QUANTITATIVE ANALYSIS OF CREDIT DEFAULT RISK ASSESSMENT USING BLACK-SCHOLES-MERTON MODEL: A CASE STUDY OF THE KENYAN MANUFACTURING INDUSTRY.

BY

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Declaration

This project is my own work and has not been presented for a degree award in any other institution.

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Be blessed.

Dedication

I dedicate this research project to my family, my dad George, my mum Millicent and my brother Filbert who always believed in me and supported me through my academic dream.

Abstract

The Kenyan manufacturing industry is a major contributor of the country's economy, contributing significantly to GDP growth, job creation, and export opportunities. However, despite its undeniable significance, the Kenyan manufacturing industry is grappling with several challenges that are hampering its growth, with credit constraints being a prominent issue. These challenge often lead to financial distress, forcing some companies to shut down or operate below their optimal potential.This research introduces the Black-Scholes Merton model, an eminent financial tool developed for option pricing, and proposes its adaptation to the context of the Kenyan manufacturing industry. The model is applied to gauge the default probabilities of manufacturing firms by integrating company-specific financial data, volatility, and credit risk factors to assess default risks. The study is based on financial reports published for sampled manufacturing companies in Kenya for the financial years 2016 to 2022. The variables used to compute the probabilities of default are total assets, time period, volatility, debt and risk-free interest rate. The data analysis shows that default probabilities are directly proportional to the company's liabilities. This research is a comprehensive guide to the assessment, analysis and credit management.

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

The Kenyan manufacturing sector is a major contributor of the country's economic development and employment generation. As this industry grows, it encounters several financial challenges with a notable concern being the potential of credit defaults and liquidity issues, which is a significant concern to stake holders. Mizan and Hossian (2014) Credit risk, which involves the possibility of a borrower failing to meet their financial commitments, is a significant worry within the Kenyan manufacturing sector.This concern arises because the sector heavily relies on financing for capital-intensive operations, expansion, and innovation.

Credit risk assessment and prediction of default probabilities play a crucial role in the manufacturing industry. Credit risk evaluation and default likelihood forecast are essential in finance. Credit risk happens when borrowers, whether corporate or individual, neglect to meet their obligation commitments, prompting vulnerability about loan specialists getting owed head and interest instalments. For moneylenders, credit chance can disrupt its cash flows and raise assortment costs, possibly requiring debt enforcement office contribution. The interest charged on a loan repays the loan specialist for bearing credit risk.

Byrn and Barron (1993)Predicting the risk of default of companies is essential for determining the creditworthiness of borrowers and managing credit portfolios effectively. Investors, lenders, and other stake holders need accurate tools to evaluate the risk associated with lending to or investing in companies.This study focuses on the Black-Scholes-Merton(BSM) model due to its wide-spread and widely-accepted application.The BSM model, originally developed for pricing of options, has been extended to assess credit risk and predict the probability of default for companies.

In Kenya, as in many other developing countries, credit risk assessment is of paramount importance due to the unique characteristics of the financial market. Factors such as limited access to credit information, regulatory frameworks, and the economic environment can significantly impact the creditworthiness and default risk of companies. Therefore, determining probabilities of credit default, particularly the BSM model, becomes vital in the Kenyan context.

This research aims to bridge the gap in the literature by assessing credit risk among manufacturing companies in Kenya by the use of the BSM model in computing default probabilities. This is done by analyzing financial data from a sample of manufacturing companies in Kenya and comparing the predicted default probabilities from the model with the actual default outcomes, this study seeks to provide insights into the applicability of the BSM model in the Kenyan context.

1.1.1 Black-Scholes-Merton Model

The Black-Scholes-Merton model, otherwise called BSM, is a numerical instrument for assessing the hypothetical cost of financial derivatives, particularly options. Created by Fischer Black, Myron Scholes, and Robert Merton in 1973, their spearheading work was perceived with a Nobel Prize in Financial Sciences in 1997. Initially intended for estimating European-style stock options, the BSM model expects specific circumstances, similar to a mathematical Brownian motion for the hidden resource and no exchange expenses or short-selling limitations. It additionally assumes that financial markets are systematic/efficient and it incorporates key variables such as the price and volatility of the underlying asset, the exercise price of the option,the risk-free rate of interest and the time period.

While originally centred around stock options, the BSM standards have been stretched out to different financial instruments, including corporate debt. Applying the BSM model to corporate obligation includes surveying the implanted choices in the obligation, frequently as callable or convertible highlights. In the domain of corporate debt, the BSM model decides a proper yield, considering early debt retirement through the call option or transformation into equity. Factors like the issuer's credit quality, the term to maturity, the issuer's stock price volatility, the value of debt , and the prevailing risk-free interest rate are considered in this model.

Key Concepts of the Black-Scholes-Merton Model include:

Geometric Brownian Motion:

Hull (2009) posits that the model operates under the assumption that the underlying asset price adheres to a Geometric Brownian Motion. In practical terms, this implies that the asset's price undergoes random fluctuations over time and follows a logarithmic normal distribution.

Define:

$$\frac{\delta V}{V} \sim \phi(\mu\delta t, \sigma\sqrt{\delta t}) \tag{1.1}$$

Where; δV is the change in asset value V, μ is the assets' expected return, σ is the volatility of the asset prices, δt is the percentage change in time t, $\mu\delta t$ is the mean of the percentage change in time, $\sigma\sqrt{\delta t}$ is the standard deviation of the percentage change in time, $\phi(\mu, \sigma)$ denotes a normal distribution with mean μ and standard deviation σ.

The model implies that

$$lnV_t - lnV_o \sim \phi[(\mu - \frac{\sigma^2}{2})T, \sigma\sqrt{T}] \tag{1.2}$$

From this it follows that

$$ln\frac{V_t}{V_o} \sim \phi[(\mu - \frac{\sigma^2}{2})T, \sigma\sqrt{T}] \tag{1.3}$$

and

$$lnV_t \sim \phi[lnV_o + (\mu - \frac{\sigma^2}{2})T, \sigma\sqrt{T}] \tag{1.4}$$

Where V_t is the future asset value and V_o is the asset value at time zero. Equation 1.4 shows that lnV_t is normally distributed. This means V_t has a log-normal distribution This assumption allows for the modelling of the asset's uncertainty and volatility.

