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Alternative SME Credit Risk Model for Cameroon

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Preface

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This issue features research spanning topics including administration & management, economics & commerce, finance, accounting & auditing, marketing, real estate, tourism management, and interdisciplinary business studies. Each paper has undergone a rigorous double-blind peer-review process to ensure analytical rigor and originality.

We would like to express our sincere gratitude to the authors for entrusting their research with us, to the reviewers for their thorough and constructive evaluations, and to our readers for their continued engagement with the scholarly discourse.

We hope that the research presented herein inspires further inquiry and contributes meaningfully to the advancement of knowledge in management and business.

The Chief Editor
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Table of Contents

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Assessment of Credit Scoring Models Performance in Cameroon: A Contextual Empirical Analysis

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Assessment of Credit Scoring Models Performance in Cameroon: A Contextual Empirical Analysis

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This paper analyses the performance of default risk prediction models in Cameroon. To do this, we first identify the predictive variables specific to the context. We then test commonly used scoring models on a sample of 448,364 credit files granted between 2003 and 2024. The results show that contextual variables such as job stability have a negative influence on the probability of default for borrowers working in the public sector, and a positive influence on that of employees in the formal and informal private sectors, as well as self-employed workers. In addition, all the models tested perform better in the presence of contextual variables. However, the logit model has better predictive power on the total number of correctly predictedcases. Indeed, it has an average correct classification rate of 90.80%, which is 4.83, 5.68 and 5.85percentage points above the probit, the NN and the SVM models respectively. On the other hand, the probit model performs better than the logit model in terms of ROC-AUC and F-score metrics. Finally, the NN and SVM models exhibit better ROC-AUC, sensitivity, and type II error rates if compared to those of the logit and probit models; yet, their performances are significantly lower than those of both the logit and probit models as shown by the terms of specificity, type I error, and F-score metrics.

Keywords: *Credit scoring, contextual variables, logit, probit, NN and SVM models*

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1. Introduction

In contemporary financial systems, credit risk management relies on credit scoring models that lie at the heart of prudential frameworks and decisional efficiency in developed economies. However, in Sub-Saharan Africa, and particularly in Central Africa, this methodological advance contrasts with a still limited and incomplete adoption of internal credit risk assessment models. In Cameroon, the integration of *credit scoring* remains partial, both at the level of the BEAC[1] ecosystem and within the internal practices of credit institutions (Abdou, et al., 2016). This raises a central question: are imported risk management tools genuinely adapted to local informational and institutional realities?

The Cameroonian banking system operates in an environment characterized by strong information asymmetry between lenders and borrowers (Mbama, et al., 2023), which is reflected in the credit portfolios quality. As at 30 June 2023, the non-performing loan ratio reached 20% in the CEMAC[2] zone (BEAC, 2023). In Cameroon, this ratio stood at 13.5% for banks as at 31 December 2024, compared with 37.6% for some financial institutions[3] and 22.3% for microfinance institutions. Yet this same ratio stands below 3% in France for the same year (BDF, 2024). This gap highlights the limitations of credit risk assessment mechanisms in a context where access to financial information remains fragmented and imperfectly structured (Nguimkeu et al., 2020). Indeed, in the absence of comprehensive and reliable databases, banks frequently resort to standardized models designed for other environments, without adequate calibration to Cameroon's economic and socio-institutional specificities.

In this context, the predominance of expert judgment in credit granting reflects less an organizational preference than an adapted response to the insufficiency of quantitative tools. While this practice embodies a form of cautious rationality, it raises questions about the comparative performance of formalized models deployable in a context of high informational uncertainty. The research problem is therefore twofold: what are the contextual variables that predict default risk? Which *credit scoring* model offers the best predictive capacity for this risk in Cameroon?

Although the international literature on *credit scoring* is extensive, empirical studies conducted in Cameroon remain scarce, or tend to reproduce models developed in institutionally distinct environments, in contradiction with the contingency logic according to which the validity of a tool depends on the context in which it is deployed (Plane, 2015).

This article therefore aims to identify the model with the best predictive performance for individual default risk in the Cameroonian banking system. It compares two parametric models (logit and probit) and two algorithmic models (neural networks and support vector machines), and assesses the contribution of integrating contextual variables into the estimation of the probability of default. By contributing to a closer alignment

[1] Bank des Etats de l'Afrique Centrale (BEAC)
[2] Communauté Economique et Monétaire de l'Afrique Centrale
[3] Crédit Foncier du Cameroun (CFC), Société Camerounaise d'Equipement (SCE), Alios Finance, and PRO-PME Financement.

between statistical modelling and institutional reality, this research aims to strengthen the effectiveness of credit allocation, reduce information asymmetry, and ultimately support financial stability and economic growth. The remainder of the article is organized as follows. We first present the theoretical framework and a review of existing work. We then describe the methodology adopted and the data used. Finally, we present and discuss the findings.

2. Modelling Default risk and Credit Scoring model performance: a Literature review

The modelling of default risk and the performance of *credit scoring* have been extensively discussed in the financial literature, from both theoretical and empirical perspectives (Abdou & Pointon, 2011; Markov, et al., 2022). Approaches grounded in information asymmetry, agency theory, and prudential frameworks constitute the principal analytical foundations mobilized in the study of credit risk (Akerlof, 1970; Jensen & Meckling, 1976). Drawing on these theoretical frameworks and on existing comparative analyses, we seek to highlight the relative performance of the principal *credit scoring* models and the contribution of contextual variables to the analysis of default risk in Cameroon.

2.1. From Statistical modelling to Algorithmic learning: Comparative performance of Credit Scoring models

Credit risk constitutes the core of banking intermediation activity. By transforming liquid deposits into risky assets, the bank assumes direct exposure to the potential default of borrowers (Allen & Santomero, 1997). This function rests on the capacity of the financial intermediary to produce, process, and transmit relevant information (Ullmo, 1988). However, in an environment characterized by information asymmetry (Akerlof, 1970), the lender does not always possess perfect knowledge of the borrower's risk profile. The contractual relationship is therefore framed within an agency logic characterized by adverse selection and moral hazard (Jensen & Meckling, 1976), making it necessary to establish formalized selection and monitoring mechanisms (Diamond, 1984).

Credit risk, defined as the possibility that a borrower fails to meet its contractual obligations, rests on three fundamental components: exposure at default, probability of default, and loss given default (Brown & Moles, 2008). Due to its direct impact on the financial stability of institutions, it remains the most critical risk for banks (Greuning & Bratanovic, 2004; Markov, et al., 2022). In the face of informational uncertainty and the bounded rationality of agents (Simon, 1964), several mechanisms can be used: risk pricing (Borch, 1967), optimal portfolio diversification (Markowitz, 1991) or credit rationing (Stiglitz & Weiss, 1981).

It is within this logic of reducing and quantifying uncertainty that the development of credit scoring models fits. Their objective is to estimate the conditional probability of default from observable information and to discriminate between borrowers likely to honor their commitments and those presenting high risk (Baesens, et al., 2003). By standardizing lending procedures, these models limit decision-making arbitrariness and reinforce internal discipline. Their development has accelerated with the evolution of prudential requirements arising from the Basel Accords, which recognize internal rating systems in the determination of capital requirements (Dedu & Nechif, 2010; Louzada, et al., 2016). Furthermore, IFRS standards relating to the calculation of expected losses have increased the need for robust, traceable, and empirically validated predictive models (Markov, et al., 2022).

Historically, the first scoring models belong to classical parametric approaches: linear discriminant analysis (LDA), logistic regression (logit), and the probit model (Greene, 1998; Abdou & Pointon, 2011). These models rest on an explicit probabilistic structure linking a vector of explanatory variables to a binary dependent variable reflecting the state of default (Lin & Chen, 2023; Dastile, et al., 2020; Min & Lee, 2022). The success of the logit model owes particularly to its simplicity of implementation, statistical robustness„ ease of interpretation and transparency ; qualities that are essential in a regulated environment requiring the justification of decisions (Baesens, et al., 2003; Dastile, et al., 2020; Giannopoulos, 2018; Dedu & Nechif, 2010).

However, these models rest on the implicit assumption of a linear relationship between explanatory variables and the probability of default in the transformed space, an assumption that may be restrictive in the presence of complex non-linear interactions (Hurlin & Pérignon, 2019). This limitation has favored the emergence of machine learning approaches, such as: artificial neural networks, capable of modelling complex non-linear relationships (Dastile, et al., 2020; Min & Lee, 2022) ; support vector machines (SVM), which maximize the separation margin between classes (Baesens, et al., 2003); decision trees (CART) and ensemble methods combining several algorithms (Wang, et al., 2018; Markov, et al., 2022).

Comparative empirical studies do not, however, establish a systematic superiority of algorithmic models. Baesens et al. (2003), drawing on several European databases, show that while LS-SVM and neural networks exhibit good performance, logistic regression and discriminant analysis remain competitive. Lee & Chen (2005) demonstrate that a hybrid model (MARS combined with neural networks) can outperform individual models, highlighting the importance of methodological combination. Ince & Aktan (2009), comparing logit, LDA, neural networks, and CART on Turkish banking data, conclude that performance varies according to the metric retained: the CART model achieves a higher overall correct classification rate, while neural networks reduce Type II errors more effectively.

The macroeconomic dimension also proves decisive. Bellotti & Crook (2009) show that the integration of macroeconomic variables significantly improves the predictive capacity of survival models compared with standard logistic regression. Similarly, Giannopoulos (2018) observes that model effectiveness deteriorates during recessions, confirming the sensitivity of credit risk to economic conditions.

The systematic review by Markov et al. (2022) highlights the lasting coexistence of three main model families: classical parametric models, ensemble models, and machine learning models. While algorithmic approaches tend to display high predictive performance, logistic regression remains one of the most widely used models in banking practice. The authors stress an essential point: predictive performance depends heavily on data quality, validation techniques, the metrics retained, and the economic context of estimation.

Thus, the literature does not establish the universal superiority of any single model. While algorithmic approaches offer greater flexibility and an enhanced capacity to capture non-linear relationships, their performance remains heavily dependent on data quality, validation techniques, and the economic context of estimation (Markov, et al., 2022). Conversely, classical parametric models, and logistic regression in particular, offer advantages in terms of stability, interpretability, and regulatory compliance, while displaying satisfactory predictive performance in a significant number of studies (Baesens, et al., 2003; Dastile, et al., 2020).

In light of information asymmetry theories, prudential requirements, and comparative empirical results, the superiority of algorithmic models cannot be postulated independently of the context where they are implemented.

In an environment characterized by specific informational and institutional constraints, algorithmic complexity does not therefore necessarily guarantee a substantial predictive gain. From this perspective, we postulate that, in the context studied, the logit model exhibits predictive performance that is superior to, or at least comparable with, that of algorithmic models such as probit, neural networks, and support vector machines.

2.2. Contextualization of Credit risk in an Economy of Informational Asymmetry: Structural determinants of Default

The question of the determinants of default cannot be dissociated from the very nature of the informational environment in which banking activity takes place. If credit scoring models aim to estimate a conditional probability of default, this probability is not merely statistical: it reflects a given institutional, contractual, and macroeconomic configuration. In other words, the predictive performance of a model depends less on its technical sophistication than on its capacity to integrate the variables that genuinely structure risk in a specific context (Markov, et al., 2022).

In the logic of financial intermediation, the bank transforms liquid resources into risky assets, thereby assuming direct exposure to the behavioral and economic uncertainty of the borrower (Allen & Santomero, 1997). This transformation rests on the production of information, the central function of the intermediary (Ullmo, 1988). Now, credit risk — defined through exposure at default, probability of default, and loss given default (Brown & Moles, 2008) — is rooted in a structural information asymmetry between lender and borrower (Akerlof, 1970). The bank does not possess perfect knowledge of the intrinsic quality of the financed project, nor of the future effort to be made by the debtor.

This asymmetry feeds the mechanisms of adverse selection and moral hazard analyzed by Jensen & Meckling (1976). Ex ante, the riskiest borrowers may be incentivized to apply more actively for credit; ex post, repayment effort may diverge from the initial commitment. In such an environment, the intermediary acts under bounded rationality (Simon, 1964) and must build filtering and monitoring mechanisms (Diamond, 1984). The quality of the variables mobilized in the selection process then becomes decisive: they are what allows radical uncertainty to be transformed into probabilistic risk.

When formal information is abundant and structured — as in developed economies — standardized financial variables (income, credit history, and debt ratios) play a central role in discriminating risk profiles. Conversely, in environments where databases are fragmented and informational history is incomplete, the very structure of risk may differ.

The work of Abdou et al. (2016) highlights that in several African economies, the institutionalization of *credit scoring* remains limited, and the credit decision remains heavily reliant on expert judgment. This situation reflects less a technological lag than a pragmatic adaptation to an imperfect informational environment.

The theoretical models of credit rationing (Stiglitz & Weiss, 1981) are particularly illuminating in this regard. When information is asymmetric, adjusting the interest rate alone is insufficient to balance the market: it may even increase the average risk of the portfolio. In this context, banks resort to non-price selection mechanisms — collateral, reputation, professional stability — to limit exposure to default. These variables, often categorical', in fact constitute strong economic signals in contexts where financial information is partial.

Portfolio theory (Markowitz, 1991) and risk pricing (Borch, 1967) provide complementary instruments for managing uncertainty, but their effectiveness remains conditional on the quality of initial probabilistic estimates. If the probability of default is poorly specified due to a lack of relevant variables, portfolio optimization or risk premium adjustment cannot compensate for this shortfall. The question of the structural determinants of default then becomes central: which variables effectively capture risk in a given environment?

The empirical literature confirms the contingent nature of credit risk. Bellotti & Crook (2009) demonstrate that the integration of macroeconomic variables significantly improves default prediction, revealing that repayment behavior also depends on aggregate economic conditions. Giannopoulos (2018) shows that model performance varies with the economic cycle, emphasizing that default is not solely a function of individual characteristics but also of the macro-financial context. Markov et al. (2022) stress that the superiority of a model depends largely on the nature of the available data and the institutional framework.

In an economy characterized by strong information asymmetry and incomplete income formalization, certain determinants take on particular importance. Employment stability can serve as an informational substitute for the absence of detailed financial statements; the existence of real collateral directly influences the anticipated recovery rate (Brown & Moles, 2008); professional stability reduces uncertainty about future repayment flows. These elements are not peripheral: they concretely structure the probability of default.

Thus, the probability of default is not solely a function of classical financial indicators, but results from an interaction between individual characteristics, contractual guarantees, and the institutional environment. The mechanical transposition of models designed for mature informational systems may lead to an underestimation or misspecification of risk in different contexts. The contingency logic, implicitly supported by comparative empirical work (Markov, et al., 2022; Giannopoulos, 2018; Bellotti & Crook, 2009), suggests that the identification of relevant determinants is a prerequisite for any performance comparison between models.

In the case of an economy such as Cameroon, where the production of financial information remains heterogeneous and where expert judgment retains a significant role (Abdou, et al., 2016), it is reasonable to consider that certain contextual variables play a structuring role in the formation of default risk. They constitute mechanisms of endogenous reduction of information asymmetry and directly influence the estimated probability of default.

In light of information asymmetry theories, credit rationing models, and empirical insights regarding the contextual dependence of models, we argue that variables specific to the Cameroonian credit system — notably those related to professional stability et and the institutional quality of the employer — significantly influence the probability of default of borrowers. They appear as structural determinants of risk, the integration of which is likely to improve the relevance and predictive performance of *credit scoring* in such a context.

3. Data and model Specification

3.1. Data

The data used in this study were collected in two phases. First, through semi-structured interviews conducted with credit, commitments, and risk managers from eight banks[4] operating in Cameroon. Data collection adopted a purposive, non-probabilistic sampling approach, consistent with the principles of exploratory qualitative research (Miles & Huberman, 1994; Patton, 2002). This phase enabled identification of whether formalized scoring models exist, the nature of the variables mobilized, the consideration of contextual factors, and the origin of the tools employed (imported or locally developed models). Second, we draw on a database from the National Economic and Financial Committee (CNEF) of Cameroon, comprising 458,364 credit files granted to individuals over the period 2003–2024, for the comparative evaluation of the performance of the main default risk prediction models.

This database exhibits a marked imbalance between performing loans (439,397) and defaulted loans (18,967). To avoid learning bias in favor of the majority class, a combined strategy of cluster sampling and simple random sampling was adopted. Files were first separated into two groups (good and bad borrowers), then 5,000 observations were randomly drawn from each group to constitute a balanced training sample of 10,000 observations. The remaining data (448,364 files) constitute the external validation sample. This procedure follows the recommendations of Crone and Finlay (2012), who highlight the importance of balancing for machine learning models. It thereby reconciles institutional grounding, statistical robustness, and external validity.

In this study, the dependent variable is payment default, defined as a delay of 90 days or more, in line with international prudential standards. The explanatory variables are structured around four dimensions: *(i)* socio-demographic characteristics (gender, marital status, place of residence, dependents, etc.) ; *(ii)* employment status (which captures job stability) ; *(iii)* financial capacity (permanent income, current or savings account operations); *(iv)* banking history and history and reputation (length of the relationship, number of previous loans, known past delays, existence of past arrears, number of past payment delays, etc.) ; *(v)* contractual characteristics of the loan (amount, maturity, nominal rate, APR, existence of collateral, existence of an insurance policy).

A strict data cleaning protocol was applied to ensure statistical consistency: exclusion of inconsistent observations (age below 18, zero amount, APR below nominal rate, banking relationship duration incompatible with age). To limit scale effects and reduce distribution asymmetry, strictly positive variables were log-transformed using the natural logarithm, while variables that could take zero or negative values were transformed using Johnson's (1949) procedure.

3.2. Model Specification and Estimation and evaluation Procedures

The empirical analysis aims to compare the predictive capacity of two parametric models (logit and probit) and two machine learning models (neural networks and support vector machine). Table 1 below provides a comparative summary of these four models.

Prior to estimation, multicollinearity is checked using the correlation matrix, the Variance Inflation Factor (VIF), and the Farrar–Glauber test. The models are then estimated on the training sample and evaluated on the external validation sample, thereby ensuring the robustness and generalizability of the results.

[4]BICEC, UBA, SGC, SCB Cameroun, CBC, CITIBANK Cameroun, Standard Chartered Bank Cameroon and AFB.

Table 1. Comparative Summary of Model Characteristics

Families	Models	Variables	Probability formulation	Estimation or optimization method	Key features	Performance indicator
Parametric Models	Logit	**Dependent Variable**: takes the value 1 in case of default and 0 otherwise ($Y = \{y_1, y_2\}$) **Explanatory Variables**: a vector of variables $X = \{x_1, \dots, x_p\}$ characterizing the borrower	$Pd(y_1 = 1 \mid x_i) = F(\eta(x_i;\beta)) = \frac{1}{1+\exp(-\eta(x_i;\beta))}$	Coefficient estimation by maximum likelihood	Assumes a distribution function for the probability of default, namely the logistic function (also known as the sigmoid function): $F(X) = \frac{1}{1+e^{-X}} = \frac{e^X}{1+e^X}$	Well predicted cases rate (TBP) $= \frac{TP+TN}{TP+TN+FP+FN}$ sensitivity (SEN): $SEN = \frac{TP}{TP+FN}$ specificity (SPE): $SPE = \frac{TN}{TN+FP}$ The false positive rate (FPR): $FPR = \frac{FP}{FP+TN}$ The false negative rate (FNR) or Type II error: $FNR = \frac{FN}{FN+TP}$ The area under the ROC (AUC): $AUC = \frac{1}{2}\left(1+\frac{TP}{TP+FN}-\frac{FP}{FP+TN}\right)$ F-Score $= \frac{2\times SEN\times Precision}{Precision+SEN}$ TN = True Negatives TP = True Positives FN = False Negatives FP = True Positives
	Probit		$P(y_i = 1 \mid X_i) = F(X_i\beta) = \Phi(X_i\beta) = \int_{-\infty}^{X_i\beta}\left(\frac{1}{\sqrt{2\pi}}e^{-\frac{t^2}{2}}\right)dt$	Coefficient estimation by maximum likelihood	Imposes a distribution function for the probability of default, namely the standard normal cumulative distribution function: $F(z) = \Phi(z) = \int_{-\infty}^{z}\left(\frac{1}{\sqrt{2\pi}}e^{-\frac{t^2}{2}}\right)dt$	
Non-parametric Models: Machine Learning	Neural Networks (NN)		Based on a learning function: $f(x_j) = \sum_{i=1}^{L}\beta_i g(w_i x_j + b_i) = y_l$	Construction of a series of layers comprising an input layer, with the process ending at an output layer	The principle of the NN is to mimic the human brain by forming a network of neurons for decision-making.	
	Support Vector Machine (SVM)		Classification function: $f(x) = \text{sign}(w^T\phi(x)+b)$	$\min_{w,b}\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i$ subject to the constraint: $y_i(w^T\phi(x_i)+b) \geq 1-\xi_i, \xi_i \geq 0$ where C is a constant, ξ is a margin vector of variables, $\phi(\cdot)$ is a transformation from the input space to the borrower's feature space	The SVM model proceeds by constructing an optimal hyperplane so as to maximize the distance between the nearest point and the hyperplane, known as the margin	

Source: (Louzada, et al., 2016; Dumitrescu, et al., 2021; Keita, 2015; Mwinkume, et al., 2025; Ying, et al., 2025; Xu & Qu, 2024; Le, et al., 2012)

4. Results, analysis, and Discussion

4.1. Results of the Exploratory Qualitative approach

The qualitative analysis yields three main findings. First, the semi-structured interviews reveal that the Cameroonian banking system remains characterized by institutional heterogeneity in the implementation of scoring systems, reflecting unequal levels of technological maturity and integration of prudential standards. Indeed, of the eight banks interviewed, only four have formalized and operational scoring models for non-financial enterprises.

Some banks, by contrast, have semi-empirical or deterministic models, while others use Excel-based scoring spreadsheets for individuals borrowers, incorporating socio-demographic and professional variables (age, seniority, contract type, salary level, professional stability) and behavioral indicators (repayment of prior loans, account activity, collateral). This practice illustrates an attempt at endogenous contextualization, based on locally collected data, but still suffering from statistical robustness and systematic empirical validation. These banks are, however, in the process of designing or migrating towards automated scoring tools, reflecting a progressive dynamic of alignment of the Cameroonian banking sector with international credit risk management practices.

Second, one observes the prevalence of models scoring models developed abroad among banks with formalized credit risk management mechanisms. These models are aligned with global prudential standards, based on internal ratings (Internal Ratings-Based Approach – IRB) as defined by the Basel directives. Their local transposition remains limited insofar as the risk parameters (probability of default, loss given default, exposure at default) are calibrated on credit portfolios built in foreign countries, and not on Cameroonian empirical data. This finding reflects the structural dependence of local subsidiaries on their parent companies, but also the difficulty of building models calibrated on reliable national data.

The third emerging trend concerns the persistence of human judgment and collegiality in credit decision-making. This finding reflects a cautious and relational rationality, better suited to an environment where informational uncertainty remains high. This pre-eminence of subjective judgment is corroborated by the work of Tversky & Kahneman (1974) on cognitive biases and heuristics in financial decision-making, but also illustrates a logic of organizational learning (Argyris & Schön, 1996), where the tacit knowledge accumulated by analysts plays a compensatory role in the face of the information deficit.

With regard to the nature of the variables used by banks in processing credit applications, the results reveal a differentiated structuring of the variables used in scoring models, according to the type of customer and the sophistication of the bank. For individuals, the most recurrent variables are: employment stability[5]; the level of monthly income and its recurring nature; credit history and regularity of past repayments; the debt-to-income ratio; type of collateral; the customer's behavior regarding their bank account. For non-financial firms, the models take into account: financial variables (profitability, liquidity, solvency, financial structure, cash flow); qualitative variables (industry sector, experience of legal representatives, quality of governance, dependence on the State or subsidies, competitive environment); behavioral and relational variables (history of the banking relationship, compliance with past commitments, frequency of overdrafts, compliance with covenants); and macroeconomic variables specific to the Cameroonian context (inflation rate, GDP growth, sector stability, budget deficit, regulatory constraints, commodity market trends).

