \varepsilon_{it}$$

Where: i , represent individual bank; t , represent time; β_0 , represent the constant; β_{1-8} , represent coefficient for the respective explanatory variables; FD , represent financial distress score of each bank and ε : represent the error term.

3.3 Research Hypotheses

3.3.1 Dependent Variable: Z''-score or FD_{it} .

As briefly discussed in the previous chapters; financial distress prediction models have been developed and used (i.e. such as univariate model, risk index model, multiple discriminant analysis (MDA), logit/probit, recursive partitioning, and using univariate model, risk index model, recursive partitioning analysis, case-based reasoning (CBR), neural networks, genetic algorithms (GA) and rough sets model) for more than five decades since they have the ability to forecast bankruptcy of a company one to three years before it actually happens. Most of the bankruptcy studies are used to implement multiple discriminant analysis (MDA) techniques to develop models for large and small firms, as well as private & publicly held firms.

The popular and widely accepted measure of financial distress i.e. Z-score model is one of the most effective Multiple Discriminant Analysis, which has been researched throughout the last 50 years. As stated above, Altman's Model has been used in various industries to predict bankruptcy. Researchers have used Altman's Z''-score model in the service industry, manufacturing industry, publically listed companies, and banks alike to predict if the business will have a downfall. All the three revision of Altman equation (original model 1968, revised

²⁸Likely hood test and Housman test to identify balanced panel data and pooled data, and to know the type of balanced panel respectively.

model 1983, and revised model with four variables 1993) has been used by different authors in their studies, with constructive predictability. Results of Altman's newest revised with four variables Z-score model exhibit a 90.9% success rate in predicting bankruptcy one year prior to firm's demise (Altman, 1993).

In Ethiopia, there are two trial of using Altman's model for financial institutions (Ephrem, 2015) and (Tadesse, 2017). Ephrem used the Zeta-score formula of Altman's credit risk model as of 2002 version. Whereas, Taddese used Altman's 1993 model as a proxy for financial distress; which was developed to emerging market²⁹. Therefore; for this study Altman's Z-score (1993) model developed for nonmanufacturing companies and without a constant term, was used as a measure of FD of Ethiopian private commercial banks as shown below. Since; it has a strong predictive ability of failure or distress classification model.

$$Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

Where:

Z''= financial distress measure of financial institution

X1= Working capital / total assets,

X2= Retained Earning / total assets³⁰,

X3= EBIT / total assets (where EBIT is earnings before interest and taxes),

X4= BVE / total debt (where BVE is the book value of equity and total debt is book value of total liabilities)

Zones of discrimination³¹

Z>2.6-Safe zone

1.1<Z<2.6-Grey zone

Z<1.1 - Distress zone

3.3.2 Independent Variable

And for independent variables (CAMELS, and GDP and CPI) variables ratio measures are calculated based on the works of literature reviewed. Based on these the following hypotheses are developed.

²⁹(there is a constant term of +3.25)

³⁰ (Ephrem 2015) used net operating profit to total asset as a measure.

³¹Altman's 1993 "the classification results are identical to the revised five variables model (z-score 1995)" (Altman E. I., Predicting Financial Distress of Companies: Revising the Z-score and ZETA Model, 1999). The model had different coefficients and cut off points Z>3.75-Safe zone 1.75<Z<3.75-Grey zone, Z<1.75 -Distress zone from (HELLEN, 2013)

Hypothesis A: Bank specific determinants (CAMELS) have a significant effect on FD of banks

- *Hypothesis A₁: Capital adequacy ratio (CAR) has a negative and significant effect on FD of banks*

Capital adequacy is the key variable considered as important in the Basel framework for ensuring healthy banks. Bank's capital serves as a lesson to absorb unexpected losses and shocks. In order to evaluate capital adequacy, most current studies used the ratio of equity capital divided to total assets (ETA) which is able to divide banks ranging from critically undercapitalized to well capitalize; although this ratio does not have fine gradation. In general, as (Rashidah et al, 2014), having sufficient capital allows a bank to absorb losses and still keeps running its daily business operations, even under higher financial distress.

- *Hypothesis A₂: non-performing loans to total loan has a positive and significant effect on financial distress of banks.*

The ratio of non-performing loans divided by total loan (NPLTL) used as a measure of asset quality of banks. This is because non-performing loans are those risk assets not generating income and/or non-performing loans are closely related to the exposure of credit risk and although this is a useful numerator, it is also able to describe on how well banks are deal with their financial challenges and distress (Sahut & Mili, 2011) cited in (Rashidah et al, 2014).

- *Hypothesis A₃: Cost to income ratio has negative and significant effect on financial distress of banks*

The ability and skill of the bank management play a crucial role in the performance and success of the institution. The higher the management competence, the lower is the vulnerability of the banks the likelihood of making wrong decision (Rashidah et al, 2014). Even if it was difficult to measure management quality with accounting data; cost to income (expenses as a percentage of revenue) of efficiency ratio was used.

- *Hypothesis A₄: Earning ability has negative and significant effect on financial distress of banks*

Earning power constitutes a fundamental incentive to operate a firm and the ratio is therefore attractive to study as an explainable variable to FD. In general, the higher levels of profitability should allow banks to improve their capital and economic performance. The common measure of earning ability of bank is ROE.

- **Hypothesis A₅**: *Liquidity ratio has negative and significant effect on financial distress of banks*

The well-known measure of liquidity is the loan-to-deposit (LNTD) ratio. Since liquidity is essential for a bank's ability to meet and repay its short-term obligation and unexpected withdrawals of depositors and creditors (David G Mayes and Hanno Stremmel, 2012). On the other hand the level of liquidity negatively influences the ability of a banking system to survive shocks. As a result of the bank managers should and must take full consideration about it especially related to the process of deposits and loans (Rashidah et al, 2014)

- **Hypothesis A₆**: *Bank size has negative/positive and significant effect on financial distress of banks*

Large firms are better managing their cash flow and/or more diversified and less exposed to liquidity shocks, and also size is a proxy for volatility of firms asset, therefore; difficult to fail or distressed (Shumway, 2012) cited in (Ahmad et al, 2017). There is also another argument (“too big to fail” hypothesis); when the size of the firm increases the likelihood of distress also increase. Accordingly large banks would decrease their cost of funding and invest in riskier assets, since they have inherent guarantee by government during insolvency (Iannotta et al. 2007). Therefore the author of this study expects one of the two effects. Beside these; natural logarithm of total assets is best measure size of the firm, since the size of total assets should be sensitive to the probability of FD (Hotchkiss 1995) cited in (Yohannes, 2014).

Hypothesis B: Macroeconomic factors determinants (GDP and inflation) have significant effect on FD of banks.

- **Hypothesis B₁**: *GDP has a negative and significant effect on financial distress of banks*

The economic growth is measured by change in the real GDP growth rate. “During periods of strong economic growth, loan demand tends to be higher, allowing banks to provide more loans. Strong economic conditions are also characterized by high demand for financial services, thereby increasing the bank's cash flows, profit and non-interest earnings” (Melaku, 2016). Accordingly, fewer loans would default in strong economic condition.

Hypothesis B₂: *Inflation has positive and significant effect on financial distress of banks*

The high inflation rate is associated with higher costs as well as higher income. As stated in different pieces of literature; inflation is expected to exert both positive and negative effect on

financial distress. But the author of this study believes that inflation has a positive effect on FD of banks in Ethiopia; this is because the banking industry in this country is not immediately volatile for such like changes and the common measure changes in consumer price index.

CHAPTER FOUR

4. Data Analysis and Interpretation

This chapter deals with data analysis and interpretation. It has three sections: the first is about descriptive statistics, then correlation analysis among z-score and determinants of financial distress, and including finally CLRM assumptions and panel data fixed effect model regression analysis are discussed.

To empirically investigate the determinants of financial distress and achieve the objectives stated in the first chapter, all banks, their year of service greater than six years, were included. Based on the stated year of service fourteen private commercial banks having financial data over six years period from (2012-2017) was included from a total of sixteen private commercial banks. Therefore, eighty-four ($6 \times 14 = 84$) observations were used to analyze the determinants of financial distress in private commercial banks in the Ethiopian context.

Based on the common analysis procedures, first descriptive statistics; then correlation analysis conducted to show the general view of the data, and make sure about the relationship between dependent and independent variables (z-score vs. CAMELS, GDP, and Inflation). Finally, after applying various diagnostic tests on the data, multiple linear regression analysis was employed. Multiple linear regressions were conducted in order to know the contribution of predictor variables in explaining the dependent/regressed variables (z-score) and the outcome of z-score is inversely interpreted to FD. The outputs of correlation and regression analysis were evaluated using 1%, 5% and 10% significance levels of a confidence interval, and finally, the results were presented by using the appropriate tables.

4.1. Descriptive Statistics

Common sample' use only the part of the sample that is available for all the series selected, whereas 'Individual sample' will use all available observations for each individual series. If the number of observations is the same for all series; similar to this study, the result would be identical for both options (Brooks, 2014 PP 88).

The distribution of dataset for dependent and independent variables used in the study is explained by descriptive statistics. The central idea of descriptive statistics is for a given study is

a measurement of location and variability. The central value of the variables denoted by location is measured mean whereas the spread of the data from mean denoted by variability is measured by standard deviation.

If the observations for a given set of data follow a normal distribution, then the mean and variance (standard deviation) are sufficient to entirely describe the series (Brooks, 2014 PP 66). But the researcher additionally discussed the minimum and maximum value of each variable as illustrated in table 4.1 below.