Risk-Neutral Valuation:

The Black-Scholes-Merton model utilizes a risk-neutral valuation method, assuming that market participants are risk-neutral and demand compensation solely for the time value of money. In this scenario, the risk-free interest rate r equals the expected return on the underlying asset.

Research in the field of pricing corporate debt using the BSM model has expanded over the years, addressing its limitations and incorporating additional factors relevant to specific contexts. This includes considering factors such as default probabilities, credit spreads and recovery rates to enhance the model's accuracy in real-world scenarios.

The BSM has been extended to pricing corporate debt instruments by incorporating the optionality embedded in these securities. Its adaptation to corporate debt pricing offers valuable insights for investors, issuers, and analysts, contributing to a better understanding of the relationship between fair value in the debt market, volatility and risk.

1.2 Statement of the Problem

Despite the growing importance of credit risk assessment and default prediction in the Kenyan manufacturing industry, there is lack of empirical research on the applicability of the Black-Scholes-Merton model to this context. This research gap presents a critical problem as it hinders the industry's ability to effectively manage credit default risk and make well-informed financial decisions.

The problem arises from the need for reliable tools to evaluate the risk associated with lending to or investing in the manufacturing industry in Kenya.Stakeholders such as investors, policy makers and financial institutions are concerned about the long-term variability of a company. Understanding default probabilities helps to assess the sustainability of a company's capital structure and its ability to meet future obligations and also serve as early warning signals for potential financial distress. The lack of research on the applicability of the BSM model in the Kenyan context hinders the development of the effective credit risk management practices tailored to unique characteristics of the Kenyan market.

Therefore, this research aims to address the problem by assessing the the probability of default for manufacturing companies in Kenya using BSM. The research seeks to provide insights into the model's applicability in the Kenyan context, contribute to the existing literature on the credit risk assessment models and offer implications for Kenya's credit risk management practices.

1.3 Objective of the Study

1.3.1 General objective

To assess the probability of default for manufacturing companies in Kenya using Black-Scholes-Merton model.

1.3.2 Specific objectives

i) To determine variables that could impact the model's effectiveness in predicting default risk in the Kenyan context.

ii) To provide insights for investors, financial institutions, and policy makers regarding the model's applicability and limitations.

1.4 Significance of the Study

This research findings will contribute to the existing literature by examining default probabilities by applying of the BSM model in an emerging market like Kenya and the understanding of credit default risk within the Kenyan manufacturing industry. Most of the research on credit risk prediction has been conducted in developed economies, and there is a need for more studies that examine the effectiveness of such models in emerging markets. The findings will provide insights into the model's effectiveness in predicting default risk and its potential limitations in a developing country context.

Additionally, by applying the Black-Scholes-Merton model to pricing corporate debt, investors and issuers can gain insights into the fair value of the debt instrument, enabling them to make informed investment decisions. It provides a framework for understanding the complex relationship between various factors that influence the pricing of corporate debt securities with embedded options.

Ultimately, this study aims to enhance credit risk management practices in the Kenyan manufacturing industry by providing empirical proof of the model's usefulness and applicability in assessing default risks in the local context.The project's findings can be incorporated into existing risk assessment frameworks to enhance the evaluation of default risk for companies in Kenya.

CHAPTER 2

LITERATURE REVIEW

The literature review highlights the existing knowledge on credit risk assessment models and previous studies on default prediction. However, there is a research gap regarding the applicability of the BSM model in predicting the risk of default for Kenyan manufacturing companies. This focuses on filling this gap by evaluating the performance of the model in the Kenyan context and providing insights for credit risk management practices in the country.

2.1 Credit Risk Assessment

Credit risk assessment models serve to quantify the likelihood of default and gauge the creditworthiness of borrowers or issuers. Conventional credit risk models, such as Moody's (KMV), Altman Z-score, and the Merton model, rely on financial ratios and accounting data in the probability of default prediction. These models have gained widespread use in developed economies and have shown reasonably accurate results in forecasting default risk.

Crosbie (2002) summarize KMV's model for default risk, which is grounded in a reduced version of the BSM structure. Within this frame, a firm's equity is conceptualized as an endless option with the point of default acting as the absorbing barrier for the asset value of the firm. Default is assumed to occur when the value of assets reaches this predefined pointof default. Determining the default probability involves three fundamental steps (Crosbie, 2003). First, asset value and volatility are estimated using the Merton approach, derived from the volatility and equity market value, as well as the book value of liabilities. Second, the ”distance to default” is computed based on value of assets and its volatility. Finally, the Expected Default Frequency is computed, assuming that asset values conform to a normal distribution.

Li (2000), representing Moody's, formulated a hybrid model for risk of default that combines two approaches for credit risk modelling: a statistical model determined through empirical analysis of historical data and a structural model rooted in Merton's options theory. This statistical approach, as developed by Foster (1986), draws a condensed set of financial variables and other pertinent information to a risk scale, effectively serving as a statistical refining of historical data to distinguish between creditworthy and risky entities.

Moody's model furnishes a default probability estimated for one-year, employing an adaptation of Merton's option theoretic model, Moody's credit ratings, company financial statements, supplementary equity market data and macro-economic variables. Similar to the KMV model, Sobehart et al. (2000) applies a variant of the Merton model to derive market values and assets volatility from equity prices. This information is then harnessed to compute the "distance to default," signifying the number of standard deviations the asset value of the firm must decline to reach the predetermined default point. Moody's consolidates this data through logistic regression and further adjusts it to account for variations in the ratio of defaulting-to-non-defaulting obligors within their sample dataset compared to real-world observations.

Kurbat (2002) endeavor to make a replica Moody's empirical outcomes (Sobehart et al., 2000) by utilizing the Merton approach (KMV). They arrive at contrasting results, with the Merton approach outperforming Moody's ratings and several accounting ratios in forecasting default. Kealhofer and Kurbat (2002) attribute this divergence to their more precise implementation of the Merton model, which they contend arises from specialized techniques used to estimate asset volatility.

Altman (1968) applies multiple discriminant analysis (MDA) to assess the potential failure of 66 publicly held manufacturing firms, utilizing five ratios as indicators. Altman's findings suggest that the Z-Score effectively predicts bankruptcy up to two years ahead of financial distress, with accuracy diminishing as the forecasting window extends. The Z-Score is computed by assigning appropriate coefficients to each financial ratio and then aggregating the results.