Overall, the interview results highlight the relevance and necessity for the Cameroonian banking system to develop an endogenous scoring model that is both scientifically robust and contextually relevant.

4.2. Results of the Estimation of Default Probability prediction models

After analyzing the correlation matrix, the Variance Inflation Factor (VIF) value, and the Farrar–Glauber test, variables highly correlated with others were removed from the default probability equation. Four models were then implemented: a *logit model*, a *probit regression*, the NN and SVM models. All four models were estimated on the same balanced training sample of 10,000 credit files, comprising 5,000 'bad borrowers' and 5,000 'good borrowers', and then tested on the same validation sample of 448,364 credit files. The importance of contextual variables was assessed by first excluding these variables from the default probability equation, then reintegrating them in a second step.

The results of the *logit* model show that professional situation, financial capacity, banking reputation, and credit characteristics significantly influence the probability of default. Specifically, the results show that employment stability reduces the probability of credit default. Public-sector employees, whose employment is considered more stable, are less risky than those in the formal private sector, the informal private sector, and the self-employed. Similarly, financial capacity — assessed by income level, average monthly checking account balance, average monthly incoming transfers and average monthly account withdrawals - has a negative effect on the probability of default. As for reputational variables, the effects are also differentiated. The number of existing loans and the length of the banking relationship have a negative effect on the probability of default; conversely, a history of past delinquencies and the number of late payments positively influence the probability of default.

Furthermore, loan characteristics such as the loan term and the effective annual percentage rate (APR) negatively influence default risk; whereas the existence of an insurance policy and the nominal interest rate have a positive effect on the probability of default. Particularly, the positive coefficient associated with the existence of an insurance policy - which is a counterintuitive result - could simultaneously reflect a situation involving moral hazard on the part of insured customers (failure to comply with contractual terms) and adverse selection (the bank requires insurance only for high-risk profiles). Concerning APR, the negative coefficient stems from an indirect relationship. Indeed, in the Cameroonian context, small loans—and particularly student loans—are associated with high APRs, then are easily repayable and not prone to default. These loans are easily repayable and are not prone to default. Moreover, among socio-demographic characteristics, being in a common-law union positively influences default risk; while single clients, who generally carry fewer family financial obligations, are less prone to default than married individuals.

The *probit* placed under the same conditions as the logit produced almost identical results. The SVM model results corroborate certain findings of the *logit* and *probit* models. They reveal that variables relating to reputation (existence of past arrears, number of past payment delays, etc.), credit characteristics (existence of an insurance policy, nominal rate, investment credit), and formal and informal private-sector employment increase credit risk. As in the *logit* model, the SVM results reveal that loan duration and APR, permanent income, the number of loans obtained, and the length of the banking relationship reduce the probability of default.

Regarding the performance of the four implemented models, the results show that the logit model has better predictive power in terms of total correct cases predicted. Indeed, it has an average correct classification rate of 90.80%, which is 4.83 points above the probit model, 5.68 above the NN model and 5.85 above the SVM model. However, the probit model performs better than the logit model in terms of ROC-AUC and F-score metrics. Finally, the NN and SVM models exhibit ROC-AUC, sensitivity, and type II error rates that are better than those of the logit and probit models, but their performance is significantly lower than that of the logit and probit models in terms of specificity, type I error, and F-score.

Overall, these results from scoring models consistently highlight four fundamental dimensions: financial capacity, banking history, socio-professional status, and credit usage patterns. Among these dimensions, banking history remains particularly important, both in terms of significance and stability of the sign of the coefficients. It acts positively on the probability of default. These results are consistent with those of Crook (2001), Thomas, Edelman & Crook (2002), and Altman & Sabato (2007), who showed that banking history constitutes a reliable indicator of borrowers' payment behavior and financial discipline. They are also consistent with the findings of Nguena, Tsafack & Soumaré (2020), who showed that financial inclusion plays a decisive role in reducing information asymmetry and strengthening financial credibility in African economies.

[5]The assessment of employment stability primarily integrates two simultaneous dimensions: the nature or duration of the employment contract (Castellanos, et al., 2025), and the private or public nature of the employer. Specifically, public-sector employment, formal private-sector employment, informal private-sector employment, and self-employment are distinguished. In general, public-sector employment, which is predominantly open-ended in duration, is considered more stable.

Beyond these classical variables considered in several prior studies, contextual variables emerge as important predictors of credit risk. This result is consistent with contingency theory (Plane, 2015), and support the view of Beck & Cull (2014), who suggest that risk modelling must draw on local institutional reality to achieve operational validity. In this case, borrower employment stability significantly influences the probability of default for individuals in Cameroon.

By taking these contextual variables into account, the results of implementing the four models (logit, probit, NN, and SVM) highlight the superior predictive performance of the logit model compared to the other three models. These results corroborate those of Hurlin & Pérignon (2019), who noted that machine learning methods yield only marginal performance gains, although they sometimes allow productivity gains in terms of data preprocessing and the capacity to handle large volumes of information. Pacelli & Azzollini (2011) similarly argue that neural networks and the logit model simply have different strengths and weaknesses. In the same vein, Ince & Aktan (2009), working on credit data from a Turkish bank, demonstrated that the average correct classification rate of the logit model is higher than that of neural networks.

5. Conclusion

This article contributes to contemporary debates in international management on the transferability of analytical tools across institutionally heterogeneous environments. It implicitly challenges a widely accepted assumption: that the superiority of machine learning models in credit risk prediction is universal, regardless of context. The empirical analysis conducted on 448,364 credit files granted in Cameroon between 2015 and 2024 leads to a more nuanced and theoretically stimulating conclusion: predictive performance is institutionally situated.

The observed determinants of default reveal that credit risk, in an economic environment characterized by an incomplete informational infrastructure, is predicted by specific relational and socio-economic variables. Employment stability, the length of the banking relationship, and the regularity of financial flows act as signals that compensate for formal information deficits. The probability of default thus appears less as a simple statistical output than as the expression of a particular institutional architecture. This perspective invites us to move beyond a purely technical reading of credit scoring and to situate it within a contextualized approach to risk management. The explicit integration of these contextual variables generates substantial predictive gains across all tested models. The improvements observed in terms of correct classification and discriminatory power confirm that the quality and relevance of the information mobilized conditions performance more than the formal sophistication of the algorithm.

The most salient finding lies in the absence of empirical superiority of machine learning approaches. Despite their nonlinear flexibility, neural networks and support vector machines do not outperform the logit model, which achieves an average correct classification rate of 90.80%.

On the theoretical level, this study contributes to the literature by showing that the performance of risk management mechanisms is inseparable from their institutional grounding. It thereby connects work on credit scoring with international management perspectives that emphasize the need to adapt managerial practices to local configurations. On the methodological level, it proposes a rigorous comparative protocol based on a large-scale database and a multi-indicator evaluation, strengthening the external validity of the conclusions. On the strategic level, it suggests that, for financial institutions in emerging economies, competitive advantage lies less in the importation of advanced technologies than in the construction of contextualized and reliable information systems.

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6. Appendices

Table 2. Logit Performance without Contextual Variables

Models	ROC-AUC	TBP	SEN	SPE	Error I	Error II	F Score
Training sample	0.8597	78.08	67.64	88.52	11.48	32.36	72.49
Validation sample	0.7772	88.08	66.67	88.77	11.23	33.33	75.89

Table 3. Comparison of Predictive Performance with Contextual Variables

Performance on training sample							
Models	**ROC-AUC**	**TBP**	**SEN**	**SPE**	**Error I**	**Error II**	**F Score**
Logit	0.8730	79.01	71.28	86.74	13.26	28.72	74.90
Probit	0.8725	78.90	70.80	87.00	13.00	29.20	74.67
NN	0.8915	80.70	75.40	86.00	14.10	24.50	79.62
SVM	0.8657	78.50	70.90	85.30	14.70	29.10	76.40
Performance on validation sample							
Models	**ROC-AUC**	**TBP**	**SEN**	**SPE**	**Error I**	**Error II**	**F Score**
Logit	0.7828	**90.80**	65.00	**91.60**	**8.42**	35.03	75.74
Probit	0.7878	85.97	71.10	86.44	13.56	28.90	77.80
NN	0.8870	85.12	75.71	85.42	16.60	23.10	24.07
SVM	0.8659	84.95	71.60	85.38	14.60	28.40	22.87

Table 4. Logistic Regression including Contextual Variables

Y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig
1) ***Employment status***							
civil servant (ref.)							
emprive_f	1.259	.089	14.19	0	1.085	1.433	***
compropre	2.364	1.318	1.79	.073	-.219	4.948	*
emprive_inf	.68	.096	7.05	0	.491	.869	***
sect1	-.079	.132	-0.60	.547	-.338	.179	
sect3	-.814	.678	-1.20	.23	-2.143	.516	
sect4	.05	.179	0.28	.781	-.302	.401	
sect5	-.288	.12	-2.39	.017	-.524	-.052	**
sect6	-.359	.76	-0.47	.636	-1.848	1.129	
sect7	.173	.2	0.87	.386	-.219	.566	
sect8	.502	.301	1.67	.096	-.088	1.092	*
sect9	-.008	.12	-0.07	.946	-.243	.227	
sect10	-.117	.228	-0.52	.606	-.564	.329	
sect11	.054	.108	0.50	.615	-.157	.266	
sect12 (ref.)							
sect13	-.294	.084	-3.51	0	-.458	-.13	***
sect14	.281	.161	1.74	.082	-.035	.598	*
sect15	.218	.543	0.40	.688	-.846	1.281	
sect16	-.328	.228	-1.44	.149	-.775	.118	
2) ***Financial Capacity***							
Revt	-.2	.063	-3.16	.002	-.324	-.076	***
Smmet	.002	.007	0.30	.766	-.012	.016	
Smmct	-.043	.003	-14.52	0	-.049	-.037	***
Dmmet	.007	.009	0.78	.437	-.011	.025	
Vmmrt	-.014	.008	-1.80	.072	-.028	.001	*
Rmmct	-.174	.017	-10.10	0	-.208	-.14	***
Rmmet	-.002	.009	-0.28	.78	-.02	.015	
3) ***Banking reputation***							
nbcredt	-.878	.07	-12.59	0	-1.014	-.741	***
eximpayes	4.784	.179	26.70	0	4.433	5.135	***
nbretard	.007	.001	6.54	0	.005	.009	***
Durelt	-.117	.038	-3.07	.002	-.192	-.042	***
4) ***Socio-demographic characteristics***							
Lnage	.247	.151	1.63	.103	-.05	.544	
Femme	-.004	.071	-0.06	.953	-.143	.135	
Enfant	.03	.034	0.90	.367	-.036	.096	
polygam	-.308	.396	-0.78	.437	-1.085	.468	
unionlibr	.143	.065	2.19	.028	.015	.27	**
celib	-1.478	.313	-4.72	0	-2.091	-.864	***
adamaoua	.242	.165	1.46	.143	-.082	.565	
est	.364	.148	2.45	.014	.073	.655	**
extrnord	-.371	.146	-2.54	.011	-.657	-.084	**
littoral	.113	.074	1.53	.127	-.032	.258	
nord	.006	.137	0.04	.965	-.263	.275	
nw	.287	.167	1.72	.086	-.041	.615	*
ouest	.14	.12	1.17	.243	-.095	.374	
sud	.073	.14	0.52	.6	-.201	.347	
sw	.155	.119	1.30	.193	-.079	.389	
5) ***Credit characteristics***							
objet1 (réf.)							
objet2	1.362	.181	7.53	0	1.007	1.717	***
lnmontant	.114	.074	1.55	.121	-.03	.259	
teg	-.061	.015	-4.03	0	-.091	-.032	***
tn	.083	.018	4.54	0	.047	.12	***
lndureecred	-1.291	.127	-10.13	0	-1.54	-1.041	***
exassur	.742	.106	7.03	0	.535	.949	***
exgarantie	-.227	.454	-0.50	.618	-1.116	.663	
Constant	6.161	1.079	5.71	0	4.047	8.275	***

Table 4. Logistic Regression including Contextual Variables (continued)

Y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig
Mean dependent var		0.500	SD dependent var				0.500
Pseudo r-squared		0.385	Number of obs				10000
Chi-square		5339.658	Prob > chi2				0.000
Akaike crit. (AIC)		8625.285	Bayesian crit. (BIC)				8993.013
**** p<.01, ** p<.05, * p<.1*							

Sensitivity	$Pr(+ \mid D)$	71.28%
Specificity	$Pr(- \mid \sim D)$	86.74%
Positive predictive value	$Pr(D \mid +)$	84.32%
Negative predictive value	$Pr(\sim D \mid -)$	75.13%
False positive rate for true $\sim D$	$Pr(+ \mid \sim D)$	13.26%
False negative rate for true D	$Pr(- \mid D)$	28.72%
False positive rate for classified $+$	$Pr(\sim D \mid +)$	15.68%
False negative rate for classified $-$	$Pr(D \mid -)$	24.87%
Correctly classified		**79.01%**

Source: the authors, based on CNEF Cameroon data

Table 5. Logistic regression without contextual variables

y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig
1) ***Situation professionnelle***							
sect1	.559	.12	4.67	0	.325	.794	***
sect3	-.097	.69	-0.14	.888	-1.45	1.256	
sect4	.651	.17	3.83	0	.318	.984	***
sect5	.171	.11	1.55	.121	-.045	.387	
sect6	.459	.775	0.59	.553	-1.059	1.978	
sect7	.84	.19	4.42	0	.468	1.212	***
sect8	1.219	.294	4.14	0	.642	1.796	***
sect9	.321	.112	2.88	.004	.102	.54	***
sect10	.437	.219	2.00	.046	.008	.866	**
sect11	.58	.096	6.05	0	.392	.767	***
sect13	-.426	.081	-5.24	0	-.585	-.267	***
sect14	.444	.158	2.81	.005	.134	.755	***
sect15	.573	.525	1.09	.275	-.457	1.603	
sect16	-.124	.223	-0.55	.579	-.561	.313	
2) ***Financial Capacity***							
revt	-.245	.062	-3.98	0	-.366	-.124	***
smmet	-.006	.007	-0.81	.419	-.019	.008	
smmct	-.042	.003	-14.58	0	-.048	-.037	***
dmmet	.009	.009	0.98	.328	-.009	.026	
vmmrt	.005	.007	0.70	.482	-.009	.019	
rmmct	-.144	.016	-8.89	0	-.175	-.112	***
rmmet	-.001	.009	-0.16	.871	-.018	.016	
3) ***Banking reputation***							
nbcredt	-.827	.068	-12.25	0	-.96	-.695	***
eximpayes	4.758	.177	26.89	0	4.411	5.105	***
nbretard	.005	.001	5.37	0	.003	.007	***
durelt	-.247	.036	-6.90	0	-.317	-.177	***
4) ***Socio-demographic characteristics***							
lnage	.589	.142	4.14	0	.31	.868	***
femme	-.04	.069	-0.57	.567	-.175	.096	
enfantt	.027	.033	0.83	.406	-.037	.092	
polygam	-.115	.384	-0.30	.766	-.868	.639	
unionlibr	.142	.064	2.22	.026	.017	.266	**
celib	-1.626	.299	-5.43	0	-2.213	-1.039	***
adamaoua	.155	.161	0.97	.334	-.16	.471	
est	.412	.144	2.86	.004	.13	.694	***
extrnord	-.407	.143	-2.84	.004	-.687	-.126	***
littoral	.195	.072	2.71	.007	.054	.336	***
nord	.013	.134	0.10	.921	-.249	.275	
nw	.252	.165	1.53	.126	-.071	.576	
ouest	.165	.118	1.41	.16	-.065	.396	
sud	.113	.137	0.83	.409	-.156	.382	
sw	.173	.117	1.48	.139	-.056	.401	
5) ***Credit characteristics***							
objet2	1.607	.173	9.27	0	1.268	1.947	***
lnmontant	.338	.064	5.29	0	.213	.463	***
teg	-.024	.011	-2.10	.035	-.046	-.002	**
tn	.072	.017	4.23	0	.039	.105	***
lndureecred	-1.297	.124	-10.49	0	-1.54	-1.055	***
Constant	2.51	.892	2.81	.005	.762	4.259	***

Mean dependent var	0.500	SD dependent var	0.500
Pseudo r-squared	0.364	Number of obs	10000
Chi-square	5044.389	Prob > chi2	0.000
Akaike crit. (AIC)	8910.554	Bayesian crit. (BIC)	9242.230

**** p<.01, ** p<.05, * p<.1*

Sensitivity	$Pr(+ \mid D)$	67.64%

Table 5. Logistic regression without contextual variables (continued)

y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig
Specificity	$Pr(- \mid \sim D)$						88.52%
Positive predictive value	$Pr(D \mid +)$						85.49%
Negative predictive value	$Pr(\sim D \mid -)$						73.23%
False positive rate for true $\sim D$	$Pr(+ \mid \sim D)$						11.48%
False negative rate for true D	$Pr(- \mid D)$						32.36%
False positive rate for classified $+$	$Pr(\sim D \mid +)$						14.51%
False negative rate for classified $-$	$Pr(D \mid -)$						26.77%
Correctly classified							**78.08%**

Table 6. Probit Regression including Contextual Variables

y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig	
1) ***Employment status***								
emprive_f	.731	.052	14.07	0	.629	.833	***	
compropre	1.325	.723	1.83	.067	-.093	2.743	*	
emprive_inf	.391	.056	6.93	0	.28	.502	***	
sect1	-.042	.079	-0.53	.594	-.196	.112		
sect3	-.527	.374	-1.41	.159	-1.26	.207		
sect4	.023	.107	0.22	.828	-.186	.232		
sect5	-.174	.071	-2.47	.014	-.312	-.036	**	
sect6	-.217	.456	-0.48	.634	-1.11	.677		
sect7	.099	.119	0.84	.403	-.133	.332		
sect8	.309	.181	1.70	.089	-.047	.664	*	
sect9	0	.07	0.00	.997	-.137	.138		
sect10	-.078	.135	-0.58	.561	-.343	.186		
sect11	.019	.064	0.30	.766	-.106	.145		
sect13	-.177	.048	-3.66	0	-.271	-.082	***	
sect14	.152	.096	1.58	.114	-.037	.341		
sect15	.138	.321	0.43	.667	-.49	.767		
sect16	-.174	.13	-1.33	.182	-.43	.082		
2) ***Financial Capacity***								
revt	-.113	.037	-3.09	.002	-.185	-.041	***	
smmet	.001	.004	0.27	.788	-.007	.009		
smmct	-.024	.002	-14.39	0	-.027	-.021	***	
dmmet	.004	.005	0.79	.427	-.006	.015		
vmmrt	-.008	.004	-1.72	.085	-.016	.001	*	
rmmct	-.097	.009	-10.27	0	-.116	-.079	***	
rmmet	-.001	.005	-0.26	.792	-.012	.009		
3) ***Banking reputation***								
nbcredt	-.512	.041	-12.64	0	-.591	-.433	***	
eximpayes	2.531	.078	32.41	0	2.378	2.684	***	
nbretard	.004	.001	6.32	0	.003	.005	***	
durelt	-.075	.023	-3.33	.001	-.119	-.031	***	
4) ***Socio-demographic characteristics***								
lnage	.154	.089	1.73	.083	-.02	.328	*	
femme	-.014	.041	-0.34	.737	-.095	.067		
enfantt	.015	.02	0.76	.447	-.024	.054		
polygam	-.21	.229	-0.92	.359	-.659	.239		
unionlibr	.086	.038	2.24	.025	.011	.161	**	
celib	-.747	.169	-4.43	0	-1.078	-.416	***	
adamaoua	.138	.097	1.43	.154	-.052	.327		
est	.212	.088	2.40	.016	.039	.385	**	
extrnord	-.205	.083	-2.48	.013	-.367	-.043	**	
littoral	.07	.043	1.62	.106	-.015	.155		
nord	.003	.08	0.04	.972	-.154	.159		
nw	.177	.097	1.83	.067	-.012	.367	*	
ouest	.087	.07	1.25	.213	-.05	.224		
sud	.032	.083	0.38	.703	-.13	.193		
sw	.089	.07	1.28	.2	-.047	.226		
5) ***Credit characteristics***								
object2	.772	.102	7.53	0	.571	.973	***	
lnmontant	.058	.042	1.35	.176	-.026	.141		
teg	-.037	.009	-4.30	0	-.054	-.02	***	
tn	.049	.01	4.72	0	.029	.07	***	
lndureecred	-.73	.072	-10.13	0	-.871	-.589	***	
exassur	.435	.062	7.06	0	.314	.556	***	
exgarantie	-.071	.253	-0.28	.778	-.566	.424		
Constant	3.586	.62	5.79	0	2.371	4.8	***	

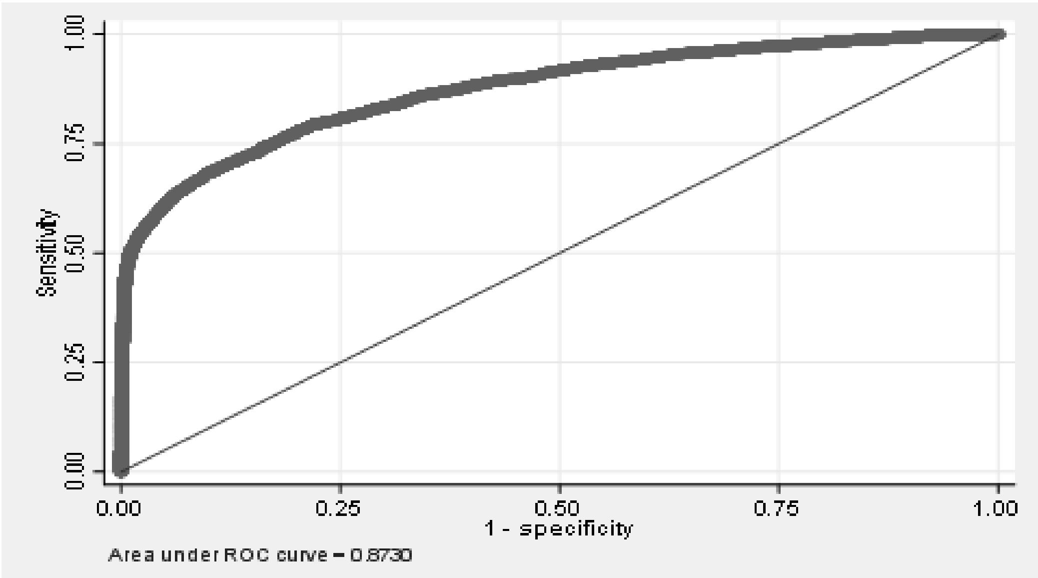
Mean dependent var	0.500	SD dependent var	0.500
Pseudo r-squared	0.384	Number of obs	10000

Table 6. Probit Regression including Contextual Variables (continued)

y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig
|Chi-square		|5319.176	|Prob > chi2			|0.000	
|Akaike crit. (AIC)		|8645.767	|Bayesian crit. (BIC)			|9013.495	
|*** $p<.01$, ** $p<.05$, * $p<.1$							
|							

