Empirical Corporate Probability of Defaults in Kenya: Merton and Modified KMV Framework

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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This Research Project has been submitted for examination with my approval as the Supervisor.

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Abstract

A firm's capital structure gives it an endogenous cause to default. Be that as it may, prior to default there is no way to precisely single out the firms that will default from those that will not. At best, we can only make a probabilistic assessment of the likelihood of default. Not to mention, depending on a firm's choice of capital structure, the probability of default varies from a firm with a low financial leverage to one with a high financial leverage. This paper used the Merton Model to determine the probabilities of default in various sectors of Kenya and their relationship with varying debt tenors. The model generated high default probabilities for firms with a high leverage indicating that firms with a high leverage bear high financial risks. Furthermore, the default probabilities increased as the debt maturity increased signalling an increase in future uncertainty. Nonetheless, caution must be taken when interpreting the results since the Merton model carries assumptions that are at odds with reality. These assumptions can be relaxed and alternative modelling techniques can be employed in order to match real world situations. This can be a possible future research agenda.

Keywords: Credit risk, Structural models, Reduced form models, Merton model, Probability of default, Market value of assets

1. INTRODUCTION

1.1 Background to the study

Credit risk is the risk of an economic loss from the failure of the counterparty to fulfil its contractual obligation (Jorion, 2011). Countries, firms and individuals all face credit risk where some have a higher exposure to it than others. For example, a consumer may fail to make mortgage payments, a business or a customer may not settle a trade invoice, a company does not pay an employee's wages, governments may default on coupon payments on treasury bonds, an insurer may fail on paying a policy obligation or a company fails to service its asset-secured debt which is also known as corporation failure. According to Lenox (1999), corporation failure occurs if a firm enters liquidation, receivership or administration. Dahiya, Saunders, & Srinivasan (1994) say that financial distress transpires when a firm is unable to service debt, both the interest component and principal repayments and a prolonged state of financial distress leads to bankruptcy and liquidation.

Adverse effects stem out when a firm defaults and declares bankruptcy. One of the most monumental credit events was the Financial Crisis of 2007 that led to the near collapse of the banking system in the United States of America and the effects spilled on to the rest of the world. During and after the Financial Crisis, economies entered a state of recession, bottom-lines in an income statement turned negative, assets lost their values, many lost their massive capital stakes in firms, unemployment hiked to its highest and families also lost their homes. Therefore, contingencies need to be placed inorder to curb the effects of a credit event and to minimise the loss given default. But how can one determine which firms will default?

Prior to default, there is no way to precisely pinpoint the firms that will default from those that will not. At most we can only make a probabilistic assessment of the likelihood of default (Crosbie, 2003). Credit risk models can help quantify these default probabilities. Generally, credit risk models can be divided into two main classes: Structural models and Reduced form models. Structural models are used to quantify the probability of default for a firm based on the value of its assets and liabilities. On the other hand, reduced form models assume an exogenous cause of default, meaning that they model default as a random event without any focus on the firm's balance sheet (Chaterjee, 2015).

A firm's capital structure gives it an endogenous cause to default. Depending on a firm's choice of capital structure, the probability of default varies from a firm with a low financial leverage to one with a high financial leverage. Therefore, Structural Models, like the Merton Model, can be employed to estimate a firm's default probability based on its capital structure. However, firms hold different types of liabilities with different tenors and since default probabilities vary with various debt tenors, a term structure of default rate should be created in order to apprehend the concept of default risk to a higher degree.

A term structure of default rates describes the relationship between default rates and different debt maturities (Bogren, 2015). By constructing a term structure of default rates, companies and investors can make elaborate financing and investing decisions. Generally, investors and firms pay a premium over the default free rate of interest that corresponds to their default probabilities. With a term structure of default rates, one can determine the level of premium they might pay when seeking debt of different tenors and thus making efficient financing decisions. Also, by studying a firm's liability section on its balance sheet and the term structure of default rates, an investor can ascertain the likelihood of default and make elegant investing decisions.

1.2 Motivation for the Study

Firstly, default risk affects the whole of the society and is crucial for many parties including creditors, bankers, regulators, managers, auditors, governments and shareholders. In recent years, big defaults such as Lehman Brothers, Enron, WorldCom and General Motors negatively impacted the interests of their employees, shareholders, creditors, clients and suppliers. In severe cases, corporate default events can lead to a global financial crisis such as the 2007 financial crises. Accordingly, assessing the likelihood of corporate default is key for both the economy and the society.

Secondly, how a firm adopts its capital structure has become a "bread and butter" topic for financial economists. Capital structure theory is inevitably linked to several important empirical issues such as the term structure of credit spreads, the interaction of financial and investment decisions, design of a bank's capital structure, etc. Various discussions on such empirical issues piqued my interest and thoughts on how a firm can drive itself to default through the choice of its capital structure mushroomed in my mind. The curiosity heightened when the thought was directed towards firms operating in frontier markets.

Lastly, reading about financial derivatives and the astonishing accomplishments by researchers in that field always gave me a kick. One of the highlights in the world of finance was the introduction of the Black Scholes option pricing formula and its various uses, especially modelling default. Therefore I had to combine my officiousness on default due to capital structure and the love of financial derivatives.

1.3 Problem Statement

Credit risk is one of the most important types of risk there exists. Countries, firms and individuals all face credit risk either as default risk, settlement risk or downgrade risk. Default rates vary with time and are affected by both endogenous and exogenous factors and investors are interested in both factors (Hilscher & Wilson, 2013). Changing economic cycles and gearing levels of firms make it more susceptible to default. Firms are more likely to default if they have suffered financial distress before and firms suffer more default risk if they are less profitable (Wang, 2011).

When corporations default, both internal and external interest groups are affected. We need to succinctly understand this default risk that individuals face and how one can predict corporate default because if it is ignored, many will lose their jobs while others will lose a colossal capital base in the defaulted firm. Additionally, by creating a term structure of default rates, we can fathom how default rates vary with different debt tenors and help firms and other investors make efficient financing and investing decisions. This is more imperative for firms operating in frontier markets, like Kenya, where the research on endogenous causes of default is still a gap that needs to be filled.

1.4 Research Questions

1. How to assess the probability of default based on a firm's capital structure?
2. What is the relationship between the probabilities of default and varying debt tenors?

1.5 Research Objectives

1. To determine the probabilities of default based on a firm's capital structure.
2. To describe the relationship between the probabilities of default and varying debt tenors.

