Optimization of the Credit Portfolio and Methodology for Evaluating a Public Support Policy: The Case of the Support Fund for Large Ivorian Enterprises (FSGE)

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2024

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SUMMARY

Keywords :
Evaluation of public policy
INTOSAI standards
Management of Covid-19 funds
Credit risk
Credit rating
Logit econometric model

This article proposes a logistic regression model to predict future unpaid debts and optimize the recovery portfolio of the Support Fund for Large Ivorian Enterprises (FSGE-COVID-19). An impact evaluation method based on the Evidence-Based Policy Making (EBPM) method will also be proposed to effectively evaluate the impact of FSGE public policies in accordance with Guide 9020 – Evaluation of Public Policies advocated by INTOSAI.
This method will involve comparing beneficiary companies to a similarly selected control group, using propensity score matching techniques to correct for selection bias related to observable company characteristics.

INTRODUCTION

The COVID-19 pandemic has resulted in unprecedented measures to contain the spread of the virus, such as travel restrictions, business closures and quarantines.

This has caused economic paralysis in many sectors, with falling sales and dwindling cash reserves.

Experts comparing this crisis to that of 1929 consider that the economic repercussions of COVID-19 are very serious because the drop in income and loss of productivity could lead to the bankruptcy of solvent but illiquid companies **(Schivardi et al., 2020) .**

Some argue that the economic crisis can be resolved through market regulation mechanisms, while others advocate government intervention to revive the economy.

Many governments, particularly in Africa, have put in place emergency measures to create business support funds **(OECD, 2020) .**

The management of COVID-19 funds is subject to controls and audits by supreme financial control institutions (Court of Auditors). The methodology applied always addresses several relevant aspects relating to the conformity of the objectives set, the performance and the evaluation of the public policy undertaken. The objective sought is to provide independent opinion on the management of public funds.

After a few months of operation, some irregularities were reported by the audit reports of the Supreme Financial Audit Institutions in the activity of funds intended to reduce the impact of COVID-19.

The results of these checks allowed the respective governments to take strong measures to avoid significant irregularities in the management of COVID-19 support funds.

Thus, we are witnessing closures of said funds in several countries. In addition, another more alarming finding also concerns the current debts relating to loans granted by these COVID-19 funds.

For example in Côte d'Ivoire, the Large Business Support Fund (FSGE-COVID-19) was created to financially support large companies in Côte d'Ivoire. Initially endowed with 100 billion FCFA, it aims to preserve production tools and jobs (Cf. Ordinance No. 2020-383 of April 15, 2020) . Several texts have been created to implement the FSGE, including guarantee agreements, regulations, a web platform for registration and information management.

The FSGE has supported more than 100 large companies in Côte d'Ivoire during its 3 years of existence. In October 2020, it financed 14,392,719,330 FCFA, this amount increasing to

29,082,719,330 FCFA in February 2021. So far, the FSGE has allocated overall funding of 32,703,399,330 FCFA to large Ivorian companies.

Furthermore, according to the monthly activity report for December 2022, the FSGE records a considerable rate of arrears (38.58%) on loans granted (32,703,399,330 FCFA). This rate will increase in 2023.

In addition, activity reports highlight that the loans have not been repaid, which represents a loss for the State. Some households struggle to honor their commitments, which raises the question of who is the right borrower and, further, questions of evaluation and impact of public support policy.

According to **Schivardi et al. (2020),** in times of crisis, the need to act quickly to avoid bankruptcy of solvent companies due to lack of liquidity, combined with the large number of applications received, reduces incentives to select borrowers appropriately. This can lead to a large influx of funds into unreliable companies, referred to as "zombies" by the authors.

In the Japanese context, **Caballero et al. (2008)** point out that "zombie" loans present a danger because they hamper restructuring and delay economic recovery by preventing the reallocation of low-productive assets to more productive uses.

It is then necessary to analyze the state of unpaid debts, optimize the FSGE credit portfolio with a credit rating model, and define a methodology to evaluate the public support policy.

This article proposes solutions to improve the FSGE credit portfolio and evaluate the public policy in place.

I- LITERATURE REVIEW

As a general rule, the financing of an economy is the activity of a set of credit providers which can be microfinance, banks or public business support funds which are often set up by States to faced with an exceptional situation. In most cases, the activity of credit providers is subject to a certain number of risks. The most important of these relates to credit risk as a supplier's credit portfolio sometimes represents more than 70% of its assets and proves to be the main source of production **(Nzongang et al., 2010)** . Thus, if such a risk is poorly understood and controlled, it could jeopardize the sustainability of the credit provider's activity.

