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Andrew Kioi Njeru

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An Alternative Approach to Estimation of the Probability of Default for Commercial Entities: The Modified KMV Merton Model

*By Andrew Kioi Njeru

Abstract

We carry out an empirical test of KMV model for using private companies that are not listed on a stock exchange and in doing so, substitute book values for market values and fluctuations of bank account balances for volatility of stock prices. This study reveals a surprising effectiveness of the KMV model and its applicability for estimating probability of default for companies that are not listed on a stock exchange but only with a modification to adopt the actual observed asset growth of the company reported in the books of accounts instead of using the risk-free rate. The adoption of the bank balances as a proxy for the asset volatility has also performed well. One other finding is that the only three companies that had material exposure and defaulted did not have the up-to-date audited books of accounts. We could therefore not test the effectiveness of the KMV model because the three had no up to date books of accounts. This makes one to conclude that absence of audited book of accounts for a significant borrower is a major negative signal that a company is likely to default. This is more significant for larger companies who have a legal requirement to prepare the audited financial statements and the absence may be inferred to as a signal of inability to conclude the closure books of accounts with external auditors due to doubts about going concern.

Keywords: *Spillover, Commercial banks, BVAR, Shocks, Volatility*

** Andrew Kioi Njeru is affliated with KCB Bank Limited*

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1.0 Background of the study

The status of risk management practices for the banking sector in Kenya can be described to be relatively young and most banks have just recently adopted the internal capital adequacy assessment process and in doing so, most adopted the standardized approach which calls for less complexity in the estimation of the credit risk.

Under this approach there is no express requirement to estimate the probability of default for each borrower. However, the need to estimate the probability of default for each borrower at the origination stage is growing given the increasing regulatory requirements arising from new regulations such as international accounting standards. The pressures to minimize credit risk is also growing in the environment of controlled interest rate regime.

There is hardly any publicly available help review the assessment of the specific methodologies used for the estimation of the credit risk for the Kenyan market. A number of the top banks have adopted the internal rating scale for corporate clients on a rating scale as proposed in the Internal ratings-based approach by Basel (2018) and then superimpose the probability of defaults from the global default rates published by rating agencies.

The evolution of the credit risk management in banks typically begins with the development of internal ratings for the commercial borrowers. The ratings scale helps the bank to differentiate the level of risk for each borrower. The internal ratings in a bank considers the financial and non-financial attributes of a firm. The non-financial attributes considered; quality of management and performance of the industry the firm operates. The banks take into account the features of the industry to which the potential client belongs, and the status of the client within its industry. The effects of macroeconomic events on the firm and its industry should also be considered, as well as the country risk of the borrower.

The financial aspects such as the profitability, the debt levels and liquidity are also considered. Each borrower is assigned a rating on a scale based on how well they rank on attributes rated. For the effective implementation of an advanced approach to risk measurement, the probabilities of default associated with each ratings class is estimated. This is the toughest challenge for local banks given the small number of defaults that are observed in any period. The impact of the default can be severe but not enough observations to assign a probability of default for each ratings class. This is the challenge that local banks face.

The task of implementation of the new accounting standard is particularly demanding because it calls for of estimation of the expected credit losses for lending in the commercial segment; The most widely adopted methodologies either all for large number of defaults not below 1,000 in number or the availability of market data such as stock prices or bond prices. These are not available for the significant portions of commercial lending portfolios for banks in Kenya.

1.1 Background to the Banking Sector and Capital market in Kenya

As at December 31, 2017, the Kenyan banking sector comprised of the Central Bank of Kenya (CBK), as the regulatory authority, 43 banking institutions (42 commercial banks and 1 mortgage finance company), 9 representative offices of foreign banks, 13 Microfinance Banks (MFBs), 3 Credit Reference Bureaus (CRBs), 19 Money Remittance Providers (MRPs), 8 non-operating bank holding companies and 73 foreign exchange (forex) bureaus. Out of the 43 banking institutions, 40 were privately owned while the Kenya Government had majority ownership in 3 institutions. Of the 40 privately owned banks, 25 were locally owned where the controlling shareholders are domiciled in Kenya, while 15 were foreign-owned many having minority shareholding by locals.

The 25 locally owned institutions comprised 24 commercial banks and 1 mortgage financier. Of the 15 foreign-owned institutions, all commercial banks, 11 were local subsidiaries of foreign banks while 3 were branches of foreign banks. All licensed forex bureaus, microfinance banks, credit reference bureaus, money remittance providers, non-operating bank holding companies and representative offices and were privately owned. The total assets held by the banking sector stood at Kenya shillings 4.0 trillion shillings. The total assets for the largest bank was Kenya shillings 555 billion.

Nairobi Stock exchange has 67 listed companies with a market capitalization of Kenya shillings 2.8 trillion as at March 2018(Capital markets Quarterly Bulletin).

Within a period of 12 years from 2006 to 2018, there were only 10 Initial Public offers with the three of the last four IPOs registering less than 80% subscription rate. There were five additional Offers during the same period.

Table1: Number of Listed Companies in Kenya's Stock Exchange

Year	Number of Listed Companies	Number of Delisted Companies	Number of Suspended Companies
2014	64	-	2 (City Trust Ltd) Readmitted and renamed I &M Holdings Ltd, Rea Vipingo -pendinga a take over bid.
2015	64	1 (Rea Vipingo)	-
2016	66	-	1 (Atlas Development & Support Services)
2017	67	1 (Marshalls EA Ltd, Hutchings Beamer and Baumann)	1 (Atlas Africa Industries Ltd)

As at end of March 2018 there were only 30 corporate bonds in the capital markets and these were issued by just 17 companies. Corporate bond market activity is very low with companies finding it hard to use the avenue for raising capital. Only one bond was issued in 2017, the Sh6 billion second tranche of East Africa Breweries Limited (EABL's) Sh11 billion paper whose first issue was in 2015. There was no corporate bond issued in 2016. (Business Daily 2017). The trading activity in the bonds market is much muted with the trading turnover for corporate bonds accounting for only 0.34% of total bond turnover. The fact that only 67 companies are listed and that only 17 companies have issued corporate bonds coupled with the illiquidity of the bonds market implies that market information is not available for the majority of large commercial borrowers. Hence the tools available for risk measurement in the developed countries are not available for risk managers of financial institutions in Kenya and similarly sized developing markets.

1.2 Problem Statement

The banking sector in Kenya is currently facing a challenge of estimating the probability of default for larger corporate customers given the fact that the industry being in a small economy where the number of large corporates is so few and default incidences too low to facilitate the adoption of a statistical approach to estimation of default probability. The financial market and securities exchange are also too shallow with very few listed corporate bonds meaning that virtually all large borrowers in a bank do not have market data relating to bond prices or stock prices hence the market approaches to estimation of default cannot also be used. The estimation of the probability of default is important for the risk managers not only for the compliance with the new accounting standards but also it helps with compliance with the Banking regulators risk guidelines under the internal Capital adequacy assessment process (ICAAP) and it is a crucial component in the determination of the optimum pricing decision for the significant exposures in the process of lending to large commercial entities.

The ability of risk managers to assign a default probability number on any significant borrower at the point of origination is a big step towards understanding the risk the bank is taking at the point of origination of the credit to a commercial entity. The estimation of Probability of default is arguably the most difficult element in the estimation of the expected Credit Loss Model as envisaged in the new accounting standard on fair valuation of financial assets. For portfolios with small incidences of defaults, the estimation of default is particularly difficult given the bias of most methodologies of using the statistical methods where a large sample of defaults is required, and this is also complemented using market data such as stock prices and bond prices for the companies. Such market data is not available for most of the commercial entities that banks in this market lend to. Looking at the portfolio of one of the commercial banks, it is worth to note that the bank is the largest in the country in terms of asset base and it holds the largest portfolio of commercial entities among the financial institutions in the country and yet out of the 300 commercial entities the bank lends to less than ten are either listed on the stock exchange have a listed corporate bond. The bank holds only two listed bonds. Out of these the liquidity of the corporate bond market is also very low implying that the market may not offer a very useful information for most of its portfolio.