Table 4.1 the summary of descriptive statistics

Date: 06/01/18 Time: 19:35

Sample: 1 84

	Mean	Median	Maximum	Minimum	Std. Dev.
Z_SCORE	0.514127	0.385	3.57	-0.59	0.67531
CA	0.178861	0.1681	0.3997	0.099	0.04639
A	0.019525	0.0163	0.0883	0	0.013736
M	0.633068	0.6282	0.9654	0.461	0.09041
E	0.205288	0.1976	0.4044	0.0266	0.067832
L	0.624168	0.6195	0.9146	0.4718	0.074517
SIZE_LOG	0.552315	0.564643	0.655851	0.375435	0.058156
GDP	0.097	0.101	0.109	0.08	0.010243
INF	0.133833	0.089	0.341	0.072	0.095545

Where: CA (capital adequacy), A (asset quality), M (management efficiency), E (earning ability), L (liquidity), GDP (gross domestic product), INF (inflation)

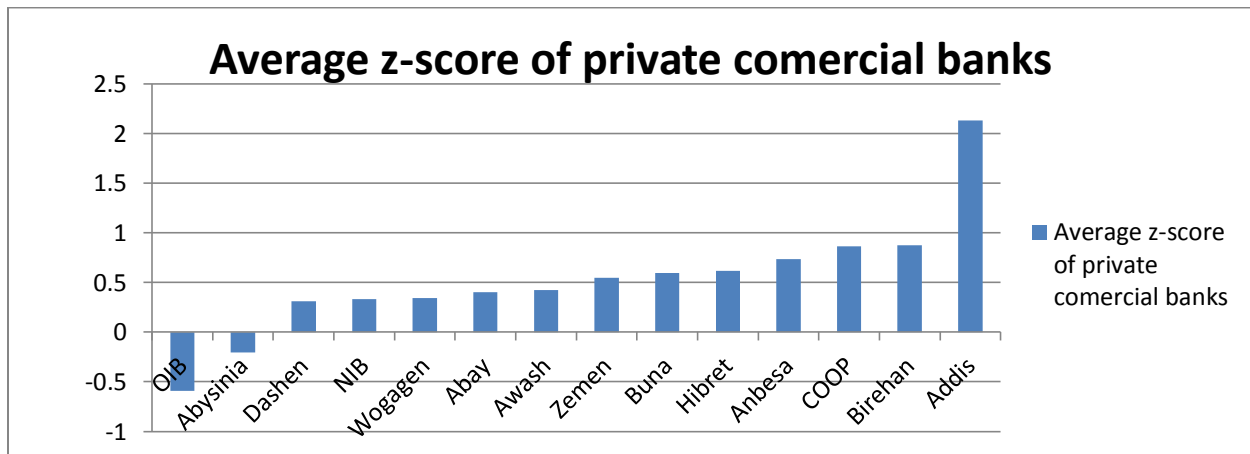
Table 4.1 above provides a summary of the descriptive statistics of the dependent and explanatory variables for 84 observations (14 private commercial banks for six years data from 2012 to 2017). Accordingly; the mean, maximum, minimum and standard deviation values of each variable discussed. As discussed above; this shows the average indicators of variables computed from the financial statements.

4.1.1 Descriptive Analysis of Dependent Variable

As shown in the above table; the dependent variable FD is measured by $Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$ ³² for eighty four observations; shows a mean of 0.5141 in the study period (2012-2017). Based on Altman (1993) classification; it expresses that private commercial banks included in the sample are on average distressed; it would likely lead to bankruptcy in coming years. With maximum and minimum value 3.57 and -0.59 respectively. The maximum was recorded by Addis International Bank in the year 2012 and it is interpreted as the bank was out of the distress zone. And the worst z-score was recorded by Oromia International Bank in the year 2017. Standard deviation is 0.6753, which implies the variation of FD from its mean between private commercial banks.

The following figure shows the average z-score of the studied banks on the sample for the studied period.

Figure 4.1 Average z-score of banks from 2012-2017



Source: own computation on excel

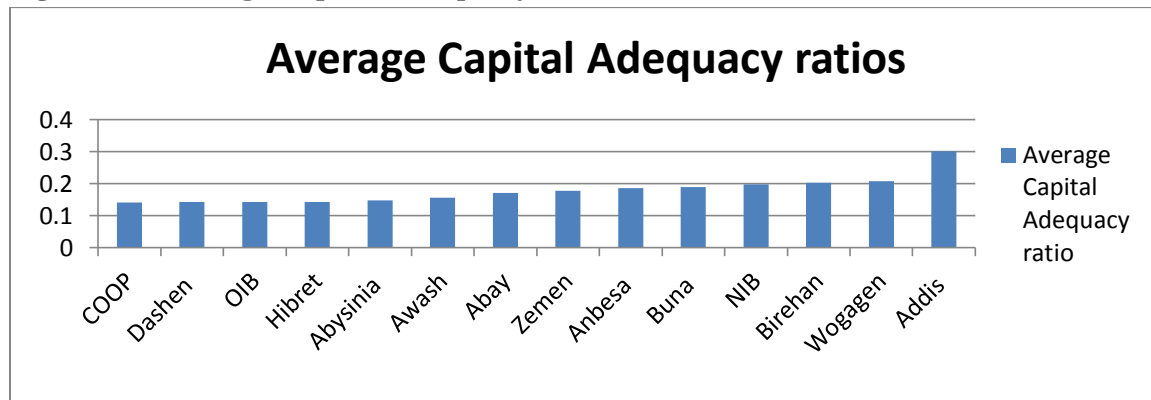
³² Z'' = financial distress measure of financial institution, X_1 = Working capital / total assets, X_2 = Retained Earning / total assets³², X_3 = EBIT / total assets (where EBIT is earnings before interest and taxes), X_4 = BVE / total debt (where BVE is the book value of equity and total debt is book value of total liabilities).

4.1.2 Descriptive Analysis of Independent Variables

As it was discussed in the literature part, capital adequacy refers to the sufficiency of funds available to absorb losses to protect depositors, creditors, etc... in the interest of maintaining financial system stability. As per Basel Committee on Banking Supervision (BCBS 2004) revised framework and NBE requirement (NBE directive no SBB/9/95) capital adequacy is measured by the ratio of regulatory capital to risk-weighted assets and accordingly a minimum of 8% ratio is required. However, the proxy for capital adequacy measurement used in this study was the ratio of equity to total asset (ETA). The higher this ratio entails the capability of the bank to absorb losses from its own capital.

As it is shown in the table above the average value of capital adequacy ratio 17.88% of private commercial banks is greater than the minimum requirement set by NBE 8%. This indicates that private commercial banks have increased their capital by mobilizing funds from the sale of additional shares and especially newly established banks make an effort to meet the increased minimum paid up capital requirement of 500 million set by the NBE on October 2011. The minimum and the maximum value of this ratio were 9.9% and 39.97% recorded by OIB and Addis international bank respectively. Whereas the average standard deviation of 4.6% for capital adequacy reveals that, there was very little dispersion towards the mean capital adequacy ratio.

Figure 4.2 Average Capital Adequacy ratios

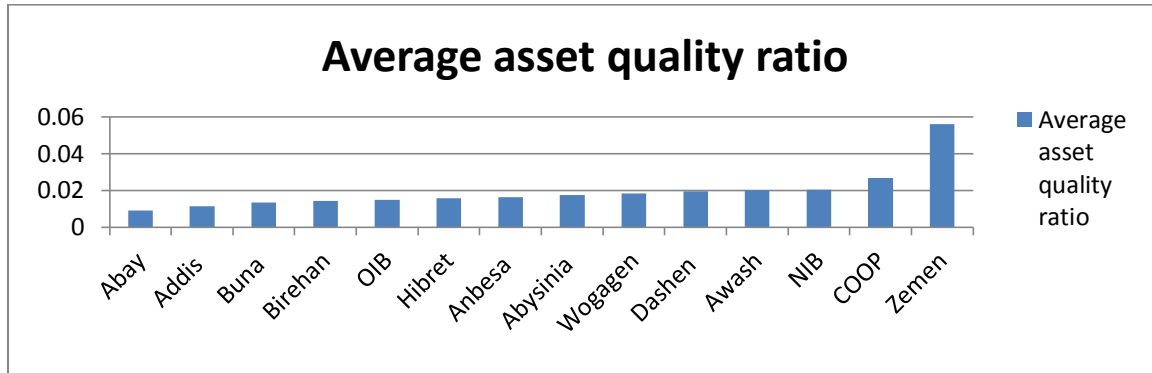


Source: own computation on excel

The second explanatory variable asset quality is measured by NPLTL; on which one can come to conclusion about the qualities of the asset section by looking on non-performing loan to total loan ratio. A larger amount of this ratio is not desirable. Accordingly, the mean value of NPLTL

of private commercial banks is 0.019 with a minimum and maximum of 0 and 0.088 respectively. The above quality of assets values is varied from one to other banks in the sample by a standard deviation of 0.013. As presented in the figure below Zemen bank has highest average NPLTL ratio whereas; Abay bank has the smallest average NPLTL ratio.

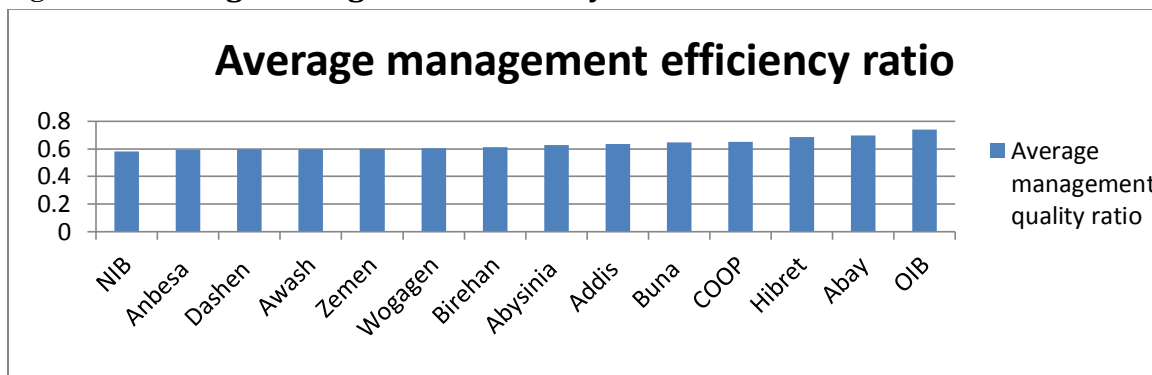
Figure 4.3 Average asset quality ratios



Source: own computation on excel

The third one is Management Efficiency which is measured by Cost to Income of the firm, measures whether they are more enough to be operationally as well as financially sustainable and cover their operational costs or not. The mean value of the variable is 0.6330, which means on average private commercial banks incur 0.633 cents to get one birr income or 63.30% of their income is cost. The minimum and maximum values are 0.4610 and 0.9654 respectively. The standard deviation from the mean is 0.0904. This implies on average the private commercial bank’s managers are more similar efficiency in generating income through their cost.