Altman (1983) refines the initial Z-Score model, introducing the Z'-model, in which the market value of equity is substituted with the book value of equity. This modification renders the model applicable to non-manufacturing and private firms. Altman (2000) further enhances the model, developing the Z”-score, tailored for emerging markets and suitable for both manufacturing and non-manufacturing companies, together with private and public entities. Companies are classified as non-bankrupt if their Z” value exceeds 2.60, fall into the gray area with an index value ranging between 1.10 to 2.60, and are categorized as at high risk of bankruptcy if their index values fall below 1.10.

Abinzano (2020) endeavours to identify the measure of default risk that best aligns with the unique settings of public companies. The results depict that the BSM measure offers the best fit for both firms categories, signifying superior predictive power compared to the Altman Z”-score model.

2.2 Previous Studies on Default Prediction in Kenya

Previous studies into default prediction within developing countries have predominantly centered around traditional credit risk models, with limited exploration of the Black-Scholes-Merton model. Research has scrutinized various factors, including financial ratios, macroeconomic variables, and governance indicators, to forecast default risk. However, there is a notable scarcity of comprehensive research concerning the accuracy and applicability of the Black-Scholes-Merton model in developing nations, including Kenya.

Makini (2015) highlighted the prevalence of financial risks among both small and large organizations. The study indicated the challenge of relying solely on financial ratios for assessing financial risk, recognizing the potential influence of other factors. Makini’s research focused on evaluating the validity of the Altman Z-score Model in predicting the financial risks of companies listed on the Nairobi Securities Exchange. Recommendations were made regarding the application of the Altman Z-score Model by firms to aid investors in assessing the financial stability of the companies they invest in.

Okarinon (2022) sought to identify the factors influencing the repayment status of credit borrowers in Kenyan Micro-finance Institutions. The study drew a conclusion that loan properties, including loan amount, periodic instalments and loan cycles played a pivotal role in determining default status in Kenyan Micro-finance Institutions. The Altman Model-Discriminant Analysis was identified as an effective model for predicting the default status of clients within these institutions.

Wanjohi (2016) endeavoured to create a regression model that overcame the limitations of underestimating the loans Probability of Default by the logistic regression model. The study aimed to model defaults of loans in Kenyan banks using the Generalized Extreme Value(GEV) Regression Model. Results were then compared with those of the logistic regression model, revealing that for events like default of loans, the GEV model outperformed the logistic regression model. The GEV model's advantage lay in its superior performance in identifying defaults, mitigating the logistic regression model's drawback of underestimating the PD, which could lead to costly misclassification.

Adem (2012) constructed a parametric logistic model to predict the probability of customer default. They utilized raw demographic data about borrowers to identify risk factors contributing to default, including loan term, occupation, gender, marital status and age . Findings indicated that male customers had a higher likelihood of default than female customers, unmarried customers were more likely to default compared to married customers, younger customers were at a higher risk of default than older customers. Financial sector customers exhibited a similar default likelihood where longer-term loans had a likelihood of default that is lower compared to short-term loans.

It was acknowledged that parametric estimation in credit risk modelling is susceptible to inconsistency if the model is incorrectly specified due to reliance on functional form assumptions. In cases where the distribution family is unknown, non-parametric estimation becomes a more attractive option, as it doesn't rely on distribution assumptions.

This research aims to bridge the gap in the literature by assessing credit risk among manufacturing companies in Kenya by the use of the BSM model in computing default probabilities. This is done by analyzing financial data from a sample of manufacturing companies in Kenya and comparing the predicted default probabilities from the model with the actual default outcomes, this study seeks to provide insights into the applicability of the BSM model in the Kenyan context.By conducting empirical analysis and offering practical recommendations, this research will contribute to the enhancement of credit risk management practices in the Kenyan context, ultimately promoting financial stability within the manufacturing sector.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter profiles the research methodology applied to achieve the study objectives. It encompasses the target population, sample population, details of data collection methods and sources, and an explanation of the tools used for data analysis.

3.2 Model Specification

Under this section, the model under consideration, BSM, will be applied to the data.

3.2.1 Black-Scholes-Merton model

Merton model (1974) is the foundational structural model for explaining default in financial contexts. This model assumes that a firm has issued both equity (E) as well as debt (D) such that its total value at time T is V where $V = D + E$. The total value undergoes changes over time due to the company's activities and it does not account for any dividend distribution on equity or interest coupon payments on its bonds.

The BSM model, though continuous, helps us understand how a company's asset value changes over time. This understanding is used to estimate the chance that the company will default on its debts, which is a discrete event. The continuous framework allows for a detailed understanding of asset value paths, enabling the calculations of default probabilities that are inherently tied to discrete events such as crossing a threshold at a specific time.

The firm partly consists of zero coupon debt with guaranteed repayment of amount D at time T. At time T the remaining firm value will be shared to the shareholders and the firm will be liquidated. In the event of the firm winding up, debt holders have priority over shareholders. Therefore, as long as the firm has adequate funds to cover the debt, shareholders will get $V - D$. Default occurs when the total assets value V is less than the debt value D at time T. i.e. $V < D$. otherwise, firm will meet its debt obligation in a timely manner i.e. $V > D$.

Taking into account these two conditions, at time T the value of equity of the firm is:

$$E = \max(V - D, 0) \tag{3.1}$$

This relationship illustrates that equity behaves like a call option on the asset value with a strike/exercise price equal to the debt. This perspective treats the firm's shareholders as holders of a European call option on the firm's assets, expiring at time T, with an exercise price equivalent to the value of debt.

The European call option formula is

$$C(S,T) = SN(d_1) - K \exp^{-rt} N(d_2) \tag{3.2}$$

where

$$d_1 = \frac{\ln(\frac{S}{K}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{\ln(\frac{S}{K}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

S is the present price of the stock, T is the time period, r is the free risk rate interest,K is the strike price, σ is the volatility of the stock and N is the CDF for a standard normal distribution, (Hull 2009; Merton 1974; Black and Scholes 1973).

It's important to note that applying the BSM model to corporate debts requires certain assumptions and simplifications. Market conditions, credit ratings, and other factors may influence the pricing of corporate debts beyond the scope of the BSM model.