Credit risks consist of all the risks associated with the non-payment of the debtor who borrowed the money from the supplier. Knowledge of the borrower's repayment capacity is therefore essential.

To this end, following the Basel agreements (2004), most credit providers have undertaken an approach through credit risk management by setting up an internal evaluation system to take into account the quality of the borrower **(Hamadi et al., 2009)** .

Thus, to determine whether credit should be granted or not, the credit provider develops a credit scoring method, which **Mester (1997)** formally defines as a statistical (or quantitative) method used to predict the probability that a loan applicant or existing borrower will default or become delinquent.

These methods are widely used to evaluate business, real estate and consumer loans **(Gup and Kolari, 2005)** . The main objective is therefore to reduce the number of delinquencies recorded from one period to another by deciding who will obtain credit, how and how much credit they should obtain, and what operational strategies will improve the profitability of the lenders' receivables (**Thomas et al., 2002).**

Over the decades, credit scoring, whose first applications date back to the second half of the twentieth century **(Lewis, 1992 ; Hand & Jacka, 1998),** has established itself as one of the most important applications of banking research. and finance.

For **Thomas et al. (2002)** , consumer credit lenders would not have been able to increase their lending effectively if they had not used an accurate and automatic risk assessment tool.

Credit scoring or evaluation involves comparing the characteristics of a customer to those of other customers who have a history with the credit provider. If the profile of the new credit applicant is close to that of customers who have repaid their debts, then the request is normally granted, otherwise the profile of the customer is close to that of customers who have defaulted and there, the request is Refused. As **Crook (1996)** points out, this procedure can be implemented using two different techniques:

- The first is the subjective evaluation of the credit officer (judgment), which consists of a credit officer judging each credit application file. In this case, the success of such a judgment procedure depends on the experience and common sense of the credit analyst. Such a method is therefore associated with subjectivity, inconsistency and individual preferences that motivate decisions. However, judgment techniques have the advantage of taking into account qualitative characteristics and the wealth of past experience of the credit analyst **(Al Amari, 2002).**
- The second technique, credit scoring, for which analysts always use their historical experience with debtors to derive this time a quantitative model making it possible to separate potential good borrowers from potentially bad borrowers. Credit scoring has the advantage of being an operational process and applied consistently to all credit decisions. It allows the credit provider to quickly assess the creditworthiness of debtors.

Areas of application of credit scoring

Credit scoring apps have been widely used in different fields.

They can be classified into accounting and finance, marketing, engineering and manufacturing, insurance, health and medicine.

In the field of accounting and finance, credit rating applications have been used for different purposes, prediction and classification of bankruptcies **(Tsai and Wu, 2008; Min and Jeong, 2009)** , classification problems **(Ben- David and Frank, 2009)** , financial distress **(Hu, 2008)** and financial decisions and returns **(Yu et al, 2009).**

In the banking sector, the multiplication of the number of credit applications and the number of banking products has motivated the development of credit rating applications. These applications

have included different banking products, such as consumer loans, which are one of the most important and essential products on which rating applications have shown their importance **(Sustersic et al, 2009 ; Lee and Chen, 2005).** , credit card rating applications around which the first applications developed in the banking field **(Greene, 1998)** , mortgage loans which are increasingly offered by banks today **(Haughwout et al, 2008) .** In addition to personal loan
application decisions, financial institutions now use credit scoring to set credit limits, manage existing accounts, and predict consumer and customer profitability **(Lucas, 2000)** . This is for example the case of Australian and New Zealand banking groups which used credit scoring to identify customers who should benefit from credit, determine the amount of credit that should be granted to them and the measures to take. in case of failure to pay loans.

Credit scoring has also been used in the insurance industry for mortgage and automobile insurance. The aim is to decide on the application of new insurance policies or the renewal of existing policies. As noted by **Prakash (1995)** , GE Capital Mortgage Corporation used credit scoring to assist in the selection of mortgage insurance applications.

Other credit scoring apps have also been reported in various areas. Consider, for example, the cases cited by the Consumer Federation **of America (2002)** reporting that landlords use credit scoring to determine whether potential tenants are likely to pay their rent on time. Additionally, in the United States , some utility providers have used credit scores to determine the type of consumer to whom they should provide their services. Finally, it happens that to grant a job to a candidate, some employers use the latter's background to develop a credit score which allows them to decide whether to hire them or not; this is all the more important when the position in question includes managing huge sums of money **(Consumer Federation of America, 2002).**

When it comes to corporate credit scoring, the nature and requirements of the rating system may be different. The procedure must be built around several steps like those suggested by Altman and **Haldeman (1995**). These steps include: applying primary customer data to the credit scoring model, then testing the scoring model and using an additional system. As for testing the model, the tests must address issues relating to the definition of risk, the integration of the time factor, the use of data from public and private companies, and the definition of the probability of failure.