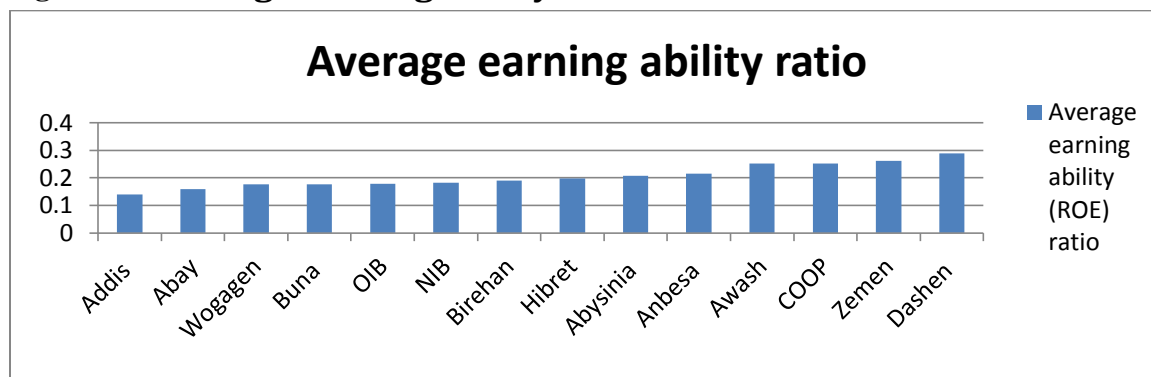
Figure 4.4 Average management efficiency ratios



Source: own computation on excel

The fourth variable Earning ability of private commercial banks are measured by ROE and has 0.2052 return on average from their invested capital with 0.0266 and 0.4044 minimum and maximum values respectively. On average the largest earning ability in the study period was recorded Dashen bank and the smallest was by Addis international bank. The variation of ROE is 0.0678; this shows that there is no such a big difference in earning ability between banks. The figure below shows the average cost to income ratio; accordingly Dashen bank has highest earning ability and Addis international bank has the lowest earning ability.

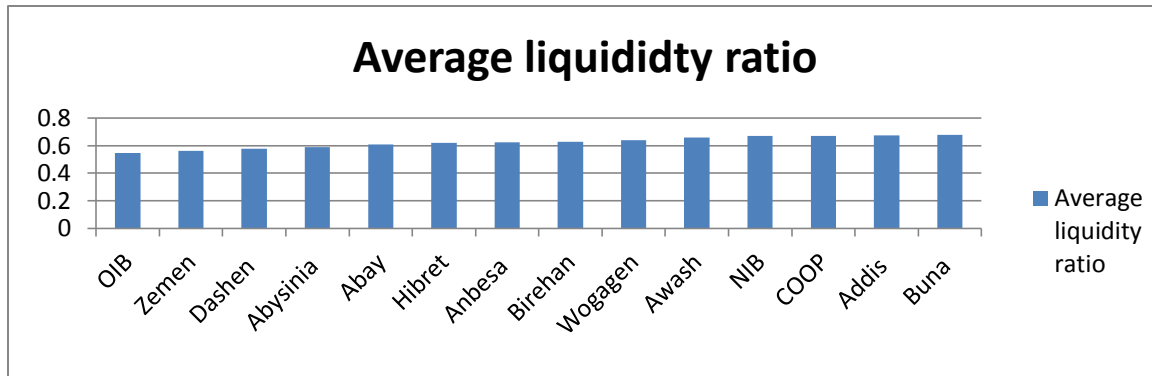
Figure 4.5 Average earning ability ratios



Source: own computation on excel

On average, these private commercial banks have 0.6242 liquidity ratio. Based on (Brigham and Huston, 2005) the liquidity ratio of a given company is at least one. But the average liquidity ratio of private commercial banks included in the sample has less than the expected one. This can be interpreted as banks in this industry have an insufficient amount of liquid assets compared to current liabilities. Maximum and minimum values for the sixth variable were 0.9146 and 0.4718 with a standard deviation of 0.0745. The variability of liquidity in the standard deviation shows the liquidity risk of sampled banks has no significant difference. This is because NBE intervenes by setting the minimum liquidity rate requirement and makes a cross check the applicability of the directive each week.

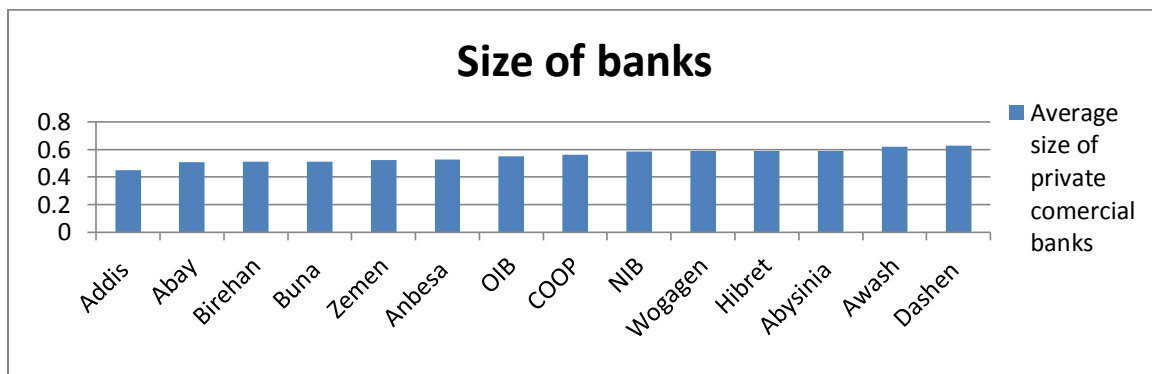
Figure 4.6 Average liquidity ratios



Source: own computation on excel

Bank size is what the bank possesses and it is useful to measure the bank’s general capability to undertake its intermediary function. In this study, the proxy used to measure bank size was the natural logarithm of the total asset. As shown in the above table the average total assets of Ethiopian private commercial banks have shown consistent growth throughout the studied period. But there was a high dispersion of the average total asset of the banks 0.058 with regard to its mean value 0.5523. This shows that there was no significant variation across the sample private commercial banks. The maximum and minimum value of the log of a total asset is 0.6558 and 0.3754 respectively. Hence the small variation of firm size (log of TA) among private commercial banks may have a significant impact on FD; that we are going to see in the regression results.

Figure 4.7 Average natural logarithm of the total asset (size)

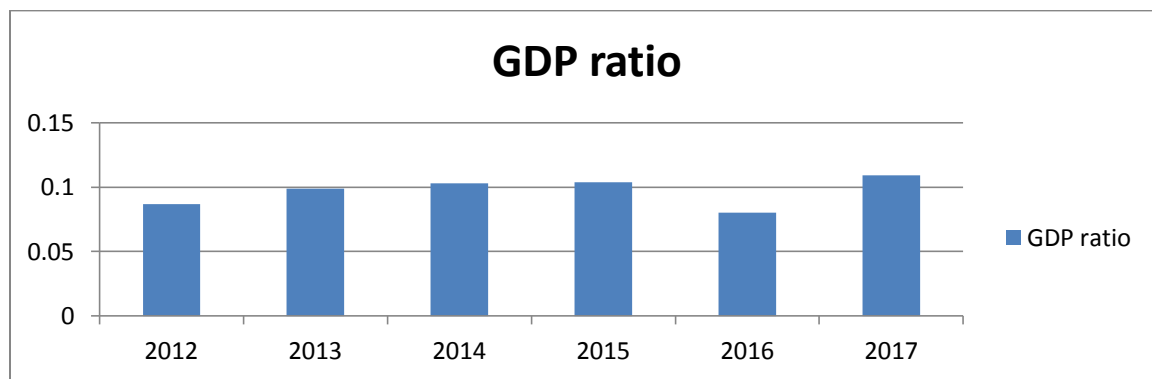


Source: own computation on excel

Similarly, the first macroeconomic variable used in the study was Gross Domestic Product (GDP); and it is an indicator of the economic health of a country as well as the gauge of a

country's standard of living. It is the measurement of the level of economic activity of a country. For the purpose of this study, GDP is measured by the annual real growth rate of the gross domestic product. As it is shown in Table 4.1 above, the average real GDP growth rate of Ethiopia for the last six years was 9.7%. The maximum real GDP growth rate was recorded in the year 2017 (i.e. 10.9%) and the minimum GDP which was also negative growth rate was recorded in the year 2016 (i.e. 8%). The country has recorded on average a double-digit (above 10%) growth rate from 2014 onwards except for the year 2016 which was 8%. The standard deviation of 0.01024 also indicates that there was little dispersion on the real GDP growth rate towards its mean.

Figure 4.8 GDP ratios on the study period



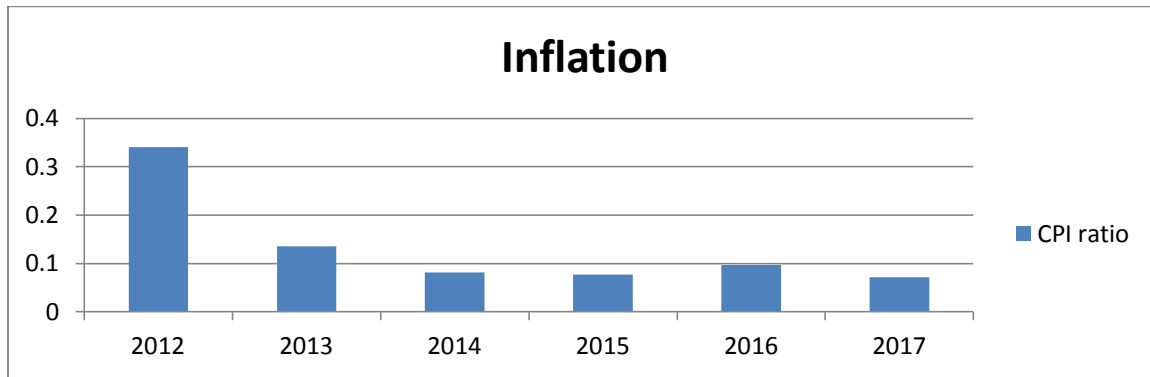
Source: own computation on excel

Another important macroeconomic variable which may affect FD of private commercial banks is the inflation which is measured by the annual consumer price index. During inflation, the central bank can raise the cost of borrowing and reduce the credit-creating capacity of commercial banks. While, it is expected that, banks will make fewer loans and the amount of liquid or short-term assets held by economic agents including banks will rise. On the other hand, during this period, the cost of living will rise and deposits are expected to be reduced and as a result, FD will be affected negatively.