The following are the assumptions used by the Merton's Model:

1. The firm's underlying assets adhere to a lognormal stochastic distribution with a consistent volatility.

2. The firm's value remains unaffected by its capital structure.

3. No transaction costs or taxes exist, and assets can be divided without constraints.

4. There are no restrictions for short-selling.

5. Assets can be traded continuously over time.

6. There exists a market where investors can buy and sell assets at the same interest rate.

7. The risk-free rate of interest used for borrowing and lending is constant all the time.

8. There exists a sufficient number of investors who are allowed to buy and sell as may assets as desired at a given market price.

The model's key result is the BSM formula, which calculates the theoretical price of a European call or put option. The formula takes into account the underlying asset price, debt value, risk-free rate of interest, time to expiration, and volatility.

The Black-Scholes for a European call option is;

$$C(V,T) = V * N(d_1) - D * \exp^{-rt} N(d_2) \tag{3.3}$$

where

$$d_1 = \frac{\ln(\frac{V}{D}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{\ln(\frac{V}{D}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

The following approach will be applied using the BSM model for pricing corporate debts:

1. Define the asset value:the firm asset value,V replaces S in BSM in Merton model, where $V = D+E$. In the BSM framework, the underlying asset represents the value of the company.

2. Determine the debt value: The strike price K in this case is the face value or the principal amount of the corporate debt D. It represents the amount the company is obligated to repay to the debt holders upon maturity.

3. Set the Expiration Date: The expiration date T corresponds to the time to maturity of the corporate debt. It indicates the time at which the company is required to repay the debt in full.

4. Estimate the Volatility σ: In the BSM model, volatility measures the uncertainty or variability of the asset's value.

5. Consider the Risk-Free interest Rate: The risk-free interest rate r in the BSM model represents the interest rate on risk-free government bonds with a similar maturity to the corporate debt. It reflects the time value of money and compensates investors for the risk of lending money to the company.

6. Incorporate Credit Risk: The BSM model assumes a risk-neutral world without default risk. However, corporate debts carry credit risk. To incorporate credit risk into the model, adjustments can be made to the volatility to reflect the market's perception of the company's creditworthiness. This will be done by considering the implied default probabilities derived from credit markets.

7. Calculate the Option Price: By inputting the relevant parameters-underlying asset value, value of debt, volatility, time to expiration and risk-free interest rate into the BSM model, you can estimate the theoretical fair value or option price of the corporate debt.

Estimating Asset Value

For estimation of the probability of default (PD) of firms using the BSM model, it is necessary to estimate two key parameters; the total value of the firm, denoted as V and its volatility represented as σ. The total firm value, V, is comprised of two primary components: the firm's its equity (E) and debt (D). The value of the firm, V, behaves according to Geometric Brownian Motion, signifying that the firm's price evolves continuously over time based on a stochastic differential equation

$$dV = V\mu dt + V\sigma dZ_t \tag{3.4}$$

where Z_t is the standard Brownian motion, μ is the expected return on V, and σ is the volatility of the firm's value (Hull 2009)

Following the principles of the Merton Model, the valuation of a company's assets at a specific time T can be formulated using the following equation:

$$V_t = V_o \exp[\sigma Z_t + (\mu - 0.5\sigma^2)t] \tag{3.5}$$

where σ is the volatility of the firms value, V_t is the value of the firm at time t, μ is the expected return on V_t, and Z_t is the standard Brownian motion.

Estimating Equity

The value of equity E is estimated by using the BSM Formula for a call option,

$$E = V * N(d_1) - D * \exp^{-rT} N(d_2) \tag{3.6}$$

where

$$d_1 = \frac{\ln(\frac{V}{D}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{\ln(\frac{V}{D}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

T is the time period, σ is the volatility of the firms value, r is the free risk rate interest and N is the cumulative standard function (CDF) for a standard normal distribution.

Estimating Volatility

The asset volatility is calculated from the assumption that the assets follow a log-normal distribution using the equation below, where V is the asset value.

$$\sigma = \sqrt{\ln(\frac{Var(V)}{(E(V))^2} + 1)} \tag{3.7}$$

Proof.

$$V \sim \log(\mu, \sigma^2)$$

$$E(V) = \exp(\mu + \frac{1}{2}\sigma^2)$$

$$Var(V) = \exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)$$

$$Var(V) = (E(V))^2(\exp(\sigma^2) - 1)$$

$$\exp(\sigma^2) = \frac{Var(V)}{(E(V))^2} + 1$$

$$\sigma^2 = \ln(\frac{Var(V)}{(E(V))^2} + 1)$$

$$\sigma = \sqrt{\ln(\frac{Var(V)}{(E(V))^2} + 1)}$$

Estimate distance to default

For calculating the distance to default, the BSM Formula for a European call option is required, represented as follows:

$$d_2 = \frac{\ln(\frac{V}{D}) + (\mu_v - \frac{\sigma_v^2}{2})T}{\sigma\sqrt{T}} \tag{3.8}$$

where D is the face value of a debt, μ_v is expected rate of return of the firm's asset and expected growth of assets is given by $(\mu_v - \frac{\sigma_v^2}{2})$

Equation 3.8 is the distance to default as a multiplier of standard deviation which is characterized as how much a firm is far off from the point of default.

Estimate probability of default

(Hull 2009; Merton 1974) The BSM model assumes a normally distributed random factor in a company's asset returns, allowing the definition of default probability using the cumulative Normal distribution.

In the context of the BSM model, the probability of default (P_d) under the risk-neutral measure is:

$$P_d = N(-d_2) = N(-\frac{\ln(\frac{V}{D}) + (\mu_v - \frac{\sigma_v^2}{2})T}{\sigma\sqrt{T}}) \tag{3.9}$$

or

$$P_d = 1 - N(d_2) \tag{3.10}$$

Where $N(.)$ is the cumulative standard normal distribution. Equation 3.9 is the probability of default i.e it is distance between the firm value and the debt value $(\frac{V}{D})$ adjusted for the expected growth related to asset volatility $(\mu_v - \frac{\sigma_{v^2}}{2})$

CHAPTER 4

RESULTS AND FINDINGS

4.1 Introduction

This chapter show data analysis, research findings and results interpretation. The research objective is to assess the the probability of default for manufacturing companies in Kenya using BSM model and to determine the variables that could impact the model's effectiveness in predicting default risk. The data has been analysed using Excel software.