To put in perspective, the largest bank had just 300 corporate customers. Even though the value of an individual default may be significant under corporate segment of the business the frequency of defaults may be too few even for the largest bank in East Africa to facilitate the adoption of a statistical or market-based methodology for portfolio wide estimation of default across rating classes. This is considered very small from the perspective of a development of a statistical model given that a statistical model calls for a sample of not less than 4,000 entities half of which should be firms that should have defaulted. There is alternative approached to estimation of the probability of default that do not require large data sets or market data; we seek to use data available for the corporate entities from a local commercial bank and assess the utility of the KMV model that relies on few data points with a few modifications.

1.3 Research Objectives

The main object of this study is to determine the suitability of the KMV model for privately owned firms that are not listed on a stock exchange. Towards this objective we seek to:

- Determine if the book values can be used as a proxy for market values for firms not listed on a stock exchange.

- Determine if the bank account activity can be used as a proxy for volatility for firms not listed on a stock exchange.

- Provide recommendations for risk managers with regard to the estimation of the Probability of default based on the findings of the study.

1.4 Significance of the Study

Given the absence of research on the effectiveness of the KMV model on private companies and this coupled with the shortcomings of models that are widely used in the developed markets being that they call for stock market data and the need to develop an effective objective measure for probability of default, it is necessary to undertake the research and see if it is possible to modify and adapt the KMV approach to fill the gap.

If successful, this can aid the local financial institutions in the process of estimating the risk of new customers and in the process make informed decision of the risks they are taking and structure the loan offerings to minimize risks.

For the compliance officers, in banks it would aid the process of compliance with the Basel requirements in the internal capital adequacy assessment process as well as compliance with the new accounting standards regarding the estimation of impairment of loans and advances portfolio.

The regulator could also use the approach to assess the quality of the assets held by financial institutions as well as compare the credit origination standards and how they compare across banks by comparing the quality of new and existing loan portfolios across banks. This can help to formulate a more advanced risk-based supervision and capital requirements framework.

2.0 Theoretical Literature

There are a few different approaches that can be used to estimate the probability of default for a commercial entity; the methodologies used have been stable over the years and there has been no major changes to the approaches and most researchers focus on testing the applicability of the approaches to different environments and economies.

The most common approaches are as follows; the credit metrics approach, the market implied approach, the actuarial approach and the KMV approach;

Credit Metrics model is used to analyze and manage credit risk of investment instruments portfolio, According to Adamko, Kliestik, Birtus (2014), the credit metrics analyses the entire portfolio based on an assessment of the credit risk of individual instruments and subsequently applied to the portfolio by taking into account the cross-correlation of bonds. The model was created by the JP Morgan bank in 1997. Since 1999, it became part of the credit risk management for almost all major banks in the developed markets.

The credit risk calculation of single bond is divided into four basic steps. First, obtain the data for bond rating and probability transition matrix. Secondly, establish the seniority bond, from which default rates were derived, respectively recovery rate; thirdly, the calculation of the bond present value for each rating category by forward curves with different credit spreads for each rating category. Final step is the calculation of the probability distribution of the current values of bond prices, from which were subsequently derived values of bond volatility expressed by using standard deviations. Volatility of bond present value expresses credit risk of the bond. This methodology is widely used in developed markets where most companies issue publicly listed bonds hence banks can easily assess the risk of the portfolio they hold. Credit Risk+ is based on mortality models developed by insurance companies. The probability of default under this model are based on historical statistical data on default experience by credit class. The other common methodology for estimating the default probability is the actuarial approach and most commonly adopted is the CreditRisk Plus. CreditRisk + applies an actuarial science framework to the derivation of the loss distribution of a bond or loan portfolio.

The market implied approach looks at the market spreads for corporate bonds and inferred the credit risk from them. Higher spreads of bonds of a company imply higher risk of default and vice versa. The market implied approaches are calibrated using credit spreads that are observable in the financial markets and they do not require balance sheet data. The data used to feed into the models is largely the credit instrument prices derived from markets such as corporate bond prices, corporate loan and credit derivatives markets. In principle, looking at the price of a credit risky securities over time and subtracting the price of similar securities that do not incur credit risk such as the risk-free treasuries, the price of credit then can be made transparent.

Altman's Z score is another commonly used approach to estimation of the likelihood of a firm to default. The Z-score model is a linear combination of four common financial ratios, weighted by coefficients (Altman, Edward 1983). A financial ratio is a quotient of two numbers, where both numbers consist of financial statement items. The coefficients were estimated by comparing a set of firms which had been declared bankrupt and then collecting a matched sample of firms which had survived, with matching by industry and approximating firm size. Altman (1968) applied Multiple Discriminant Analysis to a data set of 66 publicly held manufacturing firms.

The critical financial ratios are as follows;

X1 = working capital/total assets
X2 = retained earnings/total assets
X3 = operating income/total assets
X4 = book value of equity/total liabilities

Altman developed a model for emerging markets and the estimated coefficients are as follows:

EM Score = 6.56 (X1) + 3.26 (X2) + 6.72 (X3) + 1.05 (X4) + 3.25

A firm that scores below 1.75 is considered to be an equivalent of a default rating class, meaning that they represent a form that have failed to honor its debt obligations.

Another category of commonly used approach is the structural model approach. The most widely used approach in this category is the KMV model and is largely due to its simplicity and it has much lighter demand for historical market data (Chrouhy,M ,Galai D and Mark R.(2009). This is the focus of this study. This methodology is quite useful for portfolios with small incidences of defaults. The KMV approach has an appeal because it does not call for a large incidence of defaults and it can work with estimation of individual firms' default probability without having to rely on a large sample of defaults.

2.2 The KMV approach

KMV approach derives the expected default (EDF) also referred to as the default probability for each obligor based on the Merton (1974) option pricing type of model. The probability of default is a function of the firm's capital structure, the volatility of the asset returns and the current asset value. The EDF is firm specific and can be mapped onto any rating system to derive the equivalent rating of the obligor; EDFs can be viewed as a 'cardinal ranking' of obligors relative to default risk, instead of the more conventional 'ordinal ranking' proposed by rating-based systems. KMV's model does not make any explicit reference to the transition Probabilities which, in KMV's methodology, are already embedded in the EDFs. Koyluoglu,H U, and Hickman, (1998).

Each value of the EDF is associated with a spread curve and an implied credit rating. Credit risk in the KMV approach is essentially driven by the dynamics of the asset value of the issuer. Given the capital structure of the firm, and the stochastic process for the asset, the probability of default for any time horizon which is usually one year or more can be derived. This is the most significant utility of this model. This can be used to derive the probability of default over any time horizon and this is very useful towards the implementation of the accounting standards with respect to estimation of future credit losses.

Equation 1 below depicts how the probability of default relates to the distribution of asset returns and the capital structure of the firm. We assume that the firm has a very simple capital structure. It is financed by means of equity and a single zero-coupon debt instrument maturing at time T, with face value F, and current Market value B.

The firm's balance sheet can be represented as follows:

$$V_t = B_t\,(F) + S_t \,\dots\dots\dots\dots\dots\dots\, (1)$$

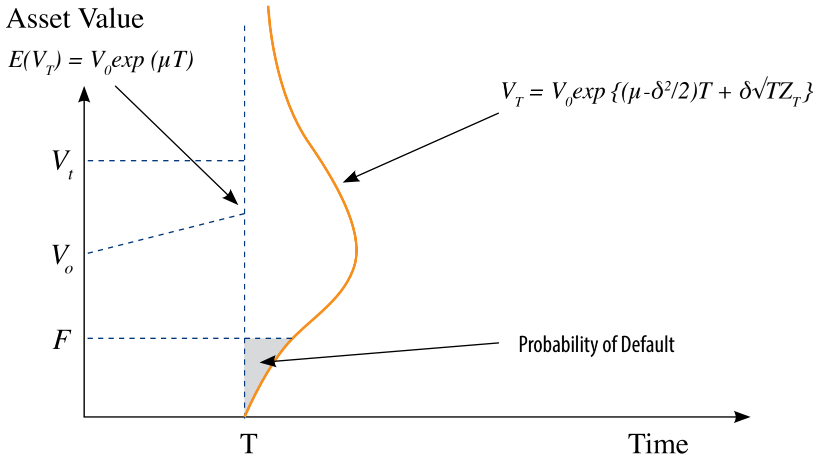
where; V_t is the value of all the assets. The value of the firm's assets $V_{t'}'$, is assumed to follow a standard geometric Brownian motion.