2. LITERATURE REVIEW

For ages efforts have been put in measuring and managing credit risk. The earliest recorded bankruptcy prediction paper dates back to FitzPatrick (1932). Since then researchers have developed more intriguing and sophisticated methods of predicting corporate default. This chapter discusses research work and theories on default prediction and credit risk models from history to date.

2.1 Structural Models for Probability of Default

2.1.1 Theoretical Discussion of Structural Models

The earliest model using the option pricing model to monitor credit risk was proposed by Black & Scholes (1973) who explained how equity owners hold a call option on the firm and that corporate liabilities can be viewed as a covered call option: own the asset but short a call option. After that Merton (1974) extended the framework and analyzed risk-debt behavior with the model. In his model, Merton models corporate default risk assuming that default is triggered when total assets are lower than total liabilities.

The model assumes that the company only has one zero-coupon debt and maturity, the debt holder either gets paid the face value of the debt, in such a case, the ownership of the company is transferred to the equity holder or takes control of the company, in such a case, the equity holder receives nothing. Therefore the debt holder faces default risk since he or she may not be able to receive the face value of his or her initial investment.

In this framework, the company balance sheet consists of issued equity with a market value at time t equal to E_t. On the liability side of the balance sheet is debt with a value equal to D issued in the form of a zero-coupon bond which matures at time T. The market value of the assets of the firm at time t is given by A_t. Hence the payoff to an equity holder is zero or the value of assets less liabilities. It follows that;

$$E = f(A_t, \sigma_A, r, D_t, \tau) \quad (1)$$

Where;

- E is the equity value.
- A_t is the market value of the assets.
- σ_A is the volatility of the market value of the assets.
- D_t is the debt value (also known as the default boundary).
- r is the risk free rate of interest.
- τ is the time to maturity of the debt.

$$E_t = \max(A_t - D, 0) \quad (2)$$

Merton (1974) assumed that the dynamics of the asset value adopts a geometric Brownian motion with a lognormal stochastic process of the form

$$dA_t = rA_t dt + \sigma A_t dW_t \quad (3)$$

Where r is the instantaneous risk-free rate which is assumed constant, σ is the percentage volatility, and W_t is the Wiener process under the *risk neutral measure* (Hull, 2008). This process has the property that the asset value of the firm can never go negative and that the random changes in the asset value increase proportionally with the asset value itself.

For a geometric Brownian motion, the asset value at time t can be calculated from the asset value at time 0 using the following relationship:

$$A_t = A_0 \exp\left(\mu - \frac{\sigma_A^2}{2}\right) t + \sigma_A \varepsilon \sqrt{t} \quad (4)$$

Where ε is the realization of a normal random variable with mean zero and unit variance, such that $\varepsilon = \frac{W_{t+T} - W_t}{\sqrt{T}}$ where W_t is a Wiener process. The drift term is adjusted by the term $\frac{-\sigma_A^2}{2}$, which must be included if there is uncertainty in the evolution of assets. In the absence of uncertainty, $\sigma_A = 0$ and in this case $A_t = A_0 \exp(\mu_A t)$ (Chaterjee, 2015).

The asset value at time t can be above or below the debt value and thus we can calculate the probability that $A_t < D_t$.

From equation 4,

$$PD = prob(A_t \leq D_t) = prob\left(A_0 \exp\left(\mu - \frac{\sigma_A^2}{2}\right)t + \sigma_A \varepsilon \sqrt{t} \leq D_t\right) \tag{5}$$

Since $\varepsilon \backsim N(0,1)$, as stated by Chaterjee (2015), and taking natural logarithm of equation 4, we can rewrite the probability of default as,

$$PD = Prob\left(\ln(A_t) - \ln(D_t) + \left(\mu - \frac{\sigma_A^2}{2}\right)T + \sigma_A \varepsilon \sqrt{T} \leq 0\right) \tag{6}$$

$$PD = prob\left(\frac{-\ln\left(\frac{A_t}{D_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \geq \varepsilon\right) \tag{7}$$

Finally, the risk neutral probability of default is defined as;

$$PD = prob(\varepsilon \leq -d_2) = N(-d_2) = N\left(\frac{-\ln\left(\frac{A_t}{D_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}\right) \tag{8}$$

Following Vassalou & Xing (2004), rearranging the probability that the assets are less than or equal to the barrier (debt value, D_t) is equivalent to the probability that the random component, ε, of asset return is less than $-d_2$. The term d_2 is called the distance to default and is the number of standard deviations the current asset value is away from the default barrier, D_t. This is shown above.

At maturity of the debt, if the asset value lies above the face value, there is no default however if the asset value lies below the face value, the company is in bankruptcy and the recovery value of the debt is the asset value of the firm (Anson, Fabozzi, Choudhry, & Chen, 2004)

Using the option pricing framework by Black & Scholes (1973),

$$E_t = \max(A_t - D, 0) \tag{9}$$

$$E_t = A_t N(d_1) - De^{-r(T-t)} N(d_2) \tag{10}$$

$$d_1 = \frac{lnA_T - lnD + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \tag{11}$$

$$d_2 = d_1 - \sigma_A\sqrt{T-t} = \frac{lnA_T - lnD + \left(r - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \tag{12}$$

Where r is the risk-free rate, σ is the asset value volatility and $N(d)$ is the probability of the standard normal density function below d (Merton, 1974).

A common problem with such a model is that the market value of a firm's asset and the volatility of the market value of assets are not observable. However one notable way of executing Merton's model estimates the market value of the firm's assets and the volatility of the assets from the market value of the firm's equity and the equity's instantaneous volatility using an approach suggested by (Jones, Mason, & Rosenfeld, 1984).

Since the equity value is a call option on the asset value, Jones *et al.* (1984), use Ito's Lemma to determine the volatility of equity from asset volatility:

$$E_0\sigma_E = \frac{\partial E}{\partial A} A_0\sigma_A \tag{13}$$

Hence equation 13 can be simultaneously solved with equation 10 to calculate the market value of assets (A_t) and its volatilities (σ_A).

2.1.2 Empirical Performance of Structural Models

Although the line of research that followed the Merton approach has proven very useful in addressing the endogenous causes of default, it has been less successful in real world situations. Many papers have been written on this topic in an effort to improve the performance of the model and overcome its several limitations. Even for firms with very simple capital structures, a Merton-type model is unable to price investment grade corporate bonds better than naïve model that assumes no default risk (Jones *et al*, 1984). This failure has been attributed to various reasons. First, under Merton's model the firm defaults only at maturity of the debt, a scenario that is at odds with reality. Second, for the model to be used in valuing debts, with high credit risk, of a firm with more than one class of debt in its capital structure, the seniority of various debts have to be specified (Altman, Resti, & Sironi, 2003). Also, this framework assumes that debts are paid off in the order of their seniority. However, empirical evidence in Franks & Torous (1994) indicate that the absolute priority rules were breached in 78% of the bankruptcies in their sample. Moreover, the use of a lognormal distribution in the basic Merton model (instead of a more fat tailed distribution) tends to overstate recovery rates in the event of a default (Altman *et al*, 2003).