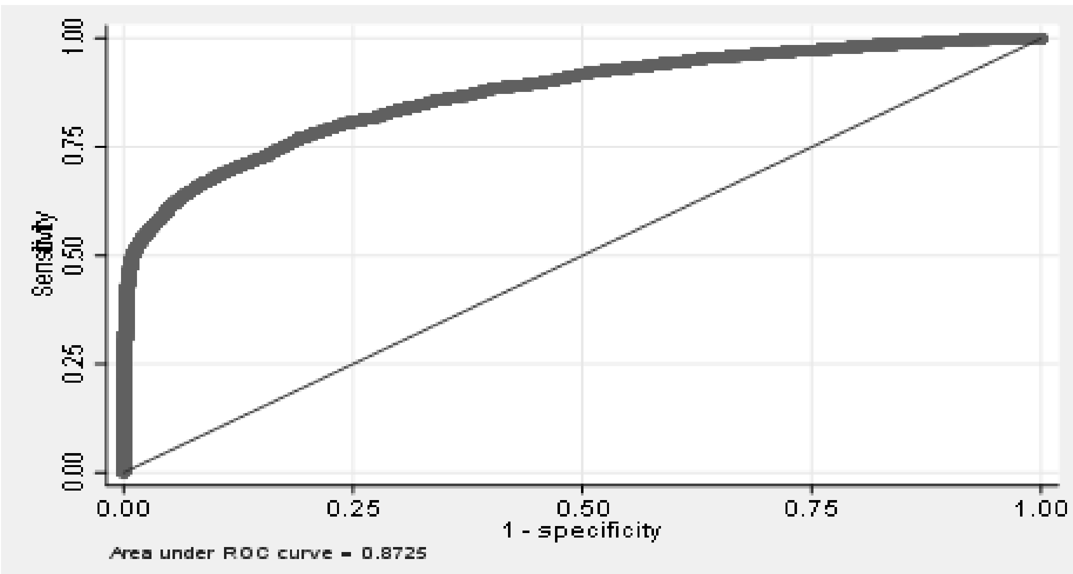
Sensitivity	$Pr(+ \mid D)$	70.80%
Specificity	$Pr(- \mid \sim D)$	87.00%
Positive predictive value	$Pr(D \mid +)$	84.49%
Negative predictive value	$Pr(\sim D \mid -)$	74.87%
False positive rate for true $\sim D$	$Pr(+ \mid \sim D)$	13.00%
False negative rate for true D	$Pr(- \mid D)$	29.20%
False positive rate for classified +	$Pr(\sim D \mid +)$	15.51%
False negative rate for classified −	$Pr(D \mid -)$	25.13%
Correctly classified		**78.90%**
Source: the authors, based on CNEF Cameroon data		

Graphic 1 : ROC curve, AUC value of the logit model with contextual variables



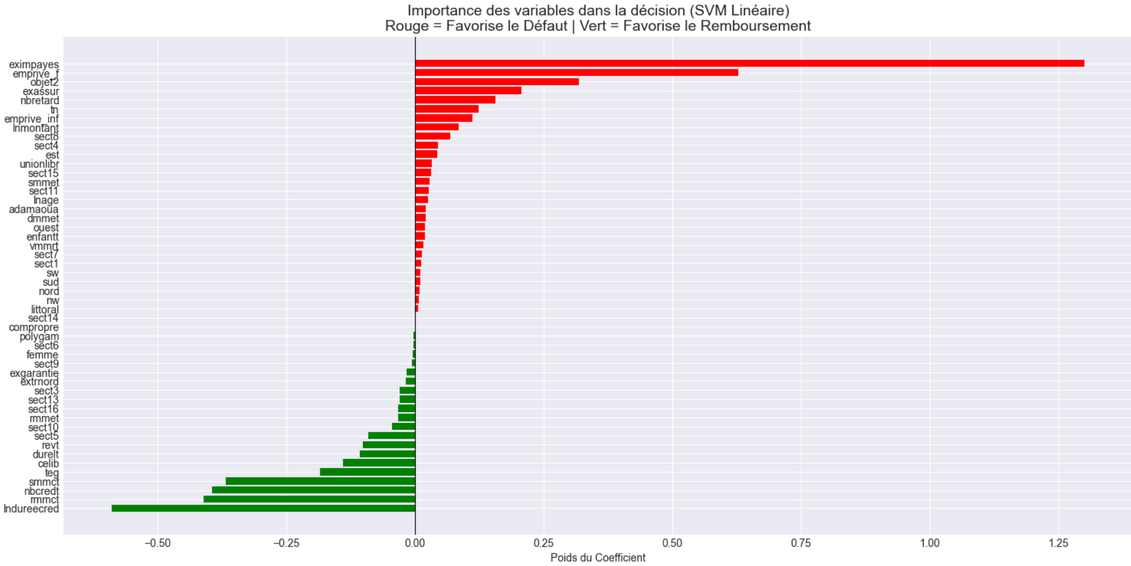
Source: the authors, based on CNEF Cameroon data

Graphic 2 : ROC curve, AUC value of the probit model with contextual variables



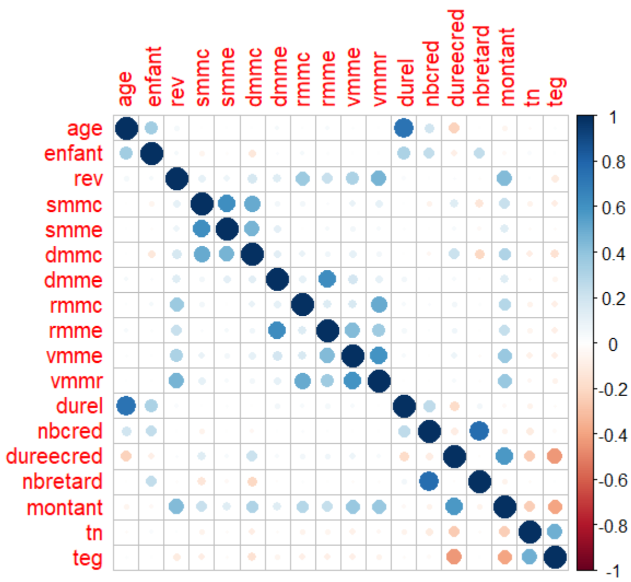
Source: the authors, based on CNEF Cameroon data

Graphic 3 : Variable weights in the SVM model decision



Source: the authors, based on CNEF Cameroon data

Graphic 4.1: Correlation heat map



Source: the authors, based on CNEF Cameroon data

7. Variables Description and Calculation Method

Table 7. Variables description and calculation method

Variables	Codes	Explanation	Observations	Authors
1. ***Dependent Variable***				
Loan status	*Y*	Binary variable measuring the costumer's creditworthiness	Default = 1 Non-default = 0	Ince et Aktan (2009), Medina-Olivares et al (2022), Bellotti et Crook (2009), Carling et al (2007), Abdou et al (2016)
2. ***Explanatory Variables***				
1. **Employment Status**				
Employment status	SOC	Measures the client's employment status Ordinal qualitative variable	Has 4 categories: 1 = Public sector employee; 2 = Formal private sector employee; 3 = Self-employed; 4 = Informal private sector worker	Abdou et al (2016), Altman (1968), Ince et Aktan (2009)
Industry	SECT	Variable relating to the economic sector of the credit recipient	The modalities of this variable follow the Nomenclature of AFRISTAT Member States (NAEMA): sect1 = Agriculture, hunting, and forestry; sect2 = Fishing, fish farming, and aquaculture; sect3 = Mining and quarrying; sect4 = Manufacturing; sect5 = Electricity, gas, and water supply; sect6 = Construction; sect7 = Wholesale and retail trade; repair of motor vehicles and household goods; sect8 = Hotels and restaurants; sect9 = Transport, auxiliary transport activities and communications; sect10 = Financial activities; sect11 = Real estate, rental, and business services; sect12 = Public administration activities; sect13 = Education; sect14 = Health and social activities; sect15 = Community or personal activities; sect16 = Activities of households as employers of domestic staff; sect17 = Activities of extraterritorial organizations	Adamou, et al. (2020), Demirgüç-Kunt & Klapper (2012), Huang et al., (2005)
2. **Financial Situation**				
Permanent income	REV	Borrower's average monthly permanent income	Transformed quantitative variable. This transformation prevents higher values from dominating lower ones and improves the precision of results (Chen & Li, 2010)	Henri Calvet (1997, Cieply (1997), Stiglitz & Weiss (1981), Beaver (1966), Ince et Aktan (2009), client Dong, et al. (2010)
Average monthly current account balance	SMMC	Fluctuations in the borrower's current account balance on a monthly average	Transformed quantitative variable. Captures other income flows in the borrower's checking account	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly savings account balance	SMME	Fluctuations in the borrower's savings account balance on a monthly average	Transformed quantitative variable. Captures other income flows in the borrower's savings account	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly deposit	DMMC	Average of monthly deposits in the savings account	Transformed quantitative variable. Captures inflows into the borrower's current account	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly savings deposit	DMME	Average of monthly deposits in the savings account	Transformed quantitative variable. Captures inflows into the borrower's savings account	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly transfers received	VMMR	Average of monthly transfers received by the borrower	Transformed quantitative variable Captures the borrower's incoming financial banking operations	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly outgoing transfers	VMME	Average of monthly transfers issued by the borrower	Transformed quantitative variable Captures the borrower's outgoing financial banking operations	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly withdrawal from the checking account	RMMC	Average of monthly withdrawals from the current account	Transformed quantitative variable Measures the management of the borrower's current account through the significance of monthly withdrawals	Abdou, et al., (2016), Chen & Pan (2019)
Average monthly savings account withdrawal:	RMME	Average of monthly withdrawals from the savings account	Transformed quantitative variable Measures the management of the borrower's savings account through the significance of monthly withdrawals	Abdou, et al., (2016), Chen & Pan (2019)
3. **Borrower reputation**				

Table 7. Variables description and calculation method (continued)

Variables	Codes	Explanation	Observations	Authors
Length of banking relationship	DUREL	Duration of the banking relationship between borrower and lender. Calculated as the difference between the loan disbursement/setup date and the date of entry into the banking relationship, divided by 30.	Quantitative variable It is expressed in number of months	Demirgüç-Kunt & Klapper (2012), (Mishkin, 1996).
Number of previously contracted loans	NBCRED	Total number of loans contracted by the borrower with the same bank	Quantitative variable Indicates the cumulative number of loans already granted to the client by the same bank	Chatterjee & Hossain (2002), Dong, et al. (2010).
Existence of repayment delays	EXRE-TARD	Binary variable measuring the existence of past payment delays	Existence of delays = 1 No payment delays = 0	Altman (1968), Adera (1987) en Éthiopie et Pischke (1991)
Existence of arrears	EXIMPAY	Binary variable measuring the existence of past arrears	Arrears exist = 1 No arrears = 0	Altman (1968), Adera (1987) en Éthiopie et Pischke (1991)
4. **Socio-demographic characteristics**				
Age	AGE	Borrower's age at the date of loan disbursement/setup. Calculated as the difference between the loan disbursement/setup date and the borrower's date of birth, divided by 365.	Quantitative variable It is expressed in number of years	Viganò (1993), Ince et Aktan (2009) Lin & Chen (2023), Diallo (2006), Abdou et al (2016), Adamou, et al (2020).
Gender	SEXE	Binary variable 1 = Female 0 = Male	Captures the influence of gender in explaining credit default	Viganò (1993), Ince et Aktan (2009) Lin & Chen (2023), Diallo (2006), Abdou et al (2016), Adamou, et al (2020).
Number of dependent children	ENFANT	Represents the number of children dependent on the borrower at the time of credit granting	Quantitative variable Captures the influence of household size in explaining credit default	Diallo (2006), Abdou et al (2016)
Marital status	SITMAT	Captures the influence of a borrower's marital status on repayment capacity	Categorical variable with 4 categories: 1 = monogamous married; 2 = polygamous married; 3 = cohabiting; 4 = single; 5 = widowed or divorced	**Variable suggested by the qualitative study.**
Region of residence	REGION	This variable indicates the borrower's location. It has 10 categories (1 = Adamaoua; 2 = Center; 3 = East; 4 = Far North; 5 = Littoral; 6 = North; 7 = Northwest; 8 = West; 9 = South; 10 = Southwest)	Captures the influence of cultural behaviors and the immediate economic environment on the borrower's repayment capacity	Adamou, et al (2020).
5. **Loan characteristics**				
Purpose of loan	OBJET	Provides information on the intended use of the funds. This variable has two values: 1 = Consumer/equipment loan; 2 = Investment loan;3 = Other use.	Captures the influence of the nature of credit use in explaining credit risk	Viganò (1993), Ince et Aktan (2009) Abdou et al (2016), Graham et Pischke (1984)
Loan amount	MONTANT	Represents the amount of the loan granted	Measures the importance of loan value in explaining the probability of default	Viganò (1993), Ince et Aktan (2009) Abdou et al (2016), Graham et Pischke (1984)
Nominal rate	TN	Measures the interest to be paid periodically by the client in addition to capital repayment	This is the commercial cost of the loan	Deng et al. (2000)

Table 7. Variables description and calculation method (continued)

Variables	Codes	Explanation	Observations	Authors
Annual Percentage Rate	TEG	Measures the cost of the loan This is a value declared by the banks.	The annual percentage rate (APR) measures the true cost of the loan. It incorporates, in addition to the nominal interest rate, ancillary charges conditioning loan setup (file processing fees, insurance premium, notary fees, etc.) It is calculated using the discounted cash flow formula: $\sum_{k=1}^{m} \frac{A_k}{(1+i)^{tk}} = \sum_{p=1}^{n} \frac{A_p}{(1+i)^{tp}}$ i: annual APR; k: order number of a disbursement; m: order number of the last disbursement; Ak: amount of disbursement k; tk: time interval between the first disbursement and disbursement k; p: order number of a repayment instalment; n: order number of the last instalment; Ap: amount of instalment p; tp: time interval between the first disbursement and instalment p.	Deng et al. (2000) **Etude qualitative** The APR calculation is governed by two regulatory texts: • Regulation No. 04/19/CEMAC/UMAC/CM of 10 August 2020 on the APR, the repression of usury, and the publication of banking conditions in CEMAC; • Instruction of the Governor of the BEAC of 4 November 2021 setting out the procedures for calculating the APR
Loan duration	DURE-CRED	This is the loan duration in months.	This is a value declared by the banks.	Brealey & Myers (2013), Dong, et al. (2010), Lin & Chen (2023), Graham et Pischke (1984)
Existence of an insurance policy	EXASSUR	Binary variable measuring whether or not an insurance policy has been purchased 1 = Yes; 0 = No	Captures the impact of the insurance policy on credit risk management	(Demirgüç-Kunt & Klapper, 2012), Cohen et Siegelman (2010), Miller et Lessard (2000), Petersen et Rajan, (1995), Altman et Saunders (1998), Banasik et al. (2003), Friedman & Rafsky (2009), Merton & Perold, (1993), Kleinbaum & Klein (2010).
Existence of a guarantee	GARANTIE	This variable measures the existence of collateral required by the bank beyond insurance. 1 = Yes; 0 = No	Captures the impact of guarantees and collateral on credit risk management	Abdou et al (2016), (Mukete, et al., (2021), Henri Calvet, 1997), Ghosh et Ghosh (2013), Baker & Smith, 2015)
Repayment frequency	FREQ	Frequency of loan repayment. It has 4 options: 1 = monthly; 2 = quarterly; 3 = semiannual; 4 = annual	Captures the impact of repayment deadlines on the probability of default.	Viganò (1993), Ince et Aktan (2009) Abdou et al (2016), Graham et Pischke (1984)

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Dividend Payments Policies and Practices in State-Owned Enterprises in India and Foreign Jurisdictions: A Critical Analysis

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Abstract

This paper critically examines the policies and practices governing dividend payments in State-Owned Enterprises (SOEs), with a focus on India and selected foreign jurisdictions. The study begins with a comprehensive literature review of dividend theory, exploring its traditional interpretations and the unique adaptations necessary for its application in SOEs, which operate under distinct mandates compared to privately held enterprises. By analyzing the theoretical underpinnings, the paper sets the stage for an informed discussion on the rationale, mechanics, and implications of dividend payments by SOEs.

dividend dilemma | dividend policy | dividends practices in Indian SOEs | foreign jurisdictions | strategic role of SOE dividends

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Abstract

This paper critically examines the policies and practices governing dividend payments in State-Owned Enterprises (SOEs), with a focus on India and selected foreign jurisdictions. The study begins with a comprehensive literature review of dividend theory, exploring its traditional interpretations and the unique adaptations necessary for its application in SOEs, which operate under distinct mandates compared to privately held enterprises. By analyzing the theoretical underpinnings, the paper sets the stage for an informed discussion on the rationale, mechanics, and implications of dividend payments by SOEs.

Keywords: *dividend dilemma, dividend policy, dividends practices in Indian SOEs, foreign jurisdictions, strategic role of SOE dividends*

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1. Introduction

Dividends represent a portion of a company's earnings distributed to its shareholders, serving as both a reward for investment and a signal of financial health and stability. Dividend policies, particularly in SOEs, carry distinct significance because these entities often balance commercial objectives with public policy mandates. Dividends provide shareholders with tangible returns on their investment, offering an incentive for continued investment in the company. For SOEs, dividends often serve as a key revenue stream for governments, helping fund public services and reduce fiscal deficits. Regular and predictable dividends indicate a company's financial stability and profitability. They signal efficient operations and can boost investor confidence, making it easier to attract capital. In SOEs, dividends represent a mechanism for redistributing wealth from commercially successful enterprises to the public via government coffers, supporting broader socio-economic initiatives. Dividends impose discipline on management by requiring efficient allocation of retained earnings. This discourages overcapitalization and ensures better utilization of resources. Dividends reduce the free cash flow available to management, thereby limiting the potential for misuse of funds and aligning management's interests with those of shareholders.

A clear dividend policy ensures consistency in payout practices, fostering trust among shareholders and helping governments or investors plan their finances. For SOEs, a dividend policy helps balance the dual objectives of generating returns for the government and reinvesting earnings for long-term growth. It ensures that dividend payments do not compromise the enterprise's financial sustainability or investment potential. A well-defined policy offers guidance on how much profit should be distributed as dividends versus its retention for future needs, providing a framework for decision-making. In SOEs, dividend policies align financial decisions with broader public policy objectives, such as infrastructure development or social welfare programs. An explicit policy facilitates benchmarking against international best practices, making the enterprise more competitive and attractive to potential investors. During economic downturns or financial crises, a robust dividend policy clarifies the adjustment of payouts, helping manage stakeholder expectations while preserving enterprise resilience.

Significance

In the context of SOEs, dividends are not just a financial obligation but a strategic tool to fulfil public policy mandates while ensuring the enterprise's commercial viability. A clear, consistent, and balanced dividend policy is essential to navigate the complex interplay between fiscal needs, enterprise sustainability, and investor expectations.

Research Methodology

The data from the Department of Public Enterprises' Annual Surveys, and its Guidelines served as the basis for this aggregative analysis. The other sources included the World Bank Annual Report, the OECD Corporate Governance Factbook, and published works on SOEs in India and a few other countries.

Limitations

The paper excludes public sector banks, Government-owned and managed insurance companies, cooperative enterprises in the corporate sector, and municipal enterprises. The Foreign Jurisdictions include only 40 countries.

2. Literature Review

Dividend policy has received considerable attention in financial research due to its impact on shareholder wealth, capital structure, and company value. This research compiles key contributions to the literature on issues, ideas, and empirical evidence related to dividend policy and dividend policy of state-owned enterprises.

Since shareholders may generate "homemade dividends" by modifying their portfolios, Miller and Modigliani (1961), in their groundbreaking study contend that dividend policy has no impact on business value in ideal markets. Subsequent research, however, has examined market flaws such as taxes, agency costs, and signalling, which make choosing a dividend policy crucial for businesses. According to the bird-in-the-hand hypothesis (Gordon, 1963; Lintner, 1962), investors value companies with consistent dividend payments more highly because they choose the certainty of dividends above possible capital gains. However, according to the tax preference hypothesis of Brennan (1970), investors may choose capital gains since they have lower tax rates than dividends. Several macroeconomic and firm-specific factors influence dividend decisions. According to Rozeff (1982), there is a trade-off between transaction costs and agency costs. While dividends might help with free cash flow issues, they may also restrict chances for reinvestment. In a similar vein, Fama and French (2001) discovered that business size, growth prospects, and profitability are important factors that influence dividend distribution practices. The catering theory of dividends is one study that highlights the importance of investor emotion (Baker & Wurgler, 2004). According to this hypothesis, companies modify their payout policy in response to market sentiment to accommodate investor desires.

The viability of several hypotheses in diverse marketplaces has been examined through empirical investigation. The agency cost perspective is supported by DeAngelo, DeAngelo, and Stulz (2006), finding that companies with concentrated earnings typically pay greater dividends. Meanwhile, Allen and Michaely (2003) offer proof that dividend changes indicate management's optimism about future profits, supporting the signalling hypothesis. According to cross-national research, institutional and legal considerations have a big impact on dividend policy (La Porta et al., 2000). Businesses are more likely to pay dividends to shareholders in nations with robust investor protection, which is consistent with the dividend outcome model.

Traditional dividend theories' applicability has been re-examined in light of the increase in share repurchases. According to Skinner (2008), companies are increasingly choosing buybacks over dividends due to their flexibility and tax effectiveness. Farre-Mensa, Michaely, and Schmalz (2014) contend, however, that buybacks and dividends have complementary functions in corporate payment strategy. Furthermore, dividend policy research has taken on new aspects as a result of the adoption of environmental, social, and governance (ESG) standards. According to research by Fatemi, Glaum, and Kaiser (2018), companies with better ESG ratings are more likely to continue paying dividends steadily, demonstrating their dedication to long-term stakeholder value.

The hybrid structure of SOEs, which combine economic and public policy aims, makes them a unique framework for examining dividend programs. The factors, theoretical underpinnings, and empirical data pertaining to dividend policy in SOEs are examined in this paper.

In contrast to private companies, SOEs frequently face two demands on their operations: making money and meeting their socioeconomic obligations. Their dividend policy and other financial actions are impacted by this dichotomy. Since dividends are frequently a source of fiscal income, SOEs with government ownership tend to pay out bigger dividends (Bai & Xu, 2005; Megginson & Netter, 2001). Decisions on dividends in SOEs are influenced by the government's significant ownership interest. Research indicates that governments, particularly in developing nations, give dividends top priority as a steady source of revenue for fiscal budgets (Lin et al., 2018). This propensity may outweigh traditional variables, such as profitability and growth possibilities. In the context of SOEs, agency theory highlights the tension between executive discretion and governmental goals. By lowering the amount of free cash flow available for perhaps wasteful investments, high dividend distributions are frequently employed as a strategy to offset agency costs (Jiang et al., 2011). Political factors frequently influence dividend policy in SOEs. For instance, governments may prioritize short-term budgetary demands above long-term company development by pushing for larger rewards during fiscal deficits or election cycles (Chen et al., 2017). SOE dividend policies are heavily influenced by institutional elements including regulatory supervision, legal safeguards, and governance norms. To satisfy political demands in countries with poor governance, SOEs may pay out disproportionate dividends, sometimes at the price of operational effectiveness (La Porta et al., 2000).

In SOEs, dividends can be used as a tool to regulate inefficiencies and limit managerial discretion, in line with Jensen's (1986) free cash flow theory. Because SOEs have preferential access to government-sourced capital, the pecking order theory's usefulness in this context is restricted. It is still useful, nevertheless, for comprehending how dividend distributions fluctuate across various SOEs. Governments employ SOEs as tools to achieve budgetary and socioeconomic goals, according to political economic viewpoints. As a result, dividend policies frequently depart from strictly economic justifications (Shleifer & Vishny, 1994).