4.2 Data Description

Secondary data collected from secondary sources is used in this research. A sample of eight manufacturing companies in Kenya have been chosen at random and data obtained from each of the firm's audited financial statements for the years 2016 to 2022, retrieved from the firms' websites.

4.3 Data Analysis

4.3.1 Variables

Assets and Debts

Assets and debt values used are obtained from each of the company's financial statements.

Volatility

BSM model assumes the firm's underlying assets adhere to a log-normal stochastic distribution with a consistent volatility. The asset volatility of each company is calculated using the formula in equation 3.7

$$\sigma = \sqrt{\ln(\frac{Var(V)}{(E(V))^2} + 1)}$$

Risk-free interest rate

A risk-free rate of interest of 0.15999 has been obtained from the Central Bank of Kenya. The model assumes a constant risk free interest rate throughout the specified period.

Time to maturity

The model uses annual 7-year data for the years 2016 to 2022.

4.3.2 British American Tobacco Kenya

British American Tobacco(BAT) is one of the largest manufacturing companies in Kenya. The table consists of the BAT assets and liabilities for the period.

YEARS	ASSETS	LIABILITIES
2016	18,499,800,000	3,357,051,000
2017	17,805,588,000	3,390,722,000
2018	18,338,257,000	3,236,980,000
2019	21,936,362,000	1,870,639,000
2020	21,705,852,000	1,576,364,000
2021	24,118,818,000	1,938,740,000
2022	23,947,044,000	2,084,113,000

The default probabilities have been calculated using the BSM model. Volatility of BAT's assets obtained is 0.084298 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of British American Tobacco.

Years	Prob. of Default		
2016	0.2912	Mean(μ)	20,907,388,714.29
2017	0.3015	Variance	7,211,200,134,684,960,000
2018	0.2843	$\exp(\sigma^2)$	1.016497
2019	0.1210	σ^2	0.007106
2020	0.0838	σ	0.084298
2021	0.1075		
2022	0.1251		

4.3.3 Carbacid Investments Plc

Carbacid Investments Plc's assets and liabilities annual data was obtained from their financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	3,081,768,000	239,938,000
2017	3,306,974,000	234,698,000
2018	3,371,233,000	214,016,000
2019	3,503,501,000	208,052,000
2020	3,627,831,000	192,441,000
2021	3,919,224,000	181,067,000
2022	4,461,747,000	215,527,000

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.08334 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of Carbacid Investments Plc.

Years	Prob. of Default		
2016	0.1003	Mean(μ)	3,610,325,428.57
2017	0.0793	Variance	210,102,526,201,624,000
2018	0.0571	$\exp(\sigma^2)$	1.016119
2019	0.0465	σ^2	0.006945
2020	0.0294	σ	0.083334
2021	0.0154		
2022	0.0192		

4.3.4 Unga Group Plc

Unga Group Plc's assets and liabilities annual data was obtained from their financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	9,199,783,000	971,166,000
2017	10,267,471,000	762,564,000
2018	9,932,664,000	1,244,070,000
2019	10,646,066,000	1,177,048,000
2020	12,050,876,000	941,340,000
2021	10,048,779,000	921,224,000
2022	10,287,650,000	161,529,000

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.055539 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of Unga Group Plc.

Years	Prob. of Default		
2016	0.1711	Mean(μ)	10,347,612,714.29
2017	0.0885	Variance	763,199,247,161,238,000
2018	0.2119	$\exp(\sigma^2)$	1.007128
2019	0.1841	σ^2	0.003085
2020	0.1003	σ	0.055539
2021	0.1379		
2022	0.0100		

4.3.5 Bamburi Cement

Bamburi Cement,s assets and liabilities annual data was obtained from their financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	40,811,000,000	3,946,000,000
2017	47,203,000,000	5,870,000,000
2018	50,357,000,000	7,471,000,000
2019	49,085,000,000	8,172,000,000
2020	49,446,000,000	8,378,000,000
2021	51,728,000,000	8,599,000,000
2022	56,087,000,000	7,987,000,000

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.062053 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of Bamburi Cement.

Years	Prob. of Default		
2016	0.1515	Mean(μ)	49,245,285,714.29
2017	0.2119	Variance	21,597,152,904,761,900,000
2018	0.2514	$\exp(\sigma^2)$	1.008906
2019	0.2743	σ^2	0.003851
2020	0.2778	σ	0.062053
2021	0.2743		
2022	0.2420		

4.3.6 Crown Paints Limited

Crown Paints Limited's assets and liabilities annual data was obtained from their financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	5,059,029,000	246,703,000
2017	5,871,607,000	296,107,000
2018	5,475,693,000	604,760,000
2019	5,521,541,000	576,033,000
2020	5,630,862,000	504,220,000
2021	7,807,348,000	338,828,000
2022	9,204,834,000	401,145,000

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.156622 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of Crown Paints Limited.

Years	Prob. of Default		
2016	0.0202	Mean(μ)	6,367,273,428.57
2017	0.0239	Variance	2,355,872,375,763,620,000
2018	0.1814	$\exp(\sigma^2)$	1.058109
2019	0.1685	σ^2	0.024530
2020	0.1314	σ	0.156622
2021	0.0107		
2022	0.0110		

4.3.7 East African Cables

Assets and liabilities annual data was obtained from East African Cables financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	7,548,406,000	1,672,873,000
2017	7,038,421,000	1,193,075,000
2018	6,603,660,000	702,010,000
2019	6,274,877,000	2,397,642,000
2020	5,932,382,000	3,013,832,000
2021	5,580,066,000	2,772,984,000
2022	5,358,094,000	2,447,462,000

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.081715 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of East African Cables.

Years	Prob. of Default		
2016	0.3264	Mean(μ)	6,333,700,857.14
2017	0.2776	Variance	621,551,385,252,812,000
2018	0.1736	$\exp(\sigma^2)$	1.015494
2019	0.3974	σ^2	0.006677
2020	0.4207	σ	0.081715
2021	0.4207		
2022	0.4129		

4.3.8 Mumias Complex

Assets and liabilities annual data was obtained from Mumias Complex financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	27,018,727,000	8,498,906,000
2017	24,091,095,000	6,313,270,000
2018	15,735,609,000	8,487,721,000
2019		
2020		
2021		
2022		

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.170289 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of Mumias Complex.