In light of such difficulties, alternative approaches have been developed which enhances the Merton framework by removing one or more of the unrealistic assumptions. The most important shortcomings of the Merton framework are oulined below;

First, In Merton's model, a firm defaults, if at the time of servicing the debt, its assets are below its pending debt. But this is not what we observe in the market where defaults can happen any time independent of the debt maturity date. Ordinarily there are covenants on the debt contracts that can provoke default of a corporate as soon as they are infringed. For example, the most common covenant is the leverage ratio: if at some point in time the firm fails to maintain a pegged leverage ratio, default occurs. As a result of this weakness, default probabilities produced by the Merton model are understated with respect to real world default probabilities as long as default is restricted to transpire only at some specific conditions. The model can be tailored to allow for early defaults by pointing out a threshold level such that a default occurs when asset value, A_t, plunges below this critical level. In other words, the method for pricing barrier options can be employed. Extensions to Merton model along this direction were pioneered by Black & Cox (1976) and these group of models are often known as First Passage Time Models.

Second, The merton model assumes a very simplified capital structure where corporates have debts exclusively comprised of zero coupon bonds. In reality, we observe corporates raising different types of debts such as zero coupon bonds, coupon paying bonds, convertible bonds, preferred stock, secured debts and interest paying bank loans. Hence the probability of default on such types of debts diverges from what Merton suggested and should be taken in to consideration when calibrating default rates. Geske (1977) relaxed Merton's assumption on firm capital structure and laid the groundwork by allowing structural models to delve with more complex capital structures.

Third, the term structure of debt, which has a significant influence on the probability of default is ignored in Merton's model. Short-term debt and long-term debt should be given different emphasis when measuring the default probability. It gets even more complicated when debt tranches and term structure are both taken in to considerations. In light of this complication, Vasicek (1984) introduces the distinction between short term liabilities and long term liabilities. He studies three disparate cases and discovers that not only a firm's mark to market asset value affects expected loss, but also a firm's maturing debt and higher priority debts would affect the expected loss for a firm.

Forth, Merton model assumes a fixed non-stochastic interest rate over time. This is a very unrealistic assumption since we observe in the real world that interest rates vary over time, in different ways between different maturities. To overcome this shortcoming, a stochastic interest rate model can be intergrated in to Merton's model or its extended versions. In this way, correlation between asset and interest rate processes can also be introduced if deemed necessary. Longstaff & Schwartz (1995) modelled the Merton model by introducing the assumption of a stochastic interest rate process following a mean reverting process. As a result they captured the effect of interest rate on default risk which is driven by the correlation between asset value and interest rate. Despite the fact that it overcomes a shortcoming of the Merton model, it also introduces a level of complexity that surmounts the benefit of having this specification (Zennaro, 2015).

There are several manners in which one can define a default boundary. Not long ago, Yildirim (2006) gave a new definition of default and introduced a new way to model default risk. He took a first passage time model and modified it by introducing the assumption that a firm survives for some time after the asset value strikes the barrier level. If total allowable time under the barrier level widens, default occurs. In other words, if financial distress prolongs, default transpires.

Moody's KMV (2003), developed a model to assess the probability of default and called it expected default frequency (EDF). Moody's KMV was the first institution to commercialize Merton's model. As many firms continue to operate even when their asset values are lower than the face values of their debt, KMV *Credit Monitor* ^{TM} defines a firm's exogenous default boundary as the book value of its short-term liabilities plus one-half of its long-term liabilities. Switzer & Wang (2013) use the KMV *Credit Monitor* ^{TM} default boundary in their model as they consider it to be relatively more realistic since the firm's equity can be regarded as a call option on its assets under the structural model, the expected value of equity is an increasing function of maturity and therefore the pressure to liquidate emanates from the firm's short-term liabilities.

The success of structural models has been driven by the high level of insight and explanation that they offer. Indeed, compared to reduced form models, structural models offers a clear relationship between the capital structure of the firm and default risk. Hence they offer an elementary and intuitive way to appraise default risk based on a firm's balance sheet and market data. As a result, structural models not only allow for securities valuation, but they also address important issues in the formation of an optimal capital structure (Zennaro, 2015). However, we must understand that these models are based on very confining and not realistic assumptions which curb their capability to imitate real world scenarios.

Structural models are mostly applied for risk analysis of corporates, analysis of corporate structures and relative value pricing of corporate securities. The compelling benefits of structural models include; defaults can be predicted, spread curves appear realistic, credit spreads have realistic dependancy on firm leverage and volatilities, useful for analysing corporate structures and can provide insights on the causes of a firm's default. Inspite of their many advantages, structural models have quixotic assumptions and the fact that default is never a surprise gives them a hitch (Anson *et al*, 2004).

2.2 Reduced Form Models for Probability of Default

2.2.1 Theoretical Discussion of Reduced Form Models

The theoretical framework for the reduced form models revolves around the Poisson Process. A poisson process can be seen as a counting process. Let's begin by defining a Poisson process that has a value of N_t at time t. The values taken by N_t are an increasing set of integers 0,1,2,3... and the probability of a jump from one integer to the next occuring over a small time interval dt is given by

$$\Pr(N_{t+dt} - N_t = 1) = \lambda dt \tag{14}$$

Where:

- λ is the intensity parameter

The relationship between Poisson process and reduced form models is that the event that causes the poisson process to jump from integer to another can be viewed as being a default. The stochastic intensity parameter λ, also known as a Cox process, describes the likelihood of N_t events occuring in the interval $(0, t)$. A higher intensity parameter, λ, corresponds to a higher likelihood of default. As dt is small, there is a negligible probability of two jumps occuring in the same time interval (Anson *et al*, 2004).

Litterman & Iben (1991) introduced a simple reduced form model where they illustrated the extraction of default rates from prices of risky bonds. The model uses three inputs;

1. The current term structure of riskless bond yields.
2. Current term structure of risky bond yields.
3. A model for the evolution of risk-free interest rates.

Using these inputs, the model derives the forward default probabilities for a risky bond and the evolution of the term structure of risky bond yields. Litterman & Iben (1991) assumed a 100% loss in the event of a default.

