Global Journal of Management and Business Research: C Finance
Volume 22 Issue 1 Version 1.0 Year 2022
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals
Online ISSN: 2249-4588 & Print ISSN: 0975-5853

Predicting SME Insolvency in Sub-Saharan Africa: A Cameroonian Evidence

By Marius Ayou Bene, Cyrille Onomo & Romuald Kenmoe Siyou

Essec Business School University of Douala

Abstract- This paper aims to propose a model for predicting SME insolvency in the Sub-Saharan context. Based on a sample of 1183 Cameroonian SMEs from 2013 to 2015, we performed a logistic regression in panel data. The results show a persistence of insolvency over time when effected in an SME. It is also seen in the results that SME insolvency is determined by financial variables related to business management, financial structure, and profitability. On the other hand, it is determined by non-financial variables such as management quality, staff compensation, and SME size, which reinforce the power of insolvency prediction models. However, some determinants of insolvency in small firms are insignificant in medium-sized firms.

Keywords: insolvency prediction, financial ratios, logistic regression.

GJMBR-C Classification: *JEL Code: G33, M41, C25*

PREDICTINGSMEINSOLVENCYINSUBSAHARANAFRICAACAMEROONIANEVIDENCE

Strictly as per the compliance and regulations of:

Predicting SME Insolvency in Sub-Saharan Africa: A Cameroonian Evidence

Marius Ayou Bene [α], Cyrille Onomo [σ] & Romuald Kenmoe Siyou [ρ]

Abstract- This paper aims to propose a model for predicting SME insolvency in the Sub-Saharan context. Based on a sample of 1183 Cameroonian SMEs from 2013 to 2015, we performed a logistic regression in panel data. The results show a persistence of insolvency over time when effected in an SME. It is also seen in the results that SME insolvency is determined by financial variables related to business management, financial structure, and profitability. On the other hand, it is determined by non-financial variables such as management quality, staff compensation, and SME size, which reinforce the power of insolvency prediction models. However, some determinants of insolvency in small firms are insignificant in medium-sized firms.

Keywords: insolvency prediction, financial ratios, logistic regression.

I. Introduction

The difficult access of Small and Medium-sized Enterprises (SMEs) to credit is an impediment to their development and stands as a major economic concern in African countries (Honohan and Beck, 2007). This constraint has been eased in developed and emerging countries thanks to the dynamism of financial markets and the establishment of interconnected systems, including the credit guarantee system (OECD, 2015). In Southern countries, financial systems offer few solutions to the problem of SME financing (Beck and Cull, 2014), especially since in these contexts, financial markets are poorly developed and bank credit financing is predominant (Masetti and Mihr, 2013, Allen et al., 2011). Because of the high uncertainty about borrowers' repayment capacities, banks considerably ration credit to SMEs (Wamba and Tchamambé, 2002).

Several factors explain the rationing of credit to SMEs. A distinction must firstly be made between micro-rationing, which consists of capping the amount of credit granted, and macro-rationing, which refers to situations in which applications for credit from certain borrowers are randomly rejected (Ghosh et al., 1990).

In general, credit rationing is justified by information asymmetries that can accentuate problems of adverse selection and moral hazard (Stiglitz and Weiss, 1981, Sharpe, 1990). In Sub-Saharan Africa, these phenomena are prevalent because firms, and especially SMEs, suffer from weaknesses in the production and dissemination of quality information (Seca Assaba, 2002). As a result, credit institutions face a significant rate of delinquency, which is the corollary of high exposure to credit risk.

In an attempt to control credit risk, these entities insist on the requirement of real guarantees (Bester, 1985) and a long-term customer relationship (Bodenhorn, 2003). However, despite the improvement in the reliability of guarantees [1], their use as a solution to the problem of non-repayment of credit remains controversial. In this vein, the rigorous use of techniques to predict borrower default is indicated (Stiglitz and Weiss, 1981). Moreover, the prudential regulations enacted by the Basel Accords encourage banks to adopt internal models for predicting the default of credit applicants, but many banks in Africa have not yet done so.

Much of the work on prediction of credit applicant default or firm failure focuses on developed economies and large firms. There are few studies on the subject in relation to SMEs (Altman and Sabato, 2007, Altman et al., 2010) and in sub-Saharan Africa. Yet the recent financial crisis has led to an increase in the number of firm failures in all countries of the world (Alaminos et al., 2016). In African countries, studies available address the consequences of credit risk for financial institutions (Kolapo et al., 2012, Afriyié and Akotey, 2012, Gizaw, 2015), credit risk mitigation mechanisms (Gweyi, 2013), and models for predicting the failure of African firms (Appiah, 2011, Ncube, 2014). A few rare studies such as Bushe (2019) or Adalessossi (2015) deal with insolvency in SMEs in Africa. However, an effective insolvency management system can facilitate access to financial resources and improve the growth and viability of SMEs (World Bank, 2013, p109).

Moreover, SME insolvency management systems in sub-Saharan Africa are less effective than those in OECD countries. Between 2014 and 2015, the insolvency management ranking of OECD countries improved. On average, these countries moved from a rank of 27 to 22. During the same period, countries in the African region moved from a ranking of 134 to 128. However, Central Africa is the area with the worst performing arrangements, and North Africa is the area with the best performing arrangements in the continent. In OECD countries, the debt recovery rate rose from

Author α σ: Essec Business School University of Douala, Cameroon.
e-mails: abmarius@hotmail.com, onomocyr@yahoo.fr
Corresponding Author ρ: Department of Management and Applied economics University of Douala, Cameroon.
e-mail: kromualdnoel@gmail.com

70.6% in 2014 to 71.9% in 2015. In the CEMAC zone, this rate rose from 6.6% to 8.8%. In Sub-Saharan Africa, it stands at 24.1% in 2015 while it is 17.3% in the OHADA area (World Bank, 2013 p109-116, World Bank, 2014, p112-118). In terms of insolvency management, Cameroon is ranked lower. It ranked 151 in 2014 and 123 in 2015. Over this period, the debt recovery rate in this country was 15.4%. However, in Botswana, which is one of the highest ranked African countries, this rate rose from 61.9% to 62.67%, which seems to justify the good quality of the insolvency management system in this country compared to Cameroon.

However, the lack of a clearly defined procedure for determining business failure in many countries in the region makes it difficult to capture SME bankruptcy. Nevertheless, because a sharp deterioration in the financial health of an SME can result in an intermediate or definitive insolvency situation and lead to the non-repayment of credit, predicting SME insolvency would promote better credit decision making in favor of these entities.