In this framework, default only occurs at maturity of the debt obligation when the value of assets is less than the promised payment F to the bond holders.

The derivation of the actual probabilities of default proceeds in three stages: First, the estimation of the market value and volatility of the firm's assets, secondly, the calculation of the distance to default, which is an index measure of default risk; and thirdly, the scaling of the distance to default to actual probabilities of default using a default database.

Credit risk in the KMV approach is essentially driven by the dynamics of the asset value of the issuer. Given the

Figure 2.1 Distribution of Firm's Asset Value at maturity of the debt obligation



capital structure of the firm and once the stochastic process for the asset value has been specified, then the actual probability of default for any time horizon, one year, two years, etc., can be derived.

We assume that the firm has a very simple capital structure. It is financed by means of equity and a single zero-coupon debt instrument maturing at time T, with face value, and current market value. The firm's balance sheet can be represented as follows: $Vt= {}^{o}\ Bt(F) + St$, where Vt is the value of all the assets. The firm's assets value Vt is assumed to follow a standard geometric Brownian motion. In this framework, default only occurs at maturity of the debt obligation, when the value of assets is less than the promised payment F to the bond holders. **Figure 2.2** the distribution of the assets' value at time T, the maturity of the zero-coupon debt, and the probability of default (i.e., the shaded area below F).

The KMV approach is best applied to publicly traded companies, where the value of the equity is determined by the stock market. The information contained in the firm's stock price and balance sheet can then be translated into an implied risk of default as shown in the next subsections.

2.3 Estimation of the Asset Value VA and the Volatility of Asset Return σA

The value of the firm's assets is assumed to be lognormally distributed, that is the log-asset return follows a normal distribution. This assumption is quite robust and, according to KMV's own empirical studies, actual data conform quite well to this hypothesis. In addition, the distribution of asset returns is stable over time, i.e. the volatility of asset returns remains relatively constant.

If all the liabilities of the firm were traded, and marked to market every day, the task of assessing the market value of a firm's assets and its volatility would be straight forward.

The firm's asset value would be simply the sum of the market values of the firm's liabilities, and the volatility of the asset return could be simply derived from the historic time series of the reconstituted asset value. In practice, however, only the price of equity for most public firms is directly observable, and in some cases part of the debt is actively traded.

The alternative approach to assets valuation consists of applying the option pricing model to the valuation of corporate liabilities as suggested in Merton (1974). In order to make their model tractable KMV assume that the capital structure of a corporation is composed solely of equity, short term debt (considered equivalent to cash), long-term debt (in perpetuity), and convertible preferred shares; Given these simplifying assumptions, it is possible to derive analytical solutions for the value of equity, S, and its volatility σs;

$$S = f(V, \sigma, L, c, r)\ldots\ldots\ldots\ldots\ldots\ldots(3.1)$$

$$\sigma s = g(V, \sigma, L, c, r)\ldots\ldots\ldots\ldots\ldots\ldots(3.2)$$

Where; L denotes the leverage ratio in the capital structure, c is the average coupon paid on the long term debt, and r is the risk free interest rate. If σs were directly observable like the stock price, we would simultaneously solve **equations 3.1** and **3.2** for V.

But the instantaneous equity volatility, σs, is relatively unstable and is in fact quite sensitive to changes in asset value; so there is no simple way to measure σs precisely from market data. Since only the value of equity S is directly observable from the market, we can solve out V from **3.1** so that it becomes a function of the observed equity value, r stock price and the volatility of asset returns (Chrouhy,M ,Galai D and Mark R.(2009).

$$V = h(S, \sigma, L, c, r)\ldots\ldots\ldots\ldots\ldots\ldots(3.3)$$

Here the volatility is an implicit function of V,S,L,c and r so to calibrate the model for σ ,KMV uses an iterative technique.

2.4 Calculation of distance to default - The iterative Approach

Using a sample of several hundred companies, KMV observed that firms' default when the asset value reaches a level that is somewhere between the value of total liabilities and the value of short-term debt. Therefore, the tail of the distribution of asset values below total debt value may not be an accurate measure of the actual probability of default. Loss of accuracy may also result from factors such as the non-normality of the asset return assumptions made about the capital structure of the firm. This may be further aggravated if the company is able to draw on (otherwise unobservable) lines of credit. If the company is in distress, using these lines may (unexpectedly) increase its liabilities while providing the necessary cash to honor promised payments.

For all these reasons, KMV implements an intermediate phase before computing the probabilities of default. As shown in **Figure 2.1**, KMV computes an index called distance to default (DD). This is the number of standard deviations between the mean of the distribution of the asset value and a critical threshold called the default point, (DPT) which is set at the par value of current liabilities including shortterm debt to be serviced over the time horizon (Short term debt,STD), plus half the long-term debt (LTD), i.e. $STD+ LTD/2$. If the expected asset value in one year is $E\ (V_1)$ and σ is the standard deviation of future asset returns, then

$$DD = [E(V_1) - DPT] /\sigma ....(3.4)$$

Given the log normality assumption of the asset values, the distance to default expressed in unit of asset return standard deviation at time horizon T is;

$$DD = \frac{(ln(V_0/DPT_T) + (\mu\text{-}0.5\sigma^2)}{(\sigma\sqrt{T})}$$

Where V_0 is the current market value of assets.

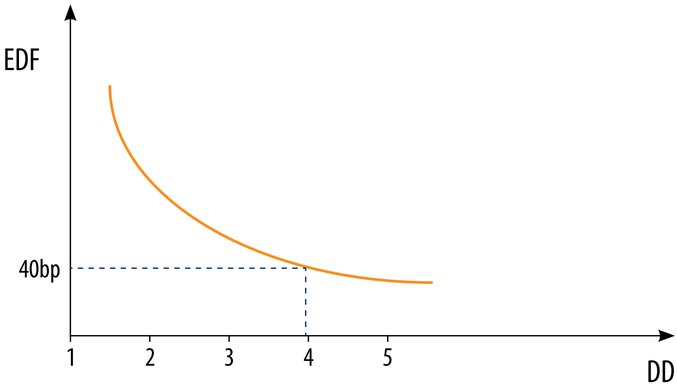
DPT_T is the default point in time horizon T

μ is the expected return on assets, net of outflows

2.5 Derivation of the Probability of Default from the Distance to default

It follows that the shaded area shown below, the default point in the **figure 2.1** is equal to $N(-DD)$. This last phase consists of mapping the distance to default to the actual probabilities of default, for a given time horizon. KMV calls these probabilities expected default frequencies. Using historical information about a large sample of firms, including firms that have defaulted, one can estimate, for each time horizon, the proportion of firms of a given ranking, say DD at 4 that actually defaulted after one year. This proportion, say 40 basis points, or 0.4%, is the EDF as shown in **figure 2.1.**

Figure 2.2 Mapping the Distance to default into the Expected Default frequency a for a given time Horizon



2.6 Empirical Literature

KMV has analyzed more than 2000 US companies that have defaulted or entered into bankruptcy over a period of 20 years. These firms belonged to a large sample of more than 100,000 company-years with data provided by Compustat, a data provider. In all cases KMV has shown a sharp increase in the slope of the EDF a year or two before default. Changes in EDFs tend to anticipate by at least one year the downgrading of the issuer by rating agencies such as Moody's and Standard & Poor's. Contrary to Moody's and Standard & Poor's historical default statistics, EDFs are not biased by periods of high or low numbers of defaults. The distance to default can be observed to shorten during periods of recession, when default rates are high, and to increase during periods of prosperity characterized by low default rates.