Jarrow & Turnbull (1995) progressed the reduced form models by creating a simple model of default and recovery based on the Poisson process. In their model they assume that no matter when default occurs, the recovery payment is made at maturity time T. Therefore under the Jarrow-Turnbull model, the bond value can be written as;

$$B(t) = P(t,T)R(T)\left(1 - e^{-\lambda(T-t)}\right) + \sum_{j=1}^{n} P(t,T_j)c_j e^{-\lambda(T_j-t)} \tag{15}$$

Where:

- λ is the intensity parameter
- c_j is the j^{th} coupon
- $P(t,T)$ is the risk free discount factor
- $R(T)$ is the recovery ratio

Duffie & Singleton (1997) take a different approach where they allow the payment of recovery to occur at any time but the amount of recovery is restricted to be the proportion of the bond price, the price of the bond is the value of the debt as if it did not default. The rationale behind this approach is that as the credit quality of the bond deteriorates, its price falls. Duffie and Singleton then derive a formula, using risk neutral measures, for the valuation of general defaultable claims under Cox processes. The Duffie and Singleton model is classed as an Intensity based model.

The inputs to the model are;

1. Riskless short-rate process (r_t)
2. Hazard Rate for default (λ_t)
3. Recovery rate (ϕ_t) in the event of a default and is stated in terms of market value

Therefore, the arbitrage free price of a defaultable security that promises to pay Z at time T is;

$$V_t = E_t^Q\left[exp\left(-\int_t^T R_s\, ds\right)Z\right] \tag{16}$$

Where;

$$R_t = r_t + \lambda_t(1 - \phi_t) \tag{17}$$

Thereafter, Jarrow, Lando, & Turnbull (1997) created a ratings based model using a ratings transition matrix. The matrix specifies, for each given initial rating level, the probability of moving to any possible rating over the given horizon (usually an year). For example, if the initial rating of an entity is given as AA, then what is the probability that in one year it will be BBB, it will be in default or still be AA? Using a Markov model, changes in credit risk and the occurrence of default can be assessed.

2.2.2 Empirical Performance of Reduced Form Models

Reduced form models were developed to overcome one of the main problems of structural models: the fact that default events cannot occur unexpectedly in the short run. The reduced form model are mainly represented by Jarrow & Turnbull (1995) model and Duffie & Singleton (1997) model. Both types of models are arbitrage free and employ the risk neutral measure to price securities. The principle difference between structural model described earlier and the reduced form model is that the cause of default is endogenous in the structural models whereas the reduced form models use an exogenous Poisson random variable to determine the default probability (Zhang, 2017). Hence the default event, that will be treated as an unpredictable Poisson event, will not be anticipated on the basis of a firm's balance sheet.

The Jarrow-Turnbull Model is mostly used for risk-neutral pricing of assorted securities. The model assumes that default is a sudden event and occurs with a certain probability (Jarrow & Turnbull, 1995). The upside of the Jarrow-Turnbull model is that it is easy to fit to market data, straightforward for pricing complex securities and that it is handy for relative value analysis. The shortcoming to this model is that defaults are always a surprise and hence cannot be predicted accurately since it gives no insight on the cause of default.

The Duffie-Singleton model is a fractional model in which a bond loses a fraction of its face value evey time it defaults, which can happen more than once (Duffie & Singleton, 1997). The model is given superiority because it can be implemented using existing interest rate models, for example the Heath, Jarrow, & Morton (1992) model. The drawback of such a model is that it cannot value instruments that pay nothing under no default like the Credit Default Swaps. With the Duffie & Singleton (1997) framework, Duffee (1999) discovers that such models have difficulties in explaining the observed term structure of credit spreads across firms of different credit risk quality.

2.3 Structural Models versus Reduced Form Models

Capuano, Chan-Lau, Gasha, Medeiros, Santos, & Souto (2009) argue that the differences between structural models and reduced form models mirrors the information available to an individual using them. While structural models assume that the individual has the same set of information as the firm's manager which includes complete knowledge of the processes of all firm's assets and liabilities, reduced form models assume that the individual has the same information set as the market in which the market has incomplete knowledge of the firm's financial condition. Another difference between the two models refers to the treatment of recovery rates. The reduced form model assume an exogenously specified recovery rate but the structural models assume the endogenously specified recovery rate i.e. the value of the firm's assets and liabilities at default will determine the recovery rate of the debt holder incase of default.

Generally speaking, structural models are more suitable for back office risk management as it focuses more on capital structures and capital compliance while reduced from models are suitable for the front desk trading activities as front office traders need fast pricing models for determining fair values, prices and for hedging purposes

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3. RESEARCH METHODOLOGY

3.1 Research Design

As stated in Saunders, Lewis, & Thornhill (2015), researchers should think about their research project in terms of the questions they wish to answer and their research objectives. Following this study's research questions, an exploratory research design is most suitable as the study seeks to describe the behaviour of default rates over time resulting from firm specific factors.

The research is quantitative in nature and employs quantitative methods in order to answer the research questions. The data analysed was annual data which was obtained from the firm's annual reports and equity statistics of firms listed in the Nairobi Stock Exchange (NSE). Necessary variables were operationalised and analysed using the framework described in the literature review hence giving it a deductive approach to theory development. Since it was a cross sectional study, data was only collected once.

3.2 Populations and Sampling

As listed firms were the unit of analysis, the population of interest was the Nairobi All Share Index components. A stratified sampling method was used where the firms were categorised in to agricultural, automobiles and accessories, banking, commercial and services, construction and allied, energy and petroleum, insurance, investment, manufacturing and allied and lastly the telecommunication and technology sector. A total of 32 firms were selected. This was done through a random selection of at least half of the listed firms from each category. The random selection was done by assigning numbers to firms in each sector. For example, the agricultural sector has six listed firms, therefore each firm was assigned a number between 1 and 6. Then using a Microsoft Excel function, three random numbers between 1 and 6 were generated and the firms relating to the generated random numbers were selected. This was done for all sectors. This reduced any biasness towards a particular firm.

The Nairobi All Share Index was selected as it is a good proxy for the whole stock market in Kenya. Furthermore, using any other market index, such as the NSE – 20 index, would not be a good representation as it only includes a fraction of the listed frims.

3.3 Data Collection

All data used in this study was from secondary sources. Data was collected for a period of 5 years. This is from the start of 2012 to the end of 2016. The data series comprises of equity prices, book value of liabilities, book value of equity and the risk free rate which will be obtained from the 91 day T-Bill rate in Kenya. This is because an asset with a shorter term to maturity is less risky than an asset with a longer term to maturity. Hence the 91 day T-Bill rate was the most suitable rate to represent the risk free rate.