The statistical models used involve the combination of a set of quantifiable, financial indicators of business performance with, perhaps , a small number of additional variable indicators that attempt to capture some qualitative elements of the credit process .

the importance of qualitative criteria should not be underestimated since for some practitioners, the so-called qualitative elements , which involve judgment on the part of the risk manager, can provide up to 30–50% of the explanatory power of the rating model **(Altman, 2002).**

As for the analysis of financial ratios for the classification of companies, the classic works in the field are those of **Beaver (1967, 1968)** who remained on a univariate analysis of a certain number of predictors of company bankruptcy. This analysis set the stage for the multivariate attempts, by this author and others, that followed. Using a range of 14 indicators, Beaver found that a number of indicators could distinguish between samples of bankrupt and non-bankrupt firms for up to five years before bankruptcy.

The methodology for building credit scoring models

The construction of credit rating models is based on a methodology generally built around a few steps. First, the analyst selects a sample of former customers and classifies them as "good" or "bad" based on their repayment performance over a past period. Then, data on these customers is compiled from their loan applications, personal and/or business credit files and various sources if available (miscellaneous reports). Finally, a statistical or quantitative analysis is performed on the data to derive a credit scoring model.

The derived model integrates weights associated with each variable retained and a threshold. The sum of the weights applied to the variables for an individual applicant or customer constitutes the credit score. The threshold helps decide whether the customer should be classified as "good" or "bad". We can also generate the probability associated with this classification.

In the literature, several techniques have already been used in the construction of credit rating models. They mostly revolve around traditional statistical methods such as discriminant analysis **(Altman, 1968; Deakin, 1972; Edminster, 1972)** and logistic regression **(Ohlson, 1980)** . In recent years, new techniques have been increasingly used to construct credit scoring models.

These are the more sophisticated models, also called artificial intelligence, which include, for example, neural networks and genetic programming **(Sustersic et al, 2009).**

We can also note the decision tree method which has become popular for the development of credit rating models thanks to the ease of interpreting the resulting decision trees.

Discriminant analysis

Discriminant analysis is the statistical method that was used in the seminal work on credit analysis. **Altman (1968)** developed univariate and multivariate models by applying a discriminant analysis approach to predict corporate bankruptcies using a set of financial ratios. This method remained the predominant statistical technique applied for many years **(Deakin, 1972; Taffler, 1977; Lussier, 1995).** However, authors who have used this technique have mentioned the fact that two of the basic assumptions that support the model are rather restrictive and are rarely satisfied in real life.

Logistic regression

The inadequacies of discriminant analysis led **Ohlson (1980)**, for the first time, to apply conditional logit to the study of credit default prediction. Logit has the advantage of being able to do without the restrictive assumptions of discriminant analysis and allows working with disproportionate samples. From a statistical point of view, logit regression appears to fit well with the analysis of predicting credit default as the dependent variable is binary (good or bad customer) and with discrete, non-overlapping groups. and identifiable.

This model gives a score between 0 and 1 which can be interpreted as the probability of customer default. After the work of **Ohlson (1980)** which was carried out on a sample of 363 listed companies of which 105 were defaulters, most of the academic literature used logit models to predict credit defaults **(Aziz, 1988; Becchetti, 2003). ; Abdou et al., 2008 ; Crook et al., 2007).**

Neural networks

Neural networks are mathematical techniques inspired by the operations of the human brain as an influence in problem-solving techniques. **Gately (1996)** points out that it is a computer program dedicated to solving artificial intelligence problems that learns through a trial and error training process. Recently, neural networks have emerged as a practical technology, with applications in many areas in financial institutions in general, and banks in particular. Some financial institutions use neural network-based systems to detect cases of credit card fraud, and deploy neural network credit scoring systems for automobile financing decisions **(West, 2000).** It should be noted that credit rating models could also take into account qualitative criteria in addition to financial indicators **(Lewis, 1992 ; Hand and Jacka, 1998)** .