A paper by Maria Larsson Birger Nilsson, (2010) tested the KMV methodology, the paper used data collected from 28 firms from EU and USA. Further, the paper used the KMV model in order to calculate the default probabilities of the companies for the period during the financial crisis. From the study they concluded that the model to a large extent is able to predict the default probability of a company. The results imply that the model is able to predict a default of a non-financial firm approximately 1.5 years before the default actually occurs. By examining the real data, the researcher conclude that KMV appears to have the ability to forecast the default of the firm, and also the result confirms the KMV's claims that the default probability is inverse proportional to the distance-to-default. They conclude that the model is successful in finding the relationship among the Distance-to-default (DD), the volatility of the firm's asset and the value of the firm's assets value.

Editors Desheng Dash Wu, David L. Olson, John R. Birge(2011); undertook a test on KMV model on Chinese market. The authors selected a wide range of sample data and calculate one by one, and use the results to analyze the applicability of the model in China from the perspective of micro level and macro level. It is cited that the model can be used to distinguish different risks of business and the model results can be associated with indicators of corporate credit risk, and the macroeconomic data also be used to validate the model. They concluded that the model can be used to distinguish different credit risks of China's Listed Companies, also cited to match with China's current credit rating system.

Other Chinese scholars achieved some progress in the combination and modification of KMV model. Research on KMV model in China market is mainly focused on basic theory, application on the empirical studies and improved model parameters. Wang Qiong and Cheng Jinxian (2002) in their book the Pricing Method and Models of Credit and Du Bengfeng (2002) in his book Real Value Option in Theory Applied to the Credit Risk Assessment the model of a theoretical foundation introduced the model of a theoretical foundation. Zhang Ling, and Zhang Jialin (2000) made a comparative study to KMV model and other model, they found that KMV model compared to the other model and is more conducive to the evaluation of the credit risk. Chen Peng and Wu Chong Feng (2002) organised enterprises into different groups and used KMV model to find that the computed default distance can match different risk categories. Based on the current researching achievements, the authors confirm the applicability and efficiency of the KMV model in Chinese market.

Amit Kulkarni Alok Kumar Mishra Jigisha Thakker (2010) this paper models the default probabilities and credit spreads for select Indian firms in the Black-Scholes-Merton framework. They show that the objective probability estimates are higher than the risk-neutral estimates over the sample period. However, the probability measure is found to be robust to the default trigger point. The model output also compares favorably with the default rate reported by CRISIL's Average 1-year rating transitions.

Christopher Crossen Xu Zhang (2011) undertook tests to validate the performance of the EDF, Expected Default Frequency model for Asian-Pacific and Japanese corporate firms during the 2001 to 2007, including the 2007 credit crisis and its recovery period. They divided the decade into two sub-periods: an early period, 2001–2007, and a later one, 2008–2010, and then compared the model's performance during these two periods. They also focused on the model's ability to prospectively differentiate between defaulters and non-defaulters, the timeliness of its default prediction, and its accuracy of levels. Overall, the EDF model's predictive power during the recent sample period was consistent with its previous longer history. On average, the model provided an effective early warning signal beginning 12 months before default occurs. EDF levels were conservative and higher than subsequently realized default rates during the crisis when compared with realized default rates. They found that EDF credit measures perform consistently well across different time horizons. Their tests indicated that EDF credit measures provide a very useful forward-looking measure of credit risk for firms in the Asian-Pacific region.

Desheng Dash Wu, David L. Olson and John R. Birge (2011) observes that foreign scholars have taken a deep study to KMV model. The authors go ahead to observe that; most of the research shows that KMV model qualifies the reliable and effective measurement functions to the credit risk, Desheng Et al, thinks that KMV model is suitable for any public companies. Vasicek (1995) confirmed that KMV model could predict the change in the revenues after he tested 108 debt rights as the study sample. Jeffrey's (1999) research shows that the highest credit quality is in the enterprise, the credit rating distribution is consistent with Standard and Poor. Crodbie and Bohn founded the financial companies formed to inspect sample KMV models to indicate that the default of the major events and KMV model was expected to be effective and sensitive, the KMV model has great predictive power. Kurba and Korablev (2003)" used the time span for 10 years, involving 4,000 American company's data as a sample of the system of KMV model to calculate the enterprises in different periods of the default to the actual rate agreement be fully corresponds, it is proved that KMV model is very effective measure to credit risk."

Norliza Muhamad Yusof, Maheran Mohd Jaffar(2017) analysed the default probabilities and its determinants using KMV model. They found that there is an increment in the forecasted probabilities of default of Malaysian airlines from 2009-2013. The highest forecasted probability of default is found in the year of 2013 and it is around 31%. The forecasted probabilities of default are said to be equivalent to the financial loss faced by MAS from 2011-2013. Therefore, the KMV-Merton Model is concluded as a valid model to be used in forecasting the current and future default of MAS. In addition, volatility and leverage are found to be the main determinants in forecasting default probabilities.

Feng Liu, Egon Kalotay, and Stefan Trueck (2017) undertook a study of KMV model. Their study assessed default risk of individual U.S. states utilizing information about default risk at the company level. Using data on Moody's KMV expected default frequencies on corporate default risk, they derived credit risk indicators for different industries. Building on these measures, they developed state level credit risk indicators encompassing industry compositions to explain the behaviour of credit default swap (CDS) spreads for individual states. They found that market-based measures of private sector credit risk are strongly associated with subsequent shifts in sovereign credit risk premiums measured by CDS spreads. The developed credit risk indicators are highly significant in forecasting sovereign CDS spreads at weekly and monthly sampling frequencies. They conclude that a strong predictive link between market expectations of private sector credit quality using KMV EDF and expectations of sovereign credit quality.

2.8 Overview of Literature

The general observation from the literature is that the KMV model is very robust for estimation of the probability of default for publicly traded firms. The methodology has not changed much over the years due to its simplicity and because it has passed the test over diverse markets both developed markets and developing markets. Most of the recent studies go to test applicability of the model to different localities and different economic cycles. The model has been validated in many countries across the economies of different sizes, from developed markets in the western countries as well as the Asian countries like China and India. There is however no literature on the effectiveness of the model on private unlisted companies, this could be attributed to the fact that such studies could be private and unpublished by financial institutions who undertake them. This study therefore aims to test the effectiveness of the model on privately owned companies not listed on any stock exchange.

3.0 Research Methodology

We choose 23 data points observe their default probabilities in 18 months window prior to default. We test the KMV model on these firms. Half of the firms defaulted about 12 months while the other half did not default. We select data from the corporate defaults observed in 2016-2017 and then pick the financial data for the 12-18 months earlier.

3.1 The Calculation Process of the KMV Model

In the option pricing framework, a default occurs when the asset value falls below the value of the firm's liabilities. Default is usually defined as the event when a firm misses a payment on a coupon and/or the reimbursement of principal at debt maturity. The calculation process of the KMV model usually includes the following steps.

3.1.1 The Calculation of Default Distance, Distance to Default

Merton's assumption regards that the firm' asset are tradable is violated by KMV. KMV Considered this and instead of this point, KMV only uses the Black-Scholes and Merton setups as motivation to calculate an intermediate phase called distance to default (DD) before computing the probability of default.

To derive the default probability of a particular firm, beside results of the values of the firm's asset and firm's volatility, we must calculate the distance to default. The default event happens when the value of firm's asset is below the default point. The face value of the debt is regarded as the default point in Merton's Model. By using the volatility of the firm's asset to measure, we can calculate the Distance-to-default. The larger the number is in the Distance to default, the less chance the company will default.

We use a model published by Chrouhy,M ,Galai D and Mark R.(2009). Under this assumption, we can regard the company's assets value as one call option on the underlying value of the firm with a strike price that equals to the company's debt. When the company's assets value is larger than the debt, the call option will be executed; otherwise, the holder will discard the call option. Yan Chen, Guanglei Chu (2014)

3.1.2 The asset growth

The asset growth used in the model by researches and KMV is typically risk free rate. It is taken to be the upper bound figure for the adoption in the model. Determination of risk free rate is based on 1 year Treasury bill rate which is officially determined by the Central Bank of Kenya. We use the average rate over the 18 month period window. The actual observed asset growth for each individual company will also be tested as an input; this is crucial because the underperforming companies may be expected to have low or negative growth in assets.