Equity prices were acquired from the NSE database, book value of liabilities were extracted from firm annual reports and the risk free rate was obtained from the website of the Central Bank of Kenya.

3.4 Data Analysis

Based on the literature reviewed, the preferred class of models for predicting default emanating from a firm's capital structure was the structural model pioneered by Merton (1974). The structural model framework requires one to determine the $N(d_2)$ value adopted in the option pricing framework where the equity value of a firm is considered to be a call option on its assets and its debt value to be the strike rate.

The market prices a firm's stock with respect to its future expectations of the total returns after accounting for financial risk. In other words, equity holders have a residual interest on a firm's earnings and assets. Furthermore, financial principles tell us that

$$Assets = Equity + Liabilities \tag{18}$$

Therefore, $$Market\ Value\ Assets = Market\ value\ of\ equity + Debts \tag{19}$$

But, $$Market\ Value\ of\ Equity = Market\ Capitalisation \tag{20}$$

$$Market\ Value\ Assets = Market\ Capitalisation + Market\ value\ of\ Debt \quad (21)$$

One of the most integral step in the Merton model is the estimate of the market value of assets A_T and its volatility σ_A. These are, undeniably, unobservable variables. Ideally, for each of the 32 firms, we computed the market value of the assets as the sum of the market capitalisation of a firm and the market value of debt as shown by equation 21 above. Howbeit, what we can actually observe in the marketplace are the market value of equity and not the market value of bank debt or any other kind of private financing that a company might have. Accordingly, the market value of debt was computed by multiplying the market capitalisation by the firm's book gearing ratio as shown below;

$$Gearing\ ratio = {}^{Debt}/_{Equity} \quad (22)$$

$$Gearing\ Ratio * Market\ Capitilisation = Market\ Value\ of\ Debt \quad (23)$$

A series of market values of assets were calculated for each firm for the 1,308 trading days between 2012 and 2016. Taking natural logarithms of each market value of assets and dividing it by its previous logarithmic value, the volatility of the market value of assets was found for each of the 32 firms.

$$\sigma_A = \sqrt{Variance\ \left[Ln\left(\frac{A_2}{A_1}\right), Ln\left(\frac{A_3}{A_2}\right), \ldots Ln\left(\frac{A_t}{A_{t-1}}\right)\right]} \quad (24)$$

This gave the daily volatility. An annual value was found by multiplying the value from equation 24 with the square root of 252.

Four default boundaries were used to unravel the behaviour of the probabilities of default with various default boundaries. The four default boundaries selected were; the default boundary specified by the KMV *Credit Monitor*^{TM} which uses the book value of a firm's short-term liabilities plus one half of its long-term liabilities, short term debt, long term debt and total debt. These are shown below;

$$Default\ Boundary\ (K_1) = Short\ term\ debt + \frac{1}{2} * Long\ Term\ Debt \quad (25)$$

$$Default\ Boundary\ (K_2) = Only\ Short\ Term\ Debt \quad (26)$$

$$Default\ Boundary\ (K_3) = Only\ Long\ Term\ Debt \quad (27)$$

$$Default\ Boundary\ (K_4) = Short\ term\ debt + Long\ Term\ Debt \quad (28)$$

Then the future value of the default boundary was found using the equation below and this was plugged as D_t in to equation 12 to find the probability of default.

$$Future\ Value\ of\ Debt\ (D_t) = K_i e^{rt} \quad (29)$$

Where K_i is the default boundary calculated in equation 25 – 28 above.

The Merton model assumes that a firm holds only a single type of debt, zero coupon debt, with a defined maturity. This is at odds with reality because firms were observed to hold various types of debt with varying maturities. The time to maturity of the call option was found by calculating each firms weighted average duration of its various liabilities.

By using the formulas below and finding the probability of the standard normal density function below d_2, probability of default was calculated.

$$PD = 1 - N(d_2) \quad (30)$$

$$d_2 = d_1 - \sigma_A \sqrt{T - t} \quad (31)$$

Where,
$$d_1 = \frac{lnA_T - lnD + \left(r + \frac{\sigma^2}{2}\right)(T - t)}{\sigma\sqrt{T - t}} \quad (32)$$

4. DATA ANALYSIS AND FINDINGS

4.1 Probability of Default and its Relationship with Capital Structure

Equity holders are viewed as holding a European call option on the company's assets. If equity holders default on debt payments, the debt holders' only recourse is to take over the company's assets. Hence if at time t, the value of assets is less than the value of debt, the firm defaults and this is the key insight of the Merton model. As a result, the probability of default is equal to the probability of the debt not being serviced which according to the option pricing framework is equivalent to $1 - N(d_2)$. Furthermore, from equation 8, the endogenous effect of a firm's capital structure can be seen on the default probability $N(-d_2)$ where the ratio A_t/D_t is the financial leverage the firm adopts.

After plugging the market value of assets, default boundary, time to maturity, risk free rate, and the volatility of the market value of assets in to equation 12, the survival probability was computed. The probability of default was found by subtracting the probability of survival from one. Appendix 1 shows the default probabilities of the selected firms under various default boundaries.

From the data analysis and its output, we realized that if the value of a firm's asset was lower than that of its debt, i.e. the firm does not have sufficient assets to cover its liabilities, the Merton model generated a higher probability of default. This was the case for firms like Car & General Kenya Ltd (C&G), Sameer Africa Ltd (FIRE), Diamond Trust Bank Kenya Ltd (DTK), East African Portland Cement Co. Ltd (PORT), Kenya Power & Lighting Co. Ltd (KPLC), KenGen Co. Ltd (KEGN), Trans-Century Ltd (TCL) and Mumias Sugar Co. Ltd (MSC).

Following this, we realized that based on our model inputs and sample, firms with a higher Asset to Debt ratio, A_t/D_t, experienced a lower probability of default. Our results were similar to those of Wang (2009), who implemented the Merton model and created credit spread term structures for low-leveraged, medium-leveraged and high leveraged firms. Wang (2009), noticed that the Merton model generated low probabilities for low-leveraged firms. Moreover, the relationship between financial leverage and probability of default can be seen when analysing the trend between the default probabilities under various default boundaries. For example, from appendix 1 we see that the fourth default boundary, where the strike rate is the total debt value, produces the highest default probabilities and this is consistent for all of the 32 firms. This may mean that as a firm's debt value increases, or as the strike rate increases, the likelihood of the firm defaulting increases too, reflecting what financial theory tells us: High leverage leads to high financial risk (Pandey, 2010). Appendix 2 gives a summary of the market value of assets to the future value of the debt ratio.