This work proposes a model for predicting SME insolvency in a sub-Saharan African country to help lenders make better credit decisions. Based on financial and managerial information drawn from a sample of 1183 Cameroonian SMEs over the period 2013-2015, a logistic regression in panel data is performed to define insolvency predictors. It emerges that insolvency is determined by business management, financial structure and profitability, management quality, staff remuneration and the size of the SME. As a result, the set of insolvency predictors changes as one moves from small to medium-sized firms.

The rest of the article is structured as follows: in Section 2, a review of the literature on the determinants and predictive models of insolvency in the SME dimension is conducted. Section 3 explains the data and methods. Finally, in section 4, empirical results are presented and discussed. The last section concludes the paper.

II. Insolvency Prediction in SMEs: A Review of the Literature

Credit decisions for SMEs are based on an assessment of their risk profile in order to mitigate the risk of non-repayment (Dohnal, 2008). This is especially true because they are very opaque in terms of information, with financial statements that are sometimes uncertified. Also, they do not have sufficient material assets to guarantee the loans requested (Blanco et al., 2012). Insolvency determines the company's inability to pay its debts and is a major credit risk event (Wood, 2012). Therefore, building insolvency prediction models becomes a feasible solution of SME financing issue (Blanco et al.,). However, the literature on insolvency prediction does not provide a unified definition of the concept, and in the absence of a theory to explain the phenomenon, insists on the variables to be included in the model and the analytical techniques used (Alaminos et al., 2016).

a) *Definition of insolvency*

Attempts to define insolvency are given by several fields: law, economics, accounting, finance. Armour (2001) presents several approaches to the analysis of corporate insolvency. From an accounting perspective, insolvency means that the book value of a firm's assets is lower than that of its debts. The argument developed by studies in finance is different. Insolvency is associated with cash flow and takes on the meaning of the situation of a firm that is unable to extinguish its debts when they come due (Cohen, 1998, p22). It is observed when the firm encounters difficulties in settling its creditors, and this depends on the structure of debt repayments and the nature of the assets used to satisfy them. The accounting and financial approaches are not always consistentand may conflict in the context of an analysis.

Insolvency is a signal of a firm's bankruptcy (Beaver, 1966), which makes it possible to distinguish between high-risk and low-risk firms (Ooghe and Van Wymeersch, 1996). It refers to a set of default situations characterized by the non-repayment of debts, the non-payment of dividends or "financial distress", which may lead to the initiation of legal proceedings (Levratto, 2013). For Wood (2012), in the dimension of the firm, the term bankruptcy is widely used to translate the insolvency process. It refers to a legal situation of insolvency and financial distress (Alaminos et al., 2016).

Nevertheless, there is a lack of consensus on the definitions of bankruptcy, insolvency and financial distress. This is why these terms are often used interchangeably in the literature (Van Der Colff and Vermaak, 2015).

b) *Predictors of insolvency in SMEs*

Work on bankruptcy prediction is helping to separate the good companies from the bad ones (Levratto, 2013). The objective is to disentangle these two types of firms and to encourage good selection in a situation of information asymmetry. For Cultrera and Brédart (2016), the prediction of bankruptcy focuses on the economic, strategic, organizational and managerial, and financial approaches, although most of the work has focused on the financial approach. Thus, in this vein, work has emphasized financial indicators as predictors of bankruptcy (Beaver, 1966, Altman, 1968). The aim was to identify the symptoms of bankruptcy from a financial perspective. For Altman and Sabato (2007), an application of models for predicting the bankruptcy of large firms in the SME dimension would lead to poor results.

In the work of Blanco et al., (2012) on English SMEs, it appears that liquidity, debt, activity, profitability and size ratios are good predictors of the bankruptcy of these entities. In the same context, Lin et al., (2012) use these main financial variables for the prediction of SME bankruptcy. Camacho-Minano et al., (2013), in predicting the insolvency of Spanish SMEs, consider indicators of financial structure, liquidity, profitability and financial viability among other indicators. Ptak-Chmielewska (2019), finds in the case of Polish SMEs, the same financial indicators. Efficient SMEs and highly liquid SMEs have a low probability of bankruptcy. For Cultrera and Brédart (2016), profitability and liquidity ratios are good predictors of insolvency in Belgian SMEs. Regarding Russian SMEs, Lugovskaya (2010) predicts insolvency based on liquidity and profitability indicators. In the case of SMEs in the hospital sector in Portugal, Pacheco (2015) concludes that only financial structure variables predict the insolvency of these entities.

In addition to financial measures, a set of non-financial factors are presented as predictors of SME bankruptcy. The quality of management (mainly strategic management errors) of the firm determines its bankruptcy (Charan and Useem, 2002). According to these authors, the experiences of several firms show that bankruptcy is related to bad managerial decisions favored by a lack of rigor linked to long periods of success, by a lesser consideration of market threats, by a management style that hinders good feedback, by excessive risk-taking, by the strategic approach and dysfunctions of the board of directors. In addition to these factors, Ooghe and Prijcker (2006), by analyzing bankruptcy as a process, point out the errors in the definition of corporate policy and external factors. From these analyses, it emerges that among the non-financial factors, managerial limitations and the inefficiency of the governance system further explain corporate bankruptcy. In SMEs, Altman et al., (2010), show that non-financial indicators reinforce the power of bankruptcy prediction models. El Kadak and Hudson (2016), Gupta et al., (2018), Mihajlovic et al., (2015) or Tobbak et al., (2017), show that the size of the SME, its sector of activity, its network and its organizational and managerial factors affect the probability of bankruptcy. Thus, non-financial measures complement financial measures for a better prediction of insolvency in SMEs.

In Africa, a few rare works have dealt with the prediction of SME bankruptcy. Bushe (2019) shows that entrepreneurial incapacity, environmental threats and weak firm skills are factors in SME failure in South Africa. In the same context, Fatoki (2014) identifies the internal and external causes of SME failure. Among the internal causes, he identifies mainly managerial shortcomings. Adalessossi (2015) draws on the financial indicators used by Altman (1968) to predict SME failure in East Africa.

From these various studies, it emerges that the causes of SME failure, even in Africa, are both financial and non-financial. For powerful predictive power, SME analysis models need to integrate financial and non-financial indicators.

c) Insolvency prediction models in SMEs

The identification of predictors of business failure is based on scoring models. These models refer to statistical methods used to determine the probability that a credit applicant, or a borrower in a credit relationship, will default or become delinquent (Mester, 1997). They thus make it possible to evaluate the quality of the firm in terms of solvency, bankruptcy, and voluntary or involuntary default. This assessment leads to the assignment of a score (Feldman, 1997), or probability of default, that classifies firms as "good" or "bad" customers.