Years	Prob. of Default		
2016	0.3745	Mean(μ)	22,281,810,333.33
2017	0.3520	Variance	34,282,321,204,257,400,000
2018	0.4247	$\exp(\sigma^2)$	1.069051
2019		σ^2	0.028998
2020		σ	0.170289
2021			
2022			

4.3.9 East African Breweries Limited

Assets and liabilities annual data was obtained from East African Breweries Limited financial statements and tabulated.

YEARS	ASSETS	LIABILITIES
2016	65,683,608,000	26,846,940,000
2017	66,666,312,000	32,694,428,000
2018	71,246,826,000	33,811,022,000
2019	87,065,627,000	37,251,495,000
2020	88,658,406,000	43,620,538,000
2021	100,117,014,000	45,562,271,000
2022	110,426,670,000	42,174,455,000

The default probabilities have been calculated using the BSM model. Volatility of assets obtained is 0.133594 and a risk-free rate of interest of 0.15999 has been used and are assumed to be constant throughout the years. The table consists of results obtained with regards to probabilities of default of East African Breweries Limited.

Years	Prob. of Default		
2016	0.4052	Mean(μ)	84,266,351,857.14
2017	0.4207	Variance	297,886,607,066,620,000,000
2018	0.4168	$\exp(\sigma^2)$	1.041951
2019	0.409	σ^2	0.017847
2020	0.4207	σ	0.133594
2021	0.4129		
2022	0.3974		

4.4 Discussion and Interpretation

4.4.1 British American Tobacco Kenya

Through the 7-year period it can be seen in the graph on figure 5.1 that BAT's assets are greater than its liabilities i.e $V > D$, which implies that there will be no default during the period because the company will be able to meet its liabilities. BAT's assets are seen to increase through the years 2016 to 2021 then drops in 2022. Its liabilities are observed to decrease through years 20166 to 2020 then start increasing.

The probabilities of default displayed in figure 5.2 are observed to increase from 0.2912 in 2016 to 0.3015 in 2017 then decreases to 2020 and finally start increasing through to 2022.The first few years have significantly higher default probabilities because the assets values are quite low while the liabilities are high. As the asset increase and liabilities decrease through the subsequent years, probabilities of default are observed to decrease. The results of BAT generally imply that the company has low likelihood of defaulting on credits before the maturity period. The study further finds the firm was qualified as a going concern by the external auditor for the entire period of study.

4.4.2 Carbacid Investments Plc

Through the 7-year period it can be seen in the graph on figure 5.3 that Carbacid Investments Plc's assets are greater than its liabilities i.e $V > D$, which implies that there will be no default during the period because the company will be able to meet its liabilities. The assets are seen to increase through the entire period. Its liabilities are observed to decrease through years 2016 to 2021 then increases in 2022.

The probabilities of default displayed in figure 5.4 are significantly low and are observed to decrease through years 2016-2021 then increases in 2022. This relation is also observed in the company's liabilities. There is an overall low default probability over the 7-year time span which can be interpreted to mean that there is low likelihood for Carbacid Investments Plc defaulting on a loan before its maturity time.The research further finds the firm was qualified as a going concern by the external auditor for the entire period of study.

4.4.3 Unga Group Plc

Through the 7-year period it can be seen in the graph on figure 5.5 that Unga Group Plc's assets are greater than its liabilities i.e $V > D$, which implies that there will be no default during the period because the company will be able to meet its liabilities. The assets are seen to fluctuate through the years but generally increasing. Its liabilities are observed to increase from the year 2016 to 2018 the decrease through to 2022.

The probabilities of default displayed in figure 5.6 are significantly low and are seen to fluctuate through the period under observation. A decrease in the default probability is observed in the year 2016-2017 then increases in 2018. This is also observed in the behaviour of the assets and liabilities difference for the same period. After 2018 the probabilities generally decrease because the company's assets increase while their liabilities decrease. This can be interpreted to mean that there is low likelihood for Unga Group Plc defaulting on a loan before its maturity time. The research further finds the firm was qualified as a going concern by the external auditor for the entire period of study.

4.4.4 Bamburi Cement

Through the 7-year period it can be seen in the graph on figure 5.7 that Bamburi Cement's assets are greater than its liabilities i.e $V > D$, which implies that there will be no default during the period because the company will be able to meet its liabilities.The assets are seen to go up for the years 2016 to 2018, down in 2019 the up through to 2022. The company's assets fluctuate through the years but generally are increasing. Its liabilities are observed to increase from the year 2016 to 2021 then decrease in 2022.

The probabilities of default displayed in figure 5.8 are observed to increase from 0.1515 in 2016 to 0.2778 in 2020 and finally start increasing through to 2022.The first few years have significantly lower default probabilities because the liabilities are quite low and increase with time. Probability then decreases in 2022 due to the decrease in the company's liabilities. The results of Bamburi Cement generally imply that the company has low likelihood of defaulting on credits before the maturity period. The research further finds the firm was qualified as a going concern by the external auditor for the entire period of study.

4.4.5 Crown Paints Limited

Through the 7-year period it can be seen in the graph on figure 5.9 that Crown Paints Limited assets are greater than its liabilities i.e $V > D$, which implies that there will be no default during the period because the company will be able to meet its liabilities.The assets are seen to go up for the years 2016 to 2017, down in 2018 the up through to 2022. The company's assets fluctuate through the years but are generally increasing. Its liabilities are observed to increase from the year 2016 to 2028, decrease through to 2021 then increases in 2022.

The probabilities of default displayed in figure 5.10 are observed to increase from 0.0202 in 2016 to 0.1814 in 2018 and finally start decreasing through to 2022.The first few years have significantly lower default probabilities because the liabilities are quite low and increase with time. Probabilities then decrease from 2019 due to the decrease in the company's liabilities and increase in their assets. The results of Crown Paints Limited generally imply that the company has low likelihood of defaulting on credits before the maturity period.The auditors commented on the firm as having material uncertainty for the period 2016 to 2018.

4.4.6 East African Cables

Through the 7-year period it can be seen in the graph on figure 5.11 that East African Cable's assets are greater than its liabilities i.e $V > D$, which implies that there was no default during the period because the company was able to meet its liabilities. The company's assets are seen to decrease through the years and its liabilities are observed decrease from 2016 to 2018 then increase highly through to the end of the period.