From option pricing theory we learn that an increase in the volatility of the underlying asset leads to an increase in the price of the call option (Hull, 2008). An empirical examination of the Black – Scholes call option pricing model by Macbeth & Merville (1979) reveals that an increase in the value of the volatility affects the values of $N(d_1)$ and $N(d_2)$. In our case, the value of the call option is the value of equity (E_t). An increase in the volatility of the market value of assets (A_t) will lead to a rise in the equity value and this means that on right hand side of equation 10, either the expected value of assets will go up or the expected value of debt will fall inorder for the equity (E_t) value to rise. Since the volatility does not affect the strike rate, also known as the default boundary, there has to be a fall in the value of $N(d_2)$ for the expected value of debt to fall. If $N(d_2)$ is the probability of survival and it falls, then it means that the probability of default rises when volatility rises. A higher volatility can also lead to high fluctuations in asset values that could easily result in insufficient assets for meeting liabilities. This may explain why some firms, like Carbacid Invesment Ltd (CARB), bear a high probability of default despite having asset values above their debt values.

Therefore the combined effect of a high ${A_t}/{D_t}$ ratio and a low volatility can be the reason for an infinitesimal default probabilities of Standard Chartered Bank Kenya Ltd (SCBK), Bamburi Cement Ltd (BAMB), East African Breweries Ltd (EABL), British American Tobacco Kenya Ltd (BAT) and Safaricom Ltd (SCOM).

Grouping the selected 32 firms in to their respective sector and calculating the average default rates per sector we see that the automobiles & accessories sector, energy and petroleum sector, the investment sector and the construction and allied sector face probabilities of default higher than 50%. This is shown in Appendix 3.

4.2 The Relationship between Default rates and Debt Tenor

To draw the term structure of default rates, a data table was created where the probabilities of default were calculated by varying the maturity periods from year 1 to year 30. Appendix 4 shows the term structures of default rates for the various sectors in Kenya.

From appendix 4 we see that the term structures for all the 10 sectors display an upward sloping curve pointing out the fact that probability of default rises as the term to maturity increases presumably due to increasing future uncertainty. With the exception of the telecommunication and technology sector curve, the curves tend to flatten out at longer maturities as more time is allowed for the company's asset value to grow and cover liabilities. This reflects one basic feature of the Merton model found in literature. That is, in a risk neutral world at the risk free rate, the firm's value drifts upwards overtime and so its leverage ratio falls (Gemmil, 2003).

The telecommunication and technology curve remains flat and then starts to rise at an increasing rate as the maturity increases. The curve does not flatten out. Safaricom Ltd (SCOM) is the only firm listed in telecommunication and technology sector at the Nairobi Stock Exchange. SCOM has no long term liability and only has short term liability which comprises 27% of its book value of assets and 4% of its market value of assets. Furthermore, it also has the lowest volatility of the market value of assets among the firms in the sample. However if the strike rate or the debt value of the firm is increased, the curve starts to flatten out. On that account, it could mean that the reason for the odd shape of the telecommunication sector's curve, compared to the other term structures, is the lack of long term debt in the capital structure of Safaricom Ltd.

Although our curves adhere to what practitioners claim: that the term structure should be upward sloping, it contradicts to what Merton (1974), Longstaff & Schwartz (1995) and Jarrow *et al* (1997) predict. According to them, firms with low leverage or high grade bonds portray a flatter but an upward sloping curve whereas firms with high leverage or low grade bonds portray a downward sloping curve. Therefore our results differ, no matter what the firm leverage is, all our curves are upward sloping. This could possibly be due to the averaging effect at the output level in order to find the sector based default probabilities.

5. CONCLUSION & A POSSIBLE FUTURE RESEARCH AGENDA

This paper has used equity prices and annual data from the financial statements of 32 firms for the past five years in order to determine probability of default based on a firm's capital structure and evaluate the relationship between the probability of default and varying debt tenors.

Based on our sample and results we conclude that firms with a high leverage exhibit a high probability of default due to high financial risk carried by the high leverage. Furthermore, the model generated high probabilities of default for firms with volatile asset values. The term structure of default rates shows us that as the maturity of the debt increases, the probability of default increases too due to an increase in future uncertainty.

The Merton (1974) model was used in order to determine the probability of default by calculating $N(-d_2)$. The maturity of the debt, face value of the debt (strike rate), risk free rate, the market value of the assets and the volatility of the assets (σ_A) are the key determinants of the probabilities of default. However caution must be taken when implementing the Merton model due to its underlying assumptions that are at odds with reality.

A trade-off exists between realistic assumptions and ease of implementation and Merton's model opts for the later one. All extensions to this model introduce more realistic assumptions trying to end up with a model not too difficult to implement. Despite this, Gemmil (2003) claims that the extensions do not explain the full proportion of credit spreads in corporate bonds. A similar study carried by Delianedis & Geske (2003) state a similar outcome and conclude that the models only explain a small fraction of the credit spreads and the rest is attributable to taxes, jumps, liquidity and market risk factors.

The structural model used generally implies that as the time to maturity of the debt approaches zero, the default probability approaches zero as well. This is contrary to empirical findings that short – dated debt securities do bear credit risk. Not to mention the fact that sudden economic events can impact the value of a firm's assets and make it more volatile. On that account, the introduction of a jump process that govern the asset prices in the structural model, which implies that the asset value of the firm can suddenly drop, can lead to better results (Elizalde, 2006). Thus default is no longer a predictable event unlike in the Merton model and the default probabilities for short maturities do not tend to zero leading to a more realistic model. Invoking such a model for firms in frontier markets like Kenya, can help explain a greater portion of default risk in their capital structure.