The work of Beaver (1966) and Altman (1968) using discriminant analysis is among the most widely cited in this area. For Beaver (1966), the probability of firm failure is conditional on the value that a given financial ratio would assume. Based on a sample of 79 healthy and 79 bankrupt firms, the author identifies predictors of bankruptcy. One of the limitations of Beaver's model is that the bankruptcy phenomenon can be explained by a single factor. This model does not take into account the existence of correlations between the explanatory variables. The author recommends a multivariate approach. Altman's Z-score (1968) is part of this approach. The author applies multiple discriminant analysis to a sample of 33 bankrupt and 33 viable firms. His model identifies financial ratios capable of better simultaneously predicting a firm's bankruptcy.

Following the Z-score model, several authors have proposed models for predicting business failure using the technique of Multiple Discriminant Analysis (MDA) in different contexts. However, the literature identifies limitations in the use of this technique, all related to the violation of the main assumptions underlying it. On the one hand, the bankruptcy explanatory variables included in the model still do not jointly follow a normal density distribution. On the other hand, the identical character of the covariance matrices of the two groups of firms in the sample is not always verified. Moreover, this type of model, whose final result is a score, does not allow for a clear identification of the contribution of each variable to the explanation of the bankruptcy phenomenon (Sabato, 2000).

Studies by Ohlson (1980), which use logistic regression to predict bankruptcy, provide an alternative. This technique makes it possible to estimate the bankruptcy probability of a firm, conditional on its membership in the group of those that have gone bankrupt. The analysis covers a sample of 2163 firms, and the author identifies determinants of bankruptcy. He also identifies a threshold value of bankruptcy probability that allows him to classify the firms in one of the two groups. Thus, a firm with a probability of less than 0.038 is considered bankrupt. Several subsequent studies analyze bankruptcy using techniques borrowed from the fields of operational research and artificial intelligence. These studies use data envelopment analysis (DEA) (Simak, 1997), artificial neural networks (Boritz et al., 1995, Charitou et al., 2004), decision trees (Friedman, 1976) and genetic algorithms (Holland, 1975).

The multitude of insolvency prediction models provides food for thought on the power of some analyses compared to others. Comparative analysis of market information is more powerful than those using accounting data. Paradoxically, univariate insolvency prediction models seem to perform better as compare to multivariate ones. According to Aziz and Dar (2006), insolvency prediction models can be grouped into three classes: statistical models, artificial intelligence models and theoretical models. The models in the second group appear to be better. However, models based on MDA or logistic regression dominate the research on the subject.

In addition, work on the prediction of bankruptcy in SMEs focuses on several statistical techniques. Some authors use the data mining technique (Tobback et al., 2017), the DEA model (Monelos et al., 2014), discriminant analysis (Lugovskaya, 2010), and the genetic algorithm (Gordini, 2014). However, most studies use logistic regression (Alaminos et al., 2016, Altman and Sabato, 2007, Altman et al., 2010, Cultrera and Brédart, 2016, Blanco et al., 2012, Pacheco, 2015).

However, few studies address the prediction of insolvency in SMEs in sub-Saharan African countries. Yet such analyses would encourage the proper allocation of resources to SMEs through good credit decision making. Especially in a context where access to credit remains very difficult for this type of enterprise.

III. Data and Specification of the Model for Predicting the Insolvency of SMEs in Cameroon

This section presents the data used in this study, specifying the sources of the data and outlining selection criteria of firms under study. Then, it presents the insolvency prediction model proposed by the study and its rationale.

a) *Study data*

The data used are taken from the accounting statements of 1183 Cameroonian SMEs over the period 2013 - 2015. They cover 3549 observations. This information is provided by the INS[1] of Cameroon. The sample of SMEs under consideration is composed of entities operating in different sectors of activity. In addition, it is made up of small companies (with less than 50 employees) and medium enterprises (with between 50 and 100 employees). The extraction of the two subgroups was done by excluding companies that changed subgroup over the study period. Thus, the subgroup of small companies accounts for 77.88% of all observations; while the subgroup of SMEs operating in the tertiary sector accounts for 84.19%.

The explanatory variables in our study correspond to the financial ratios used in studies dealing with bankruptcy prediction (Charitou et al., 2004, Ciampi and Gordini, 2009, Blanco et al., 2012) and non-financial measures such as SME size (Gupta et al., 2018), management quality (Charan and Useem, 2002) and staff remuneration. All of these variables are listed in the table below:

Table I: Study Variables

Code	Names of variables	Calculation method
Tdta	General solvency ratio	Total liabilities / Total assets
Cptd	Financial Autonomy Ratio	Shareholders' equity/ Total liabilities
Cpta	Equity Multiplier	Shareholders' equity/Total assets
Actd	Short-term repayment capacity ratio	Current assets /Total liabilities
Acpc	Current ratio	Current assets /Current liabilities
acstockspc	Quick ratio	(Current assets – Inventories)/Current liabilities
Acca	Current asset turn over ratio	Current Assets / Sales
Créances Dispopc	Reduced liquidity ratio	(Receivables<1year + cash)/ Current liabilities
Pctd	Debt structure ratio	Current liabilities / Total liabilities
Dispopc	Immediate liquidity ratio	Cash and cashe quivalents / Current Liabilities
Dispotd	Immediate debt coverage rate	Cash and cashe quivalents / Total debt
Dispota	Ability to finance assets with cash and cash equivalents	Cash and cashe quivalents / Total assets
Ebeta	Return on capital employed	Earnings before taxes & interests /Total assets
Ebecp	Gross margin ratio	Earnings before taxes & interests /Shareholders' Equity

Ebepc	Short-term debt coverage ratio	Earnings before taxes & interests /Current Liabilities
Ebetd	Debt coverage ratio	Earnings before taxes & interests /Total liabilities
Chpersoebe	Weight of personnel expenses	Personnel expenses/Earnings before taxes & interests
Chexpta	Quality of management	Operating expenses/Total assets
Logta	Size of the company	Log(total active)
Cata	Asset Turnover Ratio	Sales / Total assets
Pcca	Short-term financing turn over ratio	Current Liabilities/Sales
Ebeca	Economic margin	Earnings before taxes & interests/Sales
Rnca	Net Profitability Ratio	Net income/Sales
Rncp	Financial profitability ratio	Net income / Shareholders' equity
Rnta	Return on assets ratio	Net income/Total assets
Reta	Economic Profitability Ratio	Gross operating income /Total assets
Cperta	Asset coverage ratio	Long term capital/Total assets
Chfiebe	Ability to repay interest	Financial expenses/Earnings before taxes & interests

[1] *National Institute of Statistics in Cameroon*

Insolvent companies represent 36.99% of all observations. It emerges that in the sample studied, 95.80% of small businesses in one year remain insolvent the following year. Only 4.20% of medium-sized companies in one year change status from small companies in the previous year. However, 65.30% of SMEs that are insolvent in a given year may remain so the following year. However, this proportion is 66.72% in the small business sub-sample and 62.69% in the medium business sub-sample. On the other hand, 19.66% of SMEs insolvent in one year may be the result of those solvent in the previous year. In the group of small companies, this proportion is 20.17%, while it is 16.56% in the group of medium-sized companies. Thus, for a very large number of insolvent SMEs, poor financial health is persistent over the years. However, this persistence is stronger in small companies. Also, it is more in the small business group that entities that are solvent in one year may become insolvent in the following year.