Empirical research shows that different nations have different SOE dividend policy practices. According to Lin et al. (2018), government pressures for fiscal contributions lead Chinese SOEs to pay bigger dividends than private companies. Similarly, Gupta and Rustagi (2019) discover that government fiscal requirements have a greater impact on dividend payments in Indian SOEs than do firm-specific elements like profitability or investment prospects. In SOEs, sectoral differences in dividend policy are noticeable. For example, industrial SOEs may have more fluctuating policies because of cyclical market conditions, but energy and utility SOEs frequently maintain consistent dividends because of their strategic importance and strong profitability (Megginson et al., 1994). However, studies have highlighted potential drawbacks of politically driven dividend systems. Overpaying dividends could deter investment in SOEs, ultimately diminishing their long-term value creation and competitiveness (Chang & Jin, 2016).

The effect of corporate governance changes on SOE dividend policy has been the subject of several studies. More balanced dividend plans in SOEs have been associated with better governance systems, including independent boards and performance-based incentives (Liao et al., 2020). Furthermore, dividend decisions are rapidly being influenced by the incorporation of environmental, social, and governance (ESG) factors in SOEs, which aligns them with more general sustainability objectives (Fatemi et al., 2018).

3. Dividend Policy in SOEs in India

The dividend policy in SOEs in India has evolved over more than five decades. The first flush could be ascribed to the *Public Accounts Committee*, 1962-63, according to which declaring dividends from the general reserve funds was to be discouraged for dividend payments from the current year's earnings only. The *Committee on Public Undertakings*, 1967, stressed the idea of indicating the percentage of profit for building up internal resources for saving surplus for dividends.

The second flush emanated from the *Government of India (GoI) directive issued in* 1967 stating that annual profits were to be apportioned under various heads and the balance available be declared as a dividend. The Guidelines maintained that the SOE in the manufacturing and service sectors declare at a rate of 6-15 percent and 10-15 percent respectively. The third flush occurred in 1992 when the GoI made it obligatory for profit-making SOEs to declare at least 20 percent of PAT as dividends. SOEs already declaring dividends were required to pay 50 percent more than the existing dividend, subject to a minimum of 20 percent of PAT. SOEs were obliged to declare a minimum possible dividend to maintain both visible and feasible dividend rates over the years. The fourth flush in 2016 sought every SOE to pay a minimum annual dividend of 30 percent of PAT or 5 percent of the net worth, whichever was higher, subject to the maximum dividend permitted under the extant legal provisions. The SOEs having reserves over three times their paid-up capital should immediately consider the scope for issuing bonus shares. Companies with high market prices of shares will consider stock splits. The following are to be considered while making dividend decisions: Net worth of the CPSE and its capacity to borrow; Long-term borrowings; Capital Expenditure for Business Expansion needs; Retention of profit for further leveraging in line with the Business Expansion needs; and Cash and bank balance. Until October 2024, the policy continued to follow the basics of the 2016 policy with an accent on special dividends and quarterly payments of dividends and was heavily fiscal considerations driven. This was done to obliterate the non-achievement of disinvestment targets during the last several years (The Economic Times, 2024).

In November 2024, the Department of Public Enterprise and the Department of Investment and Capital Asset Management DIPAM (2024), Government of India, announced a new dividend policy that requires the SOEs to pay an annual dividend equal to at least 30 percent of net profit or 4 percent of net worth, whichever is higher. According to DIPAM standards, SOEs in the financial sector, such as NBFCs, are permitted to pay a minimum yearly dividend of 30 percent of PAT, subject to any applicable limits imposed by existing laws. Within its scope, the new regulation specifically mentions SOEs in the banking sector. According to the updated criteria, SOEs with a net worth of at least ₹3,000 crore and cash and bank balances of more than ₹1,500 crore may also think about repurchasing their shares if the market price of their shares has continuously fallen below the book value during the previous six months. Additionally, it states that if an SOE-defined reserve and surplus equal or exceed 20 times its paid-up equity share capital, it may think about issuing bonus shares. Any listed SOE may think about separating its shares with a cooling-off period of at least three years between two consecutive share splits if its market price has continuously exceeded 150 times its face value during the previous six months. The rule also applies to SOE subsidiaries in which the parent central public sector organization owns more than 51 percent of the share capital.

According to the updated requirements, SOEs must think about paying an interim dividend at least twice a year or every quarter following quarterly results. According to the standards, all listed SOEs must pay interim dividends in one or more payments that equal at least 90percent of the anticipated annual payout. In September of each year, shortly after the AGM concludes, the last fiscal year's dividend must be paid. By giving SOEs greater operational and financial freedom, the updated rules aim to increase their performance and efficiency while also increasing the SOE's value and overall returns for shareholders. Additionally, it would allow more investors to take part in SOE's wealth development.

Table 1. Dividend Payment Policy of the Various States

States	Policy
Assam	A minimum dividend of 20 percent on equity holding or 20 percent on profit after tax
Haryana	4 percent on paid-up share capital
Himachal Pradesh	4 percent on paid-up share capital
Karnataka	20 percent on shareholding
Kerala	20 percent of paid-up shareholding
Madhya Pradesh	20 percent on profit after tax
Maharashtra	5 percent on paid-up share capital
Odisha	20 percent on equity or 20 percent on profit after tax whichever is high.
Rajasthan	20 percent on profit after tax or 20 percent paid-up sharing whichever is lower.
Uttar Pradesh	A minimum return of 5 percent on the paid-up share capital
West Bengal	20 percent on profit after tax or 20 percent on shareholding.

(Source: Budget Documents of the Various States)

India is a union of states. The various states have their independent policy regarding the payment of dividends by SOEs owned and controlled by them. Table 1 depicts the dividend payment policy of the various states.

4. Dividend Management: Process, Mechanism, Reporting

Several committees and bodies examined the various dimensions of dividend payments. These include the Investment Committee, Capital Markets Committee, Audit Committee, Independent Directors, Ex-officio Directors, Board of Directors, Administrative Ministry, Finance Ministry, and Department of Public Enterprises. The Audit Committee considers annual financial statements, periodic cash-flow projections, business plans, investment plans, or feasibility studies. Dividend payments are reported in the annual reports and websites of the concerned enterprise, reports of the administrative ministry, and the Annual Survey by the Department of Public Enterprises.

5. Dividend Scenario in SOEs

The state's expectations for increased dividend revenue are growing each year. SOEs have consistently met these expectations by providing substantial dividend payouts. Table 2 illustrates the dividend payment trends among SOEs.

5.1. Cognate Group-wise Dividend Declared by SOEs

The prominent sectors yielding dividends are related to coal, crude oil, minerals and metals, petroleum, heavy and medium engineering, power generation, power transmission, contract and construction and technology, and financial services. Table 3 shows the cognate group-wise dividend payments by SOEs.

A further probe points out that despite the quantum of dividend payments increasing substantially, only a few enterprises dominate the dividend payment scenario. This is in line with Table 3, which points out the stronghold of a few sectors such as coal, crude oil, minerals and metals, petroleum, heavy and medium engineering, power generation, power transmission, contract and construction

Table 2. Dividend Scenario in SOEs

Particulars	2017-18	2018-19	2019-20	2020-21	2021-22
Total number of SOEs	339	348	366	389	389
Number of operating SOEs	249	249	256	255	248
SOEs under Construction	81	86	96	108	95
SOEs not under operation	9	13	14	26	46
Listed SOEs	52	56	58	61	62
SOEs declaring Dividends	120	121	120	120	125
Amount of Dividends declared	0.76	0.72	0.72	0.73	1.15
Paid up capital	2.53	2.74	3.10	3.21	3.69
Dividends as % of paid-up capital	30.04	26.28	23.22	22.74	31.16
Net Worth	11.15	12.11	12.47	13.81	15.58
Dividends as % of Net Worth	22.69	22.62	24.86	23.24	23.68

(Lakh Crore ; Source: Annual Survey of Public Enterprises: 2017-2022, DPE, GoI)

Table 3. Cognate Group-wise Dividend Payment by SOEs

Cognate Group / SOE	2021-22	2020-21	2019-20
Agro-based	73	898	1240
Coal	2139546	1506921	1844384
Crude Oil	1261386	275461	839940
M&M	614902	317646	257646
Steel	352876	47475	24089
Petroleum	2835455	1844024	1306680
Fertilizers	17268	22288	12686
Chemicals & Pharmaceuticals	22771	378	297
Heavy & Medium Engineering	318052	297938	319897
Transportation	2582	3456	2082
Industrial & Consumer Goods	49970	23038	21848
Textiles	633	0	0
Power Generation	1308422	1108457	888383
Power Transmission	1127601	685044	448877
Trading & Marketing	22571	16360	14878
Transport & Logistic Services	478572	289635	482704
Contract & Construction and Technology Services	170705	151275	139932
Hotel & Tourist Services	24000	4000	24038
Financial services	758157	702701	533280
Telecommunication & IT	11581	11792	6376
Grand Total	11517123	7308787	7169257

(Lakh ; Source: Annual Survey of Public Enterprises: 2017-2022, DPE, GoI)

Table 4. Top Five Dividend Declaring SOEs

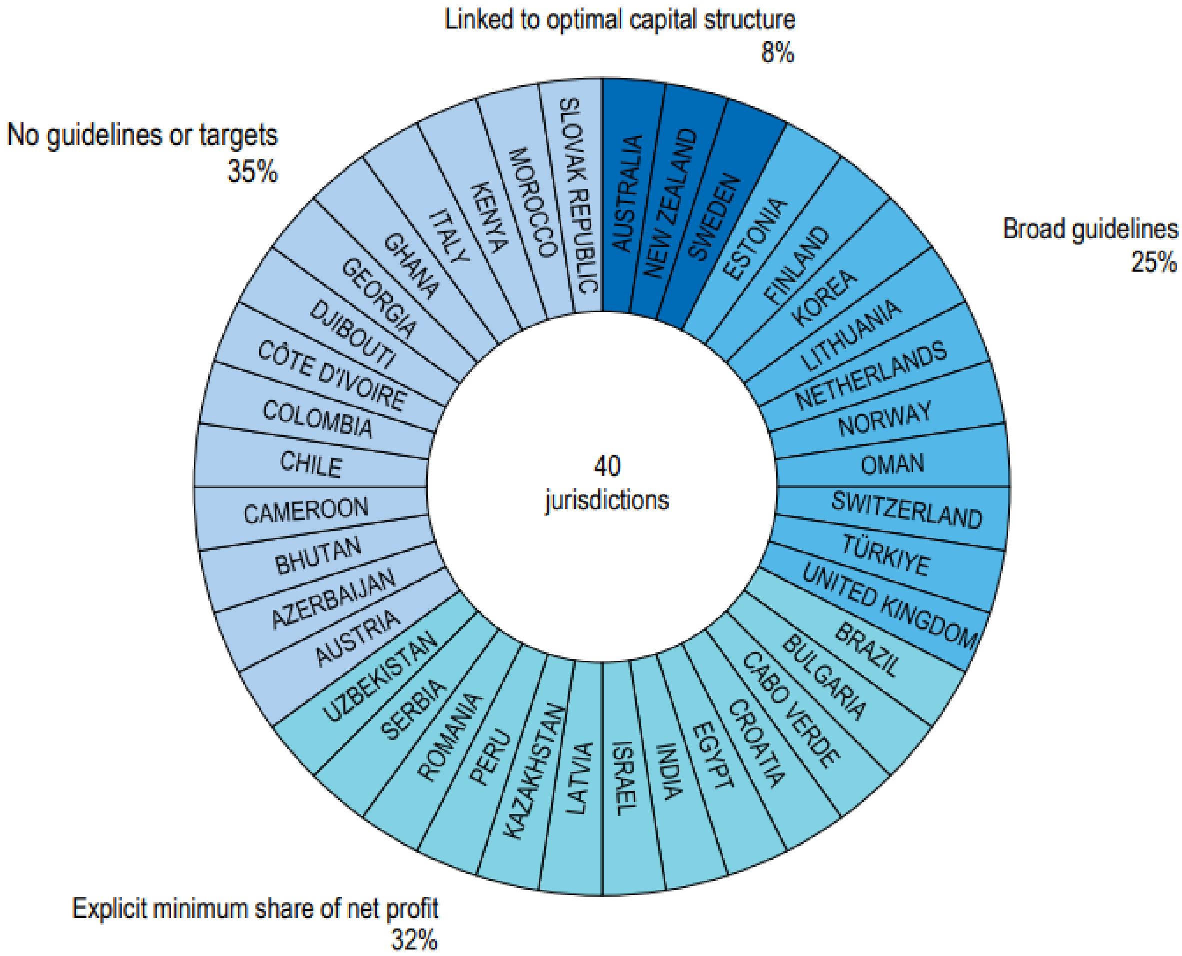
SOE Name (Sector)	2021-22		2020-21		2019-20	
	Profit reported	Dividend paid	Profit reported	Dividend paid	Profit reported	Dividend paid
Oil & Natural Gas Corporation Ltd.	4030574	11,44800	1124644	2,20200	1346368	7583080
Indian Oil Corporation Ltd.	2418410	86,5050	2183604	74,9370	131323	63,9200
Power Grid Corporation Of India Ltd.	1709376	10,81200	1193578	6,82200	1081118	4425920
NTPC Ltd.	1611142	387867	1376952	596345	1011281	3,11679
Coal India Ltd.	1120157	10,78500	764010	7,70300	1128088	16,71419

(Lakh ; Source: Annual Survey of Public Enterprises: 2019-2022, DPE, GoI)

and technology, and financial services. Table 4 depicts the top five dividend-declaring SOEs in this context.

5.2. Are Dividend Payments by SOEs Adequate?

Although the quantum of dividend payments is progressively increasing, a question crops up: are dividend payments by SOEs adequate? The SOE companies tend to declare the highest amount of dividends coupled with certain corporate groups. They have given the highest dividend yield, which also led the entire outflow to a five-year high. It has been noted earlier that only a few sectors of SOEs dominate the dividend payment scenario with a handful of SOEs taking the lead. This situation is changing with the Government's mandate of listing SOEs on bourses. However, the real question is not the quantum or the number of SOEs declaring dividends but the method of calculating dividends. In our view, SOEs have huge tangible and intangible assets. Therefore, dividends should be calculated based on the valuation balances of these assets.



Source: OECD/World Bank, 2024

Figure 1. Typology of Dividend Policies and Practices in Foreign Jurisdictions

6. Dividend Payment Policies and Practices in Foreign Jurisdictions

The OECD-World Bank Group study on dividend payment for SOEs presents a macro picture and brief case studies of select SOEs on dividend policies and practices (OECD/World Bank, 2024).

Figure 1 shows that different countries have different policies regarding dividend payments in SOEs. Certain nations adhere to minimum dividend payments. These legally required minimum payouts are based on net earnings. These nations include Chile, Bhutan, India, Brazil, Austria, Finland, and Italy. While minimum payment levels are specified in the majority of nations, a handful mandate that SOEs establish maximum dividend payout ratios. In many other nations, SOEs are obligated to pay dividends to match the dividend payout levels of private-sector businesses. Korea is included in this group of nations. In many countries, SOEs adhere to a predetermined annual schedule for dividend distribution, as exemplified by the United Kingdom, Norway, and the Netherlands. In certain nations, the preservation of a target credit rating serves as a valuable benchmark for achieving an optimal capital structure, which plays an essential role in shaping dividend expectations from SOEs. Sweden and New Zealand are notable examples within this category that successfully implement this approach for effective financial management in the SOEs.

An intriguing picture emerges from the sectoral position of SOEs concerning dividend distribution policy. The payout ratio for SOEs in the power generation industry in Finland, Bhutan, New Zealand, and Bulgaria is over 80 percent. However, in Brazil, the Netherlands, and India, the payout percentage of these businesses is less than 40 percent. In the case of Colombia, the average dividend payout ratio for the extractive sectors is 80 percent, whereas in India, Austria, and Brazil, it is less than 40 percent. The average dividend payout ratio for SOEs in the extractive sectors ranged from 20 percent in Brazil to 160 percent in Norway. Switzerland, Norway, Finland, and Austria all had SOEs in the public utilities sector that paid comparatively modest dividends. The state owner may choose to declare SOE dividends in the annual aggregate report on SOEs, the government financial statement, or both. Budget planning and implementation reports, citizen budgets, and audited yearly financial statements of SOEs are a few examples of additional transparency channels. In conclusion, dividend policies aim to reconcile the perhaps conflicting demands of sufficient transfers back to the public budget and the SOE's financial stability.

7. Conclusion and Way Forward

A crucial component of SOEs' financial management is the payment of dividends. The central and subnational levels of SOEs have steadily changed their dividend policies. Dividend payments improve public resource allocation and corporate governance. In SOEs, dividends of all kinds have made their impact. For budgetary reasons, the State is becoming more and more dependent on dividends. The range of dividend distributions has been 18 to 30 percent of net assets. SOEs have strong procedures and systems in place for formulating and disclosing dividends. Coal, crude oil, minerals and metals, petroleum, heavy and medium engineering, power generation, power transmission, contract and construction, technology, and financial services are the main industries of SOEs that declare dividends. Policy changes in operations, strategy, and the market have the potential to increase dividends. More SOEs would be eligible to join the dividend club if the government mandated that SOEs list.

Different countries have different dividend distribution rules for SOEs. Nonetheless, the different nations might be divided into three groups: those that mandate yearly negotiations for dividend payout ratios, a group of nations where SOEs are directed by a maximum payout ratio, and those where SOEs are driven by a minimum payout ratio. Public utility SOEs pay modest dividends, whereas SOEs in the energy and extractive industries pay significant dividends. Dividend policies aim to reconcile the financially viable SOE with the possibly conflicting goals of sufficient payments back to the public budget.

It is necessary to reevaluate the way dividends are computed in SOEs, both in India and in other countries. Dividends may be computed on the basis of substantial investments in both tangible and intangible assets.

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Credit Risk Assessment of SMEs in Cameroon: Limitations of Classical Approaches and Proposal of an Alternative Model to Increase Financing

Article Record

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Abstract

This article analyzes the Cameroonian banking system and the SME financing gap, highlighting the benefits of a new approach to credit risk measurement adapted to local realities. Based on a qualitative study including twenty (20) semi-structured interviews with bank managers (03), credit analysts (10), account managers (03), internal controllers (01), financial department staff (01) and risk officers (02), supplemented by a documentary and thematic analysis, this research shows that adopting an approach that integrates capacity building for promoters, financial management support, innovation in financing products, credit structuring and monitoring, as well as the promotion of networking and entrepreneurial culture, is a promising prospect for granting credit to SMEs. Risk assessment based on local criteria such as project soundness, entrepreneurs' reputation and track record, or the use of informal guarantees, promotes trust, solidarity and synergy among promoters, similar to cooptation and tontine mechanisms. This approach not only reduces the risk of default, but also stimulates job creation, wealth generation and economic development, while strengthening banks' appetite for SME financing.

financing gap | new approach | credit risk measurement adapted to local realities | qualitative thematic content analysis

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Keywords: *financing gap, new approach, credit risk measurement adapted to local realities, qualitative thematic content analysis*

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1. Introduction

Financing small and medium-sized enterprises (SMEs) is a major challenge for the economic development of sub-Saharan African countries, and particularly in Cameroon. Despite their significant contribution to job creation and growth, SMEs face persistent constraints in accessing bank credit. In practice, financial institutions rely primarily on credit risk assessment models based on international standards, notably those derived from prudential agreements and classical financial theories. These models favor a quantitative approach based on the analysis of financial statements, solvency ratios, and credit histories.

However, their application in the Cameroonian context raises significant limitations. Indeed, the Cameroonian economic environment is characterized by high levels of informality, uneven quality of financial information, and the prevalence of interpersonal relationships in economic transactions. These specificities call into question the relevance of conventional risk assessment tools.

The issue of corporate financing is not new; the work of Modigliani and Miller (1958) marked a major turning point in thinking about this topic. Their theorem, known as the "Modigliani-Miller proposition," contributed essential elements to the debate on corporate capital structure. In particular, they demonstrated that, in a perfect market (without taxes, without transaction costs, and with perfect information), a company's value is not affected by its financial structure, that is, the ratio between its equity and its debt. Modigliani and Miller's work revolutionized modern finance theory by providing a rigorous theoretical framework and highlighting important concepts such as the cost of capital and the impact of financial structure on firm value. However, the issue of business financing was already a concern long before them, but their work formalized and structured this debate in a way that continues to influence modern finance today, both in developed and emerging countries (Teufack et al., 2017). The problem of business financing remains relevant, whether in developed countries or developing countries like Cameroon. Thus, faced with the numerous challenges to overcome in order to drive development and generate growth, banks have emerged as major players in supporting the various wealth-creating actors. This near-monopoly of banks is partly explained by the embryonic nature of financial markets, particularly in the CEMAC zone, but also by the high liquidity of commercial banks. Bank financing is the primary avenue for businesses, large or small, to obtain the financing needed to meet their needs (Fogo, 2020). Despite these observations, several questions arise regarding the state of bank financing in our underdeveloped countries.

SMEs often face limited access to the capital they need to grow and develop. Access to credit for SMEs is also hampered by the information asymmetry between borrowers and banks. Indeed, only one in three SMEs produces financial statements certified by an auditor. When they do manage to present financial statements, many present several versions of their financial situation depending on the recipient—be it the bank, the tax authorities, or the company's own internal balance sheet—which undermines their credibility. This information asymmetry leads banks to overestimate risks in the face of uncertainty and to turn away from SMEs, which do not have the same transparency requirements as subsidiaries of large international groups. Banks are cautious and apply rigorous financial analysis techniques to assess the soundness of the financial structure and the strength of liquidity to allow for immediate monetization and ensure recovery in case of default. Furthermore, the personal and professional assets of the loan applicant are often intrinsically linked, complicating recovery procedures. Also, the assets available for seizure may be limited due to SMEs' lack of management capacity: they may face debt problems or insufficient cash flow, hindering banks' recovery efforts. The slowness, inefficiency, and costs of legal recovery procedures are yet another reason for banks to be cautious with these loans, which they consider risky. Overall, SMEs in Sub-Saharan Africa finance only 10% of their investments through banks, compared to 16% to 26% in other developing countries (AfDB, 2011). Many SMEs have never even applied for a loan (Sacerdoti, 2005). Despite this, the banking sector in Sub-Saharan Africa is quite dynamic, driven by economic growth. Financing constraints are considered by most analysts to be obstacles to development on the African continent. This assertion is not unreasonable, especially since a quick look at the figures sheds further light on the matter. Indeed, contrary to a widely held opinion, difficulties in accessing credit are not limited to SMEs alone; they affect the entire productive sector, which is generally composed of few medium-sized or large enterprises in Africa. Thus, credit granted to the productive sector represents only 15% of GDP, compared to 27% in South Asia and 109% in high-income countries (Khanchaoui et al., 2024).

As a poor country, Cameroon is not immune to the factors that characterize these economies, with over 80% of its economic fabric relying on small and medium-sized enterprises (SMEs). However, based on data from bank surveys, World Bank senior economist *Maria Soledad Martinez Peria* demonstrates that the volume of financing offered by banks to SMEs is more limited in African countries than in other developing countries. Indeed, in the sample of non-African developing countries used, she notes that loans intended to finance SMEs represent on average 13.1% of total bank loans, while in Africa the proportion is only 5.4%. The measurement of credit risk, which is central to this issue, highlights the fact that the traditional methods used by Cameroonian banks often rely on classic financial criteria, such as balance sheet strength, credit history, and physical collateral. However, these indicators may not accurately reflect an SME's true ability to repay a loan. Indeed, many SMEs possess untapped growth potential and innovations that are not considered in traditional assessment models (Fogo, 2021). Given this situation, we felt it was important to propose a new approach to measuring credit risk that takes into account qualitative and contextual factors. This could include assessing the viability of investment projects, analyzing managerial skills, the sector's performance history, training and support for project promoters, monitoring loans granted, the promoter's reputation and social network, the informal guarantees required, and the simplicity of the financial documents to be produced. Adopting such a methodology could not only reduce banks' perception of risk but also encourage SMEs to develop more rigorous financial management practices. Furthermore, adopting a new approach to credit risk measurement could foster the emergence of tailored financial products, such as social impact loans, which aim to support projects with positive impacts on community development (Fogo, 2021). Implementing this new approach could transform the SME financing landscape in Cameroon. This would require close collaboration between banks, the government, regulatory bodies, academics, and SME representatives to create a more inclusive and dynamic financial ecosystem. Such a change would not only promote the sustainability of SMEs but also sustainable economic growth for the benefit of the entire country (Fogo, 2021). Shortcomings related to the application of Western financial orthodoxy often refer to errors or inadequacies in the use of financial models and practices typical of developed economies when applied in different contexts, particularly in emerging or developing economies. These shortcomings may include negligence in risk assessment, flaws in financial modeling, and irregularities in the management of financial resources that do not take into account local realities (De Soto, 2021).