Discriminant analysis **(Deakin, 1972; Taffler, 1977; Lussier, 1995)** and logistic regression are the statistical methods most commonly used to construct these models **(Aziz, 1988; Becchetti, 2003; Abdou et al., 2008 ; Crook et al., 2007)** . However, they have certain limitations, which has led to the use of new, more advanced techniques (**Thomas et al., 2002**) .

Ultimately, credit scoring is an essential tool for credit providers, enabling them to make informed decisions and effectively manage credit risk **(Sustersic et al, 2009 ; Lee and Chen, 2005)** .

When reading the credit rating, we understand quite easily that risk management has always been at the heart of all financial activity and even of public policy.

Jean-Claude Thoenig defines public policies as legitimate interventions of governmental authority on a specific society or territory. However, an unbreakable link exists between public policy and its evaluation. This link depends very strongly on the executive power.

To guarantee the impartiality and transparency of evaluations and audits, the International Organization of Supreme Audit Institutions (INTOSAI) was created as an autonomous, independent, professional and apolitical institution. Its objectives are to mutually support SAIs, to encourage the exchange of ideas and experiences, to be the global public voice of SAIs, to establish standards in public sector auditing and evaluation , promote good governance and strengthen the capacities and cooperation of SAIs. The organization provides its members with technical assistance.

In terms of evaluation, these guidelines aim to help the Supreme Audit Institutions and the entities in charge of evaluation to analyze in a neutral and independent manner the different criteria allowing the expression of an assessment on the usefulness of a public policy.

They highlight the importance of combining scientific research methods, examining the role of different public authorities and civil society, and including all stakeholders in the evaluation process.

In 2010, the INTOSAI Working Group published a first document on program evaluation, which aimed to present a general definition of evaluation and provide recommendations for its planning. The working group then broadened its scope from program evaluation to public policy evaluation. The latter encompasses broader concepts than performance auditing and includes non- programmatic components such as regulatory initiatives and soft law.

The guidelines describe the main characteristics of public policy evaluation and propose an approach for conducting this type of evaluation in a scientific and independent manner.

These guidelines do not set specific standards, as there are different assessment practices between SAIs. However, they encourage SAIs to take an interest in the evaluation of public policies and provide indications for carrying out evaluations for the benefit of citizens and decision-makers. If the performance audit focuses on monitoring the economy, efficiency and effectiveness, the evaluation of public policies aims to assess the overall impact and the short and long term relevance of a policy.

Furthermore, the recommended evaluation approach is very close to the Evidence-Based Policy Making (EBPM) method.

Indeed, the Evidence-Based Policy Making (EBPM) method analyzes the effect of political commitments on the scientific credibility of research decisions linked to social and economic interests. It is more structured because it takes into account quantifiable and qualitative aspects.

II- RESEARCH METHODOLOGIES

- **Careful analysis of a sample of the collection portfolio and construction of an optimal econometric model**

Our choice to use a logit econometric regression model is explained by the fact that the information collected does not allow another model depending on the objective pursued.

If the data collected allowed it, we would have used other econometric models such as the panel etc. For confidentiality concerns, we took values close to the realities of the bidders' files. We would like to highlight the scientific approach for developing the econometric model.

1- The data source

The data used comes from a base made up of 120 credit files granted by the fund to large Ivorian companies between 2020 and 2022. The information collected concerns certain characteristics of the beneficiary companies and their managers. The financial statements contained in the credit files made it possible to calculate certain financial ratios which make it possible to assess the state of financial health of the company at the time of the loan.

1- Variable selection

- **The dependent variable**

The dependent variable we use is the borrower performance variable. We define a borrower's performance as their debt repayment capacity. Good borrowers are therefore those who have repaid the loan correctly and bad borrowers are those who have not. As in most credit rating studies **(Diallo, 2006; Agboussou, 2018; Bouazzara et al., 2020)** , our performance variable is binary and for each client of the FSGE credit portfolio, it is worth 1 if the latter records unpaid debts and 0 otherwise. We consider a loan to be overdue if it is overdue in accordance with the instructions relating to downgrades of unpaid loans as prescribed by the BCEAO (2020). For this purpose, a loan is in arrears situation if at least one repayment due date is more than 90 days late.

- **Independent or explanatory variables**

In light of the existing literature, we have retained two types of variables that can help explain the credit default of companies that have benefited from the financial support granted by the FSGE:

The first category consists of certain qualitative criteria which according to **Altman (2002)** can provide between 30 and 50% of the explanatory power of the rating model.

As part of this study and in accordance with the availability of data, we retained the sector of activity in which the company operates, its legal form, the type of control to which the company is subject, its geographical location, gender and the level of education of the leader. The description of the sample in relation to these variables can be found in the table below.