3.1.2 The Determination of Default Point

For the determination of default point is based on experience, KMV reach an empirical formation through long and large of statistics, so we take KMV's proposals in accordance with the flow of long-term debt plus half of the debt.

3.1.4 The Asset Volatility:

Theoretical Foundation of the adoption of account balance as a measure of volatility. It is a standard practice for bank credit policies to detail the attributes that point to the likelihood of distress and eventual default. There are two critical pointers to default; one critical trigger is the bank account activity and secondly the debt levels: The debt or leverage is well captured in the KMV model and this perhaps gives the model the strong predictive power as has been reviewed in the literature.

The bank account activity has been a long established as a key predictor of distress or default. Indeed, there is a common adage in the banking industry that "Cash is King". A study of 597,000 businesses by JPMorgan Bank in 2018 notes that for most business, cash reserves are a critical tool for meeting liquidity needs. Cash reserves provide a readily available means to pay employees and suppliers in normal times and are an important buffer to draw upon during adverse times. This is particularly true for small businesses with limited access to credit and other sources of liquidity. In other words, cash reserves are a key measure of the vitality and security of a small business.

Cash reserves provide small businesses with liquidity, a resource to draw upon when times get tough and an easy way to pay employees, vendors and suppliers. In other words, cash reserves ensure a small business' security. As JPMorgan observes, Cash is king, and as cash flow management is a deciding factor in whether or not a business succeeds or fails, it is a critical factor for businesses to get right. Even profitable businesses have gone bankrupt because of poor cash management.

A business in distress tend to have their bank account operate in a manner that banks describe as hardcore. This implies that there is little movement in bank account balances from day to day. Statistically, this can be measured as a low standard deviation and such businesses in distress have low standard deviation on bank balances. Such a business would hardly hold any credit balances and if they have a credit line in form of an overdraft, the balance would be at the maximum limit.

We shall adopt the standard deviation of bank account balances as a proxy for volatility. We argue that the low volatility is a true indicator of higher default risk. Sudheer Chava and Amiyatosh Purnanandam (2009) establishes that actual observation of the relationship between volatility and default tend to be inverse. Companies with low volatility do not tend to have higher defaults. This contradicts the efficient market hypothesis that states that less stable companies tend to have higher volatility. We find that this assumption of low volatility being a predictor of higher default probability fits very well in the predicted default. In fact, the formula itself as used by KMV shows an inverse relationship between the volatility and default. As per our data, companies with highly volatile bank account balances have lower default probability and this is in line with the expectations of credit managers and banking policies adopted in most banks We normalize the bank balances by dividing bank balances with the annual turnover to put the numbers into context and proceed to calculate the standard deviation.

Volatility is a value of the standard deviation, here we first calculate of the log of change of ratio of daily bank balances and annual turnover, then we calculate the standard deviation; the relationship between yearly standard deviation and daily standard deviation is:

$$\sigma_{B/T}^{year} = \sigma_{B/T}^{daily}\sqrt{313}$$

Where $\boldsymbol{B}$ is the bank account balances and $\boldsymbol{T}$ is the annual turnover of the specific company. Here we use 313 points of the daily standard deviation of bank account balances to measure the company's market volatility, and daily changes is obtained by natural logarithm of the ratio of the opening balance to turnover and closing bank balance to turnover. The daily balances available are for all days except Sunday, thereby having to use 313 days, excluding 52 Sundays in a year where data is not available because bank systems do not keep the data for Sundays. We use a full year data to deal with the variations across industries. Some firms operating industries such as agriculture tend to have seasonality in cash flows, since they get most cash around the harvesting season.

3.1.5 Market value of Assets

We propose to use the book asset values as published by the individual companies. Ewing, Maurice (Euromoney Training 2008-16) suggests that the book value of assets can be used where market values are unavailable.

3.1.6 Net Expected Growth of Assets

The standard practice for estimation of the growth is to adopt the risk-free interest rate. Yuqian Steven Lu (2008) In this case, we use the 364-day Treasury bill rate over the period covered in the research. The data are from CBK website. But since this rate fluctuates from month to month, we take the average risk-free rates for the entire period of data analyzed. The findings were not significantly different when we used the 90-day Treasury bill for the asset growth. We will also test the model taking the latest figure for growth of assets from the books of accounts. It was observed that companies under distress tend to have declining asset values and these observations is quite in line with the expectations as per most bank policies and procedures.

3.1.7 Time horizon

In general, the firm has a complex liability structure, and also, we can't gain the access to the details of the maturity time of this structure. Here, we assume the firm's liabilities will be matured in the time of one year. Any other duration can be used, and this is the utility of this model especially when estimating the life time probability of default.

Default point is calculated as the short-term liabilities plus half of long-term liabilities. These are book values as stated in the annual reports of the respective companies, these were obtained from the records stored and validated in the banks IT system used for making decisions on lending.

4.0 Empirical Findings and Discussions

As mentioned in chapter three, we test the model on a sample of firms that defaulted and a sample of firms that were good performers and on a few marginal firms.

We estimate the EDF for 80 financial statement years, this means that we look at financial statements of entities for 80 reporting data points. We have 27 companies that we look at 80 financial reporting periods. The findings are as follows: We group the entities into two categories, the ones who defaulted and the ones who did not default. Then we look at the ones whose default rate are over the cutoff point of probability of default at 26.78%. According to standard and poor's the highest default frequency for an entity that has not defaulted at the lowest rating of CCC, triple C is 26.78%. We therefore consider that any forecast default frequency above this threshold as a trigger for a default within the next one year to 18 months' time horizon.

Table 4.1: Default Frequencies.

NPL	Percentage	Count	Average of Default Probability, N(-DD)
No	45.52%	66	11.9%
NPL	54.48%	79	37.5%
Grand Total	100.00%	145	25.9%

From the results we observe that the ones who eventually defaulted had an average default frequency of 37.5%. This is above the trigger point for default frequency of 26.78%. The S&P has a threshold of 26.78%. Standard and Poor's (2017). The rest of the sample that did not default had an average default frequency of 11.9%. On this account, the KMV seems to predict with some reliability.

Table 4.2: Default Prediction using risk free rate as the asset growth.

KMV PD Over 26.78%	True NPLs		
	No	NPL	Grand Total
No	82.61%	64.84%	72.50%
Yes	17.39%	35.16%	27.50%
Grand Total	100.00%	100.00%	100.00%

The table clearly shows that the model performed very poorly; only 35.16% of the sample was correctly predicted to default. 64.84% of the sample was predicted to default but never defaulted within the following 12 months period. We adopt the model as-is and use the data available. Then we drop the use of the risk-free rate as the asset growth number and we adopt the actual observed asset growth as per the financial statements. This helps to minimize the adverse impact of absence of market data for assets. We derive the following results.

Table 4.3: Default Frequencies using the observed asset growth for the specific companies

KMV PD Over 26.78%	True NPLs		
	No	NPL	Grand Total
No	75.00%	29.73%	40.82%
Yes	25.00%	70.27%	59.18%
Grand Total	100.00%	100.00%	100.00%

We observe that 70.27% of the sample actually was predicted to default and went on to default. This shows promising results and that the KMV model can be used to predict default for portfolios with small sample where a financial institution does not have a well-established internal corporate rating system. The higher default frequencies are due to the lower asset growth rates for companies who are on the path to default. Such companies tend to have negative asset growth rates. This table shows the distribution of distance to default to the EDF, the Probability of default. This is based on the model that adopts the actual observed asset growth instead of the risk-free rate.

Table 4.4: Default Frequencies using the observed asset growth for the specific companies

Distance to default	Average of Default Probability, N(-DD)	Average Asset Growth
0.5 to Negatives	95.60%	(6.49)
0.5 to 1	28.79%	1.77
1 to 1.5	8.26%	5.78
1.50 to 2	4.00%	3.10
2.5 to 3	0.46%	3.89
3 to 3.5	0.09%	2.79
3.5 to 5	0.00%	17.43
over5	0.00%	11.04

4.1 Other Findings

It is worth to mention that about three companies that had significant exposure had no up to date books of accounts and went on to default. These are the only ones left out of the sample. We could therefore not test the effectiveness of the KMV model because they had no up to date books of accounts. This makes one to conclude that absence of audited book of accounts for a major private company is a negative signal that a major company is likely to default.