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Appendices

Appendix 1: Firm Specific Probability of Default

Sector	Firm Ticker	Default Probability Based on the Following Boundaries			
		KMV Boundary	Only Long-Term Debt	Only Short-Term Debt	Tot Deb
Agricultural	LIMT	0.0007	0.0006	0.0001	0.00
	SASN	0.0783	0.1674	0.0008	0.26
	KUKZ	0.0905	0.0850	0.0059	0.26
Automobiles & Accessories	C&G	0.9377	0.0048	0.9174	0.95
	FIRE	0.6229	0.00E+00	0.6210	0.62
Banking	COOP	0.0245	0.00E+00	0.0144	0.03
	DTK	0.7205	0.00E+00	0.6405	0.78
	SCBK	3.30E-05	0.00E+00	3.28E-05	3.32E-
	KCB	0.2832	0.00E+00	0.2477	0.32
	EQTY	0.0007	0.0675	0.00E+00	0.07
Commercial & Services	SGL	0.3035	0.0157	0.2288	0.37
	TPSE	0.9508	0.9455	0.9195	0.96
	SCAN	0.9906	0.6975	0.9895	0.991
	NMG	0.0072	0.00E+00	0.0071	0.00
Construction & Allied	PORT	0.9352	0.8402	0.8420	0.96
	BAMB	4.52E-10	0.00E+00	3.91E-12	1.42E-
	BERG	0.3447	0.0008	0.3294	0.35
Energy & Petroleum	KPLC	0.9490	0.9873	0.2000	0.99
	KENO	0.0009	0.00E+00	0.0008	0.001
	KEGN	0.7977	0.8965	0.2560	0.911
Insurance	KNRE	0.0272	0.00E+00	0.0205	0.035
	BRIT	0.1897	0.4048	0.0011	0.468
	CFCI	0.2529	0.4985	0.0009	0.531
	JUB	0.0082	0.1479	0.00E+00	0.148
Investment	ICDC	0.0498	0.3730	0.00E+00	0.380
	TCL	0.9844	0.0755	0.9795	0.988
Manufacturing & Allied	EABL	4.87E-09	2.26E-14	3.16E-10	3.93E-
	MSC	0.9290	0.7352	0.8372	0.966
	BAT	0.00E+00	0.00E+00	0.00E+00	1.77E-
	BOC	0.0003	N/A	0.0003	0.000
	CARB	0.5529	0.5634	0.4605	0.602
Telecommunication & Technology	SCOM	0.00E+00	N/A	0.00E+00	0.00E+

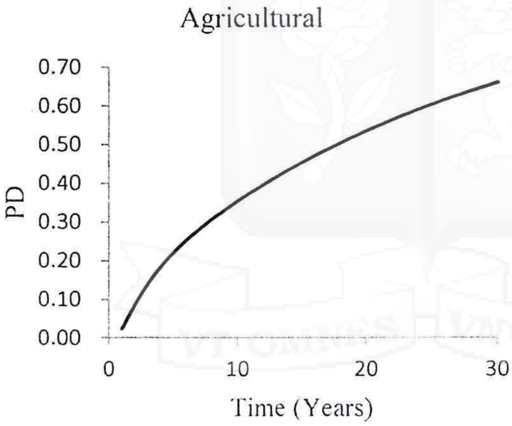
Appendix 3: Summary of Various Parameters of each firm

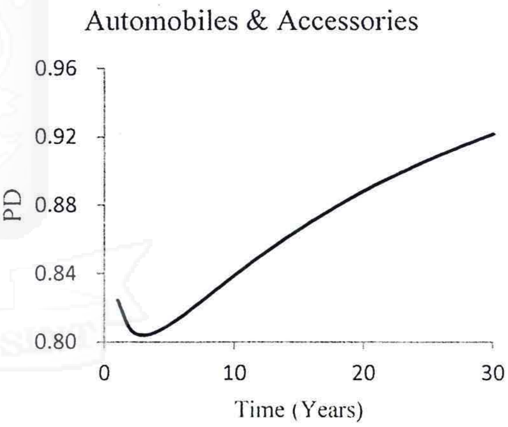
	Firm Ticker	A/D	Volatility	Time to Maturity	Is A>D?
Agricultural	LIMT	21.8559	0.4187	5.2269	YES
	SASN	2.5053	0.4178	2.3356	YES
	KUKZ	2.1675	0.4161	1.8814	YES
Automobiles & Accessories	C&G	0.4918	0.4665	1.0642	NO
	FIRE	0.8867	0.4567	1.0057	NO
Banking	COOP	1.3677	0.2647	0.4055	YES
	DTK	0.8813	0.2800	0.4361	NO
	SCBK	1.7488	0.2555	0.3173	YES
	KCB	1.0982	0.2623	0.7159	YES
	EQTY	3.1270	0.2787	1.8651	YES
Commercial & Services	SGL	1.6356	0.5453	1.7675	YES
	TPSE	1.0847	0.3769	2.2739	YES
	SCAN	2.1445	0.4196	1.0005	YES
	NMG	6.6329	0.7037	1.0022	YES
Construction & Allied	PORT	0.3533	0.5660	1.9339	NO
	BAMB	7.5758	0.2580	1.7832	YES
	BERG	2.5056	0.7295	1.6702	YES
Energy & Petroleum	KPLC	0.4496	0.2578	2.5706	NO
	KENO	3.5180	0.4020	1.0109	YES
	KEGN	0.5194	0.5503	4.5008	NO
Insurance	KNRE	1.6494	0.3012	0.8389	YES
	BRIT	1.8704	0.3903	3.5335	YES
	CFCI	1.8656	0.4431	3.6349	YES
	JUB	3.0791	0.3053	2.7789	YES
Investment	ICDC	2.2102	0.3477	2.1417	YES
	TCL	0.3110	0.5617	1.0676	NO
Manufacturing & Allied	EABL	23.2741	0.3929	2.3895	YES
	MSC	0.3899	0.4688	2.1210	NO
	BAT	20.5203	0.3482	1.1685	YES
	BOC	4.0398	0.4051	1.0000	YES
	CARB	12.8688	1.2653	1.2944	YES
Telecommunication & Technology	SCOM	23.6149	0.2348	1.0000	YES

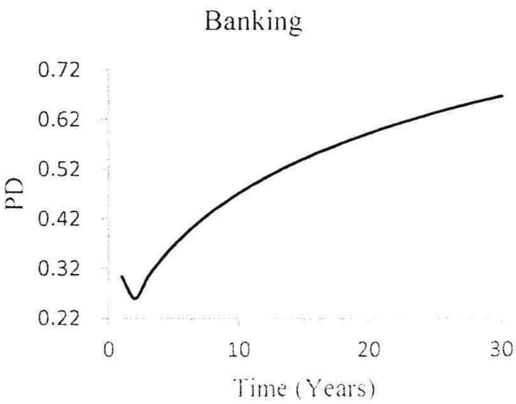
Appendix 3: Sector Averages of Probabilities of Default and Gearing Ratios