The probabilities of transition from solvency to insolvency from one year to the next are given in the table below.

Table II: Transition Matrix

Set					Small Businesses				Medium-sized companies			
		Solvency			Solvency				Solvency			
		0	1	Total		0	1	Total		0	1	Total
Solvency	0	80,34	19,66	100	0	79,83	20,17	100	0	83,44	16,56	100
	1	34,70	65,30	100	1	33,28	66,72	100	1	37,31	62,69	100
	total	63,44	36,56	100	Total	61,77	38,23	100	Total	69,82	30,18	100

Source: data of current study

In companies in the sample, equity represents 71.76% of the volume of debt. It represents 126.29% of the volume of debt in solvent SMEs and -21.11% of the volume of debt in insolvent SMEs. In the same vein, it represents 80.18% of the debt volume in small companies and 42.12% in medium-sized companies. Medium-sized enterprises, compared to small enterprises, finance themselves more with debts. In these entities, current assets represent 86.3% of the volume of debts. Also the current ratio is 111.09%, the reduced liquidity ratio is 99.36% and the immediate liquidity ratio is 29.97%. The immediate liquidity ratio show an average value of 31.38% in small firms, and 25% in medium ones. These entities are therefore not very exposed to liquidity risk.

The SMEs in the sample bear operating expenses per unit of assets of 1.85. This ratio is 1.79 in solvent SMEs and 1.97 in insolvent SMEs. Thus, insolvent SMEs appear to have a low quality of management compared to solvent SMEs. Also, this ratio is 1.88 in small firms and 1.77 in medium firms. The latter would then be better managed than the former. Moreover, the SMEs studied have an average financial profitability of 32.93%. Paradoxically, it is 30.19% in the group of solvent SMEs and 37.58% in the group of insolvent ones. In the group of small enterprises, it is

33.57% and 30.66% in the group of medium enterprises. The economic profitability ratio is on average -1.37% for all SMEs. It is 6.91% in solvent SMEs and -15.47% in insolvent structures. This ratio is respectively -1.63% in small and -0.45% in medium-sized companies. In these structures, long-term resources per unit of assets are 11.51%. They are 42.75% in solvent SMEs and -41.69% in insolvent ones. These long-term resources represent 8.33% of the volume of assets in small companies and 22.71% in medium-sized companies.

Table 3: Descriptive statistics

Sample			All		Solvent		Insolvent		Primary		Secondary		Tertiary		SE		ME	
Observations			3549		2236		1313		48		561		2940		2764		785	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Cptd	0,72	1,86	1,26	2,13	-0,21	0,53	0,39	1,60	0,44	1,36	0,78	1,95	0,80	1,98	0,42	1,32		
Cpta	0,01	1,10	0,37	0,57	-0,61	1,45	-0,21	1,04	0,04	0,78	0,01	1,15	-0,01	1,18	0,09	0,69		
Actd	0,86	1,00	1,15	1,15	0,37	0,28	0,70	1,07	0,74	0,70	0,89	1,05	0,88	1,08	0,80	0,65		
Acpc	1,11	1,30	1,43	1,44	0,56	0,78	0,81	1,10	1,06	1,16	1,13	1,33	1,10	1,36	1,14	1,07		
Créancesdispopc	0,99	1,34	1,30	1,50	0,47	0,77	0,62	1,30	0,88	1,12	1,02	1,38	1,00	1,39	0,97	1,15		
Pctd	0,86	0,24	0,87	0,23	0,84	0,26	0,88	0,20	0,82	0,26	0,87	0,24	0,88	0,23	0,80	0,25		
Acstockspc	0,69	1,05	0,89	1,17	0,34	0,68	0,50	0,89	0,66	0,92	0,69	1,08	0,68	1,10	0,70	0,84		
Dispota	0,12	0,19	0,13	0,19	0,12	0,18	0,09	0,17	0,10	0,16	0,13	0,19	0,13	0,19	0,10	0,15		
Dispotd	0,24	0,66	0,34	0,81	0,07	0,12	0,16	0,52	0,17	0,50	0,26	0,69	0,26	0,70	0,17	0,48		
Dispopc	0,30	0,75	0,41	0,90	0,12	0,28	0,17	0,52	0,21	0,57	0,32	0,78	0,31	0,76	0,25	0,68		
Ebeta	0,10	0,53	0,16	0,45	-0,01	0,64	0,08	0,29	0,10	0,50	0,10	0,54	0,10	0,55	0,10	0,45		
Ebepc	0,43	1,29	0,63	1,52	0,08	0,63	0,18	0,46	0,34	1,13	0,45	1,33	0,47	1,34	0,27	1,09		
Ebecp	0,45	1,64	0,74	1,47	-0,05	1,79	0,72	1,76	0,45	1,78	0,44	1,61	0,43	1,63	0,49	1,67		
Ebetd	0,34	1,09	0,53	1,32	0,03	0,36	0,16	0,38	0,25	0,82	0,37	1,15	0,39	1,15	0,18	0,85		
Acca	0,68	1,09	0,66	1,11	0,70	1,05	0,79	1,22	0,72	0,95	0,67	1,11	0,68	1,16	0,66	0,81		
Rnca	-0,08	0,48	-0,02	0,45	-0,18	0,51	-0,04	0,22	-0,11	0,51	-0,07	0,48	-0,09	0,51	-0,03	0,33		
Cata	1,86	1,66	1,88	1,59	1,83	1,76	1,71	1,97	1,61	1,39	1,91	1,70	1,88	1,68	1,78	1,57		
Chpersoebe	0,69	2,08	0,94	1,86	0,28	2,34	0,26	1,77	0,76	2,08	0,69	2,08	0,63	2,09	0,91	2,01		
Chexpta	1,86	1,63	1,79	1,51	1,97	1,81	1,72	1,95	1,61	1,33	1,91	1,67	1,88	1,65	1,78	1,58		
Logta	18,05	1,76	18,17	1,73	17,86	1,78	18,55	1,49	18,59	1,76	17,94	1,74	17,57	1,52	19,74	1,47		
Pcca	1,11	1,55	0,76	1,26	1,70	1,78	1,77	2,10	1,12	1,47	1,09	1,55	1,16	1,61	0,92	1,26		
Ebeca	0,03	0,45	0,07	0,43	-0,06	0,48	0,08	0,19	0,02	0,42	0,03	0,46	0,02	0,48	0,06	0,32		
Rncp	0,33	1,03	0,30	0,93	0,38	1,17	0,38	1,17	0,32	1,17	0,33	0,99	0,34	1,01	0,31	1,09		
Rnta	-0,01	0,58	0,07	0,44	-0,15	0,73	-0,01	0,30	-0,01	0,55	-0,01	0,58	-0,02	0,59	0,00	0,50		
Reta	0,04	0,55	0,12	0,44	-0,10	0,67	0,02	0,29	0,02	0,50	0,04	0,56	0,03	0,56	0,07	0,50		
Cperta	0,12	1,09	0,43	0,57	-0,42	1,48	-0,09	1,06	0,16	0,76	0,11	1,14	0,08	1,16	0,23	0,73		
Chfiebe	0,04	0,63	0,06	0,46	0,00	0,85	0,05	0,29	0,07	0,65	0,03	0,63	0,03	0,34	0,05	1,18		