5.0 Conclusion and recommendations

The study reveals a surprising effectiveness of the KMV model and its applicability for estimating probability of default for companies that are not listed on a stock exchange but only with a modification to adopt the actual observed asset growth of the company reported in the books of accounts.

The adoption of the bank balances as a proxy for the asset volatility has also performed well. One other finding is that the only three companies that had material exposure and defaulted did not have the up-to-date audited books of accounts. We could therefore not test the effectiveness of the KMV model because the three had no up to date books of accounts. This makes one to conclude that absence of audited book of accounts is a major negative signal that a large borrower is likely to default. This is more significant for larger companies who have a legal requirement to prepare the audited financial statements and the absence of audited statements for a large company borrowing significant amounts could be taken as a major signal of inability to conclude the closure books of accounts with external auditors due to doubts about its going concern.

Annex /Appendix

Although the research was primarily focused on the privately-owned firms that are not listed on a stock exchange, we set out to also test the efficacy of the KMV model on a sample of listed firms.

We estimate all model parameters using the conventional formula as adopted by research without any modification. Chrouhy, Galai and Mark (2009). Volatility is a value of the standard deviation of stock returns; here we first calculate the return, being the change of log of weekly stock prices then calculate the standard deviation of the yield from weekly prices, so the relationship between yearly standard deviation and weekly standard deviation is:

$$\sigma_S^{year} = \sigma_S^{weekly}\sqrt{52}$$

Where S is the stock prices. Here we use 52 points of the weekly standard deviation of stock prices to measure the company's market volatility, and week yield is obtained by logarithm of ratio of the opening balance and closing bank balance.

Market value of Assets

We propose to use the daily market values of listed companies from the stock exchange. Values are obtained for *www.mystocks.co.ke*

Net Expected Growth of Assets

The standard practice for estimation of the growth is to adopt the risk-free interest rate. Yuqian Steven Lu (2008). In this case, we use the 364 day Treasury bill rate over the period covered in the research. The data are from CBK website. But since this rate fluctuates from month to month, we take the average risk free rates for the entire period of data analyzed.

We will also test the model taking the latest figure for growth of assets from the books of accounts. It was observed that companies under distress tend to have declining asset values and these observation is quite in line with the expectations as per most bank policies and procedures.

Time horizon

For a defaulting firm, value of the firm's assets tends to be roughly equal to the short-term liabilities plus half of the long-term liabilities. Default point is calculated as the short-term liabilities plus half of long term liabilities. These are book values as stated in the annual reports of the respective companies, these were obtained from published books as posted in the website *https://africanfinancials.com/document/*

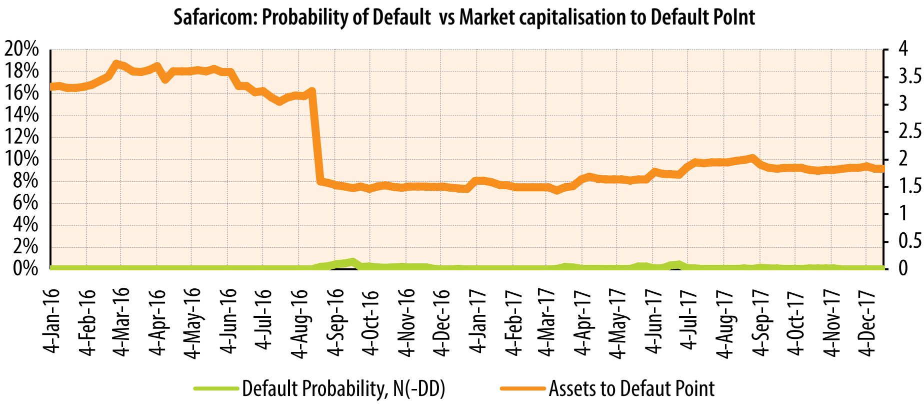
We pick 11 listed firms, this sample comprise of firms that defaulted on their debt, and a sample of the other firms who did not exhibit signs of financial distress. The information about default or financial distress is publicly available at the stock exchange filings and on the auditor's opinion contained in the audited books of accounts. The financial data was obtained from https://africanfinancials.com while stock market data was obtained from the website mystocks.co.ke. The following are the firms selected.

No.	Name of the firm	Comments
1	Safaricom Ltd	No signs of financial distress
2	East Africa Breweries	No signs of financial distress
3	East Africa Cables	Signs of financial distress observed
4	Kenya Airways	Signs of financial distress observed
5	East Africa Portland	Signs of financial distress observed
6	Mumias Sugar	Signs of financial distress observed
7	Bamburi Cement	Signs of financial distress observed
8	Deacons	Signs of financial distress observed
9	ARM cement	Minor signs of financial distress observed
10	Uchumi Supermarkets	Signs of financial distress observed
11	East African Breweries	No signs of financial distress

We carried out an analysis over a longer time span for thee specific companies that have a long history of default. These include the companies such as; Mumias Sugar, Uchumi Supermarkets, ARM cement, and Kenya Airways. For more financially sound companies, we did an analysis of two years.

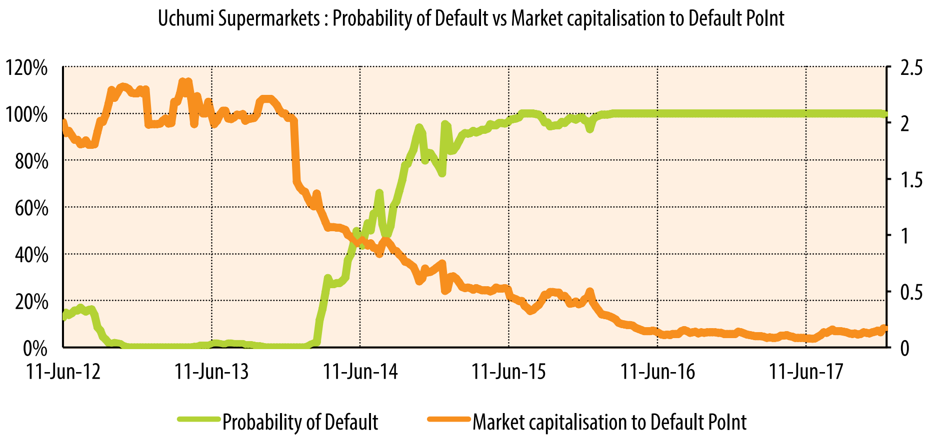
Safaricom Limited

The default probability has been zero for the last two years. The market capitalization for the company is very high compared to the liabilities on the books of the accounts. As at the end of 2017 financial year, the company had total liabilities at Kenya shillings 43.5 billion compared to a market capitalization of 1.04 trillion as at end of 2017. The possibility of inability to pay their debts can be viewed as close to zero. We also plot the ratio of asset values to default point; a ratio of above 1 indicates an elevated possibility of default.

