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

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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..

Index terms— insolvency prediction, financial ratios, logistic regression.

1 Introduction

he 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 **??**ihr, 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 microrationing, 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 **??**eiss, 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 **??**abato, 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 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.

2 II.

3 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).

4 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 nonpayment 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).

5 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 Pacheco (2015) concludes that only financial structure variables predict the insolvency of these entities.

In addition to financial measures, a set of nonfinancial 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 nonfinancial indicators.

6 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 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.

7 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 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. 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

8 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 **??**abato, 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 andGordini, 2009).

A logit model describes the relationship between a dependent variable that can assume the value 1 (bankrupt firm) and 0 (healthy firm), and ?? other explanatory variables that can be quantitative or qualitative ?? 1 , ?? 2 , ? , ?? ?? .

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

The estimated model considers an endogenous variable which is a linear combination of the exogenous variables:?? * = ???? ?? + ?? ?? (1)

where ?? is the error term and ?? the vector of coefficients and where?? ?? = 1 ???? ?? ?? * > 0; ?? ?? = 0 ???? ?? ?? * ? 0

The probability of non-default (a posteriori) of company ?? is given:??(?? ?? = 0) = ??(?? ?? * ? 0) = ??(???? ?? + ?? ?? ? 0) = ??(?? ?? ? ????? ??) ??(????? ??) = 1 ? ??(???? ??) = 1 ? ?? ?? (2)

Similarly, the probability of insolvency (a posteriori) of firm ?? is represented by:??(?? ?? = 1) = ??(?? ?? * > 0) = ??(???? ?? + ?? ?? > 0) = ??(?? ?? > ????? ??) 1 ? ??(?? ?? ? ????? ??) = ??(???? ??) = ?? ??**(3)**

The Logit model assumes that the error terms follow a logistic law where the distribution function is:??(??) = (1 + ?? ???) ?1 (4)

Therefore, it is possible to calculate the probability of non-default of firm?? as follows:??(?? ?? = 0) = ??(????? ??) = ?1 + ?? ?? ?? ?? ? ?1 = 1 ? ?? ?? (5)

Similarly, the probability of default of firm ?? is:??(?? ?? = 1) = ??(???? ??) = ?1 + ?? ??? ?? ?? ? ?1 = 1 ? ?? ?? (6)

The estimation of the parameters ?? 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.

9 Figure I: Selection process for financial ratios

Source: Ciampi and Gordini (2009) 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

10 Univariate Analysis

Multicollinearity (VIF method)

11 Elimination of Predictor with VIF >6

Stepwise Methods IV.

12 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 **??**uo (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), **??**ultrera 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), **??**ultrera 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. V.

13 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 decisionmaking 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. [1]

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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,

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Figure 1:

Figure 2:

I

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Code	Names of variables	Calculation method
Tdta Cptd Cpta Actd Acpc acstockspc Acca Créances Dispopc Pctd Dispopc	General solvency ratio Financial Autonomy Ratio Equity Multiplier Short-term repayment capacity ratio Current ratio Quick ratio Current asset turn over ratio Reduced liquidity ratio Debt structure ratio Immediate liquidity ratio	Total liabilities / Total assets Shareholders' equity/ Total liabilities Shareholders' equity/Total assets Current assets /Total liabilities Current assets /Current liabilities (Current assets -Inventories)/Current liabilities Current Assets / Sales (Receivables<1year + cash)/ Current liabilities Current liabilities / Total liabilities 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

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[Note: 1 National Institute of Statistics in Cameroon]

Figure 3: Table I :

II

		Set				Small Businesses				Medium-sized companies		
			Solvency			Solvency				Solvency		
		0	1	Total		0	1	Total		0	1	To
	0	80,34	19,66	100	0	79,83	20,17	100	0	83,44	16,56	100
Solvency	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

Figure 4: Table II :

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Figure 5: Table 3 :

IV

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

Figure 6: Table IV :

V

Predicting SME Insolvency in Sub-Saharan Africa: A Cam

Model 1				
	ACTD	PCTD	CHPERSEBE	CHEXPTA LOG
Parameters	-2,55***	-0,45**	- 0,12***	
E.S.	0,17	0,21	0,02	
Wald	351,24	4,70	25,61	
Model 2				
	ACTD	PCTD	CHPERSEBE	CHEXPTA LOG
Parameters	-2,10***	-1.34***	- 0,13**	
E.S.	0,40	0,52	0 ,07	
Wald	27,66	6,66	4,21	
Model 3 Parameters -2,55*** ACTD E.S. 0,15 Wald 305,62		PCTD	CHPERSEBE	CHEXPTA LOG
Model 4	ACTD	PCTD	CHPERSEBE	CHEXPTA LOG

***,**,* significant at 1%, 5% and 10% respectively ??. ?? 2 = ?????????????????????? 2 ??????????

Model 2 (tertiary sector companies) Model 3 (primary and secondary sector companies) Model 5 (me

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Figure 7: Table V :

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