First column lists the covariates analyzed and their failed and non-failed status. The remaining columns report the Mean and standard deviation (SD) of firms of the primary, secondary and tertiary sectors, small and medium sizes firms.

b) Specification of the empirical insolvency prediction model

To predict the insolvency of SMEs in Sub-Saharan Africa based on the financial variables that characterize their health, we use a binary logit model in panel data. Logistic regression was chosen firstly because it does not depend on the constraining assumptions of other statistical techniques frequently used in the literature, such as multiple discriminant analysis or linear models for predicting the probability of default (Ohlson, 1980, Sabato, 2010). Furthermore, this is the most widely used model in studies on the prediction of insolvency in SMEs (Altman and Sabato, 2007, Altman et al., 2010). Finally, the dependent variable in our solvency model is dichotomous, as in the case of several studies that have dealt with this issue (Ohlson,1980, Ciampi and Gordini, 2009).

A logit model describes the relationship between a dependent variable that can assume the value 1 (bankrupt firm) and 0 (healthy firm), and n other explanatory variables that can be quantitative or qualitative $x_1, x_2, \dots, x_n$.

Since the dependent variable is binary, it follows a Bernoulli distribution such that $P_i = P(y_i = 1)$is the probability of bankruptcy and $1 - p_i$ is the probability of non-failure.

The estimated model considers an endogenous variable which is a linear combination of the exogenous variables:

$$y^* = \beta X_i + \varepsilon_i (1)$$

where ε is the error term and β the vector of coefficients and where

$$y_i = 1 \; if \; y_i^* > 0; y_i = 0 \; if \; \; y_i^* \leq 0$$

The probability of non-default (a posteriori) of company i is given:

$$P(y_i = 0) = P(y_i^* \leq 0) = P(\beta X_i + \varepsilon_i \leq 0)$$
$$= P(\varepsilon_i \leq -\beta X_i)$$
$$F(-\beta X_i) = 1 - F(\beta X_i) = 1 - P_i (2)$$

Similarly, the probability of insolvency (a posteriori) of firm i is represented by:

$$P(y_i = 1) = P(y_i^* > 0) = P(\beta X_i + \varepsilon_i > 0)$$
$$= P(\varepsilon_i > -\beta X_i)$$
$$1 - P(\varepsilon_i \leq -\beta X_i) = F(\beta X_i) = P_i (3)$$

The Logit model assumes that the error terms follow a logistic law where the distribution function is:

$$F(x) = (1 + e^{-x})^{-1} (4)$$

Therefore, it is possible to calculate the probability of non-default of firm$i$ as follows:

$$P(y_i = 0) = F(-\beta X_i) = \left(1 + e^{\beta x_i}\right)^{-1} = \; 1 - P_i (5)$$

Similarly, the probability of default of firm i is:

$$P(y_i = 1) = F(\beta X_i) = \left(1 + e^{-\beta x_i}\right)^{-1} = \; 1 - P_i (6)$$

The estimation of the parameters β is made by the Maximum Likelihood Method. Our analysis approach is strongly based on the study of Ciampi and Gordini (2009). First, a considerable number of financial and non-financial ratios are retained, based on the literature. Then, significant ratios are selected after a univariate analysis. Subsequently, a choice of variable is made with the objective of alleviating collinearity problems. Finally, to determine the predictors, a logistic regression is performed using the stepwise method. This approach is clearly defined in the figure below.

Selection of financial ratios based on:
-frequency of use in the literature
-Ability to describe the essential features of a company's economic and financial profile

⇓

Univariate Analysis

⇓

Multicollinearity (VIF method)

⇓

Elimination of Predictor with VIF >6

⇓

Stepwise Methods

Source: Ciampi and Gordini (2009)

Figure I: Selection process for financial ratios

Global Journal of Management and Business Research (C) Volume XXII Issue I Version I Year 2022

Table IV: Collinearity test

Sample	Collinearity statistics	
	Tolerance	VIF
ACTD	,186	5,379
ACPC	,152	6,593
ReceivablesDispoPC	,042	23,641
ACStocksPC	,065	15,407
PCTD	,460	2,176
DispoPC	,118	8,480
EBETA	,122	8,226
EBECP	,773	1,294
EBETD	,345	2,898
ChpersoEBE	,914	1,094
ChEXP/TA	,620	1,612
LogTA	,659	1,517
PCCA	,629	1,591
EBECA	,570	1,754
RNCP	,761	1,314
RNTA	,153	6,551
RETA	,138	7,221
CperTA	,510	1,961
ChfiEBE	,908	1,102
CPTD	,339	2,952

IV. Results and Discussions

Table III above presents descriptive statistics for default firms and the non-default firms. We can see that the average values of ratios in the non-default firms tend to be positive while in bankrupt firms they are mostly negative. In general, the financial ratios of insolvent firms tend to fluctuate more than those of non-default firms. It can therefore be inferred that financial results in bankrupt firms are highly volatile. This result corroborates that of Guo (2008). Indeed, it is very easy to find extreme values in the balance sheets of insolvent firms, especially when insolvency has just occurred.

The multicollinearity between the explanatory variables is tested by using the variance inflation factor (VIF). Referring to studies by Ciampi and Gordini (2009), where the VIF>6 condition is adopted, we exclude the following explanatory variables: ACPC, Creances DispoPC, ACstocsPC, DispoPC, EBETA, RNTA, RETA. In order to reduce the number of explanatory variables by retaining only the important ones in the insolvency prediction model, we used the stepwise method. The variables retained differ according to the models contained in Table V.