Supporting and training SME promoters in the operational process and management system are practices and strategies to be implemented to optimize the functioning of these businesses and thus improve their managerial effectiveness. This includes training in technical skills, financial regulations, risk management, as well as the development of soft skills for staff and managers (Meyer, 2021).

From the above, the fundamental question that emerges is: ***To what extent are traditional credit risk assessment approaches suited to Cameroonian SMEs, and how can a more relevant alternative model be proposed?***

2. Theoretical Reviews of SME Financing

Financing small and medium-sized enterprises (SMEs) is a central issue in developing economies, particularly in sub-Saharan Africa. Despite their crucial role in wealth and job creation, SMEs face structural constraints in accessing financial resources. In order to analyze these constraints, several theoretical frameworks have been used in the economic and financial literature. These theories make it possible to explain the behavior of economic agents, the imperfections of financial markets as well as alternative financing mechanisms.

2.1. Classical Theories of Financial Structure

2.1.1. The theory of Franco Modigliani and Merton Miller

The theory of Modigliani and Miller (1958) forms the basis of modern financial structure analysis. It posits that in a perfect market characterized by the absence of taxation, transaction costs, and information asymmetry, the value of a firm is independent of its financing structure. In the context of Cameroonian SMEs, this theory has significant limitations due to imperfections in the financial market, particularly information asymmetry and credit rationing. Nevertheless, it remains relevant as an analytical framework.

2.1.2. Transaction Cost Theory - Ronald Coase and Oliver Williamson

Transaction cost theory highlights the costs associated with economic exchanges, particularly the costs of information gathering, negotiation, and monitoring. In SME financing, these costs are particularly high for financial institutions because:

- Due to the limited availability of reliable information;

- The small size of the projects;
- High perceived risk.

Banks therefore select their clients and limit credit because financing SMEs is expensive for them due to the lack of information and monitoring of these SMEs. This theory thus explains the imbalance in the allocation of financial resources, leading to a study that proposes simplified models and a more suitable approach.

2.2. Information Theories

2.2.1. Agency Theory - Michael Jensen and William Meckling

According to Jensen and Meckling (1985), an agency relationship is "a contract in which one or more persons use the services of another person to perform some task on their behalf, which implies a delegation of decision-making power." Thus, according to agency theory, the lender faces two types of uncertainty regarding lending: "moral hazard," due to the fact that the borrower may change their behavior once in possession of the loan, and "adverse selection," linked to the lender's application of more onerous loan conditions (interest rate and collateral), forcing borrowers with "lower risk" to forgo the loan, because the rates of return they anticipate are relatively low.

In the context of SMEs, these asymmetries translate into:

- A difficulty for banks in assessing the quality of projects
- A risk of moral hazard after the granting of credit
- Adverse borrower selection

These factors lead financial institutions to demand high guarantees or to ration credit, limiting SMEs' access to formal financing.

2.3. Socio-Economic Approaches to Financing

2.3.1. The theory of social embeddedness - Mark Granovetter

Social embeddedness theory posits that economic relations are embedded in social networks. Economic decisions are not solely guided by economic rationality, but also by relationships of trust and social interactions. In the African context, this approach is particularly relevant. SME financing relies heavily on:

- Tontines;
- Family networks;
- Interpersonal relationships.

This reality underscores the importance of social capital in accessing financing; in other words, social relationships influence economic decisions. This theory therefore allows for the integration of a major innovation: relational variables. This variable leads to the analysis of the qualitative dimension of the entrepreneur, which must be taken into account, namely: the entrepreneur's trustworthiness, reputation, and network.

2.3.2. The Resource-Based View – Edith Penrose

This theory emphasizes the role of a company's internal resources in its performance and growth. It considers organizational capabilities, managerial skills, and human resources to be essential determinants. In the case of SMEs, weaknesses in management and structure limit their access to financing. This justifies the implementation of support mechanisms aimed at strengthening their capacities.

2.4. The Behavioral Approach to Financing

2.4.1. Behavioral finance

Daniel Kahneman, Amos Tversky, Richard Thaler, and Robert Shiller, some authors in behavioral finance, develop the central idea in their work that:

- Agents are not always rational;
- Biases (loss aversion, overconfidence, etc.);
- Psychological and emotional factors;
- Social and contextual influences.

While in classical finance risk is a purely objective function, in behavioral finance, perceived risk differs from actual risk. Biases affect banks and SMEs, leading to excessive risk aversion and consequently credit rationing, as well as overconfidence that often results in poor project assessment. Furthermore, the herding effect can encourage decisions based on the actions of other banks.

To explain banking behavior:

- Banks can refuse credit even with excess liquidity;
- Institutions may exaggerate the risk associated with SMEs;

To explain the behavior of the promoters:

- Entrepreneurs may overestimate the profitability of their projects.

These biases contribute to increased difficulties in accessing funding. *Cognitive* biases will therefore be corrected through: training; support; and monitoring. In the context of Cameroonian SMEs, this model helps explain the discrepancy between the actual risk and the risk perceived by banks, as well as the impact of entrepreneurs' perceptions and behaviors on repayment capacity. It justifies the integration of behavioral variables into the model, particularly the quality of the entrepreneur and support mechanisms, and supports the idea that reducing credit risk requires not only financial and organizational measures, but also correcting cognitive biases and taking behavioral factors into account.

Analysis of various theories highlights the complexity of SME financing. No single theory can fully explain the observed constraints. An integrated approach, combining information theory, socio-economic approaches, and behavioral dimensions, appears necessary to understand the realities of financing for Cameroonian SMEs. In this context, the development of innovative mechanisms, such as institutional support programs, could help reduce information asymmetries and improve SMEs' access to financing.

2.5. Empirical Review of SME Financing

2.5.1. Study by Joseph Stiglitz & Andrew Weiss (1981)

These authors conclude that banks ration credit even if borrowers are creditworthy, and that raising interest rates increases risk. Regardless of the creditworthiness of the demand or whether the investment project is bankable or not, the bank refuses financing.

2.5.2. Study by Allen Berger & Gregory Udell (1998)

These authors emphasize the importance of relationship lending and highlight the role of qualitative information, which is essential for financing SMEs. They therefore stress the importance of close relationships between the borrower and the lender.

2.5.3. Financial structure and behavior of SMEs

2.5.3.1. Study by Colin Mayer (1990):

According to this study, financial systems influence the financing of businesses and in Cameroon more specifically the banking system is dominant.

2.5.3.2. Works of Laurent Ndjanyou (2001) in Cameroon:

In contrast, Laurent Ndjanyou (2001) in Cameroon analyzed "Risk, Uncertainty, and Bank Financing of Cameroonian SMEs: The Need for a Specific Risk Analysis." After providing a theoretical explanation of risk and uncertainty, he identified information asymmetry as a factor hindering the development of the bank-SME relationship in Cameroon. To address this, we proposed a risk analysis adapted to the context of Cameroonian SMEs. This analysis incorporates a redesign of traditional financial analysis, emphasizing proximity and trust, while recognizing that effective information management in credit granting reduces risk and uncertainty. He employed financial ratio analysis as his methodological approach.

2.6. Informal Financing and Social Embedment

2.6.1. Study by Marcel Fafchamps (1999)

According to this author, social networks play a key role in financing, hence the importance of trust.

2.6.2. Study by Abhijit Banerjee & Esther Duflo (2011)

According to these authors, informal mechanisms compensate for the failures of the financial system.

2.7. Specific Constraints in Africa

2.7.1. World Bank Study (Enterprise Surveys)

The results of this study reveal the existence of major constraints to SME financing: difficulties in accessing financing, corruption, and regulatory instability.

2.7.2. African Development Bank Study

The results of this study reveal a financing gap for SMEs in Africa, estimated at several hundred billion USD. This demonstrates the scale of the problem and justifies our research.

3. Limits of Empirical Literature

Existing works have several limitations:

3.1. Fragmented Approach

We observed little integration between formal and informal finance. We noted that empirical research uses scoring financial, solvency ratios, and credit history. However, in African economies, they suffer from a lack of reliable data, poor predictive capacity, and therefore the exclusion of informal SMEs.

3.2. Weak African Contextualization

The models are often imported from developed countries: excessive focus on financial data, insufficient consideration of mechanisms for reducing asymmetry. Formal SMEs have easier access to credit, and proper accounting improves the likelihood of financing. Banks require substantial collateral, and SMEs are often excluded due to insufficient assets. Large companies have easier access to credit, while young SMEs are perceived as riskier. Credit rationing exists despite project profitability, and innovative or informal SMEs are excluded. Key qualitative variables such as the quality of the entrepreneur, social relationships, support, and the role of the entrepreneur's behavior are underestimated.

3.3. Lack of an Integrated Institutional Approach

We found no studies on support and assistance structures for SMEs, let alone hybrid public schemes. This literature review sufficiently demonstrates that:

- SMEs are structurally constrained
- Information asymmetry is central
- Banks are rationing credit
- Financing is crucial
- The institutional environment is crucial

Our research therefore aims to propose:

- **A hybrid model integrating:** Bank financing, institutional support, the SME development and assistance window (GDAP) and structured informal financing.
- **A reduction of: information** Asymmetry and credit risk.

The research therefore aims to propose an integrated approach to credit risk, combining: financial variables, qualitative variables, relational variables, behavioral variables and support mechanisms.

3.4. Synthesis of work on the new approach to measuring credit risk by banks and specific research proposals

The theory of social embeddedness in the loan relationship, developed by numerous authors, proposes a new approach to the bank-SME relationship that goes beyond the market-based definition often used to measure it. It involves incorporating social interactions to account for the trust and transparency they can generate. Considering these elements offers a very rich perspective, promising advances in the theory of financial intermediation (Ferrary, 2003).

Granovetter's theory of social embeddedness, developed in 1985, proposes that economic actions are profoundly influenced by social networks and personal relationships, rather than by purely rational calculations or abstract market rules. Granovetter emphasizes the importance of interpersonal ties in economic transactions, arguing that these ties provide the trust and information necessary for markets to function properly. In this sense, social embeddedness theory suggests that economic transactions through social links have beneficial consequences for firms seeking to meet their financing needs (trust, access to information, better governance).

Trust is a key variable for describing social interactions. Harhoff and Körting (1998) examined the role of mutual trust as perceived by business leaders in a credit relationship. In their interview, the authors used a nominal variable to indicate whether the interviewee believed that the banker and the business leader trusted each other. This variable was found to have a significant negative impact on the interest rate of credit lines. Similarly, Howorth and Moro (2006) showed that entrepreneurs who perceive their banker as trusting them are more likely to act reliably.[1] Consequently, the probability of moral hazard and/or default is reduced. A high level of trust thus translates into lower agency costs. The authors concluded that, from the bank's perspective, trust mitigates adverse selection and moral hazard, thereby reducing scoring and monitoring costs and leading to increased profits. For the entrepreneur, trust reduces both the effort required to

[1] Interviews were conducted with twenty entrepreneurs and six financial advisors in a region of Southern Italy.

provide information for bank monitoring purposes and the need for collateral, thus facilitating access to credit for SMEs to finance their growth.

In another study of the SME banking market, Uzzi (1999) suggests that embedded social relationships and networks formed by a mix of ties (embedded and act) benefit firms seeking financing. According to him, this promotes informal governance mechanisms and facilitates the transfer of private information—factors that can motivate banks and firms to find solutions to financing problems that market relationships have failed to resolve. Uzzi (1999) first analyzed how embedded and act social ties affect the borrowing relationship. Second, he attempted to demonstrate the advantages of a complementary network formed by these two types of relationships: the advantages of partnership associated with embedded relationships and the advantages of brokering offered by act relationships. Uzzi's (1999) results are consistent with his hypotheses. Indeed, the more embedded the commercial transactions between the bank and the firm are in social relationships, the greater the firm's access to credit at a low rate. The author concludes that embeddedness is a determining factor in the borrowing relationship because it facilitates access to credit for SMEs, thus enabling them to grow. He concludes that the quality of the bank-firm relationship is a cause of a firm's financial performance, not a consequence. Given this reasoning, we are led to formulate the following research proposals.

Proposition 1: Shortcomings related to the application of Western techniques, which adhere to a certain financial orthodoxy less suited to our local realities, constitute a major obstacle in the decision-making process for granting credit to SMEs in Cameroon.

Proposal 2: Training and support for entrepreneurs enables them to better understand banks' expectations, thereby reducing credit risks and information asymmetry, and constitutes a major asset in the decision-making process for granting credit to SMEs in Cameroon.

Proposal 3: The implementation of the optimal strategy for reducing credit risks and information asymmetry constitutes a major asset in the decision-making process for granting credit to SMEs in Cameroon.

4. Methodology

Research methodology is the way in which the researcher approaches and answers research questions. It includes study design, data collection methods, sample selection, data analysis, and approaches used to interpret results (Sekaran et al., 2016). Our study adopts an **inductive research** approach.

4.1. Field Interview Procedure

This article briefly outlines the approach used to contact key personnel (those in positions of responsibility) within Cameroonian banks who could provide important and necessary information regarding SME financing mechanisms for this research, which was conducted in various Cameroonian cities. The approach involved some individuals scheduling appointments with the secretary, while others, more open and friendly, simply made phone calls to their personal numbers obtained from their department or an acquaintance, and then scheduled interviews at a location agreed upon by the interviewee.

4.1.1. Survey using the reasoned choice method

The survey technique chosen for our research is a reasoned choice survey because in our semi-structured individual cross-sectional interviews, we only address resource personnel (holding a position of responsibility) within the banks of Cameroon and likely to provide important and necessary information on SME financing mechanisms.

4.1.2. Status of field data collection

An interview guide is a set of questions, themes, and instructions designed to guide the researcher during interviews with participants. It can be flexible and allow for adjustments based on responses and interactions with participants (Creswell et al., 2018). Our research method is primarily an interview-based survey; indeed, throughout this research, the various interviews will constitute the main method for collecting qualitative information. The semi-structured interview allows us to delve into the realm of individual representations and practices. It enables the formalization and systematization of data collection and allows us to create a homogeneous data corpus, making a comparative study of the interviews possible. It is an interactive process between the researcher and the participants, where questions are adapted according to the responses and where emotional expression is encouraged (Patton, 2015).

We used an interview guide administered to twenty (20) resource personnel (holding a position of responsibility) within banks in Cameroon and likely to provide important and necessary information on SME financing mechanisms for the completion of this research encountered in the cities of Cameroon.

Table 1. Profile of the actors interviewed

Codification	Sex	Age	Marital status	Occupation	Seniority	Respondents
Interview 1	Male	48 years	Married	Bank manager	12 years	R1
Interview 2	Male	38 years	Married	credit analyst	8 years	R2
Interview 3	Male	43 years	Married	Account Manager	6 years	R3
Interview 4	Female	35 years	Married	credit analyst	4 years	R4
Interview 5	Male	45 years	Married	Account Manager	11 years	R5
Interview 6	Male	49 years	Married	credit analyst	15 years	R6
Interview 7	Male	40 years	Married	Account Manager	7 years	R7
Interview 8	Male	42 years	Married	credit analyst	4 years	R8
Interview 9	Female	39 years	Married	credit analyst	6 years	R9
Interview 10	Female	37 years	Married	credit analyst	8 years	R10
Interview 11	Male	48 years	Married	Bank manager	10 years	R11
Interview 12	Male	38 years	Married	credit analyst	9 years	R12
Interview 13	Male	43 years	Married	Account Manager	6 years	R13
Interview 14	Female	35 years	Married	internal controller	4 years	R14
Interview 15	Male	45 years	Married	Risk officer	11 years	R15
Interview 16	Male	49 years	Married	Agency Manager	12 years	R16
Interview 17	Male	40 years	Married	credit analyst	7 years	R17
Interview 18	Male	42 years	Married	credit analyst	8 years	R18
Interview 19	Female	39 years	Married	credit analyst	6 years	R19
Interview 20	Female	37 years	Married	Risk officer	8 years	R20

Source: author based on data from the interview guide.

4.2. Analysis of the thematic content of the information in the interview guide

Content analysis lies at the heart of qualitative research and is one of the ways to leverage data. It can be defined as the systematic analysis of ideas expressed during research. It can be applied to written documents as well as verbal and non-verbal communications, such as transcripts of observations and interviews. Therefore, no element should be overlooked for any reason. It allows for an objective description of information from interviews, open-ended questionnaires, or various other documents (Marshall et al., 2016).

5. Assessment of Methods and Tools Currently used by Banks to Measure the Credit Risk of SMEs in Cameroon

The aim here is to present the results of the operationality of the methods and tools currently used by banks to measure the credit risk of SMEs in Cameroon.

5.1. Current approach to measuring credit risk by banks

Regarding the presentation of the methods and tools currently used by banks to measure the credit risk of SMEs in Cameroon, these testimonies gathered are reflected in several statements:

> ”Banks base their lending decisions to SMEs on a combined and structured risk analysis, integrating the examination of financial statements (profitability, solvency, liquidity), the use of scoring models based on financial and sector variables, and the requirement of real or personal guarantees. This assessment is enhanced by a qualitative analysis of the SME’s management, sector, and market, while digital risk management tools enable statistical and algorithmic data processing. Finally, regular loan monitoring ensures the early detection of signs of financial deterioration, thus strengthening the control of default risk” (R1, R2, R4, and R10).

5.2. Analysis of the limitations and shortcomings of the current approach

Regarding the analysis of the limitations and shortcomings of the current approach to measuring the credit risk of SMEs in Cameroon, the results obtained in the field indicate that the current approach has several limitations and shortcomings that can compromise the financial health of lenders and the viability of borrowing companies:

> ”The current approach to measuring the credit risk of SMEs in Cameroon has major limitations: the lack of reliable data and financial history compromises risk assessment, while an excessive reliance on tangible collateral neglects the actual repayment capacity. Furthermore, standardized rating models are insufficiently adapted to the local specificities of SMEs, such as their operating cycles, supplier-customer dependence, or economic fluctuations” (R3, R2, R5 and R9).

And for others:

> ”The current approach to measuring SME credit risk in Cameroon suffers from several limitations: the lack of reliable and up-to-date data complicates risk analysis, while the rating models used are not always adapted to the specific characteristics of SMEs, potentially leading to an underestimation or overestimation of default risk. Furthermore, the absence of regular monitoring and continuous assessment, combined with the sensitivity of SMEs to economic fluctuations and political changes, limits the ability of financial institutions to anticipate risks, highlighting the need to improve the approach to better reflect local realities and strengthen the security of credit decisions” (R1, R12, R14 and R11).

5.3. Advantages of orthodox Western financial management techniques in the local context

Regarding the advantages of traditional Western techniques, the testimonies gathered are reflected in several statements:

> ”Western financial management techniques, based on international accounting principles and standardized methods, enable Cameroonian companies to ensure a high level of professionalism, transparency and financial communication, thereby strengthening the confidence of investors and partners. They also offer tools for assessing and managing financial risks, facilitating the anticipation of crises and access to financing, including international financing, while contributing to the improvement of the profitability and competitiveness of companies in local and global markets.” (R1, R2, R3, R4, R5, R6, R8, and R20)

5.4. Main shortcomings identified in the application of Western techniques in SME lending

> ”The application of Western techniques to the SME lending process in Cameroon can encounter several obstacles related to the local context: they do not always take into account business culture, commercial practices, and specific economic conditions, while the lack of transparency and financial reporting complicates access to reliable information. Strict solvency criteria and standardized credit products can exclude many SMEs, limiting their financing and growth opportunities. Furthermore, the risks of fraud and non-repayment pose additional challenges for financial institutions. It therefore appears necessary to adapt these techniques to local realities in order to strengthen access to credit and support the sustainable development of Cameroonian SMEs.” (R1)

And for others:

> ”Western techniques used to assess the creditworthiness of SMEs in Cameroon have limitations due to local socio-economic specificities. Rigid guarantee criteria and standardized financing products can restrict access to credit, while the lack of proximity and support from banks limits the assistance SMEs can provide for business development and loan repayment. Furthermore, the complexity of the creditworthiness criteria applied can generate misunderstanding, frustration, and a lack of confidence among entrepreneurs, highlighting the need to adapt these approaches to the needs and realities of Cameroonian SMEs.” (R2)

And for others:

> ”Western credit risk assessment techniques, based on rigorous criteria and standardized practices, require adaptation to the Cameroonian context, where many SMEs are informal and lack standardized accounting practices. These strict criteria limit access to financing for small businesses lacking solid collateral or a credit history, while the introduction of suitable financial products, such as microcredit or loans guaranteed by public institutions, facilitates their financial inclusion.” (R18, R19 and R17)

5.5. New risk measurement approach better adapted to local realities

Regarding ways to improve Western techniques to better suit the local realities of SMEs in Cameroon, the testimonies gathered are reflected in several statements.