Table 4.1 above shows that the mean value of the consumer price index (CPI) of Ethiopia over the past six years was 13.38%, which was more than that of the average real GDP growth rate. The maximum inflation rate was recorded in the year 2012(34.10%) and the minimum inflation rate which was recorded in the year 2017 (i.e. 7.2%).The inflation rate was shown consistent decrement from 2012 to 2014 and then increased in the year 2016, but again decreased on the

next year. These inconsistencies are expected because of the devaluation of local currency within the study period twice. The rate of inflation was highly dispersed over the periods under study towards its mean with standard deviation of 9.55%.

Figure 4.9 Inflation (CPI) ratios on the study period



Source: own computation on excel

4.2 Correlation analysis

To find the association of the independent variables with dependent variables Pearson Product Moment of Correlation Coefficient³³ was used. The correlation coefficient between two variables ranges from +1 (i.e. perfect positive relationship) to -1 (i.e. perfect negative relationship) and a correlation coefficient of zero, indicates that there is no linear relationship between the two variables (Brooks 2014 PP).

Table 4.2 Correlation coefficient of z-score and independent variables

Dependent Variable	Independent Variables							
	Ca	A	M	E	L	S-log	GDP	INF
Z_SCORE	0.7575	-	-	-	0.1510	-	-	0.3385
	29	0.09002	0.29511	0.05061	86	0.69587	0.10624	78
		5	1	5		8	7	

Source: own computation on Eviews

Table 4.2 above, shows the correlation coefficient between the dependent variables and independent variables. Among the bank-specific variables, capital adequacy and liquidity are positively correlated to Z-score but CA has strong correlation coefficient 0.7575 while liquidity

³³.... is a measure of the strength of the linear relationship between two variables.

has a weak coefficient of 0.1510. On the other hand asset quality, management efficiency, earning ability and size are negatively correlated with Z-score; except for asset quality and earning ability; others have strong correlation coefficient -0.09, -0.2951, -0.0506, and, -0.6958, respectively. The coefficient of both capital adequacy and management efficiency with z-score are strongly positive and negative compared to others respectively; while asset quality and earning ability has the lowest negative coefficient of -0.09 and -0.0506 respectively and liquidity has shown the lowest positive coefficient of 0.1510 in relation with z-score. With regard to macroeconomic variables, inflation (INF) is positively correlated with z-score with a correlation coefficient of 0.33. The other macroeconomic variables, gross domestic product (GDP) has negatively correlated with z-score and the correlation coefficient is -0.1062.

Generally when we see the sign and magnitude of explanatory variables; anyone who has knowledge about the inverse relationship of z-score and FD; can understand/ interpret as CA ratio, TDTL ratio, and CPI are a negative association with FD of private commercial banks. On the other hand NPLTL ratio, a cost to income ratio, ROE ratio, the natural logarithm of total asset and annual GDP rate are positively correlated with FD of private commercial banks. From these entire signs and magnitudes capital adequacy, asset quality, liquidity, size of the banks and inflation has sign as expected. All of these variables have a significant relationship with z-score, except asset quality and liquidity ratios. But management efficiency, earning ability, and GDP signs are not as what the researcher expected; from these variables, only management efficiency is statistically significant relationship with z-score. On the other hand; the insignificance of asset quality and GDP are found similar with that of the regression result that will be discussed later. But the significant and negative relationship between management quality and z-score is not similar with that of the regression result.

4.3 Result of Regression Analysis

This section discusses the result of the model that determines the position of FD of private commercial banks in Ethiopia. As discussed in the previous chapters Altman's 1993 Z-score model is used as a proxy of FD, and it is measured by four financial ratios i.e.

$6.5X1+3.26X2+6.72X3+1.05X4$ ³⁴. The independent variables used in this regression are CAMELS plus GDP and inflation. Accordingly, the following model presents you the regression result of these dependent and independent variables from table 4.9 below and in appendix 1.

$$\text{FD} = 1.45 - 8.46\text{CA} + 1.92\text{A} - 1.35\text{M} - 4\text{E} - 1.66\text{L} + 4.91\log \text{Size} - 3.56\text{GDP} - 1.06\text{INF}$$
³⁵

Table 4.4.1 above shows the results of the regression analysis on the determinant of the dependent variable (FD) which was measured by the revised Altman's Z-score 1993 model and the independent variables which include both bank-specific variables and macroeconomic variables for the sample of fourteen Ethiopian private commercial banks. The coefficient of determination in this model is given by R-squared of 0.74 and Adjusted R-squared of 0.71, which means 71% of the variation of Ethiopian private commercial bank's FD can be explained by the firm-specific and macro variables included in the regression. The remaining 29% of changes were explained by other determinants which are not included in this model. Thus, the explanatory power of the model is high. The value of F-statistics is 26.37 with a p-value of 0.000000 which is used to measure the overall significance of the model. Thus, the p-value of F-statistics is zero at six digits, the null hypothesis is rejected and the model is significant even at 1% significant level. The t-statistic of individual variables also indicates that the bank-specific factors, such as capital adequacy, earning ability, liquidity, and size, were statistically significant at 1% confidence level. On the other hand, asset quality, management efficiency was not significant even at 10% of significant level. While the macroeconomic factors inflation is significant at 1% but GDP were not significant even at 10% of the significant level. Hence, in general, we can conclude that both bank-specific and macroeconomic factors have a significant effect on the level of financial distress of private commercial banks in Ethiopia.

³⁴X1= Working capital / total assets, X2= Retained Earning / total assets³⁴, X3= EBIT / total assets (where EBIT is earnings before interest and taxes), X4= BVE / TD (where BVE is the book value of equity and TD is book value of total liabilities).

³⁵NB: There should be care while determining the relationship between z-score and financial distress to explanatory variables; that means, the positive coefficient of explanatory variable on Z-score indicates the explanatory variable as having negative effect on financial distress of commercial banks and vice versa.

A. Five Assumptions of OLS

Before using the ordinary least square (OLS) estimator to test the significance of the slopes and analyzing the results; Carrying out relevant diagnostic testing for any violation of the underlining assumption of the classical linear regression model (CLRM) is very important. Five assumptions were made which ensures that the estimation technique, ordinary least squares (OLS), to have a number of desirable properties (BLUE), and that hypothesis tests regarding the coefficient estimates could validly be conducted. These are; error terms have zero mean, variances of the errors are constant, co-variances between the error-terms are zero, explanatory variables are not correlated and the error terms are normally distributed.

Assumption 1: $E(U_t) = 0$

According to (Brooks, 2014) this assumption requires that the average value of the error is zero. In fact, if a constant term is included in the regression equation, this assumption will never be violated. Therefore, it will not be the problem for this study since it has a constant term (c).

Assumption 2: $\text{var}(u_t) = \sigma^2 < \infty$ (Homoscedasticity)

The second OLS assumption is known as the assumption of homoscedasticity, meaning the variance of the errors is constant. If the errors do not have constant variance, they are said to be heteroscedastic (Brooks, 2014). Further, Brooks raises a question “How can one tell whether the errors are heteroscedastic or not?” Accordingly, there are a number of methods used to test this constant variance assumption: they are the graphical method, Goldfeld–Quandt (1965) and White’s (1980). The first one is the graphical method; this method is done by estimating the regression, the residuals, have been calculated and then plotted against explanatory variables. Then looking at the graph one can say there is constant variance or not. But unfortunately one rarely knows the cause or the form of the heteroscedasticity, so that a plot is likely to reveal nothing (Brooks, 2014).

The second simplest method is called Goldfeld–Quandt (1965); which is formal statistical tests for heteroskedasticity. GQ approach is based on splitting the total sample of length ‘T’ into two subsamples of length T1 and T2. The regression model is estimated on each sub-sample and the two residual variances are calculated. The null hypothesis is that the variances of the

disturbances are equal against a two-sided alternative³⁶. Generally, the GQ test is simple to construct but its conclusions may be contingent upon a particular, and probably arbitrary, choice of where to split the sample.

A third and most popular test is White’s (1980) general test for heteroskedasticity. The test is particularly useful because it makes few assumptions about the likely form of the heteroskedasticity. Because of this; the researcher used White’s (1980) general test for heteroskedasticity for this study. The test first assumes that the regression model estimated is of the standard linear form, obtain R^2 from the auxiliary regression and multiply it by the number of observations ‘T’ after running the auxiliary regression³⁷. Finally if the X^2 -test statistic from is greater than the corresponding value from the statistical table then reject the null hypothesis that the errors are homoscedastic: the following table shows White’s test of the study.

Table 4.3 White’s test for hetroskadesticity

Heteroskedasticity Test: White			
F-statistic	1.5046995...	Prob. F(9,73)	0.1624
Obs*R-squared	12.987991...	Prob. Chi-Square(9)	0.1631
Scaled explained SS	13.383457...	Prob. Chi-Square(9)	0.1460

Source: *own computation on Eviews*

The F- and X^2 (‘LM’) versions of the test statistic give the same conclusion that there is no evidence for the presence of heteroscedasticity since the p-values are considerably in excess of even 10%. Therefore; the errors in the regression have a constant variance or it is known as homoscedasticity.

Assumption 3: $cov(u_i, u_j) = 0$ for $i \neq j$ (No Autocorrelation)

The third assumption states that the covariance between the error terms over time (or cross-sectional, for that type of data) is zero. According to (Brooks, 2014) “it is assumed that the errors are uncorrelated with one another. If the errors are not uncorrelated with one another, it would be

³⁶Or it is simply the ratio of the two residual variances where the larger of the two variances must be placed in the numerator. The test statistic is distributed as an $F(T1 - k, T2 - k)$

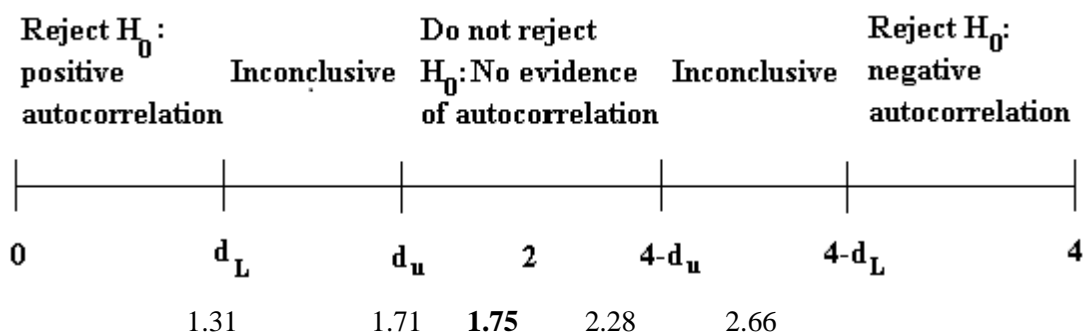
³⁷The reason that the auxiliary regression takes this form is that it is desirable to investigate whether the variance of the residuals varies systematically with any known variables relevant to the model.

stated that they are ‘auto-correlated’ or that they are ‘serially correlated’”. Therefore; a test of this assumption is required on the residuals; since population disturbances cannot be observed.