From the logistic regression carried out, it appears that, overall, the insolvency of the SME depends on several exogenous variables. It is strongly explained by the management of the operations, productivity, quality of management, financial structure and profitability of the company.

The probability that a firm is insolvent is not related to the different liquidity ratios. Thus, this result is contrary to those obtained by Ptak-Chmielewska (2019), Cultrera and Brédart (2015), Camacho-Minanoet al., (2013), Blanco et al., (2012) in the SME field, who find a negative link between the probability of insolvency and the liquidity of these entities. On the other hand, it corroborates that of Pacheco (2015) in Portuguese SMEs.

In the SMEs investigated, short-term repayment capacity is negatively related to insolvency. An increase in the volume of current assets per unit of debt induces a decrease in the probability of SME insolvency. This relationship is observed in SMEs operating in the secondary and tertiary sectors, in groups of small and medium-sized enterprises. Indeed, in Cameroon, the debt recovery rate is only 24.1% (World Bank, 2014, p114). In this context, inventories and cash and therefore current assets are more mobilized to extinguish debts in SMEs. The short-term financing turnover ratio is positively related to insolvency. Thus, an increase in current liabilities per unit of sales leads to an increase in the probability of insolvency of the SME. These results show that business management ratios determine the probability of SME insolvency as advocated by Blanco et al., (2012).

Moreover, insolvency is negatively related to the debt structure in SMEs as a whole. In these entities, the lower the proportion of short-term debt increases, the lower the probability of insolvency. Indeed, the current liabilities in these companies are essentially made up of operating and non-operating debts, and to a small extent of bank loans. In this context, an increase in current liabilities helps to reduce the working capital requirement and ensure the financial equilibrium of the company. However, this relationship is not observed in the medium-sized companies group. Also, equity per unit of debt is negatively related to the insolvency of the SME. An increase in equity per unit of debt is associated with a reduction in the probability of insolvency of the entities studied. Indeed, an increase in the weight of equity capital results in a reduction in the weight of debt in relation to the SMEs assets, and thus a decrease in the insolvency ratio. These results show that in Cameroonian SMEs, insolvency is determined by financial structure ratios. These results confirm those of Pacheco (2015) or Camacho-Minano et al., (2013).

The insolvency of the SME is negatively related to the gross margin ratio. An increase in gross wealth creation per unit of equity in an SME contributes to reducing the probability of insolvency of that structure. As a result, profitable SMEs are more solvent. These results confirm those obtained by Blanco et al.,(2012), Cultrera and Brédart (2015). Thus, profitability determines the insolvency of the SME.

In the firms investigated, regardless of their size or sector of activity, the weight of personnel expenses is negatively related to insolvency. A decrease in total staff compensation relative to a level of gross operating surplus is associated with an increase in the probability of SME insolvency. Therefore, for SMEs, good employee compensation leads to solvency. However, operating expenses per unit of assets are positively related to the company's insolvency ratio. An increase in operating expenses per unit of assets leads to an increase in the probability of insolvency of the SME. Therefore, low quality of management in the SME is associated with insolvency. This result corroborates that obtained by Charan and Useem (2002). Thus, in insolvent structures, bad managerial decisions can be observed, favored by lack of rigor, lesser consideration of market threats, a management style that hinders smooth bottom-up reporting, and excessive risk-taking. To ensure its solvency, an SME must improve the quality of its management and the remuneration granted to its employees in view of its gross operating surplus. In the different models, the size of the SME is negatively related to insolvency. Thus, whether in the overall sample, in the small business group or in the medium business group, an increase in the size of the SME reduces its probability of insolvency. These results confirm those of Gupta et al., (2018) and are contrary to those of Blanco et al., (2012).

In addition to financial variables, the models highlight the importance of non-financial variables in predicting SME insolvency in the Cameroonian context. Staff remuneration, quality of management, and SME size are key explanatory factors for insolvency in these entities. These results corroborate the findings of Altman et al., (2010). Therefore, in order to improve their probability of solvency and provide an attractive credit profile, Cameroonian SMEs need to ensure better business management and high profitability of their activities. They must also improve the remuneration of their staff in view of the increase in gross operating surplus and adopt more professional management styles.

Table V: Logit regression (dependent variable: bankruptcy)

Model 1											
	ACTD	PCTD	CHPERSEBE	CHEXPTA	LOGTA	PCCA	CPTD	EBECP	EBETD	CONST	$N.R^2$
Parameters	-2,55***	-0,45**	-0,12***	0,14**	-0,17***	0,28**	-1,51***	-0,39***	0,55***	4,33***	60%
E.S.	0,17	0,21	0,02	0,04	0,03	0,04	0,10	0,03	0,1	0,69	
Wald	351,24	4,70	25,61	13,26	27,77	52,49	215,15	139,29	30,58	39,23	
Model 2											
	ACTD	PCTD	CHPERSEBE	CHEXPTA	LOGTA	PCCA	CPTD	EBECP	EBETD	CONST	$N.R^2$
Parameters	-2,10***	-1.34***	-0,13**	0,19	-0,38***	0,40***	-3,42***	-0,29***	0,30	8,60***	65%
E.S.	0,40	0,52	0 ,07	0 ,14	0,10	0,12	0,48	0,07	0,29	2,05	
Wald	27,66	6,66	4,21	1,87	14,91	10,76	51,62	18,37	1,87	17,59	
Model 3											
	ACTD	PCTD	CHPERSEBE	CHEXPTA	LOGTA	PCCA	CPTD	EBECP	EBETD	CONST	$N.R^2$
Parameters	-2,55***	-0,35	-0,12***	0,13***	-0,14***	0,25***	-1,43***	-0,41***	0,59***	3,73***	59%
E.S.	0,15	0,23	0,03	0,04	0,04	0,04	0,11	0,04	0,11	0,74	
Wald	305,62	2,36	20,23	10,82	14,98	38,19	176,02	122,21	28,05	25,24	
Model 4											
	ACTD	PCTD	CHPERSEBE	CHEXPTA	LOGTA	PCCA	CPTD	EBECP	EBETD	CONST	$N.R^2$
Parameters	-2,47***	-0,43*	-0,12***	0,12***	-0,16***	0,30***	-1,32***	-0,36***	0,38***	4,08***	59%
E.S.	0,15	0,24	0,03	0,04	0,05	0,04	0,10	0,04	0,11	0,88	
Wald	272,42	3,24	20,16	7,48	12,61	47,22	160,06	99,58	11,42	21,33	
Model 5											
	ACTD	PCTD	CHPERSEBE	CHEXPTA	LOGTA	PCCA	CPTD	EBECP	EBETD	CONST	$N.R^2$
Paramètres	-3,07***	-0,42	-0,11*	0,24**	-0,2*	0,19*	2,96***	-0,47***	1,63	5,06	60%
E.S.	0,36	0,46	0,06	0,1	0,11	0,1	0,40	0,08	0,35	2,25	
Wald	72,62	0,86	3,34	6,12	3,49	3,80	55,51	36,16	21,54	5,06	