The probabilities of default displayed in figure 5.12 are significantly high and are seen to fluctuate through the period under observation. A decrease in the default probability is observed in the year 2016-2018. This is also observed in the decrease in liabilities for the same period. After 2018 the probabilities increase because the company's assets decrease while their liabilities increase at a high rate. This can be interpreted to mean that there is likelihood for East African Cables defaulting on a loan in future dates. It was recommended by the auditors that the firm as has material uncertainty for the period 2018 to 2022.

4.4.7 Mumias Complex

Through the 3-year period it can be seen in the graph on figure 5.13 that Mumias Complex assets are greater than its liabilities i.e $V > D$, which implies that there was no default during the period because the company was able to meet its liabilities. The company's assets are seen to decrease through the years and its liabilities are observed decrease from 2016 to 2017 then increase in 2018.

The probabilities of default displayed in figure 5.14 are significantly high and are seen to fluctuate through the period under observation. A decrease in the default probability is observed in the year 2016-2017. This is also observed in the decrease in liabilities for the same period. After 2017 the probabilities increase because the company's assets decrease while their liabilities increase at a high rate. This can be interpreted to mean that there is likelihood for Mumias Complex defaulting on a loan in future dates. This study further finds that Mumias was qualified as having material uncertainty for the entire period of the study.

4.4.8 East African Breweries Limited

Through the 7-year period it can be seen in the graph on figure 5.15 that East African Breweries Limited's assets are greater than its liabilities i.e $V > D$, which implies that there will be no default during the period because the company will be able to meet its liabilities. East African Breweries Limited's assets are seen to increase throughout the years 2016 to 2022. Its liabilities are observed to increase through years 2016 to 2021 then decreases in 2022.

The probabilities of default displayed in figure 5.16 are observed to fluctuate through the period under observation.For the year 2016 to 2017 probability increases then decreases in 2018 and 2019. This is because of the initial decreased difference between the company's assets and liabilities then increase thereafter. The same is observed in the subsequent years. The results of East African Breweries Limited generally imply that the company has low likelihood of defaulting on credits before the maturity period.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This research seeks to assess the the probability of default for manufacturing companies in Kenya using Black-Scholes-Merton model and to determine the effects of the factors affecting the probabilities. Eight manufacturing companies in Kenya were sampled and their financial data analyzed for probabilities of default. Merton (1974)states that under the BSM model, default occurs when the value of the firm's assets is less than its liabilities.

The BSM model has successfully been used to obtain the default probabilities. Assets and liabilities of a company are directly proportional to its default probabilities. An increase in a company's liabilities results to an increase in its default probabilities and vice versa. An increase in the assets and a decrease in liabilities results to low probabilities of default and a decrease in the assets with an increase in liabilities increases the firm's risk of default. This research provides insights in the valuation of credit risk. This work can be used as a comprehensive reference guide in the area of assessment and management of credit risk in the manufacturing sector in the hopes of maintaining the financial economy.

5.2 Recommendations

The BSM model is based on a few assumptions, such as efficient markets,continuous trading, constant volatility and interest rates and no taxes and transaction costs exist. These assumptions may not hold in real-world scenarios, leading to deviations between the model's predictions and the actual market. Further studies can be carried out with regards to the assumptions. This study suggests further research using the BSM model to assess the default probability for manufacturing companies in Kenya and other sectors. Such extensive study can be done on the relationship between probabilities of default models and strategies for rescue that can be applied on companies that are in other fields.

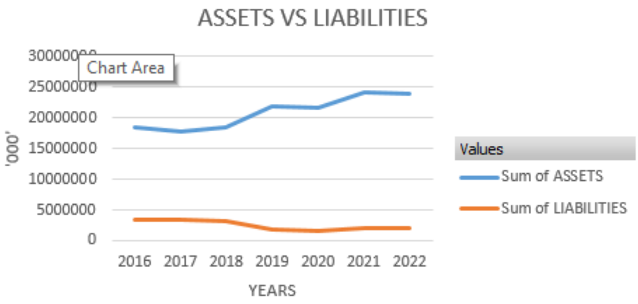
A V L.png 

Figure 5.1: BAT Assets vs Liabilities graph

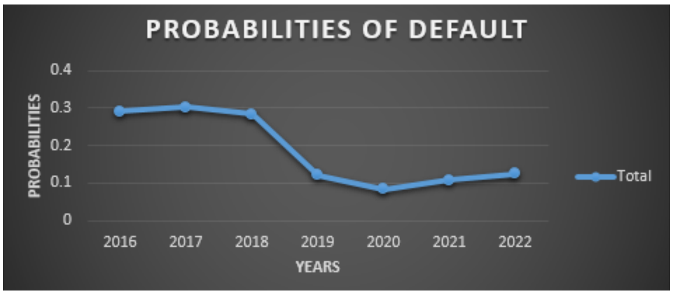
PD.png 

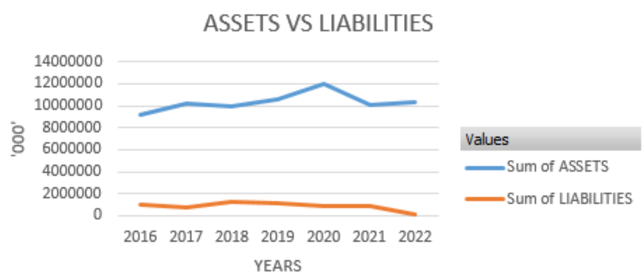
Figure 5.2: BAT Probabilities of default

A V L.png 

Figure 5.3: Carbacid Investments Assets vs Liabilities graph

PD.png 

Figure 5.4: Carbacid Investments Probabilities of default



A v L.png

Figure 5.5: Unga plc Assets vs Liabilities graph

pd.png

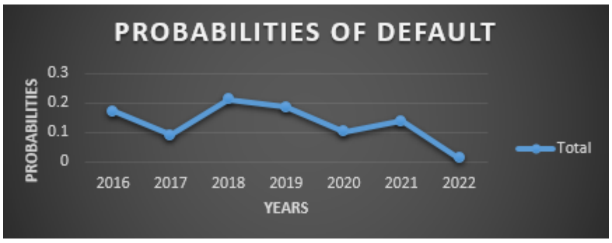
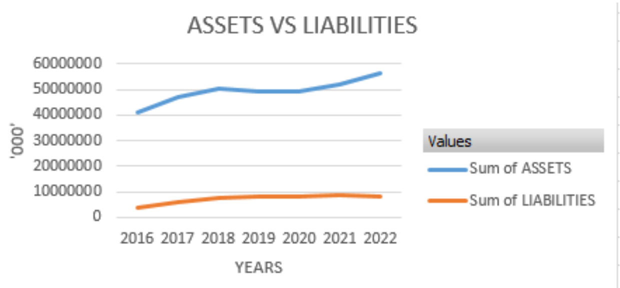