In order to test for autocorrelation and to consider possible relationships between the current residual and immediately previous one period, via plotting the residual in the graph is the first step. But the graphical method is difficult to interpret in practice. But there are also other statistical methods that should be applied. One of these tests is Durbin and Watson (1951); it is a test for the first order autocorrelation i.e. it tests only for a relationship between an error and its immediately previous value. (Brooks 2014) discusses that, DW test statistic is approximately equal to $2(1 - \hat{\rho})$. Since $\hat{\rho}$ is a correlation, it implies that $-1 \leq \hat{\rho} \leq 1$. That is, $\hat{\rho}$ is bounded to lie between -1 and $+1$. Substituting in these limits for $\hat{\rho}$ to calculate DW from $DW \approx 2(1 - \rho)$ would give the corresponding limits for DW as $0 \leq DW \leq 4$. (Brooks, 2014) further explain the drawbacks of DW; that is not following standard statistical distribution such as at, F, or χ^2 . DW has 2 critical values: an upper critical value (d_U) and a lower critical value (d_L), and there is also an intermediate region where the null hypothesis of no autocorrelation can neither be rejected nor not rejected! The rejection, non-rejection and inconclusive regions are shown on the number line in figure 4. =

Accordingly, this study wishes to test for first-order serial correlation in the residuals from a linear regression. The DW test statistic value is 1.75. The relevant critical values for the test even based on 85 observations (T) and 8 explanatory variables (K’); Lower and upper 1% critical values for Durbin–Watson statistic were $d_L = 1.312$, $d_U = 1.714$, so $4 - d_U = 2.286$ and $4 - d_L = 2.688$ (Brooks, 2014 Pp 674) and (Gudjrati, 2009,Pp888). The test statistic is clearly presented between the uppercritical value and four mines upper critical value; hence the null hypothesis of no autocorrelation is not rejected.

Figure 4.10 Durbin–Watson statistic test of autocorrelation



But the most serious problem with the DW test is the assumption that the regressors are non-stochastic, that is, applied most often if their values are fixed in repeated sampling. Unless, then the DW test is not valid either infinite, or small or large samples. And since this assumption is usually difficult to maintain in economic models involving time series data, one author contends that the Durbin–Watson statistic may not be useful in econometrics involving time series data (Gudjrati, 2009 Pp435).

Furthermore; there will also be many forms of residual autocorrelation that DW cannot detect. Therefore, it is desirable to examine a joint test for autocorrelation that will allow examination of the relationship between error terms and several of its lagged values at the same time.

Thus, even if there is no particular test has yet been judged to be unequivocally best [i.e., more powerful in the statistical sense]; to avoid some of the pitfalls of the Durbin–Watson test of autocorrelation, statisticians Breusch and Godfrey have developed a test of autocorrelation that is more general test up to the r^{th} order. So this study uses BG test for the test of autocorrelation.

Table 4.4 BG test for autocorrelation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.7407832...	Prob. F(2,71)	0.1827
Obs*R-squared	3.8797521...	Prob. Chi-Square(2)	0.1437

Source: *own computation on Eviews*

The conclusion from both versions (X2 and F-statistics) of the test, in this case, is that the null hypothesis of no autocorrelation should be not-rejected since the p-values are greater than 0.05. and it is consistent with the DW test result.

Assumption 4: the X_t are non-stochastic

Multicollinearity is an assumption of a linear relationship between explanatory variables; on which it is possible to identify the existence of a correlation between regressors and to avoid the double effect of explanatory variables. According (Brook’s 2014); If there is no relationship between the explanatory variables, they would be said to be orthogonal to one another. In practice, the correlation between explanatory variables will be a non-zero and relatively small

degree of association between regressors is fine. However, a problem occurs if one or more of the explanatory variables are very highly correlated with each other, and this problem is known as multicollinearity. As a result of this, the OLS estimator will not even be consistent.

There are two classes of multicollinearity: perfect multicollinearity and near multicollinearity. The second one is much more likely to occur in practice and would arise when there was a non-negligible, but not perfect, relationship between two or more of the explanatory variables. Based on this the researcher tried to see near multicollinearity of explanatory variables. The simplest method to investigate the presence of near multicollinearity is looking at the matrix of correlations between individual variables; since it is difficult to test.

Table 4.5 correlation matrix between independent variables

	CA	A	M	E	L	SIZE_LOG	GDP	INF
CA	1.000000							
A	-0.104572	1.000000						
M	-0.255430	-0.035685	1.000000					
E	-0.297813	0.228287	-0.680196	1.000000				
L	0.179285	-0.143596	0.172046	-0.186981	1.000000			
SIZE_LOG	-0.663993	0.096038	0.089007	0.309123	0.151101	1.000000		
GDP	-0.065411	0.003117	0.050817	-0.019642	0.076778	0.146855	1.000000	
INF	0.184550	-0.057570	-0.342794	0.119697	-0.254462	-0.391678	-0.499828	1.000000

Source: own computation on Eviews

The exact cut off point of near multicollinearity is steel controversial argument; some of them argue that correlation coefficient below 0.9 may not cause serious multicollinearity problems³⁸; while (Malhotra, 2007) and (Kennedy, 2008) stated that the problem of multicollinearity between explanatory variables exists when the correlation coefficient among variables is greater than 0.75 and 0.70 respectively. As illustrated in the above figure; there is no near multicollinearity in all of the above argument; since relatively the largest value in this matrix is -0.68, which is existed between management efficiency and earning ability and -0.66 between capital adequacy and size of the bank.

Assumption 5: (ut ~N (0, σ2)) the disturbances are normally distributed

Even if there are several tests for normality assumption, some of them are the histogram of residuals, normal probability plot (NPP), the most commonly applied one is (Bera –Jarque 1981).

³⁸ Hair et al 2006(cited in Habtamu 2012)

A normal distribution is not skewed and is defined to have a coefficient of kurtosis of 3. The null hypothesis of BJ (Bera –Jarque) tests whether the coefficient of skewness and coefficient of excess kurtosis are jointly zero. “If the residuals are normally distributed, the histogram should be bell-shaped and the Bera–Jarque statistic would not be significant. This means that the p-value given at the bottom of the normality test screen should be bigger than 0.05 to not reject the null of normality at the 5% level” (Brooks, 2014).

Table 4.6 BJ test for Histogram-Normality

Series: Residuals

Sample 2012 2017

Observations 84

Mean 1.17e-15

Median -0.009016

Maximum 1.372126

Minimum -1.122110

Std. Dev. 0.455678

Skewness 0.331169

Kurtosis 2.873407

Jarque-Bera 1.591515

Probability 0.451239

Source: *own computation on Eviews*

As the figure above shows; the residuals from the z-score regression seem to be symmetrically distributed. Application of the Bera-Jarque test shows that the skewness is -0.33 and kurtosis is 2.87 and furthermore; the BJ statistic is about 1.59 and the probability of obtaining such a statistic under the normality assumption is about 45 percent. Therefore, we do not reject the hypothesis that the error terms are normally distributed even 10 percent.

B. Fixed and Random effect model

As briefly discussed in chapter three (methodology part); this study used balanced panel type of data since the study has the same number of cross-sectional units at each point in time or has the same number of time series observations for each cross-sectional unit (Gujarati , 2009). Most of panel data literature classifies panel data into short panel and long panel; in a short panel the

number of cross-sectional subjects, N, is greater than the number of time periods, T. while the long panel is viewed the other way around (T that is greater than N).

On the other hand, there are two classes of panel estimator approaches that can be employed in financial research: fixed effect and random effect models. Fixed effect model is more appropriate when the entities in the sample effectively constitute the entire population (Brooks, 2014). On the other hand, according to (Gujarati , 2009), the random effects model is more appropriate when the entities in the sample can be thought of as having been randomly selected from the population; while if the number of time series data is large and the number of cross-sectional units is small, there is likely to be little difference in the values of the parameters estimated by both fixed and random effect model.

FE regression was implemented in this study, because; fixed effect statistical model typically used in regression and will probably produce smaller standard errors (more powerful); on the other hand the number of cross-section units (fourteen) greater than number of time series data (six) on this study and besides these the sample of private commercial banks were not selected randomly.

Farther more; it is possible to know whether the fixed effects are necessary or not by running a redundant fixed effects test. It is implemented by estimating the unrestricted specification that includes effects of interest first; it is possible to test the significance of FE regression. Accordingly the results for the unrestricted estimated FD are given by Table 4.7, and finally as shown in table 4.8 random effects model were estimated to determine whether the random effects model passes the Hausman test (i.e. the random effects being uncorrelated with the explanatory variables).

Table 4.7 Redundant Fixed effect – Likelihood ratio test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	5.239257	(13,62)	0.0000
Cross-section Chi-square	62.264876	13	0.0000

Source: own computation on Eviews

The two statistic values (“Cross-section F” and “Cross-section Chi-square”) p-values associated with the test statistics are zero to four decimal places, indicating that the restrictions are not supported by the data and that a pooled sample could not be employed (Brooks 2014).

Table 4.8 Housman random effect test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	49.394393	8	0.0000

Source: own computation on Eviews

The p-value for the test is less than 1%, indicating that the random effects model is not appropriate and that the fixed effects specification is to be preferred (Brooks 2014).