> ”Financial institutions can support the development of Cameroonian SMEs by conducting market research and tailored analyses to identify their specific needs and promising sectors. They can design flexible financial products, such as low-interest loans, asset-backed loans, or innovative instruments that take local economic cycles into account, and offer training programs in management, accounting, and finance to familiarize entrepreneurs with proven practices adapted to the local context. Furthermore, by establishing partnerships with governments, NGOs, and other stakeholders, they contribute to creating an ecosystem conducive to the growth and sustainability of SMEs.” (R6, R13 and R18)

And for others:

> ”Banking support and training for stakeholders significantly influence the decision-making process for granting credit to SMEs, by reducing information asymmetry and improving the assessment of project viability. Trained and competent project promoters inspire confidence in bankers, facilitating access to financing, while a better understanding of their needs allows for the offering of suitable financial products. Furthermore, training enhances the efficiency and speed of decision-making, which is essential for meeting the ad hoc financing needs of SMEs and seizing growth opportunities.” (R16, R15, R17 and R19)

And for others:

> ”Personalized support is a major asset in the SME lending process, as it strengthens the confidence of financial institutions by demonstrating sound management and access to expert advice. It enables SMEs to prepare complete and compelling loan applications, including realistic financial forecasts and structured business plans, while tailoring financing requests to their specific needs. Furthermore, SMEs that receive support generally demonstrate better financial performance, facilitating access to future loans.” (R4, R6 and R8)

5.6. Strategies used to reduce risks and information asymmetry

Regarding the various strategies used to reduce risks and information asymmetry in the SME lending process in Cameroon, these testimonies are reflected in several statements:

> "Granting credit to SMEs in Cameroon faces high risks and information asymmetry, requiring tailored strategies to mitigate these effects. Detailed project assessments allow for a better evaluation of their viability and reduce the risk of default, while post-financing monitoring further reduces default risks. Ongoing training and support strengthen the skills and support of managers. Local partnerships with NGOs and specialized SME training and support organizations facilitate access to reliable information on SME performance and reputation, thereby increasing lender confidence. Improved financial transparency enhances business credibility, and the use of financial technologies accelerates the credit process and leverages alternative data to assess creditworthiness." (R3, R5, R6, R9, R11 and R13)

5.7. Advantages of the new approach compared to the traditional approach

Regarding the tools and methods used to implement the optimal strategy for reducing risks and information asymmetry in the SME lending process in Cameroon, it appears that:

> "The new approach to measuring SME credit risk in Cameroon goes beyond the limitations of the traditional approach centered on financial statements by integrating alternative data such as entrepreneurial culture, relationship networks, project relevance, innovation, managerial integrity, product specificity, and market information, thus offering a more comprehensive view of financial health. By developing models adapted to the local context and using machine learning and predictive analytics, it makes it possible to better anticipate payment defaults, reduce biases that disadvantage certain SMEs, and make assessment less dependent on formalization or tangible guarantees. Thanks to digital tools and automation, this approach facilitates real-time monitoring, reduces operational costs, and makes financing more accessible and tailored to the specific needs of SMEs, thereby strengthening credit risk management in the Cameroonian context." (R1, R2, R3, R4, R5, R6, R7, R9 and R12)

5.8. Feasibility of implementing the new approach by Cameroonian banks

Regarding the discussion on the feasibility of implementing this new approach to measuring the credit risk of SMEs in Cameroon by Cameroonian banks, it appears that:

> "Implementing a new approach to measuring SME credit risk in Cameroon presents both challenges and opportunities. SMEs, often informal and unstructured, face barriers to accessing finance due to the difficulty in assessing their creditworthiness. A suitable approach must take into account the diversity of businesses, rely on reliable data collected through partnerships such as the GDAP, and integrate digital and fintech technologies to reduce information asymmetry. Success also depends on training and awareness-raising for banks, SME associations, regulators, and public or international institutions, as well as on SMEs adopting a good credit history. If these conditions are met, the new approach would allow for more accurate risk assessment, better decision-making, broader access to credit, and a reduction in defaults, thereby stimulating national economic growth." (R1, R6, R18, R19, R15, R16, R17, R19 and R20)

5.9. Changes the new approach could bring to the financial sector

Regarding the changes that this new approach could bring to the financial sector in Cameroon, it appears that:

> "The new approach to measuring SME credit risk in Cameroon, which incorporates non-traditional data such as payment behavior, cash flow, and professional networks, allows for a more comprehensive and accurate assessment of their creditworthiness, even without solid balance sheets. By strengthening the confidence of financial institutions, it facilitates the granting of credit and promotes the development of suitable financial products, such as flexible credit lines or pooled loans. This approach encourages the entry of new players, increases competition, reduces collateral requirements, and makes financing more accessible, thereby stimulating SME growth, job creation, innovation, and economic diversification, while making the Cameroonian financial system more inclusive and dynamic." (R2, R3, R4, R6, R8, R11, R17, R18 and R20).

6. Triangulation and Validation of Research Proposals

In the context of our research, we have retained the triangulation of collection tools which refers to the use of more than one tool (for example, using interviews, observations, and document analysis).

6.1. Shortcomings of Western techniques in the local context (Validation of P1)

Regarding the shortcomings related to the application of Western techniques, which adhere to a certain financial orthodoxy less suited to our local realities in the decision-making process for granting credit to SMEs in Cameroon, it appears that the application of Western financial techniques, when transferred without adaptation to local realities, can raise several concerns. Here are a few points to consider:

> "Credit models developed in advanced economic contexts are often poorly adapted to Cameroonian realities, where informality, community practices, and insufficient financial

> data render Western criteria inapplicable. The requirement for high collateral, complex procedures, and a lack of access to technological infrastructure limit credit access for SMEs, stifle innovation, and exclude certain populations, particularly young people and women. To address these shortcomings, it is crucial that financial institutions adapt Western methods to the local context by making criteria more flexible, taking into account cultural and economic specificities, and collaborating with local stakeholders to develop inclusive and relevant financing solutions." (R1, R3, R4, R5, R8, R12, R15, R16 and R20)

And for others:

> "Western credit assessment methods, based on standardized criteria and physical guarantees, are often ill-suited to the Cameroonian context, where a significant proportion of SMEs operate in the informal sector and have informal financial statements. Their rigidity limits access to financing, ignores human relationships and trust, which are essential in the local economy, and can lead to loan refusals. To support economic growth, employment, and financial inclusion, it is therefore necessary to adapt these techniques to local specificities, incorporating flexibility, cultural and economic particularities, and the knowledge of local stakeholders in order to create a more efficient and inclusive credit environment." (R2, R6, R5, R7, R9, R13, R14, R17, R18 and R19)

This validates the first proposition P1, according to which the shortcomings linked to the application of Western techniques respecting a certain financial orthodoxy less adapted to our local realities constitute a major obstacle in the decision-making process of granting credit to SMEs in Cameroon.

6.2. Support and training as assets in credit granting (Validation of P2)

Regarding the link between support and training in the operational processes and management systems of SMEs in terms of financing and the bank lending decision-making process for SMEs, it appears that the support and training offered to SMEs in Cameroon play a crucial role in improving their operational processes and management systems. This perspective can be understood on several levels:

> "The training and support provided to SMEs by the GDAP strengthen entrepreneurs' skills in financial management, business plan development, and economic analysis, while promoting rigorous accounting practices and transparency in financial information. This reduces information asymmetry and allows banks to more accurately assess the financial health of businesses, facilitating the granting of appropriate loans. The support also helps managers identify and anticipate risks, adopt mitigation strategies, and innovate in response to market trends, thereby strengthening the viability and competitiveness of SMEs. By creating a bond of trust between SMEs and financial institutions, this process improves the relevance of financing offers and optimizes the banking decision-making process. Thus, training and support represent a major lever for the growth, sustainability, and stability of the Cameroonian economic sector." (R3, R4, R6, R8, R10, R11, R12, R18 and R19)

And for others:

> "The support and training provided by GDAP to Cameroonian SMEs are essential for improving their financial management, reducing risks, and mitigating information asymmetry with banks. These programs strengthen entrepreneurs' skills in cash management, budgeting, and financial analysis, enabling them to prepare more credible and structured loan applications. Furthermore, this support facilitates risk identification and management, reduces the risk of default, and increases SMEs' attractiveness to lenders. It also promotes transparency and builds trust with financial institutions, while encouraging innovation and the adoption of best practices adapted to local realities. Thus, by improving access to finance and business competitiveness, GDAP contributes to sustainable growth and the consolidation of the Cameroonian economic ecosystem." (R1, R5, R9, R10, R13, R14, R17 and R20)

This validates the second proposition P2 according to which, Support and training of entrepreneurs in the operational process and the managerial system of SMEs in terms of financing reduces risks and information asymmetry and constitutes a major asset in the decision-making process of granting credit to SMEs in Cameroon.

6.3. Implementation of optimal risk reduction strategy (Validation of P3)

Regarding the link between the implementation of the optimal risk reduction strategy and information asymmetry regarding the credit granting decision-making process, it is noted that implementing an optimal strategy for reducing risks and information asymmetry in the credit granting decision-making process in a Cameroonian SME can have significant impacts in terms of added value. Some concrete points to consider include:

> "Implementing an effective strategy to reduce risks and information asymmetry in the credit granting process provides significant added value to Cameroonian SMEs. By improving the transparency and reliability of financial data, this approach allows decision-makers to more accurately assess borrowers' creditworthiness, thereby reducing the risk of default and the rate of unrecoverable debts. The use of appropriate risk assessment tools makes it possible to adjust credit terms to repayment capacity, offering better-tailored financial products while ensuring the profitability of SMEs. Clear communication and transparent management strengthen the trust of customers and partners, build customer loyalty, and attract new borrowers, increasing the customer base. Furthermore, rigorous risk management and operational transparency improve the company's image

> with investors and financial institutions, facilitating access to external financing and favorable terms."

Thus, implementing such a strategy optimizes decision-making, secures credit operations, and supports the sustainable growth and financial stability of SMEs in Cameroon (R1, R2, R7, R9, R3, R4, R18, R11, R13, R16, R17, R15, R19 and R20).

This validates the third proposition P3 according to which, The implementation of the optimal strategy for reducing risks and information asymmetry constitutes a major asset in the decision-making process for granting credit to SMEs in Cameroon.

7. Discussion of Results

Our results for Proposition P1 state that the mechanical application, without recalibration to local specificities, of "orthodox" financial techniques of Western origin (standard scoring, formal collateral requirements, financial ratios calibrated for formal businesses) constitutes a significant obstacle to the decision-making process for granting credit to Cameroonian SMEs: these procedures raise the acceptability threshold for applications and lead to credit rationing for economically viable units characterized by weak accounting formalities, informal collateral, and short cash cycles. This interpretation aligns with the conceptual framework of Beck & de la Torre (2007), who advocate distinguishing between supply and demand constraints through the concept of *access possibilities frontier*, showing that instruments not adapted to local state variables reduce access to financial services. Multi-country analyses (Beck, Demirgüç-Kunt & Maksimovic, 2002) using firm-level databases and econometric methods show that small businesses in countries with weak institutions have, on the one hand, less recourse to bank credit and, on the other hand, that the form and access to financing depend strongly on the institutional context, which corroborates the idea that the importation of unadjusted Western practices biases credit decisions. In the Cameroonian context, Piabuo & Tieguhong (2015) use the Cameroon Enterprise Survey (2009) and an endogenous model switching regression analysis shows that interest rates, loan size and maturity, lack of formal collateral, and legal status are among the determinants of credit constraints. These results empirically explain the negative sensitivity of lending to formal criteria. Qualitative surveys of loan officers (Souleymanou, 2020), analyzed thematically, document that internal decisions favor standardized parameters and few contextual field assessments, reinforcing the discriminatory nature of banking procedures towards informal SMEs. Finally, the literature on credit scoring in microfinance (Schreiner, 2000) shows that statistical scoring can improve risk forecasting, but only if it is designed with relevant local variables and/or supplemented by a "high-touch" approach; in other words, the uncritical application of Western tools without empirical recalibration leads to credit refusals even for viable borrowers. Collectively, these studies validate our conclusion: reducing credit rationing requires combining recalibrated quantitative metrics (localized scoring) and contextual qualitative assessments in banking risk assessment procedures in Cameroon.

Our results from Proposition P2: Support and operational and managerial training for entrepreneurs reduce information asymmetry and the risks perceived by lenders, and therefore constitute a major asset in the decision-making process for granting credit to Cameroonian SMEs. Indeed, training that improves bookkeeping, cash flow forecasting, and the quality of loan applications reduces the areas of uncertainty that credit analysts typically penalize, increasing the likelihood of loan approval. This conclusion is consistent with randomized controlled trials. Similarly, Bruhn and Zia (2011) (World Bank WPS, study of young entrepreneurs in Bosnia and Herzegovina) document, through a rigorous evaluation (experimental/quasi-experimental depending on the program design), that programs combining management training and financial literacy increase managerial skills and the formalization of businesses—plausible channels through which banks revise their risk assessment downwards. McKenzie & Woodruff's (2013) critical synthesis, which reviews RCTs and quasi-experimental evaluations of entrepreneurship training in developing countries, shows that training consistently improves practices (record keeping, invoicing), even if the effect on profits is heterogeneous, highlighting the importance of appropriate design and post-training follow-up to convert these management gains into sustainable improvements in access to credit. Closer to the African context, Custódio, Mendes, and Metzger (2019) (RCT in Mozambique) use survey data and financial statements to demonstrate that financial training for managers modifies certain financial policies and leads to performance gains. Finally, national assessments and empirical studies in Cameroon confirm the practical-operational link between financial skills, accounting formalization, and access to credit: the study by Mukete et al. (Mezam Division, Cameroon) using logit regression models identifies a lack of formal accounting practices and weak managerial skills as major negative determinants of access to bank credit, which corroborates our interpretation that support and training reduce information asymmetry and local credit rationing. Collectively, this experimental evidence, these syntheses, and local studies support the following policy and managerial implication: linking loan application procedures to certified training programs and support modules (accounting, cash flow forecasting, application preparation) would reduce information asymmetry and significantly improve lending decisions for Cameroonian SMEs.

Our results for Proposition P3: implementing an optimal strategy combining risk reduction instruments and measures to limit information asymmetry (recalibrated scoring, information sharing via registries/credit bureaus, targeted guarantees, training/mentoring, and post-grant monitoring) significantly increases the probability of credit being granted to Cameroonian SMEs. This conclusion is based on the theoretical framework of credit rationing and information asymmetry developed by Stiglitz & Weiss (1981), which explains why lenders ration supply in the presence of uncertainty and adverse incentives, thus necessitating non-price instruments to overcome rationing. The analytical framework of Beck & de la Torre (2006) then demonstrates, through a conceptual approach based on *access possibilities frontier*, that improving access requires acting simultaneously on supply and demand constraints, empirically justifying a multi-lever strategy rather than a single solution. Operationally, experience with credit scoring in microfinance (Schreiner, 2000) documents that statistical scoring, when properly calibrated to local data, improves risk predictability and reduces operational costs, confirming the role of a quantitative tool in optimal strategy. Empirical studies from Africa and Cameroon corroborate these mechanisms: Piabuo & Tieguhong (2015, Cameroon) used the Cameroon Enterprise Survey (2009) and estimated an endogenous model switching regression. Studies show that credit constraints (interest rates, loan size/maturity, formal collateral, legal status) reduce SME productivity, indicating that policies reducing these constraints (guarantees, information, support) can alleviate rationing. Finally, a local study (Mukete et al., 2021, Mezam Division, Cameroon) using logit models identifies accounting formalization and managerial skills as positive and significant determinants of access to bank credit, empirically validating the training/support and information channel in the optimal strategy. Thus, the theoretical and empirical literature converge: to reduce rationing and improve lending to Cameroonian SMEs, an integrated strategy involving recalibrated scoring, information sharing, and social capital is needed. The promoter's reputation and certified support/training programs are necessary, each lever acting on a separate channel of information asymmetry and risk and collectively maximizing the impact on the credit decision.

8. Conclusion

In conclusion, the rigid application of Western techniques to lending to Cameroonian SMEs reveals major limitations, including a lack of contextualization to local realities, the exclusion of informal or emerging businesses, and a strong reliance on guarantees and formal financial statements. These shortcomings restrict access to financing and hinder economic growth. This article highlights the limitations of traditional approaches to credit risk assessment in SMEs within the Cameroonian context. It proposes an alternative, multidimensional model integrating financial, informational, relational, and behavioral dimensions.

This approach constitutes a theoretical and practical contribution that can improve credit allocation and promote financial inclusion.

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A Study of Financial Literacy, Mobile Banking Convenience, and Spending Attitudes Among Working Millennials in General Santos City

Article Record

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Abstract

The use of mobile banking has influenced on how people save and spend their money. This study investigated the relationship between Financial Literacy (FL), Mobile Banking Convenience (MBC), and Spending Attitudes (SA) among working millennials in General Santos City. Using Cochran's formula, the computed sample size of the study is 385 working millennials. To achieve objectives of the study, the researcher employed quantitative research design specifically employing descriptive correlational research which aims to determine the demographic trend of the working millennials in General Santos City and to get the relationship between FL and SP, and MBC and SA. The result on the correlation shows the relationship between the FL and SP is statistically significant but weak. This suggest that as the level of FL among working millennials increase, their impulsive buying behavior decreases. The same result was found on the correlation between MBC and SP which shows negative and weak correlation with p-value of 0.003 indicating the observed correlation is significant.

Financial Literacy | Mobile Banking Convenience | Spending Attitudes | Financial Awareness | Financial Experience | Subjective Financial Knowledge | Financial Skills

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No generative AI was used for analysis or results.

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Abstract

The use of mobile banking has influenced on how people save and spend their money. This study investigated the relationship between Financial Literacy (FL), Mobile Banking Convenience (MBC), and Spending Attitudes (SA) among working millennials in General Santos City. Using Cochran's formula, the computed sample size of the study is 385 working millennials. To achieve objectives of the study, the researcher employed quantitative research design specifically employing descriptive correlational research which aims to determine the demographic trend of the working millennials in General Santos City and to get the relationship between FL and SP, and MBC and SA. The result on the correlation shows the relationship between the FL and SP is statistically significant but weak. This suggest that as the level of FL among working millennials increase, their impulsive buying behavior decreases. The same result was found on the correlation between MBC and SP which shows negative and weak correlation with p-value of 0.003 indicating the observed correlation is significant.

Keywords: *Financial Literacy, Mobile Banking Convenience, Spending Attitudes, Financial Awareness, Financial Experience, Subjective Financial Knowledge, Financial Skills, Financial Capability, Financial Goals, Access Convenience, Search Convenience, Evaluation Convenience, Transaction Convenience, Possession Convenience, Lifestyle, Consumptive Behavior*

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1. Introduction

Technological advancement led to many changes which contributed to the change in lifestyle especially for millennials where access to different products is made easy through the use of technology contributing to their impulsive buying decisions (Lissitsa & Kol, 2016). This technological advancement includes the introduction of online banking and electronic payments which provides more convenience as financial transactions are made easier and accessible anytime (Team, 2024). As mentioned by Chen (2026), users can now access mobile banking features anytime and anywhere saving them the time and effort. But the 24/7 features of mobile banking resulted to irrational shopping behavior of many users resulting to impulsive buying decisions (Pontororing & Pontororing, 2019).

In the United States of America, an estimated 60% of the citizens are living paycheck to paycheck, which means that they spend everything that they earn and leave nothing to save (Caditz-Peck, 2023). As highlighted by Simeon (2024), there is a gap between those who are financially practical versus those who are not financially wise. According to the World Bank Survey of 2021, 42% of adults have understanding of inflation and 25% are aware of the basic financial concepts.

Hence this study will delve into the factors that influence spending attitudes of working millennials in General Santos City. Previous authors such as Zahra and Anoraga (2021) recommended to explore other factors that could influence spending attitudes. Thus, this study aims to investigate the impact of financial literacy, convenience towards spending behavior among working millennials in General Santos City.

This study aims to address the demographic profile of the respondents, the level of financial literacy (FL), the mobile banking convenience (MBC) level, and the level of spending attitudes (SA).

1.1. Hypothesis

H_{01}: There is no significant relationship between the FL and SA among working millennials in General Santos City.

H_{02}: There is no significant relationship between MBC and SA among working millennials in General Santos City.

1.2. Conceptual Framework

This study explored the relationship between FL and SA, and MBC and SA as shown in Figure 1. FL was measured using six indicators namely: Financial Awareness (FA), Financial Experience (FE), Subjective Financial Knowledge (SFK), Financial Skills (FS), Financial Capability (FC), and Financial Goals (FG). While MBC was measured using Access Convenience (AC), Search Convenience (SC), Evaluation Convenience (EC), Transaction Convenience (TC), and Possession Convenience (PC). While SA was measured through Lifestyle (L) and Consumptive Behavior (CB).

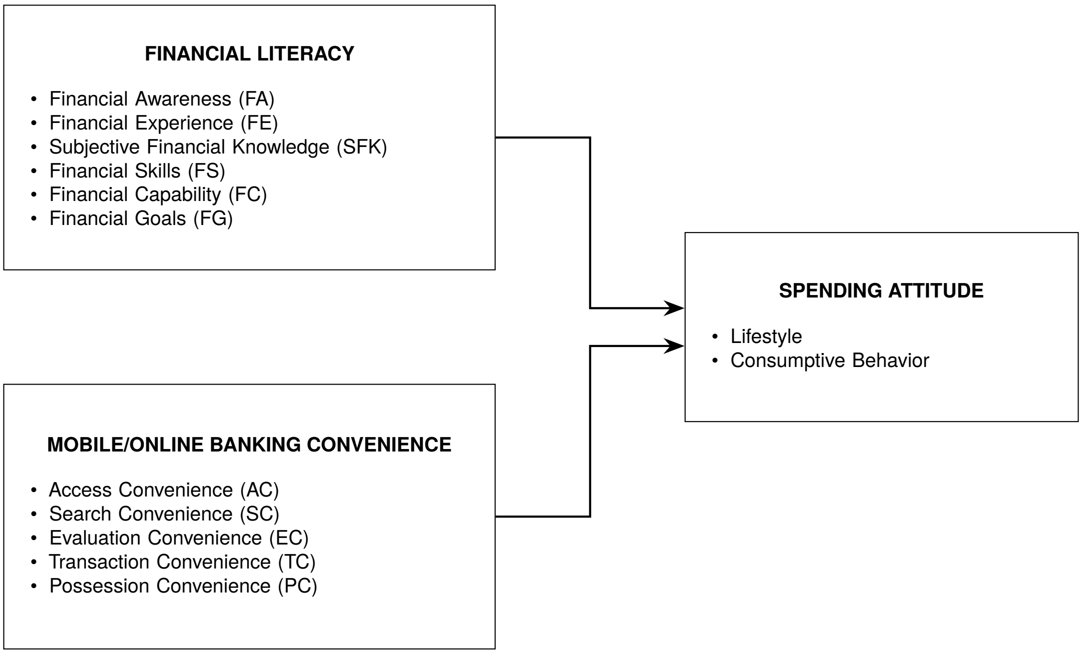

Figure 1. Conceptual Framework

1.3. Definition of Terms

Access Convenience refers to the feature of mobile/online banking that makes purchase experience of working millennials easy.

Consumptive Behavior refers to the desire of working millennials to spend irrationally for things which are not important.

Convenience refers to the feature of mobile/online banking which provides opportunity for working millennials to do transactions such as online purchasing and payment anytime they want.

Evaluation Convenience means the degree to which the application offers comprehensive service specifications, adequate information for distinguishing various products, and an interactive interface utilizing icons, images, and animations.

Financial Awareness refers to the strategies employed to track spendings and making list of things as guide before buying things to prevent purchasing beyond what is needed and avoid spending beyond the budget.

Financial Capability refers to the ability to handle money well in real life. This includes paying bills on time, handling cash transactions, buying things when needed, and gathering information in a systematic way before making a purchase.

Financial Experience includes being involved in financial matters in a practical way, such as setting up emergency savings, keeping track of financial records, managing personal assets, investing in the stock market, and saving money through non-bank financial institutions.

Financial Goals refers to the systematic development of financial plans, strategic planning for long-term goals such as retirement, and the discipline of saving money to facilitate cash purchases instead of relying on credit.

Financial Literacy means having the knowledge, skills, and confidence to make smart and responsible money decisions at different points in life, such as when budgeting, saving, investing, and planning for future financial goals.

Financial Skills are the practical competence to organize bills and receipts in accessible locations, routinely review savings financial statements, mitigate risks via insurance acquisition, and continuously assess and oversee debt.

Lifestyle is the behavioral pattern characterized by the pleasure derived from purchasing and acquiring products.

Possession or Post Convenience refers to the perceived ease and effectiveness with which consumers can obtain precisely what they desire, address issues related to failed transactions, and experience timely service delivery through the m-banking platform.

Search Convenience refers to how easy it is for users to use the m-banking app, find the information they need without having to search for it elsewhere, and get useful information that the app gives them.

Spending Attitude refers to the desire to buy things because of attractiveness and temptation, or the desire to show off expensive things and go with what is trending.

Subjective Financial Knowledge refers to a person's documentation of expenses accurately, and the understanding of fundamental principles of financing such as risk and return as well as active engagement in financial talks.

Transaction Convenience pertains to the perceived simplicity with which users can effectively finalize transactions on the m-banking platform, the optimal time frame necessary for completion, and the sense of security experienced when sharing personal and confidential information during the transaction process.

2. Related Literature

2.1. Financial Literacy

Financial literacy forms the foundation that molds individuals' awareness, behavior, and normative influence regarding their financial circumstances (Ardhiani & Panjaitan, 2023). However, being financially literate does not only mean having knowledge about the fundamentals of finance but on the behavior of how someone dealt with money, which makes someone capable of making sound decision on how to save and spend money wisely (DiGangi, 2021).