Figure 5.6: Unga plc Probabilities of default



A v L.png

Figure 5.7: Bamburi cement Assets vs Liabilities graph

pd.png

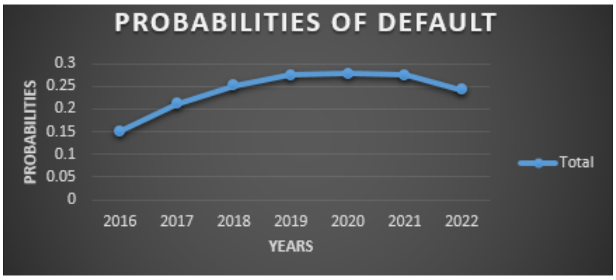


Figure 5.8: Bamburi cement Probabilities of default

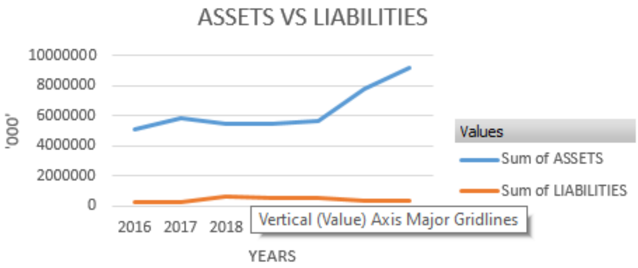
A v L.png 

Figure 5.9: Crown Paints Assets vs Liabilities graph

pd.png 

Figure 5.10: Crown Paints Probabilities of default

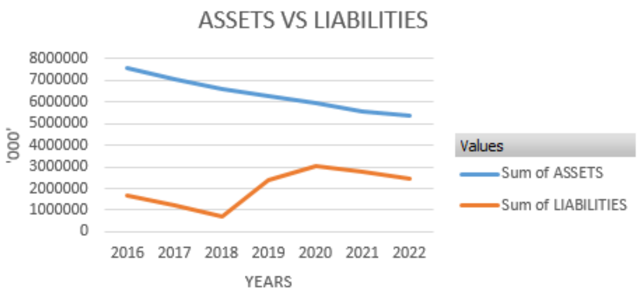
Cables A v L.png 

Figure 5.11: E.A Cables Assets vs Liabilities graph

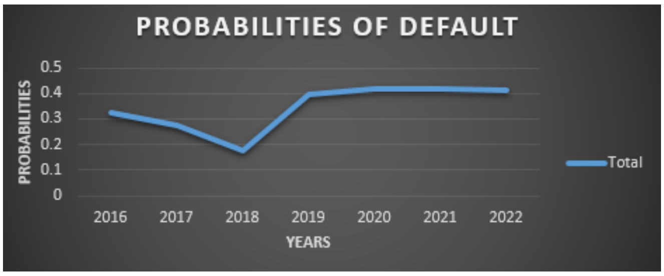
Cables pd.png 

Figure 5.12: E.A Cables Probabilities of default

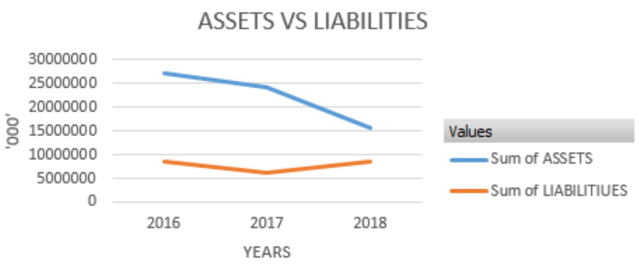
A v L.png 

Figure 5.13: Mumias Assets vs Liabilities graph

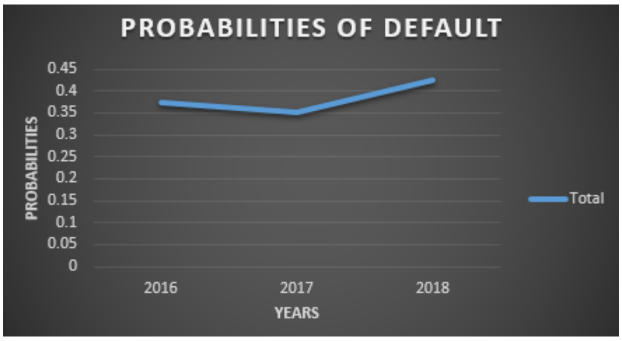
pd.png 

Figure 5.14: Mumias Probabilities of default

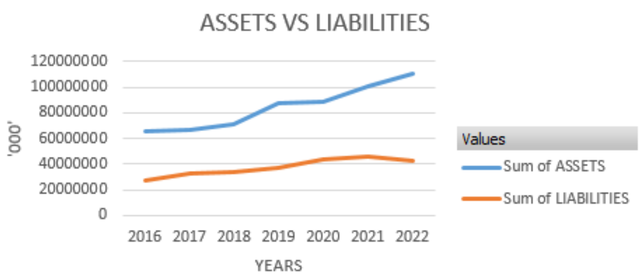
A V L.png 

Figure 5.15: EABL Assets vs Liabilities graph

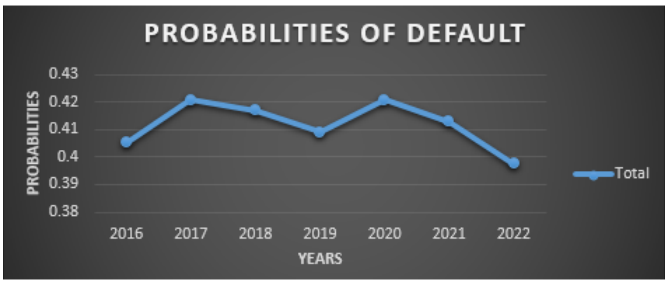
PD.png 

Figure 5.16: EABL Probabilities of default

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