Table 4.9 Regression result of the model

Dependent Variable: Z_SCORE
Method: Panel Least Squares
Date: 06/01/18 Time: 20:26
Sample: 2012 2017
Periods included: 6
Cross-sections included: 14
Total panel (balanced) observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CA	8.461083	1.562200	5.416133	0.0000
A	-1.926290	3.084228	-0.624562	0.5342
M	1.351269	0.875623	1.543208	0.1270
E	4.009202	1.134601	3.533579	0.0007
L	1.664056	0.623067	2.670748	0.0093
SIZE_LOG	-4.916591	1.092736	-4.499339	0.0000
GDP	3.563473	4.594100	0.775663	0.4404
INF	1.385285	0.549347	2.521694	0.0138
C	-1.451524	1.360508	-1.066899	0.2894

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.737737	Mean dependent var	0.514127
Adjusted R-squared	0.709762	S.D. dependent var	0.675310
S.E. of regression	0.363815	Akaike info criterion	0.484888
Sum squared resid	9.927084	Schwarz criterion	1.121530
Log likelihood	-29.49773	Hannan-Quinn criter.	0.740813
F-statistic	26.37152	Durbin-Watson stat	1.752218
Prob(F-statistic)	0.000000		

Source: own computation on Eviews

Bank specific factors of FD

1. **Capital adequacy:** the result of panel data regression model as presented in Table 4.9 indicates that CA as a function of ETA indicate has a positive relationship with z-score, or negative effect on FD by coefficient 8.46 and p-value 0.0000. The result is parallel with the first hypothesis i.e. negative and significant relationship with the dependent variable FD. Based on the beta coefficient; holding other things constant; if one unit increase in capital adequacy result increase in Z-score or decrease in FD by 8.46 units on average and the null hypothesis is rejected since the relationship is statistically significant at 1% significance level. Hence, as a bank increases capital, it becomes strong enough to absorb losses; and continue operations even under distressed environment and reduce the likelihood of failure and/or insolvency.

This finding is consistent with previous piece of literature (Rashidah et al, 2014) and (Tadesse, 2017). Who found that, Higher ETA ratios which portray a good performance of capital adequacy; less likely to go to distress. The same results were found by (ZHEN, 2014) conducted in bank distress in the ASEAN, NIC, G20, and G8 countries. Bank's capital serves as a lesson to absorb losses and shocks (David G Mayes and Hanno Stremmel, 2012)

But it is not stick with positive and significant influence on the financial health of banks finding by (yuori, 2012); they argue that increasing minimum capital requirement had only accounted for a short-term improvement in the liquidity position of banks and improvement in their asset quality but were not have a long-term effect on forestalling distress.

2. **Asset quality:** the positive and in-significant sign of NPLTL on FD of Ethiopian private commercial banks is inconsistent with the second hypothesis. Holding other things constant; a unit increase in an NPLTL lead to increase in FD on average by 1.92 units and the relationship is statistically insignificant even at 10% significant level. Because of this, the null hypothesis is not rejected even at 10% significant level. That means the ratio of NPLTL had a chance to be no effect on the dependent variable FD.

According to (Rashidah et al, 2014) all banks did not have a possibility of FD as they are able to handle their nonperforming loans throughout the year. (ZHEN, 2014) found the same result significantly negative correlation with bank distress in the G20, G8 which contradicts

his own finding, significantly positive correlation with bank distress in the NAFTA, OECD and ASEAN, EU, NIC countries; but consistent with Ephrem 2015, statically significant negative influence on the financial health of the banks.

On the other hand; (Taddese, 2017), (Mulyaningrum, 2008) and (Almilia, 2005), argues that asset quality has a positive effect for predicting bankruptcy of a bank but it is insignificant. Although, the effect is not significant as such; weak management of nonperforming loan leads banks in to financially unstable.

3. **Management efficiency:** the negative and in-significant sign of cost to management on FD of Ethiopian commercial banks is not stick with the third hypothesis. When interpreting the result; *ceteris paribus*; when the management efficiency increase by one unit then FD of Ethiopian commercial banks will decrease by 1.35 on average and their relationship is statistically insignificant even at 10% significant level. Thus; the researcher is unable to reject the null hypothesis with the maximum possible tolerance level. This can also be interpreted as there is a chance that the management efficiency effect on FD is zero.

This result is against (Edward et al, 2006) they take management inadequacy is usually the core of the problem. The findings of two previous authors in this country; manager's efficiency has negative and significant influence on FD of banks, found by (Taddese, 2017); similarly (ANDUALEM, 2011)also found out that; cost to management efficiency ratio has significant influences on dependent variable: Debt Service Coverage (DSC) but the sign is positive. The positive and significant result by Andualem is lacking reliability on the sign; since financial distress on a company with efficient management is less likely; and/or the selection of dependent variable: DSC. However, the negative influence of management efficiency FD on banks found by (Taddese, 2017), is stick with the result of this research; but the significance is under a question mark since there are companies who are not failed because of their management in-efficient.

On the other hand management efficiency did not appeared significant on the studies conducted by (Rashidah et al, 2014), (Poghosyan and Cihak, 2009) and (Ephrem, 2015); they found out that higher managers efficiency reduces the possible insolvency of selected companies. Furthermore; (Bou-Said and saucier, 2003), had also reported that some of the

distressed banks had had good cost to income ratios. This lets the researcher agree with the theoretical works of literature reviewed; “the higher the management competence, the lower is the vulnerability of the bank and the likelihood of making wrong decisions”, even though there is the possibility of no influence on financial distress prediction.

4. **Earning ability:** similarly, the negative and significant effect of ROA (EAT/SHE) on FD of Ethiopian commercial banks is consistent with the fourth hypothesis. Obviously, higher levels of earning ability should allow banks to improve their capital and economic performance. Accordingly; based on the table above, a unit increase in ROE brings a decrease in FD of Ethiopian private commercial banks by 4 units on average and their relationship is statistically significant even at 1% significant level.

Ephrem 2015 and (ANDUALEM, 2011) finding contradicts with this finding. Based on their argument the company with a higher earning ability is more likely to incur financial distress, has positive and significant influences relationship with Zeta score and Debt Service Coverage (DSC) respectively. Whereas; research conducted by (Yohannes, 2014), (Mulyaningrum,2008), and (Almilia, 2005) concluded that profitability of the companies has no significant impact on the status of firm’s financial distress.

On the other hand; similar to this research finding, other previous researchers state that a company with better performance will less likely to face FD; but it is in terms of ROA (Rashidah et al, 2014). Similarly; (ZHEN, 2014) and (Taddesse, 2017) also found earning ability of companies have a significant and negative correlation using ROE as a measure. The companies who have better-earning ability can survive bad conditions.

5. **Liquidity:** it was measured by TLTD and the fifth test for a negative and significant relationship with FD of Ethiopian private commercial banks is consistent with this finding. Accordingly, FD of selected private commercial banks decreased by 1.66 units on average as a result of a unit increase in TLTD and their relationship is statistically significant even at 1% significant level.

The result is consistent with (Mulyaningrum, 2008), (Taddesse, 2017), (Yohannes, 2014) and (ANDUALEM, 2011). According to (Mulyaningrum, 2008); loan to deposit ratio (LDR) has a significant influence on a bank's bankruptcy prediction. Furthermore (Rashidah et al, 2014),

states that banks have a large number of loans but they have sufficient liquid assets in order to cover their liabilities and commitments. But (Konstandina N.V., 2006), (Poghosyan and Cihak, 2009) and (Almilia, 2005) were identified liquidity as insignificant in affecting EU banking distress.

6. **Size:** is measured by the natural logarithm of total asset, this indicates how large the company's in terms of its asset size in order to survive FD. The positive and significant sign of Log of the total asset on FD of Ethiopian commercial banks is consistent with the sixth hypothesis. Citrus paribus a unit increases in size of the bank increases FD of Ethiopian private commercial banks on average by 4.91 and their relationship is statistically significant even at 1% significant level.

This finding contradicts with the finding of Ephrem and Tadesse; the size of the banks has no significant effect on FD. Even if; a company, which has high assets, tends to not get financially distressed easier due to a high conversion of the assets to cash; the insignificant effect may imply that z-score and FD are unresponsive to the level of increase in the asset of the bank.

However; large banks would decrease their cost of funding and invest in riskier assets since they have an inherent guarantee by the government during insolvency (Iannotta, 2007). Thus the finding of this research corresponds to the well-known "too big to fail" hypothesis. According to (Edward et al, 2006); "even if it is adjusted for inflation; size is no longer a proxy for corporate health and there is little evidence, except in very rare circumstances, of the old adage "too big to fail". This result is also supported by (Yohannes, 2014), (ANDUALEM, 2011) and (Baklouti et al, 2016). Based on their finding; the size of banks are positively related with FD and statistically significant.

2. Macroeconomic factors of FD

7. **GDP:** with regard to macroeconomic factor; the test for real GDP is a negative relationship with FD of Ethiopian private commercial banks is in line with the sevens hypothesis, but it is insignificant. Based on the coefficient and t-statistic, one could understand that; holding other things constant one percent increase in real GDP brings decrease on FD of Ethiopian private

commercial banks by 3.56 units on average and their relationship is statistically insignificant at 10% significant level.

This implies that during the study period, the growth rate of GDP of Ethiopia does not have a significant impact on the FD of Ethiopian private commercial banks. The result is consistent with (Yohannes, 2014), (Athanasoglou, 2005) and (Konstandina, 2006) who found a statistically negative and in-significant relationship between financial distress and GDP. On the other hand (Baklouti et al, 2016) states that when the economic growth becomes weaker it is more likely that businesses and households will reduce their inflows, which result in higher level of financial distress.

8. **Inflation:** the test for a significant relationship of CPI with FD of Ethiopian private commercial banks is in line with the eighth hypothesis. But the negative sign is not as expected; this is may be because commercial experienced immediate adjustment for change in inflation. The beta coefficient indicates that holding other things constant if the CPI increase by one percent then FD is on average decrease by 1.38units and their relationship is statistically significant even at 1% significant level.

According to (Kevin et at, 2001) cited in (Yohannes, 2014); inflation is expected to exert a negative effect on financial distress when its costs increase faster than its income. It is the actual scenario we observing in Ethiopia this day. Additionally banking industry in this country is not immediately responding to changes in CPI. On the other hand, (Tadess, 2017) and others were not found a statistically significant relationship between financial distress and inflation. In general, based on the P-value (i.e., 0), the researcher able to reject the null hypothesis; i.e., inflation had a significantly negative effect on financial distress.