Table 1: Description of qualitative variables

Variable	Modality	Effective	Percentage
Activity area	AGRO INDUSTRY	14	11.67
	BUILDING BTP	26	21.67
	TRADE	24	20.00
	IMPORT EXPORT	5	4.17
	INDUSTRY	18	15.00
	SERVICE	13	10.83
	TOURISM AND HOSPITALITY	5	4.17
	TRANSPORTATION	15	12.50
Legal status	COOPERATIVE	9	7.50
	SA	51	42.50
	SARL	48	40.00
	SAS	12	10.00
Type of control	Under national control	105	87.50
	Under foreign private control	15	12.50
Geographical location	ABIDJAN	103	85.83
	Outside Abidjan	17	14.17
Gender of manager	Feminine	6	5.00
	Male	114	95.00
Level of education Manager	PRIMARY	11	9.17
	SECONDARY	21	17.50
	SUPERIOR	88	73.33
	Grand total	**120**	**100.00**

Source: Author's analyses.

The second category consists of non-financial quantitative variables linked to company characteristics and certain financial ratios obtained from the financial statements contained in credit files. It is :

- Company size we measured by taking the natural logarithm of the number of employees.
- The age of the company on the national territory

When it comes to financial ratios, they are the variables most often used in credit risk forecasting models. Their number and nature varies from one study to another depending on the context and availability of data. Research such as that carried out by **Beaver (1966)** only used a single ratio while we find 6 ratios in those **of Bardos (1989)** and **Laitinen (1991)**.

Elsewhere, some have used more than 7 ratios **(Zavgren, 1985; Bouazzara et al., 2020).** Nevertheless, **Dumontier (1990)** underlines the fact that most studies carried out on failure show the predominant nature of the debt, profitability and flow of funds dimensions in the explanation of business failure. The table below summarizes the quantitative variables that we adopted as part of this study.

Table 2: Financial variables

Ratios	**Variable title**	**Measure**
	Debt	
R1	Coverage ratio of short-term debts by turnover	Total current liabilities / turnover
R2	Liquidity value	Total Liabilities/Total Assets
	Profitability	
R3	Economic profitability	(Operating result) / (equity + financial debt)
R4	Financial profitability	Net income / equity.
R5	Gross margin	Gross operating surplus / turnover
R6	Profitability of assets	Net income / Total assets
	Turnover ratios	
R7	Fixed asset turnover ratio	Turnover / total fixed assets
	Structural ratios	
R8	Financial autonomy	Equity / permanent capital
R9	Structural balance	Non-Current Liabilities/Total Assets
	Operating ratios	
R10	Working capital ratio	Working capital / Total current assets
R11	Sales ratio	Total revenue/assets
	Other variables	
	Degree of debt rationing	(Loan amount requested-Loan amount actually received) / Loan amount actually received.
	Amount	Loan amount received from the fund

Source: Author's analyses.

All of these ratios are taken from existing credit rating literature. Some studies can go up to 50 financial ratios **(Duffy, 1977)** for credit rating. In this study, we selected 16 for which data were available for all companies in the sample. Ratios such as those presented by **Altman (1968)** are kept in this study because of their importance in the analysis of the solvency and liquidity of companies. These include, among others:

- Working capital ratio which measures the company's ability to repay its debts as they come due without disrupting the normal course of its operations.
- Sales ratio that illustrates the ability of the company's assets to generate sales. As **Altman (1968)** points out, this ratio measures the ability of the company's management to cope with competition.

- Solvency ratio which measures how much the value of the company's assets can decline before liabilities exceed assets and the company becomes insolvent (**Altman, 1968)**

It should be noted that in this study, no variables are devoted to the measurement of credit guarantees or credit history between the company and the fund. This is explained by the fact that the fund is recent and the loans are granted without collateral requirements. To this end, the analysis of the state of financial health of the company and certain of its qualitative characteristics appears to be essential for predicting its ability to honor its commitments.