***,**,* significant at 1%, 5% and 10% respectively

$N.R^2 = NagelkerkeR^2 adjusted$

Model 1 (general model)

Model 2 (tertiary sector companies)

Model 3 (primary and secondary sector companies)

Model 4 (very small businesses)

Model 5 (medium-sized companies)

V. Conclusion

Easy access to credit for SMEs remains one of the most important economic problems in sub-Saharan African countries. Inadequate or non-existent accounting and financial information provided by these entities feeds the reluctance of credit institutions to provide them with financing. To alleviate this problem, in addition to the use of collateral and customer relationships, it is necessary for lenders to develop models to predict SME default.

By analyzing insolvency as a vector of SME default, this study aimed at identifying the predictors of SME insolvency in order to promote good credit decision making by lenders and improved credit market efficiency in this context. The study conducted on Cameroonian SMEs using panel data logistic regression shows that insolvency is dependent on financial variables related to the management of the operations, financial structure, and profitability of the SME. On the other hand, it is also determined by non-financial variables relating to the quality of management, size, and remuneration of the staff of these entities. As a result, SMEs must take financial measures concerning the management of their business, financial structure and profitability in order to reduce the probability of insolvency. They must also improve the quality of management through rigorous managerial decision-making that takes into account market threats. To achieve this, they must ensure that their staff is properly remunerated.

For the SMEs investigated, insolvency, when it is observed, remains persistent over time. This persistence of insolvency is more pronounced in small enterprises compared to medium-sized enterprises. Moreover, while debt structure and debt coverage ratios determine insolvency in small firms, they do not explain it in medium-sized firms. Thus, with respect to SMEs, rather than adopting a systematic credit rationing behavior, an analysis of the financial and non-financial variables specified by the models defined can encourage the selection of the right firms, and especially the adoption of a differentiated analysis depending on the group to which the SME belongs.

The prediction rate could be increased if the insolvent sample can be paired with non-insolvent. Furthermore robustness check of the model can be also investigated. Further investigations in that sense will be the object of future research.

References Références Referencias

1. Adalessossi, K. 2015. Prediction of corporate bankruptcy: Evidence from West African SME's, Journal of Economics, Finance and Accounting, Vol. 2, No3.
2. Afriyie, H.O. and Akotey, J.O. 2012."Credit risk management and profitability of selected rural banks in Ghana", Ghana: Catholic University College of Ghana. www.econrsa.org/.../2012/afriyie-credit-ris management.
3. Alaminos, D., DEL CASTILLO.and FERNANDEZ M.A.2016. A global model of bankuptcy prediction, Plos One, Vol 11, No 11,
4. ALLEN, F., OTCHERE, I.and SENBET, L. W. 2011. African financial systems: A review. Review of Development Finance, vol. 1, pp. 79-113
5. Altman, E.I.1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, Vol.23, n°4, pp.589-609
6. Altman, E.I and Sabato, G. 2007. Modelling credit risk for SMEs: Evidence from the US market. Abacus, Vol. 43, No3, pp.332-357.
7. Altman, E.I., Sabato, G. and N. Wilson 2010. The value of non-financial information in SMEs risk management. Journal of Credit Risk, Vol 6, No2, pp.95-127.
8. Appiah, K.O. 2011. Corporate failure prediction: some empirical evidences from listed firms in Ghana. China-USA Business Review, Vol.10, no 1, pp.32-41
9. Armour, J. 2001. The law and economics of corporate insolvency: A review. Centre for Business Research, University of Cambridge Working Paper No. 197
10. Aziz, A.M. and Dar, H.A. 2006. Predicting corporate bankruptcy: Where we stand? Corporate Governance, Vol. 6, No.1, pp.18-33.
11. Beaver, W.H. 1966. Financial ratios as predictors of failure. Journal of Accounting Research, vol.4, No.3, pp.71–111
12. Beck, T. and Cull, R. 2014. SME finance in Africa. World Bank Group Policy Research Working Paper No. 7018
13. Bester, H. 1985. Screening vs. rationing in credit markets in imperfect information. American Economic Review, No. I75, pp. 850- 861
14. Blanco, A., Irimia, A. and Oliver, M. D. 2012. The prediction of bankruptcy of Small firms in the UK using logistic regression Analisis Financiero, No118, pp.32-40.
15. Bodenhorn, H.2003. Short-term and long-term relationships: Relationships lending in early. Journal of Money, Credit, and Banking, vol. 35, no 4, pp. 485-505
16. Boritz, J.E, Kennedy, D.B. and Albuquerque, A.1995. Predicting corporate failure using a neural network approach, Intelligent Systems. Accounting, Finance and Management, Vol. 4, pp. 95–11.
17. Bushe, B. 2019. The causes and impact of business failure among small to micro and medium enterprises in South Africa. Africa's Public Service Delivery and Performance Review, Vol 7, No.1
18. Calice, P., Chando, V. and Sekioua, S. 2012.Bank financing small and medium enterprises in East Africa: Finding of a survey in Kenya, Tanzania, Uganda and Zambia. Africa Development Bank Group Working Paper Series No. 146.
19. Camacho-minano, M.M., Segovia-vargas, M-J., and Pascual-ezama, D. 2013, Which characteristics predict the survival of insolvent firms? An SME reorganization prediction model. Journal of Small Business Management,
20. Charan, R. and Useem, J. 2002.Why Companies Fail—CEOs offer Every Excuse but the Right One: Their own Errors. Here are Ten Mistakes to Avoid. Fortune, Vol. 145, No. 11, pp. 50-62
21. Charitou, A., Neophytou, E. and Charalambous, C. 2004. Predicting corporate failure: empirical evidence for the UK. European Accounting Review, Vol. 13, No. 3, pp. 465-497
22. Ciampi, F. et Gordini, N. 2009. Default prediction modeling for small enterprises: Evidence from small manufacturing firms in Northern and Central Italy. Oxford Journal, Vol.8, No.1, p13 -29
23. Cohen, E. 1998. Gestion financière de l'entreprise et développement financier, EDICEF, Universités Francophones, 302p
24. Cultrera, L.and BRÉDART, X. 2016.Bankruptcy prediction : The case of Belgian SMEs. Review of Accounting and Finance, Vol. 15, No.1, pp.101-119.
25. Dohnal, M., 2008. Basel II implementation – retail credit risk mitigation. Bank and Bank systems, Vol. 3, No.2, pp. 54-68
26. EL KADAK, I. et R. HUDSON 2016. The effect of size on the failure probabilities of SMEs: An empirical study on the US market using discrete hazard model, International Review of Financial Analysis, Vol. 43
27. Fatoki, O. 2014. The Causes of the Failure of New Small and Medium Enterprises in South Africa. Mediterranean Journal of Social Sciences, Vol. 5 No. 20
28. Friedman, J.H 1976. A recursive partitioning decision rule for nonparametric classification, SLAC-PUB-1373, Stanford Linear Accelerator Center www.slac.stanford.edu/cgi-wrap/getdoc/slac-pub-1573.pdf
29. Feldman, R. 1997. Small Business Loans, Small Banks and a Big Change in Technology Called Credit Scoring. Federal Reserve Bank of Minneapolis, pp. 19-25
30. Ghosh, S., Collins, E. and Scofield, L. 1990. Prediction of mortgage loan performance with a