Individuals who are aware of the consequences associated with overspending tend to make prudent financial decisions that positively contribute to long-term financial well-being (Depano, 2023). According to Sujaini (2024), financial literacy is the initiative to save for financial security and retirement. In the study conducted by Munawar (2023), financial literacy has a significant and positive relationship with financial decision-making. This means that when someone has a high level of financial literacy, he makes wise decision on spending and financial transactions. The study conducted by Widiyanti et al. (2022), Setiabudhi (2023), and Mengga et al. (2023) showed insignificant relationship between FL and CB. However, this was contradicted in the findings of Azsahrah et al. (2023), Fauzia and Nurdin (2019), and Septiani et al. (2023) which found a positive and significant correlation between FL and CB.

2.2. Mobile Banking Convenience

Consumers now depend on financial technology (fintech) for various purposes, which includes the use of mobile banking for financial transactions (Fadila et al., 2022). Mobile banking saves users from the hassle of transporting and falling in line, giving them the convenience to access mobile transactions anytime. However, this can also stimulate consumptive behavior (Syahla and Sudrajat, 2023). As emphasized in the study of Legaspi et al. (2016), Filipino consumers' buying patterns had diversified through an increased accessibility to products and services with online options. Mamoona et al.'s (2021) study revealed that search convenience and evaluation convenience do not exert a significant influence on the adoption of mobile banking. The study of Mamoona et al. (2021) and Shankar & Rishi's (2020) showed that among the indicators of MBC, only the AC, TC, and PC were found to have influence on the adoption of mobile banking. While other dimensions such as SC and EC do not show any significant impact on the adoption of MB. While the impact of MBC towards CB is yet to be explored. Hence, this study explored how MBC could potentially impact CB among working millennials in General Santos City.

3. Research Design

This study employed descriptive-correlational research design to address the problems highlighted in this study. The descriptive design will help in understanding the demographic profile of the respondents and their level of FL, perception of MBC, and SA. The correlation design will help to analyze the interplay between FL and SA, and MBC and SA.

The respondents of the study were 385 working millennials in General Santos City. The researcher used Cochran formula using precision level of 5%, confidence level of 95%, and population assumption of 0.5. The respondents were chosen using probability sampling method particularly convenience sampling method.

The instrument was divided into 3 sections where first section gathered the demographic profile of the respondents using checklist. The second and third section aimed to determine the level of financial literacy and spending attitude of the respondents respectively using 5-point Likert Scale.

3.1. Respondents of the Study

The primary data of this study came from the working millennials in General Santos City who were the respondents of this study. The respondents had to meet the minimum criteria set by the research, also known as the inclusion criteria. This included that respondents must be between 28 to 44 years old or those who belonged to the generation of millennials and currently working in General Santos City.

3.2. Data Analysis

To understand the data and derive meaningful information, the researcher utilized SPSS (Statistical Package for the Social Sciences) for analyzing the responses from the questionnaire.

Table 1. Qualitative Interpretation of Financial Literacy, Mobile/Online Banking Convenience, and Spending Attitude

Rating	Range Interval		Qualitative Interpretation
	From	To	
5	4.50	5.00	The level of financial literacy, mobile/online banking convenience, and spending attitude is Very High.
4	3.50	4.49	The level of financial literacy, mobile/online banking convenience, and spending attitude is High.
3	2.50	3.49	The level of financial literacy, mobile/online banking convenience, and spending attitude is Neutral.
2	1.50	2.49	The level of financial literacy, mobile/online banking convenience, and spending attitude is Low.
1	1.00	1.49	The level of financial literacy, mobile/online banking convenience, and spending attitude is Very Low.

The table above presented the qualitative interpretation for the data that were generated from this study. This was used in interpreting the result for the descriptive statistics especially in answering the problems pertaining to the demographic profile of the respondents, the level of financial literacy, mobile/online banking convenience, and consumptive behavior.

4. Result

Table 2. Demographic Profile of the Respondents

Variable	Category	Frequency	%
Gender	Male	163	42.3
	Female	222	57.7
Civil Status	Single	257	66.8
	Married	128	33.2
	Widowed	0	0.0
Educational Attainment	Bachelor's Degree	231	60.0
	Master's Degree	58	15.1
	Doctoral Degree	50	13.0
	Vocational/Technical Education	46	11.9
Employment Status	Self-Employed	89	23.1
	Public Sector Employee	102	26.5
	Private Sector Employee	194	50.4
Total		**385**	**100.0**

The result on gender shows that a large number of respondents are female with a total count of 222 or 57.7% of the total respondents. While male respondents are composed of 163 counts or 42.3% of the total number of respondents. In terms of civil status, majority of the respondents are single or unmarried which is composed of 257 counts or 66.8%. The status on the educational attainment shows that majority of the respondents have earned their bachelor's degree with 231 counts comprising more than half of the total respondents are equivalent to 60%. While in terms of employment status, a large number of respondents are Private Sector Employees with a total count of 194 or 50.4% of the total respondents.

4.1. Level of Financial Literacy

On the level of financial awareness, the highest-rated indicator, with a mean of 4.17, was the statement "I compare financial products before making a decision." This suggests that working

Table 3. Financial Awareness

Financial Awareness	Mean	Description
I evaluate spending regularly.	3.95	High
I make a list before shopping.	3.75	High
I compare financial products before making a decision.	4.17	High
I keep a record of bills.	3.84	High
I gather information related to financial issues.	3.52	High
I am willing to discuss financial issues (e.g., with family or financial professionals).	3.84	High
Weighted Mean	**3.85**	**High**

millennials are generally mindful in evaluating financial options, reflecting deliberate and informed decision-making.

Table 4. Financial Experience

Financial Experience	Mean	Description
I have experience holding emergency savings.	3.79	High
I have experience maintaining financial records.	3.78	High
I have experience managing personal assets.	3.74	High
I have experience investing in the stock market.	2.47	Neutral
I have experience saving with non-bank financial institutions.	3.27	Neutral
Weighted Mean	**3.41**	**Neutral**

The respondents rated their financial experience as neutral (WM=3.41). Many respondents have experienced preparing for emergency (WM=3.79), while many respondents have less involvement or experience with investing in stock market (WM=2.47).

Table 5. Subjective Financial Knowledge

Subjective Financial Knowledge	Mean	Description
I write down where my money is spent.	3.58	High
I have knowledge of risk and return.	3.80	High
I discuss economic and financial issues.	3.38	Neutral
Weighted Mean	**3.59**	**High**

The result on SFK shows that many respondents have high FK (WM=3.59). The data shows that many respondents having high level of knowledge on financial risk and return (WM=3.80) which is crucial in investment decisions. While the lowest rated statement shows that respondents do not frequently discuss matters on economic and finances with peers (WM=3.38).

Table 6. Financial Skills

Financial Skills	Mean	Description
I keep bills and receipts where they are easy to find.	3.72	High
I evaluate my savings and financial statements on a regular basis.	3.77	High
I manage risks by purchasing insurance.	3.29	Neutral
I evaluate my debt on a regular basis.	3.99	High
Weighted Mean	**4.65**	**High**

The result shows a high level of FS among respondents (WM=3.65). The data shows that respondents are responsible in managing their financial obligation by constantly evaluating their debts (WM=3.99). However, when it comes to securing the future by purchasing an insurance remains neutral (WM=3.29). This means that some respondents do not recognize the value of insurance as a financial protection against emergency.

Table 7. Financial Goals

Financial Goals	Mean	Description
I pay bills on time.	4.43	High
I keep money in cash.	3.28	Neutral
I buy things when they need to be bought.	4.28	High
I gather information before deciding to buy.	4.18	High
Weighted Mean	**4.04**	**High**

The result on FG shows the high commitment of respondents in managing their finances (WM=4.04). The highest rated statement shows the commitment of the respondents in paying their financial obligation (WM=4.43), followed by being financially disciplined by only buying things when needed (WM=4.28), and gathering enough information about the products and services which shows thoughtful buying behavior. While keeping money in cash received a neutral rating which means that some respondents may prefer keeping their money in banks or through e-wallet applications.

4.2. Level of Mobile Banking Convenience

Table 8. Access Convenience

Access Convenience	Mean	Description
I can avail m-banking services anytime I want.	4.35	High
I can avail m-banking services wherever I am.	4.28	High
The m-banking service is always accessible for me.	4.34	High
Weighted Mean	**4.32**	**High**

The result shows that respondents perceived the use of mobile banking as highly accessible (WM=4.32). This is evident by the high rating on the ability to access MB anytime (WM=4.35), always (WM=4.34), and anywhere (WM=4.28). This suggests that MB is highly flexible and convenient to use for many working millennials in General Santos City.

Table 9. Search Convenience

Search Convenience	Mean	Description
I find it easy to navigate the m-banking application.	4.37	High
I can find what I want without having to look elsewhere.	3.81	High
I find the application provides useful information.	4.26	High
Weighted Mean	**4.15**	**High**

The result on search convenience shows that perceived search feature of MB banking as highly reliable (WM=4.15). The highest rated item was easy navigation of MB application (WM=4.37), followed by the useful information it provides (WM=4.26), and lastly on ability to use the MB without requiring for additional information (WM=3.81).

In terms of evaluation convenience, respondents perceived that it provides effective features that help a more efficient and effective banking experience (WM=4.07). MB aids in making financial decisions through the detailed service specifications (WM=4.15), supported by having interactive interface (WM=4.06), and having enough information to differentiate products and understand the options.

Most respondents rated transaction convenience high (WM=4.04), indicating satisfaction with this aspect of mobile banking. The statement with the highest mean score of 4.30 is, "I find my transactions are completed easily over the m-banking platform" which suggests that respondents find it easy to complete transactions seamlessly by using mobile banking applications. While the statement with the lowest mean score of 3.59 is, "I feel safe providing my personal and private data over the m-banking platform," although still rated high, indicates that many users harbor concerns about data privacy and security, which could pose risks of information leakage.

Possession convenience received varied ratings. Most of the respondents believe that they get what they want whenever they use mobile-banking application with a mean score of 3.97 described as high. This suggests that most of the respondents are generally satisfied with the mobile/online banking features, as it allows them to access services that they need for their transactions. While the statement with the lowest score of 3.43 which is described as neutral is, "I find it easy to take care of failed transactions over the m-banking platform."

Table 10. Evaluation Convenience

Evaluation Convenience	Mean	Description
I find the application provides detailed service specifications.	4.15	High
I find there is sufficient information to identify different products.	3.99	High
I find the application provides an interactive interface using icons, images, and moving pictures.	4.06	High
Weighted Mean	**4.65**	**High**

Table 11. Transaction Convenience

Transaction Convenience	Mean	Description
I find my transactions are completed easily over the m-banking platform.	4.30	High
I find it does not take a long time to complete transactions over the m-banking platform.	4.23	High
I feel safe providing my personal and private data over the m-banking platform.	3.59	High
Weighted Mean	**4.04**	**High**

Table 12. Possession Convenience

Possession Convenience	Mean	Description
I get exactly what I want over the m-banking platform.	3.97	High
I find it easy to take care of failed transactions over the m-banking platform.	3.43	Neutral
I find services are delivered in a timely fashion over the m-banking platform.	3.87	High
Weighted Mean	**3.76**	**High**

Table 13. Lifestyle

Lifestyle	Mean	Description
I enjoy the process of making purchases without considering my financial goals.	2.44	Low
I buy products to build a collection (different colors and shapes with the same function).	2.09	Low
I buy products used by mid-to-high-level consumers without considering affordability.	2.31	Low
I feel confident owning quality products.	3.84	High
I buy premium products to reflect my status.	2.06	Low
I prefer sticking to trusted, well-known brands.	3.75	High
I make spontaneous purchases.	2.66	Neutral
I prefer flexibility over detailed planning before making purchases.	3.02	Neutral
Weighted Mean	**2.77**	**Neutral**

Table 14. Consumptive Behavior

Consumptive Behavior	Mean	Description
I buy items due to prizes offered, without considering the functionality of the item.	2.21	Low
I buy products because the packaging is attractive.	2.09	Low
I buy products to maintain my appearance and prestige.	1.99	Low
I buy products based on price rather than benefits or uses.	1.96	Low
I buy products to maintain a status symbol.	1.80	Low
I use products because they are endorsed by my favorite artists/models.	2.04	Low
I believe that buying expensive products boosts my confidence.	2.23	Low
I try more than two similar products from different brands.	2.76	Neutral
Weighted Mean	**2.13**	**Low**

4.3. Level of Spending Attitudes

The result shows that working millennials do not demonstrate impulsive buying behavior as evident by the neutral result in the Lifestyle dimension of SA (WM=2.77). While many millennials value quality products (WM=3.84). High quality products mean more value for money due to its longer life and durability, which suggests that working millennials have put emphasis on the value they get from the price they paid. While the lowest item was on buying products to reflect status which suggests that working millennials do not buy products to show off their social status. This suggests that buying decision of millennials is more practical focusing on the products' value and affordability.

The result shows that working millennials do not exhibit consumptive behavior to maintain prestige or status symbol (WM=2.13). While two similar products received neutral rating (WM=2.76), this also means that working millennials sometimes explore other brands perhaps to compare which one fits their preference and provides more value. While the response on buying products to maintain status symbol is low suggesting that working millennials are careful with their purchasing decision supporting previous results.

4.4. Test of Relationship Between Financial Literacy and Spending Attitude

The correlation between FL and SA was analyzed using Spearman's statistical tool. The result shows that the correlation coefficient is -0.268 which suggests that the relationship between the two variables is negative and weak. While the p-value of $< .001$ suggests that the observed correlation between the FL and SA is statistically significant. This suggests that individuals with higher FL tend to be more cautious with their spending. This also suggests

Table 15. Correlation Between Financial Literacy and Spending Attitude

Variable	Spearman's rho	p-value	Remark
Financial Literacy	−0.268	$< .001$	Negative Weak Significant Relationship

Table 16. Correlation Between Mobile Banking Convenience and Spending Attitude

Variable	Spearman's rho	p-value	Remark
Mobile Banking Convenience	−0.151	.003	Negative Weak Significant Relationship

that the higher the FL of an individual the lesser is their impulsive buying behavior.

4.5. Test of Relationship Between Mobile Banking Convenience and Spending Attitude

The data on the table above presented the relationship between mobile banking convenience and spending attitude using Spearman's Rho correlation. The result revealed a correlation of −0.151 which indicates a negative weak correlation. Negative correlation denotes that as the level of the mobile banking convenience increases, spending attitude decreases. The p-value of .003 which is below the standard threshold of statistical significance of .05 which means that the relationship is statistically significant and is not due to random chance. This suggests that as mobile banking becomes more convenient, impulsive buying slightly decreases.

5. Conclusion

In conclusion, having adequate knowledge on financial literacy has significant relationship on how individuals spend their money. The higher the financial literacy the lower the spending attitude of an individual exhibits. This further implies that the first null hypothesis is rejected.

The relationship between mobile/online banking convenience and spending attitude also revealed that as mobile/online banking convenience increases, spending attitude decreases. Thus, the second null hypothesis is rejected.

6. Recommendations

Millennials. While the overall result for financial literacy among working millennials is high, a notable gap on their financial experience exists particularly with investing in stock market, opening account in non-bank financial companies, and utilizing insurance for a secured future. Hence, millennials are recommended to join seminars offered by the Philippine Stock Exchange which provides educational trainings on fundamentals of stock market investments and analysis. This will help in providing millennials with knowledge on how stock market works, how to start investment in stock market, and how to safeguard investment to generate more profit.

Millennials may consult financial advisors from insurance companies available in General Santos to explore opportunities that will help them save for unexpected expenses and retirement. Free consultation is conducted by financial advisors to those who are interested in safeguarding their future from emergencies and maximizing their retirement benefits.

Many Non-Bank Financial companies are also available in General Santos City. Millennials may explore opportunities from these companies that will help them save and at the same time grow their money through dividends. Exploring this alternative may help them save while at the same time earn passive income from raising capital through savings.

Financial Institutions. Financial institutions may implement system-level enhancements that directly address user concerns regarding transaction reliability and service responsiveness. A prominently displayed "Report a Problem" or "Failed Transaction Assistance" feature may be embedded within the main transaction interface of mobile banking applications. This feature may include automated attachment of transaction reference numbers, real-time case tracking, and estimated resolution timelines to improve transparency and reduce uncertainty. These improvements may be coordinated through internal digital transformation teams, fintech partners, and regulatory guidance from the Bangko Sentral ng Pilipinas to ensure compliance with consumer protection standards.

In addition, institutions may design segmented financial programs based on civil status and gender, given their significant influence on financial literacy perception and spending attitudes. Data analytics units within banks may develop tailored digital tools, such as starter savings modules and milestone-based deposit campaigns for single clients, and shared budgeting dashboards or family financial planning consultations for married clients. Gender-responsive interface refinements, guided by user experience testing, may focus on improving navigation efficiency, spending visibility, and personalized financial prompts. Partnerships with industry associations such as the Bankers Association of the Philippines may further support the development of standardized best practices in inclusive digital banking design. Through these targeted and data-driven initiatives, financial institutions can strengthen digital trust, promote responsible spending behaviors, and improve overall client engagement.

Educational Institutions. Educational institutions may institutionalize comprehensive, skills-based financial education that moves beyond general awareness campaigns. Higher education institutions in General Santos City, in coordination with the Commission on Higher Education, may integrate a required personal finance course across disciplines. The curriculum may include applied modules on emergency fund planning, insurance evaluation, retirement preparation, and introductory stock market investing, culminating in the development of a personalized financial plan aligned with each student's life stage and risk profile.

To reinforce practical competence, institutions may establish campus-wide investment simulation programs supervised by finance faculty and industry practitioners. Formal partnerships with licensed financial planners, insurance professionals, and representatives from the Philippine Stock Exchange may facilitate workshops centered on interpreting insurance contracts, comparing savings instruments, and evaluating employment benefit packages. The creation of a Financial Wellness Center within universities, managed by trained faculty advisers and guidance counselors, can provide sustained coaching on budgeting, savings discipline, and entry-level investment planning. Program effectiveness may be evaluated using measurable indicators, such as the proportion of students who establish emergency funds or open legitimate savings and investment accounts. Through structured curriculum integration, industry collaboration, and outcome-based monitoring, educational institutions can produce graduates who are not only financially aware but also financially capable.

Future Researchers. Future researchers may use the result of this study as a basis for their future research endeavors especially focusing on the aspects that were not addressed in this study. This study uses quantitative research design which utilized close-ended questions which limits responses of millennials. Future studies may consider applying qualitative research to further capture the challenges experienced by millennials in using mobile/online banking applications.

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Dynamic Optimization of Portfolios 2018 to 2024

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Abstract

Investors are always willing to receive more data. This has become especially true for the application of modern portfolio theory to the institutional asset allocation process, which requires quantitative estimates of risk and return. When long-term data series are unavailable for analysis, it has become common practice to use recent data only. The danger is that these data may not be representative of future performance. Although longer data series are of poorer quality, are difficult to obtain, and may reflect various political and economic regimes, they often paint a very different picture of emerging market performance. This paper presents an application of a stochastic nonlinear optimization model of portfolios including transaction costs in the Brazilian financial market. In order to have that, portfolio theory and optimal control were used as theoretical basis. The first strategy tries to allocate the whole available wealth, not considering the risk associated to portfolio (deterministic result). In this case the investor obtained profits of 7,23% a month, taking into account the three risk aversion levels during the whole planning period [see column (7)]. On the contrary, the results from of the stochastic algorithm obtained profits of 1,34% a month and 18,06% a year, if the investor has low risk aversion. The profits would be 0,88% a month and 11,02% a year for a medium risk aversion investor. And with high risk aversion, the investor obtains 0,62% a month and 7,66% a year.

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Investors are always willing to receive more data. This has become especially true for the application of modern portfolio theory to the institutional asset allocation process, which requires quantitative estimates of risk and return. When long-term data series are unavailable for analysis, it has become common practice to use recent data only. The danger is that these data may not be representative of future performance. Although longer data series are of poorer quality, are difficult to obtain, and may reflect various political and economic regimes, they often paint a very different picture of emerging market performance. This paper presents an application of a stochastic nonlinear optimization model of portfolios including transaction costs in the Brazilian financial market. In order to have that, portfolio theory and optimal control were used as theoretical basis. The first strategy tries to allocate the whole available wealth, not considering the risk associated to portfolio (deterministic result). In this case the investor obtained profits of 7,23% a month, taking into account the three risk aversion levels during the whole planning period [see column (7)]. On the contrary, the results from of the stochastic algorithm obtained profits of 1,34% a month and 18,06% a year, if the investor has low risk aversion. The profits would be 0,88% a month and 11,02% a year for a medium risk aversion investor. And with high risk aversion, the investor obtains 0,62% a month and 7,66% a year.

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1. INTRODUCTION

Emerging markets have as their main feature, volatility that increases investors' potential interest for entering in such markets with the aim of possibly obtaining a higher expected return. As in Mullin (1993), for instance, just from 2000 to 2023 investments in emerging markets triplicated. This fact indicated a speculative euphoria, which occurred in other financial markets around the world.

According to Jorion & Goetzmann (2015) the last 20 years of capital market history have witnessed a dramatic expansion of opportunity for global investors, led primarily by emerging markets in Asia, South America, Africa, the Middle East, and Eastern Europe. In many countries, equity markets have grown rapidly from tiny, fledgling markets with little volume and limited international participation, to important sources of capital with short but impressive track records of share price appreciation. Although the fundamental shift in the global political environment is undoubtedly a major factor in the growth of emerging markets, consideration of a longer term view is also worthwhile.

Adding to this, Mullin (2020) suggests that share's return in emerging markets are correlated to macroeconomic variables as well as the opening of the economy that is represented by the export growth rate.

The emerging countries have faced a serious liquidity crisis which caused their exclusion from international financial markets.

In this stand, Leal & Silva (1998) show that the issue of links and integration among the markets has important implications for the benefits of the international diversification, considering that the more markets are close economically, the more they would tend to move together.

However, he emphasized in his article that the links in international markets indicate relationship among them, which could be highlighted through the correlation coefficient. While the financial integration has as a significant point that the price of assets (from the same risk class) will be the same in different markets. Thus, he concluded that two markets can be correlated without being integrated, since their movement in a group could be influenced by an external common factor.

Nowadays, it is possible to notice that the markets are more and more integrated. This fact can lead to the reduction of the international diversification benefits, considering that the crisis prominence in a certain country can be spread to another countries very swiftly. This paper presents an application considering a dynamic model of stochastic non-linear optimization of portfolios with some transaction costs for international diversification benefits. It was based on the risk-return binomial and on the Quadratic Utility Function (FUQ) of an investor who will determine his/her expected wealth in the end of the planning period and the risks in relation to the portfolio, also his/her risk aversion level.

The model was implemented in an Excel spreadsheet from Microsoft using optimization resources from Solver. Besides, the statistical and econometric results for fifteen-step forecasts, which were out of the sample, were calculated through PcGive software version 8.0. Some coefficients were estimated in order to determine the portfolio-planning period and afterwards they were implemented in the developed spreadsheet. A group of simulated mistakes was added to that based on a normal distribution. Also expected value and variance of stochastic solution were calculated and incorporated to the investor's utility function, which was optimized in a deterministic step. In such step, the proportions were also determined as well as variance and expected wealth.

Afterwards, in order to have a better understanding of the model's operation, portfolio theory and investor's utility theory were used as theoretical basis. Once the model is established, it will allow portfolio analysts to incorporate their preferences and subjective information, through a utility function, taking into consideration a group of restrictions that was incorporated to the model. Moreover, through the Excel spreadsheet, that is easily manageable, anyone can choose a portfolio that suits better his/her preferences.

This paper is divided in five sections. The second section explains the determination of the consideration coefficients for the expected wealth and the portfolio's variance through the quadratic utility function. The third section approaches briefly assets' forecasts that make part of the portfolio. The fourth section presents an empirical usage through the dynamic model of stochastic non-linear portfolio optimization with some transaction costs and finally the fifth section has some final remarks and suggestions for further studies.