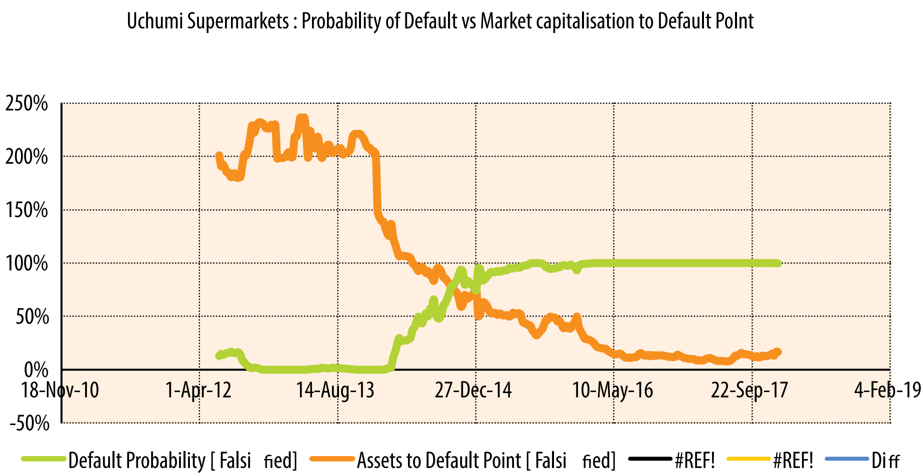


Uchumi Supermarkets

The default probability crossed the 26% threshold in the month of March 2014 and stayed above that threshold up to 2017. The Standard and Poors consider that if a company rated Tripple C, CCC, has a probability of default of 26%. This implies that this ratio is the trigger threshold for a company's inability to pay. It is worth noting that the probability of default rose sharply in 2014 despite the lack of doubt of going concern by the auditors in that year. It is worth noting that the audited books of 2014 were restated in 2015 when the company got a new chief executive. (Daily Nation Newspaper 2015). Despite the errors and falsification in the 2014 audited books, KMV model was able to raise the probability of default estate even before the corrections were made.

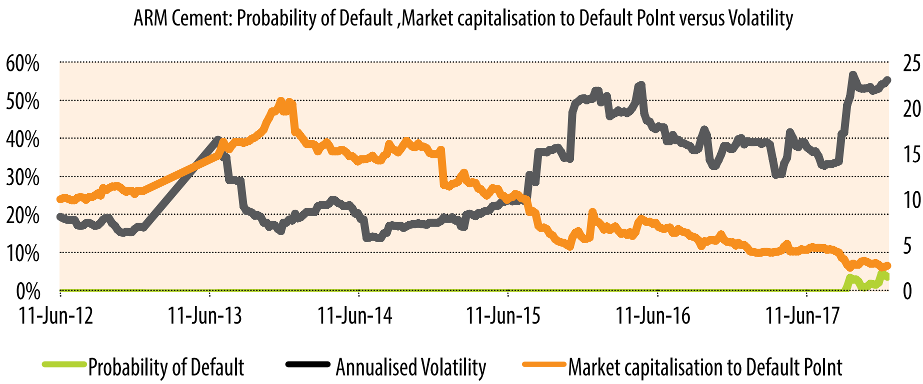


Uchumi Supermarkets: Falsified Books of 2014



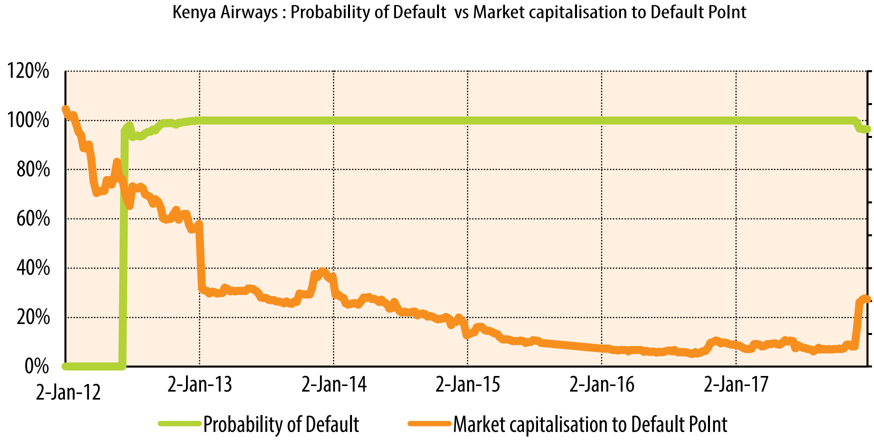
ARM cement

For ARM cement, the default probability has been rising steadily after years of low observed figures and this could explain the recent filing by the company that is has sought a restructuring of its debt with the main financier and the news that the auditor raised doubts of going concern of the company. Business daily 2018



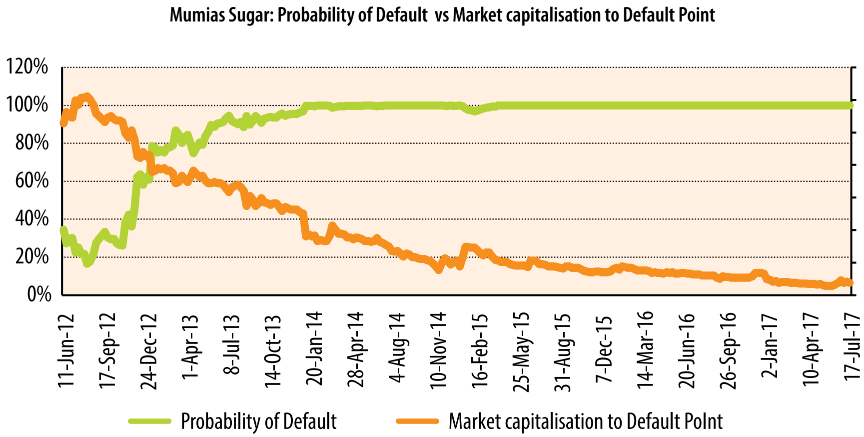
Kenya Airways

The default probability crossed the 26% threshold in 2012 and stayed above that threshold up to 2017. The recent conversion of bank debt to equity has helped to raise the market capitalization and reduce the probability of default marginally but the trend is reversing for the worst. As at 2015, the auditors expressed concerns about the doubts of the ability of the airline to continue as a going concern due to a net loss of KShs 3,382 million during the year ended 31 March 2015 and, as of that date, the Group's current liabilities exceeded its current assets by KShs 40,701 million (2014 – KShs 34,120 million) and the Group's total liabilities exceed its total assets by KShs 5,963 million.



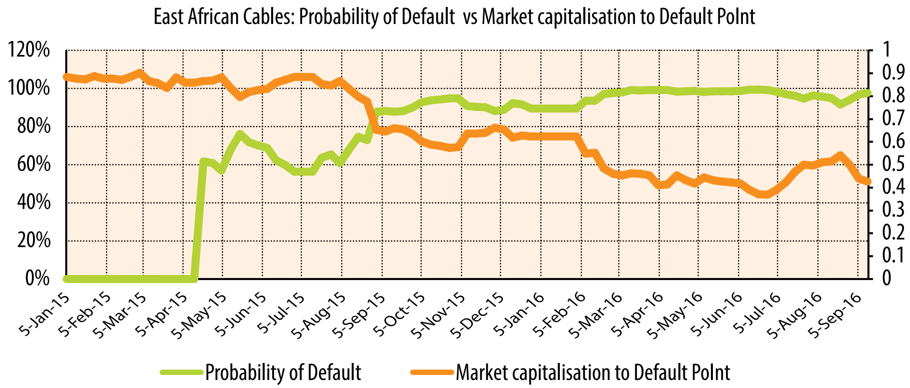
Mumias Sugar

The default probability has been permanently above 20% since 2012 and it has stayed above that threshold up to 2017. This is in line with a qualification of the financial statements of the company by the auditor in the year 2017. The auditor general's conclusion in the audited books of accounts of 2017 indicate that there was material uncertainty that casts doubt on the going concern of the company. The stock market was able to price the uncertainty into the share price and eventually leading to a high probability of default.



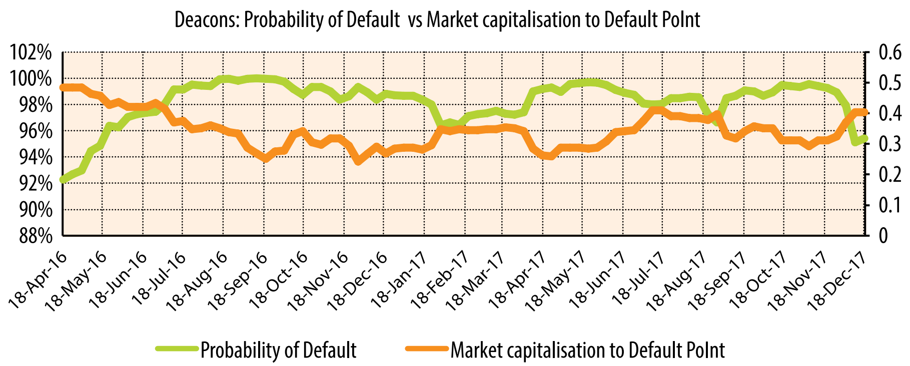
East African Cables

The default probability crossed the 26% threshold in April 2015 and stayed above that threshold up to 2017.