multiple neural network learning system, proceeding of Eurasip. Workshop, Sesmbra, Portugal, pp. 439.
31. Gizaw, M., Kebede, M. and Selvaraj, S. 2015. The impact of credit risk on profitability performance of commercial banks in Ethiopia. Academic Journals, vol. 9, No.2, pp.59-66
32. Gordini, N. 2014.A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy, Expert Systems with Applications, doi: http://dx.doi.org/10.1016/j.eswa.2014.04.
33. Gupta, J., Barzotto, M. and Khorasgani, A. 2018.Does Size Matter in Predicting SMEs Failure?
34. Gweyi M,. 2013. Credit risk mitigation strategies adopted by commercial banks in Kenya. International Journal of Business and Social Science, Nol.4, No 6, pp. 71-78, ijbssnet.com/journals/Vol.4_No.6_June_2013.
35. Honohan, P. and Beck, T. 2007. Making finance work for Africa. The World Bank, 264p
36. Kauffmann, C. 2005. Financing SMEs in Africa. OECD, Policy Insights No. 7
37. Kolapo, T.F., Ayeni, R.K. and Oke, M. 2012. Credit risk and commercial banks performance in Nigeria: A panel model approach. Australian Journal of Business and Management Research, Vol. 2, No 2, pp. 31-38
38. Levratto, N.2013. From failure to corporate bankruptcy : A review. Journal of Innovation and Entrepreneurship, Springer Open Journal.
39. Lin, S-M., Ansell, J. and Andreeva, G. 2012. Predicting default of small business using different definitions of financial distress. Journal of the Operational Research Society, Vol. 63, pp. 539-548.
40. Lugovskaya, L. 2010.Predicting default of Russian SMEs on the basis on financial and non-financial variables. Journal of Financial Services Marketing, Vol. 14, pp.301-313.
41. Masetti, O. and Mihr, A,. 2013. Capital markets in Sub-Saharan Africa", Deutsche Bank Research. Mester, L.J. 1997. "What's the point of credit scoring?" Business Review (September/October) pp. 3-16.
42. Mihajlovic, I. 2015. The Reasons for SME's Failure, Comparative Analysis and Research. Proceedings of FIKUSZ '15 Symposium for Young Researchers, 7-22
43. Monelos, P., Piñeiro Sánchez, C. and Rodríguez López, M. 2014. DEA as a business failure prediction tool : Application to the case of galician SMEs. Contaduría y Administración, Vol. 59, No2, pp. 65-96.
44. Ncube, T.2014. Predicting corporate failure: Insight from the financial sector in Zimbabwe. International Journal of Economics, Commerce and Management, vol. 2, no11,jecm.co.uk/wp-content/uploads/2014/11/21130
45. OECD, 2015.New approaches to SME and entrepreneurship financing: broadening the range of instruments. OECD, 119p
46. Ohlson, J.1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, vol. 18, no3, pp.109-131
47. Ooghe, H. and Van wymmersch, C. 1996. Traité d'analyse financière, 6e édition, Presses Universitaires de Namur.
48. Ooghe, H. and S. Prijcker, 2006. Failure processes and causes of corporate bankruptcy: A typology. VLG Working Paper series, 2006/21.
49. Pacheco, L. 2015. SMEs probability of default: The case of hospitality sector. Tourism and Management Studies, Vol 11, No1, p 153-159.
50. Ptak-chmielewska, A. 2019. Predicting Micro-enterprise failure using data mining techniques. Journal of Risk and Financial Management.
51. Sabato, G. 2000. Credit risk scoring models. Working paper, http://ssrn.com/abstract = 1546387
52. Seca assaba, P. 2002.Information et communication financière dans les entreprises en Afrique subsaharienne : contraintes et perspectives. In : Drumaux, A. etMattijs, J (ed), Défis de l'information et pilotage des entreprises, AUF, Jouves, pp. 21-35
53. Sharpe, S.A, 1990.Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships. The Journal of Finance, Vol.45, No.4, pp. 1069-1087.
54. Simak, P.C, 1997. DEA Based Analysis of Corporate Failure. Thesis submitted in conformity with the requirements for the Degree of Masters of Applied Science, Department of Mechanical and Industrial Engineering, University of Toronto.
55. Stiglitz, J. and Weiss, A. 1981. Credit rationing in markets with imperfect information. American Economic Review, vol. 71, no3, pp. 393-410.
56. Tobback, E., Bellott,I. T. Moeyersoms, J., Stankova, M. and Martens, D. 2017.Bankruptcy prediction for SMEs using relational data. Decision Support Systems, doi:10.1016/j.dss.2017.07.004
57. Van der colff, F. and Vermaak, F. 2015. Predicting financial distress using financial and non-financial variables. Journal of Economics and Financial Sciences, Vol. 8, No.1, pp. 243-260.
58. Wamba, H. and Tchamanbe, L .2002.Information financière et politique d'offre de crédit bancaire aux PME: Cas du Cameroun. Revue Internationale PME, Vol. 15, No. 04, pp.87-113
59. Wood, A.P, 2012. The performance of insolvency prediction and credit risk models in UK: A comparative study, development and wider application. Thesis for the degree of Doctor of Philosophy in Accountancy, University of Exeter.
60. World bank, 2013. Doing Business 2014: Understanding Smarter Regulations for Small and

Medium-Size Enterprises, Washington, DC: World Bank Group. DOI: 10.1596/978-0-8213-9615-5
61. World bank, 2014. Doing Business 2015: Going Beyond Efficiency,
62. Washington, DC: World Bank Group. DOI: 10.1596/ 978-1-4648-0351-2