2. THE CONSIDERATION COEFFICIENTS FOR THE EXPECTED WEALTH AND THE PORTFOLIO'S VARIANCE BELONGING TO THE QUADRATIC UTILITY FUNCTION

Brafman, Engel (2009) shows specifying a multi-variate utility function is known to be a difficult task, and often considered a bottleneck in implementation of intelligent systems. It requires quantifying one's preferences a non-trivial cognitive task which involves contemplating a large number of questions about the relative desirability of uncertain outcomes, or gambles. Furthermore, the very personal and subjective nature of utility information restricts their reuse, in contrast to probabilistic knowledge, which can often be learned from data and reused for various instances of a system. Yet, the preference and utility elicitation tasks must be carried out when analyzing decision problems. A number of attempts have been made to ensure that the questions to be answered are simpler and/or the number of questions is smaller. Often, this process is aided by some graphical structure that captures some properties of the utility function.

The suggested dynamic model of stochastic portfolio optimization uses a quadratic utility function, in which it is supposed that individual investors make their decisions based only in the expected wealth and in the standard wealth's deviation. Therefore, considering a deterministic quadratic utility function (FUQ), we can have:

$$U = aW + bW^2(1)$$

If the mathematical average operator is used (1), we can obtain:

$$E(U) = aE(W) + bE(W^2)$$

As the last term of the previous expression $[E(W^2)]$ can be determined through an elementary statistical result that is $E(W^2) = s^2 + E(W)^2$ then, we just have to substitute such expression from (2) in order to come up with the expression that determines the expected utility function of a portfolio, such as:

$$E(W^2) = s^2 + E(W)^2$$

Where:
$E(U)$: Expected Utility Value;
$E(W)$: Expected Wealth Value;
s^2: Portfolio's Variance;
a and b: Consideration Coefficients of the Expected Wealth and Portfolio's Variance.

The consideration coefficients for expected wealth and portfolio's variance must be defined in order to specify the area in which the subjective values of (a and b) satisfy the expression (3). Hence, the partial derivatives from the expected utility function can be taken in relation to the expected wealth and the risk, in order to calculate the marginal utilities of the function through (3) and to determine the marginal utilities' behavior. So, we can have:

$$\frac{\partial E(U)}{\partial E(W)} = a + 2bE(W); \quad \text{for: } \frac{E(U)}{E(W)} > 0$$

It is possible to verify that the relationship between the expected utility and the expected wealth is positive by definition, since $a > -2bE(W)$. Also, the increase of an additional unit of expected wealth will implicate in a bigger expected utility for the investor. Besides, the partial derivatives of the expected utility in relation to the risk (marginal risk utility) will be:

$$\frac{\partial E(U)}{\partial s^2} = 2bs; \quad \text{for: } \frac{E(U)}{\partial s^2} < 0$$

On the other hand, the relationship between the expected utility and the risk will be negative by definition, considering that an additional risk unit (the other variables are maintained constant), which will implicate in a smaller expected utility, what guarantees the established hypotheses for the model. Yet, a third condition is necessary to provide maximization of the analyzed function.

$$\frac{\partial^2 E(U)}{\partial E(W)^2} = 2b; \quad \text{for: } \frac{\partial^2 E(U)}{\partial E(W)^2} < 0$$

The values assumed by the coefficient (b) in the equation (7) (the other variables are maintained constant) will be negative, what guarantees the down concavity of the analyzed curve. It is important to mention that in all cases, the value of the coefficient (a) was maintained fixed or established. Tobin [1958] shows that the coefficient (b) can vary in the following way: $[0 < b < 1]$ if the investor is a risk lover. While if the investor is averse to the risk, it will be $[-1 < b < 0]$. However, it is also important to point out that the quadratic utility function cannot be used in the whole interval of (W), since the marginal utility of the expected wealth becomes negative, which is not appreciated by an investor.

Considering the marginal utility of the expected wealth, which was calculated through (5) and (6) and equaled to zero, it is easy to determine which coefficient values (a and b) are able to maximize the Quadratic Utility Function (FUQ) based on the following expression:

$$b = -\frac{a}{2E(W)}$$

It is possible to observe through an example that: if $a = 1$ and $E(W) = 10$, the coefficient value (b) that will maximize the Quadratic Utility Function (FUQ) will be equal to -0.05.

3. FORECAST MODEL OF PORTFOLIOS' ASSETS

A forecast model is usually built up based on temporal series analyses that are consisted of collecting previous observations of a certain item or activity in regular time intervals. Such observations can be regarding to weekly sales of a certain product, daily shares' quotations or monthly car rents, among other series.

During the analyzes it is important to verify special behavior patterns, considering that such patterns will be predominant in the future, so that the forecasts can be determined for the planning period. In this paper, the estimated forecast model is established through the Ordinary Least Square Method including all the selected assets that are used as auxiliary tools during portfolio optimization process.

The price daily quotations of the selected assets were collected a database called Economática Software for Investimentos LTDA, considering the period between 2018 and 2024.

The collected variables for the estimates are Ibovespa (an exchange market index), Savings account, Dollar, Gold and Treasury Rates (LFT) (considering just the business days of each month). All the variables were homogenized (expressed in their return rates) in order to avoid discrepancies among the characteristics of each element as references and misunderstanding in further interpretations.

In all the estimated econometric models, twenty-two lags were established for each variable, that is equivalent to one month (considering only the business days). It is worth to mention that there was not any problem with freedom degrees, which could affect the estimates.

Not only the binary variables for weekdays, but also the error correction method (ECM) were considered in the estimated model in order to identify long-run relationships between the saving account return variables and the Treasury rates returns, which are the only first-order integrated series in the estimates.

In conclusion, models estimated through OLS will be used as basis for building up dynamic stochastic non-linear portfolios with some transaction costs.

4. EMPIRICAL APPLICATION OF DINAMIC MODEL OF STOCHASTIC AND NON-LINEAR PORTFOLIO OTIMIZATION WITH TRANSACTION COSTS

The following subsections present the consideration coefficient for the expected wealth and the portfolio risk through the spreadsheet Excel. Also, the proposed model scenarios are highlighted.

4.1. Determination of Consideration Coefficients (*a e b*) of the (FUQ)

The problem of choosing the consideration coefficients of the expected wealth and of the portfolio variance, which will optimize determined objective function, influences strongly on the optimal path to be followed. Different considerations for the variables will result in different paths over time, due to the fact that they obtain varied criteria functions to be optimized.

The Marginal Tax of Technical Substitution (TMST) was used as measure to determine the consideration coefficients of the quadratic utility function in the optimization, as well as the investor's aversion level of. It represents the ratio among the slopes of the quadratic utility function in relation to the expected wealth and to the portfolio risk. It can be seen as:

$$TMST = -\frac{\frac{\partial E(U)}{\partial E(W)}}{\frac{\partial E(U)}{\partial s^2}}$$

The interpretation of TMST is in accordance with the level of importance considered to one of two ratios above. Through (8) we can see that if the considered level of importance for the expected wealth is higher than the risk (the other variables are maintained constant), TMST will decrease, which means that the investor possesses a low-risk aversion. Therefore, such investor should invest big part of his/her wealth on the riskiest assets, since that it is possible to change an additional risk unit, as long as it is rewarded by a higher wealth. On the contrary, if a higher importance is considered for the standard deviation-risk (the other variables are maintained constant), TMST will increase, which highlights a high-risk aversion. Therefore, the investor should invest big part of his/her wealth on conservative assets.

The table above shows the consideration coefficients (a and b) that will define the investor's aversion level as basis for the quadratic utility function optimization. A model with different variance-covariance matrixes in different periods of time and with some transaction costs is considered in the scenarios.

4.2. THE SCENARIOS IN THE PORTFOLIO MODEL

The scenarios take into account low, medium and high individual investor's risk aversion for a stochastic non-linear dynamic portfolio with different variance-covariance matrixes in different periods of time and with some transaction costs. It is worth to emphasize that the portfolio-planning period had fifteen business days of forecast.

4.2.1. Optimization of stochastic non-linear portfolio's model with different variance-covariance matrixes in different periods of time and with some transaction costs

In this subsection, three risk aversion levels were considered, such as: low, medium and high investor's risk aversion, in relation to the consideration coefficients of the expected wealth's value and of the optimized portfolio's variance through the quadratic utility function.

■ SCENARIO 1: OPTIMIZATION OF THE STOCHASTIC MODEL WITH DIFFERENT VARIANCE-COVARIANCE MATRIXES IN DIFFERENT PERIOD OF TIME AND WITH SOME TRANSACTION COSTS

Table 1. Consideration Coefficients (a and b) of the Risk and of the Expected Wealth

Aversion Levels	a	b	$\frac{\partial E(U)}{\partial E(W)}$	$\frac{\partial E(U)}{\partial s^2}$	$E(W)$	$s_{initial}$	$TMST$
Low Risk Aversion	1	-0.039	0.22	-0.0011	10	0.0143	-198.62
Medium Risk Aversion	1	-0.0105	0.79	-0.0003	10	0.0143	-2649.14
High Risk Aversion	1	-0.008	0.84	-0.0002	10	0.0143	-3697.05

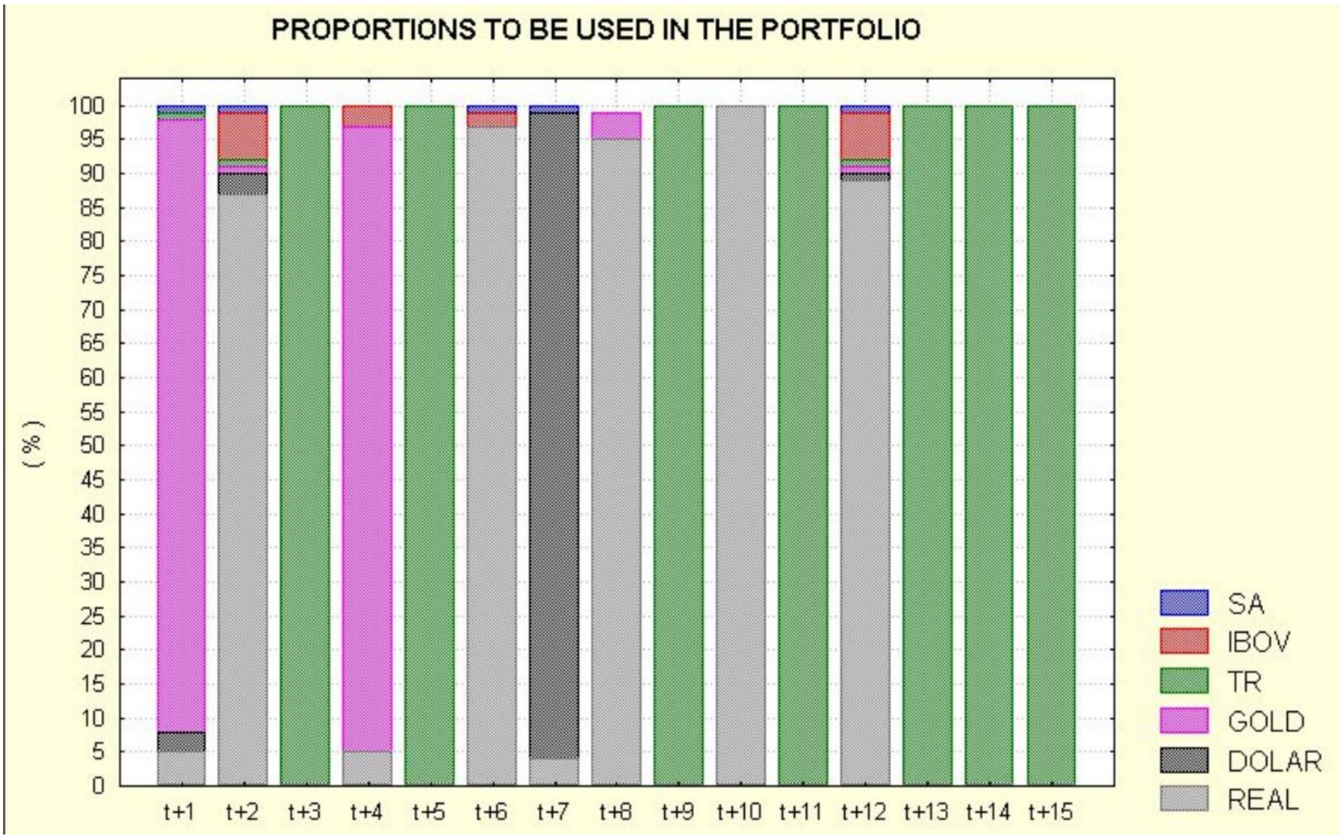

Figure 1. Optimization with Low Risk-Aversion and with: $a = 1$ and $b = -0.039$.

5. SCENARIO 2: Optimization of stochastic model with different variance-covariance matrixes in different periods of time with some transaction Costs

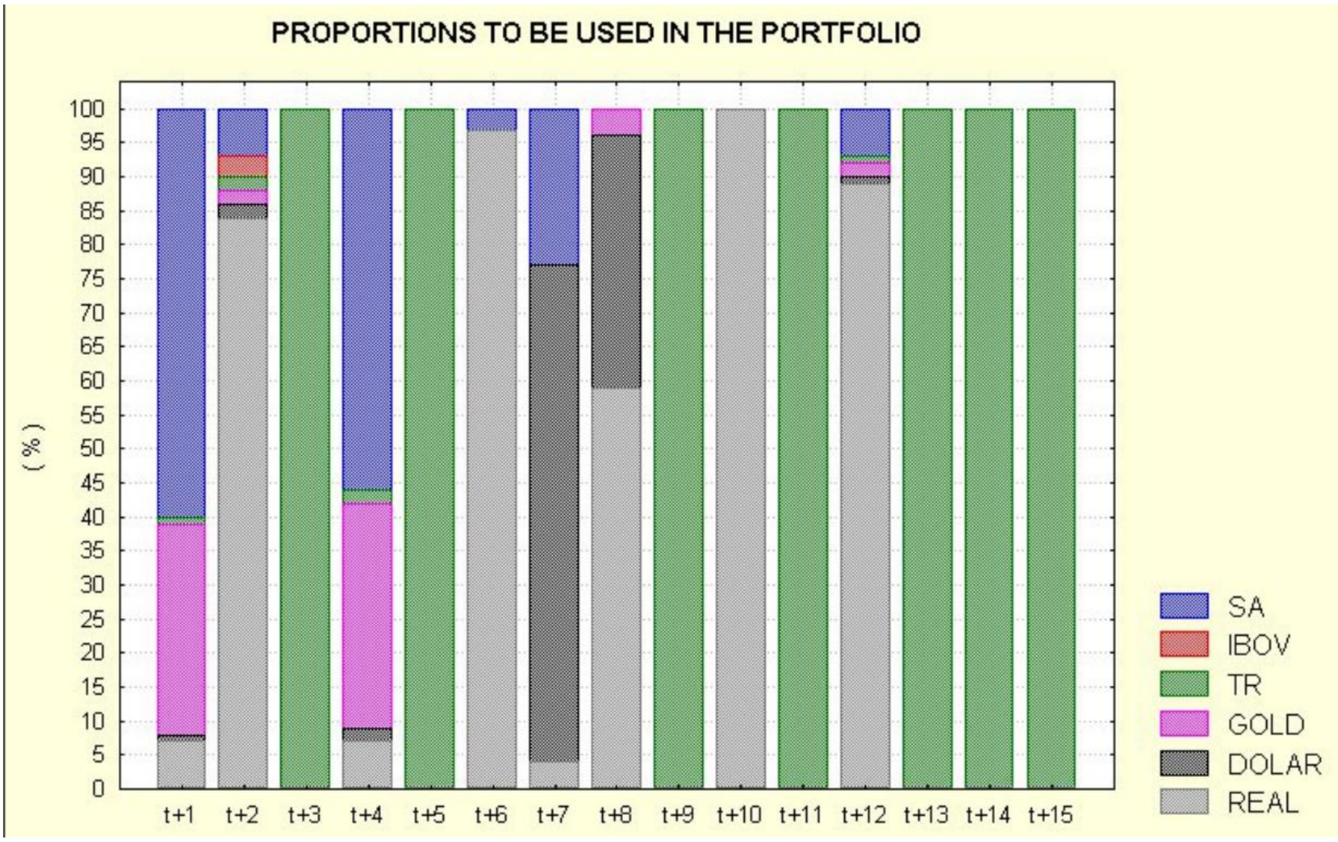

Figure 2. Optimization with Medium Risk-Aversion and with: $a = 1$ and $b = -0.0105$.

Table 2. Summary of the optimized portfolio's scenarios with the predicted returns considering: Different Variance-Covariance matrixes in different periods of time and with some transaction Costs

Aversion Levels	a (1)	b (2)	$E(W)$ (3)	Portfolio Var (4)	Accum. Ret. (%) (5)	Annual Ret. (%) (6)	Det. Ret. (%) (7)
Low Aversion	1	-0.039	10.179	0.01431	1.34	18.06	7.23
Medium Aversion	1	-0.0105	10.101	0.01422	0.88	11.02	7.23
High Aversion	1	-0.008	10.062	0.01420	0.62	7.68	7.23

6. SCENARIO 3: Optimization of stochastic model with different variance-covariance matrixes in different periods of time with some transaction costs

Through Table 2 it is possible to verify that: in case the individual investor invests R$ 10.00 and, takes high risks (Low Aversion), at the end of one year, his/her portfolio will pay about 18.06% just as it is specified in the column (6). Yet, in case he does not want to take any risk (High Aversion), after one year, he will gain a profitability tax of about 7.68%.

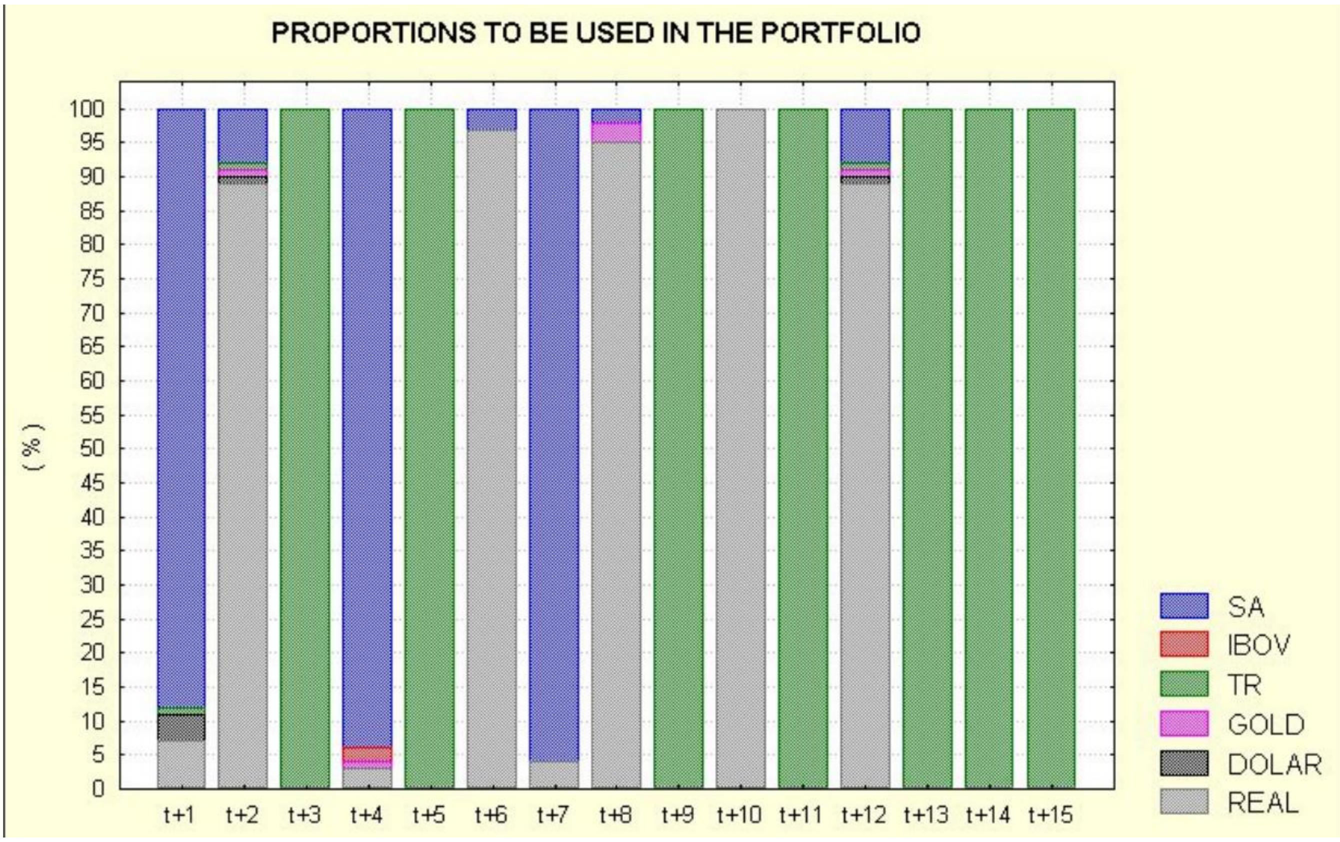

Figure 3. Optimization with High Risk Aversion and with: $a = 1$ and $b = -0.008$.

7. FINAL REMARKS

The purpose of this article was to accomplish a practical application through a dynamic model of stochastic and non-linear portfolio optimization with some transaction costs. It was based on the algorithm, which had been previously suggested by Hall and Stephenson [1990].

A portfolio was built with three investor's risk aversion levels. The dynamic portfolio of stochastic and non-linear optimization possesses different variance-covariance matrixes in different periods of time and with transaction costs. The algorithm that was tested in this paper showed to converge quickly in four steps at the most what made the proportions' values did not modify from a step to another other. Such fact caused a significant reduction in the computational effort. In addition to that, It is worth to point out, that all convergence criteria of the proposed model were covered.

This model has the assumption that each decision was associated to a normal probability distribution based on application of mathematical techniques in all simulations.

In addition to that, it was verified that in this portfolio, the three risk-free asset return rates, such as: Savings account, Treasury Rates (LFT) and Money (R$), can be classified as dominant assets, since they increased their participation significantly in the portfolio after each optimization process. Moreover, it is possible to observe that 50% of the portfolio's assets can be classified as riskfree, since there is a great possibility that a considerable part of an investor's wealth is designated for those investments, which corroborate for the portfolio's conservatism.

Regarding to the quadratic utility function, in spite of some limitations, it is easily manageable, as long as the viability area of the consideration coefficients is defined. Besides, possible non-linearity problems, which are present in the estimated equations, should be analyzed in further studies.

In relation to transaction costs, just the CPMF (Contribuicao Provisoria sobre Movimentacao Financeira), which is a temporary tax over financial transactions, and Brokerage Cost were incorporated to the model. Other costs should be included in further studies.

Through analyzes of returns from figure 2, we can find some investment strategies that can be designed for the investor. The first strategy tries to allocate the whole available wealth, not considering the risk associated to portfolio (deterministic result). In this case the investor obtained profits of 7.23% a month, taking into account the three risk aversion levels during the whole planning period [see column (7)]. On the contrary, the results from of the stochastic algorithm obtained profits of 1.34% a month and 18.06% a year, if the investor has low risk aversion. The profits would be 0.88% a month and 11.02% a year for a medium risk aversion investor. And with high risk aversion, the investor obtains 0.62% a month and 7.66% a year.

Finally, it is recommended to also test other utility functions in further studies, with the aim of comparing them with the one used in this paper. In addition to that, it is recommended to include macroeconomic variables as well as to incorporate other transaction costs in the model in order to turn it even more operational.

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