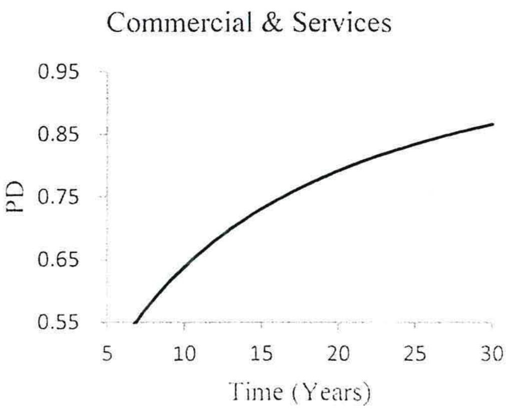
Sector	PD	Average Maturity
Agricultural	0.0860	3.1480
Automobiles & Accessories	0.8074	1.0349
Banking	0.3037	0.7480
Commercial & Services	0.2968	1.5110
Construction & Allied	0.4365	1.7958
Energy & Petroleum	0.6363	2.6941
Insurance	0.1549	2.6966
Investment	0.5274	1.6047
Manufacturing & Allied	0.2546	1.5947
Telecommunication & Technology	0.0000	1.0000

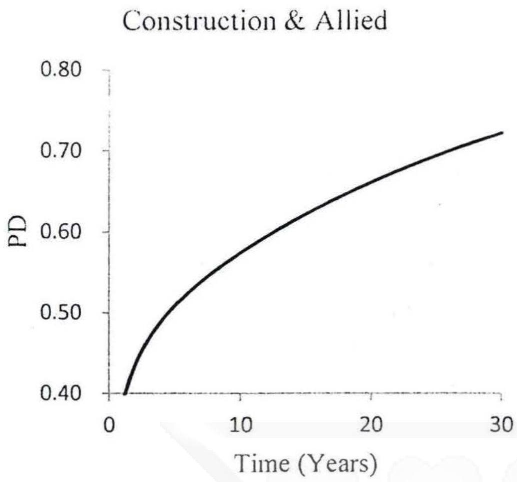
Appendix 3: Term Structure of Default Rates for Each Sector

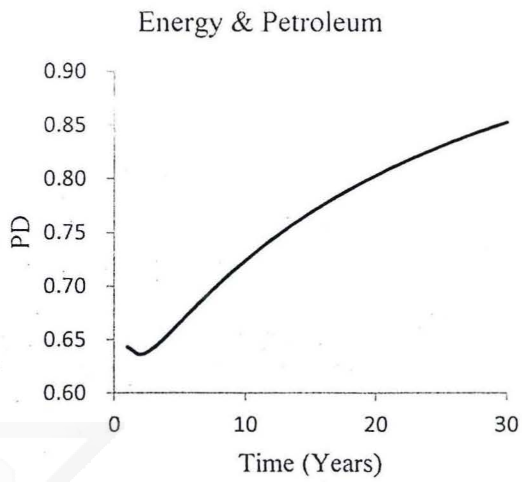









Construction & Allied
PD
0.80
0.70
0.60
0.50
0.40
0
10
20
30
Time (Years)


Energy & Petroleum
PD
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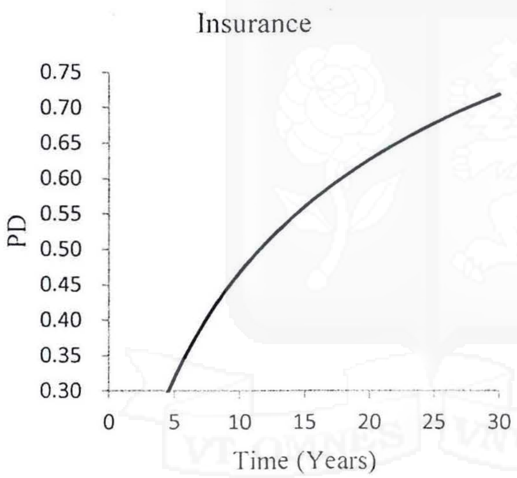
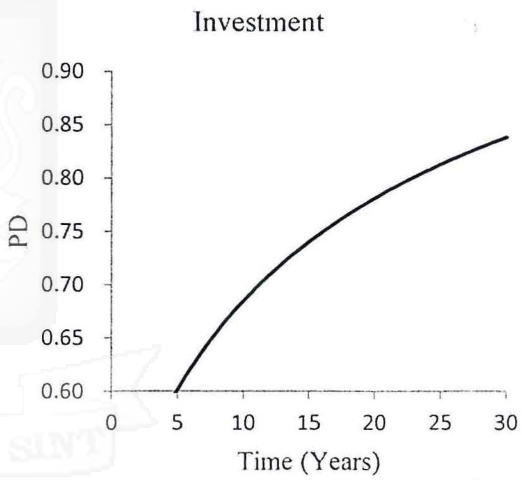
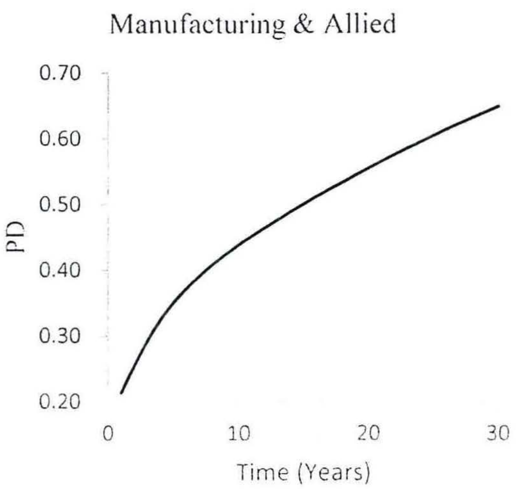
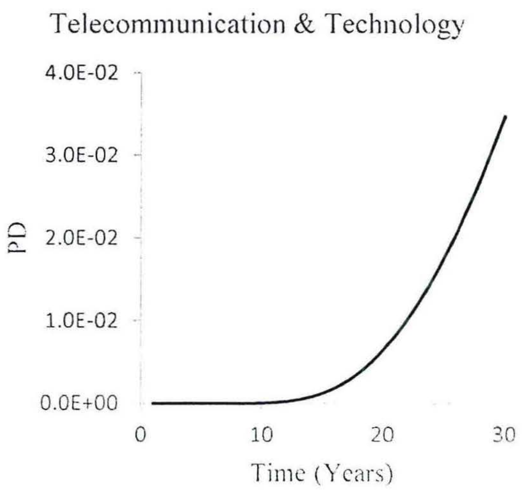
0.85
0.80
0.75
0.70
0.65
0.60
0
10
20
30
Time (Years)


Insurance
PD
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0
5
10
15
20
25
30
Time (Years)


Investment
PD
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0
5
10
15
20
25
30
Time (Years)


Manufacturing & Allied
PD
0.70
0.60
0.50
0.40
0.30
0.20
0
10
20
30
Time (Years)


Telecommunication & Technology
PD
4.0E-02
3.0E-02
2.0E-02
1.0E-02
0.0E+00
0
10
20
30
Time (Years)