Deacons Limited

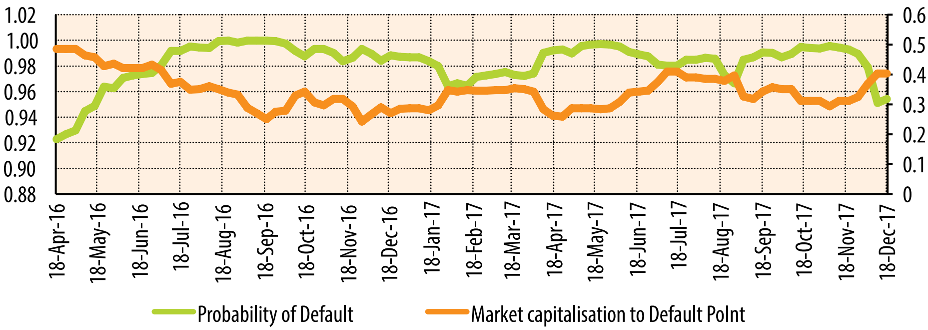
In the annual report dated 2016, the auditor expressed concern regarding the value of slow moving inventories held by the company whose value was indicated to be Kenya shillings 900 million. This is material given that the annual turnover of the company was 2.3 billion and gross profit for the year at for the same year at Kenya shillings 1 billion.This information is seen to be priced in the stock price of the company leading to a high probability of default.



East African Portland Cement

The default probability has been above 90% for the duration of two years covered. This corroborates the auditor general's conclusion in the audited books of accounts of 2016 that there was material uncertainty that casts doubt on the going concern of the company. The stock market was able to price the uncertainty into the share price and eventually leading to a high probability of default.

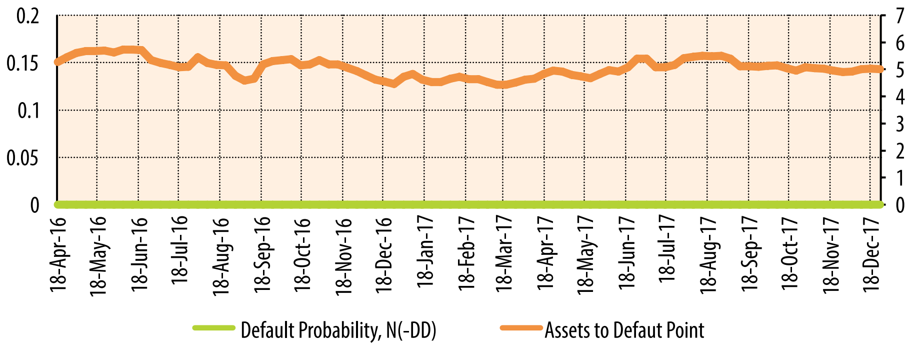
EA Portland Cement Probability of Default vs Asset to Default PoInt



East African Breweries

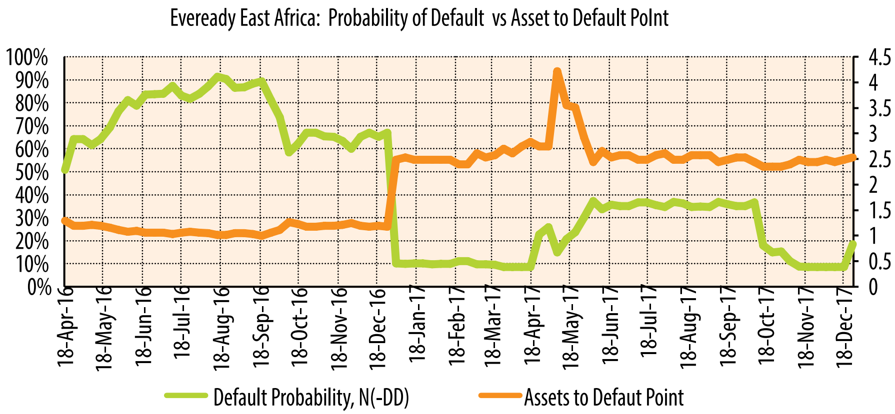
The default probability has been zero for the last two years. The market capitalization for the company is very high compared to the liabilities on the books of the accounts. As at the end of 2017 financial year, the company had total liabilities at Kenya shillings 54.6 billion compared to a market capitalization of 192 billion shillings as at end of 2017. The possibility of inability to pay their debts can be viewed as negligible.

EA. Breweries: Probability of Default vs Asset to Default PoInt



Eveready East Africa Limited

The results for this company are mixed. The probability of default was estimated to be very high the beginning of the year 2016 but it dropped. This drop could be attributed to improvement in the operating income of Kenya shillings 267 million in 2017 from previous loss of Kenya shillings 216 million posted in 2016.



Conclusions on the survey of listed firms

The model is quite robust, and it can complement the other methodologies for estimation of the probability of default; the only shortcoming is that it can only be used on the listed firms which are only 67. The model does not apply to the eleven publicly listed financial institutions and the six insurance companies.

Testing the Altman's Z score on privately owned unlisted firms

Edward Altman (2006) developed the Z score model for emerging markets. The critical financial ratios are as follows;

X1 = working capital/total assets

X2 = retained earnings/total assets

X3 = operating income/total assets

X4 = book value of equity/total liabilities

Altman developed a model for emerging markets and the estimated coefficients are as follows.

$$\textbf{EM Score} = 6.56\,(X1) + 3.26\,(X2) + 6.72\,(X3) + 1.05\,(X4) + 3.25$$

A firm that scores below 1.75 is considered to be an equivalent of a default rating class, meaning that they represent a form that have failed to honour is debt obligations.

Table : Altman's Z score

Z score range	Did not default	Defaulted	Grand Total
Negatives	1.11%	0.52%	1.62%
Zero to 1.75	75.68%	8.25%	83.94%
1.75 to 2.30	7.15%	0.44%	7.59%
2.30 to 2.50	0.88%	0.07%	0.96%
2.50 to 2.90	1.03%	0.07%	1.11%
2.70 to 2.90	0.66%	0.07%	0.74%
2.90 to 3.10	0.59%	0.00%	0.59%
3.1 to 3.3	0.44%	0.00%	0.44%
3.3 to 5	1.84%	0.07%	1.92%
over 5	1.11%	0.00%	1.11%
Grand Total	**90.49%**	**9.51%**	**100.00%**

Using the financial ratios of the privately-owned firms and the check on the firms that defaulted, we find that the model predicted that a total of 85.56% (83.94 plus 1.62%) of the sample would default but only 8.75 defaulted (8.25 plus 0.52%). The model therefore over predicts default hence it is not fit for purpose.

Average Z score across size of firm

Size of firms total Assets in Kenya shillings	Average of Fin Score	Count of Firms
0 to 500,000	9	10.44
500,000 to 1,000,000	6	0.22
1m to 5 m	147	-2.92
5m to 50 m	2351	6.66
50m to 100m	966	5.34
100m to 250m	1253	5.01
250m to 1billion	1637	4.24
1 billion to 5 billion	1744	4.18
Over 10 billion	884	2.69

The larger firms tend to have lower z scores, with 884 firms that have total assets at Kenya shillings 10 billion and above having an average z score of 2.69. The small we firm have much higher z scores, though the trend reverses for firms with total asset size of between 5 million to half a million. The number of firms in that bracket are also quite low.

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33. Yuqian (Steven) Lu 2008. Dissertation for MSc Mathematical and Computational Finance, University of Oxford.

Notes

Kenya Bankers Association
13th Floor, International House, Mama Ngina Street
P.O. Box 73100– 00200 NAIROBI
Telephone: 254 20 2221704/2217757/2224014/5
Cell: 0733 812770/0711 562910
Fax: 254 20 2221792
Email: research@kba.co.ke
Website: www.kba.co.ke

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