Table : Summary of Independent variables and Expected sign on FD and Z-score

Variables	Description/Measure	Expected sine		Final result		Significance level
		Z-score (1993)	FD	Z-score (1993)	FD	
(C) CAR	Share Holder's Equity to Total Asset (ETA)	+	-	+	-	Significant @1%
(A) Asset Quality	Non-performing Loans to Total Loans	-	+	-	+	In-significant
(M) Management Efficiency	Cost to Income (Non-interest income to Non-interest expense)	+	-	+	-	In-significant
(E) Earning ability	ROE: Earning After Tax (EAT) to Share Holder's Equity (SH _s E)	+	-	-	+	Significant @1%
(L) Liquidity	Loan to Deposit	-	+	+	-	Significant @1%
(S) Size of bank	Natural logarithm of total assets	+/-	-/+	-	+	Significant @1%
GDP	Gross Domestic Product	+	-	+	-	In-significant
Inflation	Consumer Price Index (CPI)	-	+	+	-	Significant @5%

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

The objective of this study is to examine the determinants of financial distress in private commercial banks in Ethiopia. As discussed in the first three chapters; the researcher used z'-score to measure FD; which is MDA based model developed by (Altman E. , 1993). The study used panel data during the period 2012-2017 and selected fourteen banks as a sample out of sixteen commercial banks that were operating on these periods. In the fourth chapter descriptive statistics, correlation analysis and balanced FE regression analysis were performed to describe the determinants of financial distress in private commercial banks in Ethiopia. The final chapter presents a conclusion of the study by summarizing the study's findings and provides a recommendation for stakeholders as well as for further studies.

5.1. CONCLUSIONS

To analyze the descriptive statistics, the researcher used mean, maximum, minimum and standard deviation to describe overall picture of private commercial banks in Ethiopia. After that, the study briefly discussed the correlation analysis of dependent and independent variables based on Pearson Product Moment of Correlation Coefficient. And finally fixed effect (FE) regression analysis made to identify the determinants of banking financial distress. Therefore, by considering, if all private commercial banks are used Altman z-score 1993 model to predict their financial distress and the above three analysis's the research reached on the following conclusions.

The study investigates the impact of micro as well as macro factors on the dependent variable over the period of six years from 2012 to 2017. Accordingly; Capital adequacy, asset quality, management efficiency, earning ability, liquidity and bank size are firm-level characteristics, and from macro factors GDP growth rate and inflation are selected as explanatory variables while z-score is taken as dependent variable.

The co-relational analysis of the study shows that variables like capital adequacy, liquidity, and inflation are positively correlated to Z-score; while asset quality, management efficiency, earning ability, size and GDP are negatively correlated with Z-score. From these only CA, management

efficiency, and inflation has a strong correlation with the dependent variable. The results of FE regression analysis reveal that capital adequacy, earning ability, liquidity, bank size, and inflation is most important determinants of financial distress in private commercial banks in Ethiopia since they are statistically significant; whereas asset quality, management efficiency and GDP growth rate has a statistically insignificant relationship with z-score. Generally, the mean score of the dependent variable of both descriptive statistics and FE regression is 0.5141, thus based on (Altman E. , 1993) classification, the research confirmed that the banking sector had been distressed.

The most important determinant of FD i.e. Capital adequacy appeared significant and negatively affects financial distress of Ethiopian private commercial banks. This implies that, increasing capital tends to reduce the level of financial distress and probability of failure, since as a bank increases capital it becomes strong enough to absorb losses; and continue operations even under distressed environment; as is consistent with “bank’s capital serves as lesson to absorb losses and shocks” finding by (David G Mayes and Hanno Stremmel, 2012).

The coefficient of variable asset quality is positive and statistically insignificant. The positive effect communicates that increase in asset value measured by NPLTL increases the probability of insolvency and exposed private commercial banks to financial distress and failure. Since nonperforming loans are those risk assets not generating income and/or non-performing loans are closely related to the exposure of credit risk. The insignificance of the NPLTL ratio is maybe because value used to measure NPL. That is Loan Loss Provision (LLP), and the amount is very small and even reducing from time to time since private commercial banks are efficiency in collecting loans on their maturity.

The coefficient of variable management efficiency is negative but not found statistically significant. The higher the management competence, the lower is the vulnerability of the bank and the likelihood of making wrong decisions, which lets them financially distressed. Surprisingly the effect on FD was insignificant; it is may be because of measurement of the variable management quality (i.e. Cost to income). Management quality is treated as a qualitative aspect and considered as the hardest one to measure with accounting data (Rashidah et al, 2014).

Earning ability of banks was measured by ROE; the coefficient is negative and statistically significant. This implies that higher ROE leads banks to survive unexpected insolvencies or risks, since earning power constitutes a fundamental incentive to operate a firm. This finding contradicts the gamblers ruin theory, which expected banks to take excessive risk and exposed to distress to get higher return until their net worth becomes negative.

The negative coefficient of variable liquidity measured by LNTD ratio specifies significantly negative relationship with the dependent variable. The higher the firm's liquid assets, the higher the ability of the firms is cover its fixed charges and the lower the probability of the firm to go into financial distress.

The coefficient of variable firm size is positive and statistically significant at 1% level. This predicts that performances of large size banks are better than small size companies in order to go to financially distress. The positive relationship between firm size and FD implies that large banks are better placed in distress than smaller ones. And is consistent with 'too big to fail' argument which states that when the size of the firm increases the likelihood of distress also increase because large banks to take excessive risk in an anticipation of government support whenever they face difficulties.

From macro variables included in the regression (i.e. GDP and Inflation) only inflation is appeared to be a significant determinant of FD, but GDP wasn't. The negative effect of GDP on financial distress indicates that an increase in economic activity is associated with lower level of banking distress and failure. Whereas the negative effect of inflation on FD implies that private commercial banks are less likely to go to distress as a result of an increase in CPI. In Ethiopia at the time of inflation costs increase faster than its income. The insignificance of GDP on FD of banks is may be as a result of the nature of the business. The banking sector has less contribution on the computation of GDP compared to others in the study period. Or it is may be the contribution of PCB to GDP was very small since the market share of all PCB is very small and does not have significant effect on computation of GDP compared to dominant CBE.

5.2. RECOMMENDATIONS

Based on the major findings obtained from the result, the researcher provided the following recommendations.

Since on average all banks under this study have appear in distress zone; they should take remedies by observing the result of individual variables obtained in this research and measures of revised z'' -scores; unless they will possibly be bankrupt soon. Beside this, All commercial banks should take a consideration and implement the early warning system having high predictive power than others i.e. Altman's z'' - score to analyze their own current situation and predict their future.

The EWS developed by different scholars starting from Beaver's 1660: ratio analysis up to the recent z-score, logistics, etc ... needs the distinction of companies into distressed and non-distressed to observe the main variables effect on both sides. These data can be obtained from the nationally authorized organization of the country e.g. NYSE for the USA, NSE for the Kenya, etc ... NBE is in charge of such like activities i.e. comparison of banks in the country, since it is the only financial regulatory institution in this country; even if regular regulatory supervision is very important for sound banking; but beside controlling their activities; NBE should disclose the periodic ranking based on their operation and comparison of banks publicly; therefore; obtaining afore mentioned vital data is impossible.

The negative relationship between bank size and FD revealed the "too big to fail" hypothesis, in which big banks may encourage to disburse more loans and advances. Thus, big banks need to manage their liquidity position and shall give due attention to resource mobilization and loan and deposit management.

In general, the findings of the study reveals that, bank-specific variables i.e. CA, ROE, L, Bank size and inflation from macro variables have statistically significant impacton the determination of FD in Ethiopian private commercial banks, since they are internal variables that can be controlled by management, special emphasis shall be given to those significant variables. Furthermore, Asset quality and management efficiency, and GDP are not appeared significant both from firm-specific and macro variables respectively.

The prediction of company's survival is essential for management and company owners to anticipate the possibility of potential bankruptcy. Thus; to prevent this problem before bankruptcy; bank managers, BODs, and stockholders should take the following action suggested by (Brigham and Huston, 2005) since private banks included in the study are under distress zone on average based on Altman's 1993 z-score classification. "The first useful information when a company experiences financial distress is to accelerate action to prevent problems before the bankruptcy. Then the second is the management can take merger action/ take over the model. The third, the company is more capable to pay the debt and run itself better; and the fourth is giving an initial sign in bankruptcy existence".

Recommendation for **further study**: As this study identifies only limited bank-specific and macroeconomic variables for six years with a sample of fourteen out of sixteen private commercial banks in Ethiopia, there have to be further researches which include more time period, bank-specific variables, macroeconomic variables and regulatory factors that affect the FD of Ethiopian private commercial banks.

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Appendix

Appendix 1. FE regression result

Dependent Variable: Z_SCORE
 Method: Panel Least Squares
 Date: 06/01/18 Time: 20:26
 Sample: 2012 2017
 Periods included: 6
 Cross-sections included: 14
 Total panel (balanced) observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CA	8.461083	1.562200	5.416133	0.0000
A	-1.926290	3.084228	-0.624562	0.5342
M	1.351269	0.875623	1.543208	0.1270
E	4.009202	1.134601	3.533579	0.0007
L	1.664056	0.623067	2.670748	0.0093
SIZE_LOG	-4.916591	1.092736	-4.499339	0.0000
GDP	3.563473	4.594100	0.775663	0.4404
INF	1.385285	0.549347	2.521694	0.0138
C	-1.451524	1.360508	-1.066899	0.2894

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.737737	Mean dependent var	0.514127
Adjusted R-squared	0.709762	S.D. dependent var	0.675310
S.E. of regression	0.363815	Akaike info criterion	0.484888
Sum squared resid	9.927084	Schwarz criterion	1.121530
Log likelihood	-29.49773	Hannan-Quinn criter.	0.740813
F-statistic	26.37152	Durbin-Watson stat	1.752218
Prob(F-statistic)	0.000000		

Appendix 2. Redundant FE test

Redundant Fixed Effects Tests
 Equation: Untitled
 Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	5.239258	(13,62)	0.0000
Cross-section Chi-square	62.264878	13	0.0000

Cross-section fixed effects test equation:
 Dependent Variable: Z_SCORE
 Method: Panel Least Squares
 Date: 06/01/18 Time: 18:31
 Sample: 2012 2017
 Periods included: 6
 Cross-sections included: 14
 Total panel (balanced) observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CA	8.461083	1.562200	5.416133	0.0000
A	-1.926290	3.084228	-0.624562	0.5342
M	1.351269	0.875623	1.543208	0.1270
E	4.009202	1.134601	3.533579	0.0007
L	1.664056	0.623067	2.670748	0.0093
SIZE_LOG	-4.916591	1.092736	-4.499339	0.0000
GDP	3.563473	4.594100	0.775663	0.4404
INF	1.065639	0.578912	1.840761	0.0696
C	-1.451524	1.360508	-1.066899	0.2894

R-squared	0.737737	Mean dependent var	0.514127
Adjusted R-squared	0.709762	S.D. dependent var	0.675310
S.E. of regression	0.363815	Akaike info criterion	0.916613
Sum squared resid	9.927084	Schwarz criterion	1.177057
Log likelihood	-29.49773	Hannan-Quinn criter.	1.021309
F-statistic	26.37152	Durbin-Watson stat	1.751522
Prob(F-statistic)	0.000000		

Appendix 3. Housman test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	49.394393	8	0.0000

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
CA	7.815028	8.182981	2.340239	0.8099
A	-5.212384	-1.886901	9.064387	0.2694
M	-0.330536	1.115777	0.382960	0.0194
E	0.351583	3.495738	0.663279	0.0001
L	0.752116	1.525994	0.153017	0.0479
SIZE_LOG	-3.216915	-4.888237	3.378473	0.3632
GDP	2.613530	3.401549	0.172072	0.0575
INF	1.034952	1.028815	0.090675	0.9837

Cross-section random effects test equation:

Dependent Variable: Z_SCORE

Method: Panel Least Squares

Date: 06/01/18 Time: 18:34

Sample: 2012 2017

Periods included: 6

Cross-sections included: 14

Total panel (balanced) observations: 84

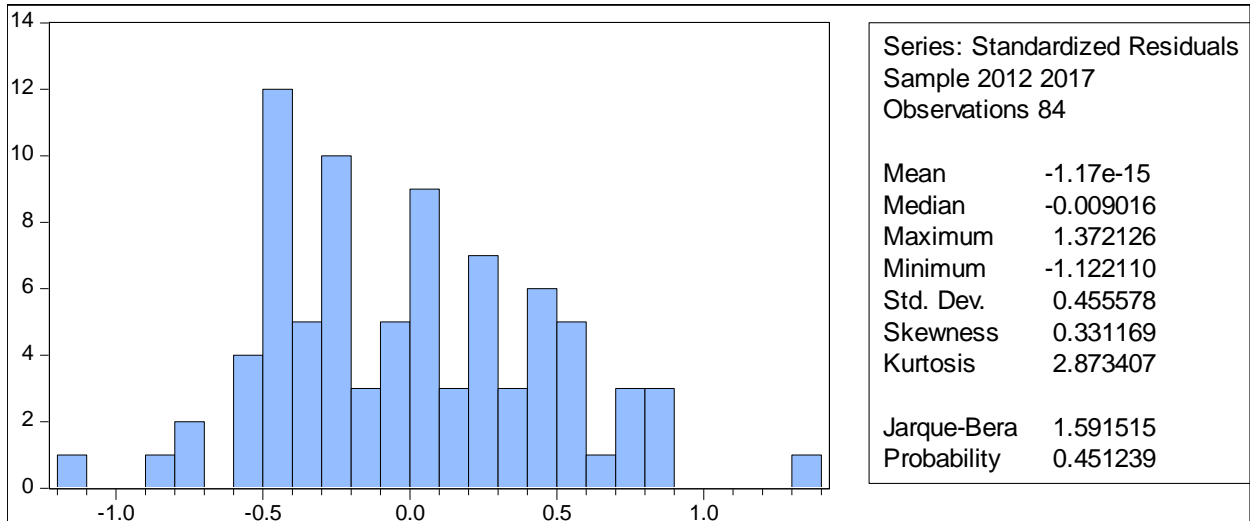
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.451524	1.360508	-1.066899	0.2894
CA	8.461083	1.562200	5.416133	0.0000
A	-1.926290	3.084228	-0.624562	0.5342
M	1.351269	0.875623	1.543208	0.1270
E	4.009202	1.134601	3.533579	0.0007
L	1.664056	0.623067	2.670748	0.0093
SIZE_LOG	-4.916591	1.092736	-4.499339	0.0000
GDP	3.563473	4.594100	0.775663	0.4404
INF	1.065639	0.578912	1.840761	0.0696

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.737737	Mean dependent var	0.514127
Adjusted R-squared	0.709762	S.D. dependent var	0.675310
S.E. of regression	0.363815	Akaike info criterion	0.484888
Sum squared resid	9.927084	Schwarz criterion	1.121530
Log likelihood	-29.49773	Hannan-Quinn criter.	0.740813
F-statistic	26.37152	Durbin-Watson stat	1.752218
Prob(F-statistic)	0.000000		

Appendix 4. Normality test



Appendix 5. Heteroskedasticity test: White

Heteroskedasticity Test: White

F-statistic	1.504700	Prob. F(9,73)	0.1625
Obs*R-squared	12.98799	Prob. Chi-Square(9)	0.1632
Scaled explained SS	13.38346	Prob. Chi-Square(9)	0.1460

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 06/01/18 Time: 22:13

Sample: 2012 2017

Included observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005044	0.235585	0.021412	0.9830
CA^2	1.750022	1.221204	1.433030	0.1561
A^2	-6.982200	15.17939	-0.459979	0.6469
M^2	0.181979	0.216704	0.839760	0.4038
E^2	1.599307	0.911684	1.754234	0.0836
L^2	-0.184092	0.199900	-0.920923	0.3601
SIZE_LOG^2	0.233494	0.425089	0.549283	0.5845
GDP^2	-12.80956	10.10689	-1.267409	0.2090
INF^2	0.649297	0.582552	1.114573	0.2687

R-squared	0.156482	Mean dependent var	0.096419
Adjusted R-squared	0.052486	S.D. dependent var	0.158335
S.E. of regression	0.154124	Akaike info criterion	-0.789533
Sum squared resid	1.734062	Schwarz criterion	-0.498106
Log likelihood	42.76562	Hannan-Quinn criter.	-0.672454
F-statistic	1.504700	Durbin-Watson stat	1.983437
Prob(F-statistic)	0.162484		

Appendix 6. Serial autocorrelation test: BG

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.740783	Prob. F(2,71)	0.1828
Obs*R-squared	3.879752	Prob. Chi-Square(2)	0.1437

Test Equation:

Dependent Variable: RESID

Method: Least Squares

Date: 06/01/18 Time: 22:06

Sample: 2012 2017

Included observations: 84

Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CA	-0.108353	1.466359	-0.073893	0.9413
A	1.140860	2.892208	0.394460	0.6944
M	-0.293161	0.881606	-0.332530	0.7405
E	-0.482205	1.115070	-0.432444	0.6667
L	0.011459	0.624617	0.018346	0.9854
SIZE_LOG	-0.546819	1.238707	-0.441443	0.6602
GDP	-2.346341	4.368252	-0.537135	0.5929
INF	-0.427622	0.655980	-0.651883	0.5166
C	0.902677	1.474266	0.612289	0.5423
RESID(-1)	0.273341	0.154047	1.774402	0.0803
RESID(-2)	-0.061816	0.138637	-0.445883	0.6570

R-squared	0.046744	Mean dependent var	9.26E-16
Adjusted R-squared	-0.100944	S.D. dependent var	0.312402
S.E. of regression	0.327790	Akaike info criterion	0.740110
Sum squared resid	7.628696	Schwarz criterion	1.089822
Log likelihood	-18.71456	Hannan-Quinn criter.	0.880605
F-statistic	0.316506	Durbin-Watson stat	1.999305
Prob(F-statistic)	0.979962		

Appendix 7. Correlation matrix

	CA	A	M	E	L	SIZE_LOG	GDP	INF
CA	1.000000							
A	-0.104572	1.000000						
M	-0.255430	-0.035685	1.000000					
E	-0.297813	0.228287	-0.680196	1.000000				
L	0.179285	-0.143596	0.172046	-0.186981	1.000000			
SIZE_LOG	-0.663993	0.096038	0.089007	0.309123	0.151101	1.000000		
GDP	-0.065411	0.003117	0.050817	-0.019642	0.076778	0.146855	1.000000	
INF	0.184550	-0.057570	-0.342794	0.119697	-0.254462	-0.391678	-0.499828	1.000000

Appendix 8. Descriptive statistics

	Z_SCORE	CA	A	M	E	L	SIZE_LOG	GDP	INF
Mean	0.514127	0.178861	0.019525	0.633068	0.205288	0.624168	0.552315	0.097000	0.133833
Median	0.385000	0.168100	0.016300	0.628200	0.197600	0.619500	0.564643	0.101000	0.089000
Maximum	3.570000	0.399700	0.088300	0.965400	0.404400	0.914600	0.655851	0.109000	0.341000
Minimum	-0.590000	0.099000	0.000000	0.461000	0.026600	0.471800	0.375435	0.080000	0.072000
Std. Dev.	0.675310	0.046390	0.013736	0.090410	0.067832	0.074517	0.058156	0.010243	0.095545
Skewness	1.540478	1.781705	3.276199	0.603698	0.542065	0.567366	-0.603047	-0.571293	1.609650
Kurtosis	7.200852	8.272333	15.43357	4.323198	3.572486	4.376388	2.895070	1.829541	3.844177
Jarque-Bera	94.98807	141.7338	691.3464	11.23030	5.260767	11.13721	5.129847	9.364166	38.76785
Probability	0.000000	0.000000	0.000000	0.003642	0.072051	0.003816	0.076925	0.009260	0.000000
Sum	43.18670	15.02430	1.640100	53.17770	17.24420	52.43010	46.39442	8.148000	11.24200
Sum Sq. Dev.	37.85160	0.178618	0.015660	0.678435	0.381903	0.460887	0.280712	0.008708	0.757692
Observations	84	84	84	84	84	84	84	84	84

Appendix 9. Correlational analysis

Dependent Variable	Independent Variables							
	Ca	A	M	E	L	S-log	GDP	INF
Z_SCORE	0.757529	-0.090025	-0.295111	-0.050615	0.151086	-0.695878	-0.106247	0.338578