2- Modelization

The objective of the credit scoring model is to classify the risks of new or existing customers based on the assumption that the future will be similar to the past. Indeed, we start from the hypothesis that the behavior of old or new customers is linked in the same way to a certain number of their characteristics. Thus, if an applicant or an existing client had a certain behavior in the past (for example, had arrears or not), it is likely that a new applicant or client, with similar characteristics, displays the same behavior (**Sabato , 2008).**

Thanks to the sample of clients who received credit from the fund between 2020 and 2022, we can observe their performance and explain it by their characteristics at the start of the period. To this end, the conditional probability (logistic) model is widely used in the literature. The procedure used to obtain the parameter estimates is presented by **Gujarati (2003)** and consists of maximizing the log-likelihood function of the following logit model:

$$P(X_i) = \frac{1}{\left[1+e^{-(\alpha_0+\alpha_1 X_{i1}+\alpha_2 X_{i2}+\cdots+\alpha_n X_{in})}\right]} = \frac{1}{\left[1+e^{-(D_i)}\right]}.$$

Here, $P(X_i)$is the score of the feature vector $X_i$of customer i, it varies between 0 and 1 and represents the probability that the customer is classified as risky.

The $\alpha_j$are the coefficients to estimate of the different explanatory variables which constitute the vectorX_i.

$X_{ij}$is the value of the j-th characteristic of customer i in the sample.

3- Model validation

It is important to evaluate the stability and performance (i.e. the accuracy of predictions) of the resulting model. In the literature, we found several criteria that were used to evaluate the performance of the models. These include, for example, the average correct classification rate (ACC), type I and type II error rates which quantify the accuracy of each model in correctly classifying "good" and "bad" customers.

As pointed out by **(Sabato, 2008),** any credit scoring model has a "gray" area where it is not able to separate with an acceptable level of confidence between the expected "good" customers and the expected "bad" customers. To this end, there are two types of prediction errors likely to occur: type I errors which correspond to the fact of wrongly classifying a good credit as being bad and type II error which corresponds to the fact of classifying bad credit as good. The type I and type II error rates thus make it possible to evaluate the precision of the model.

Each of these error rates depends on the threshold score (cut-off) allowing a customer to be classified as "good" or "bad" depending on the score that the model attributes to it. In implementing such a model, the challenge for credit risk managers is to define the most appropriate and effective solutions. Thus, to maximize the effectiveness of the scoring model, a threshold must be set taking into account the misclassification costs linked to type I and type II errors **(Altman, 1977; Abdou, 2009b ; Abdou & Pointon, 2009)** .

As pointed out by **Abdou and Pointon (2011)** , in the literature there is no ideal credit rating modeling procedure that would guide the manager in the choice of the threshold score. However, **Sabato (2008)** believes that the optimal threshold value can only be found after careful analysis and consideration of the particularities of the credit provider (e.g. risk tolerance, profitability, earning goals, costs and effectiveness of the recovery process). The idea is to find a threshold that minimizes the costs of accepting loan applications from customers that become doubtful (type II) or rejecting loan applications that would be profitable for the credit provider (type I).

Thus, the procedures and mode of operation of the Support Fund for Large Ivorian Enterprises (FSGE) made it possible to undertake a careful analysis to determine the threshold which minimizes the costs linked to poor classifications.

- **Optimal evaluation approach planned for the FSGE in order to determine the impact of the support policy undertaken**

INTOSAI in Guide 9020-Evaluation of Public Policies specifies the efficient approach in terms of relevant and optimal evaluation. We will give the main essential points for an evaluation expert in accordance with Guide 9020-Evaluation Evaluation of Public Policies.

This involves evaluating the financial impact of the support provided by the FSGE to beneficiaries.

The main activity of the fund is to lend financial support to companies affected by COVID-19 and then, through partner banks, defer repayment over a minimum period of 6 months.

The three aspects covered by the covid-19 loan are:

1. Employment;
2. Financial performance;
3. Labor productivity of large Ivorian companies supported by the fund.

To do this, a two-part evaluation method will be used:

On the one hand, questionnaires will be used to collect the opinions of beneficiaries on the execution of the strategy and the effects of FSGE support.

On the other hand, an impact assessment will be carried out by comparing the beneficiary companies to a control group. To correct selection bias, we will use the propens ity score matching method, called " **Matching** " in econometrics. This allows the causal effect of a treatment to be assessed by comparing treated and untreated individuals with similar characteristics.

The objective is to compare companies supported by the FSGE to other similar companies that have not benefited from the support in order to determine the impact of the loan granted and then field visits to see the reality.

In this study, we combined this method with a double-difference approach to account for time- invariant unobservable characteristics.

We are studying two cohorts of companies which correspond to those having benefited from support from the fund in 2020 and 2021. Each cohort is made up of:

- Companies listed in the FSGE portfolio having benefited from T-shaped support (2020 or 2021)
- Companies listed in the directory of large companies (compiled from tax administration data) that did not benefit from support from the fund in period T.

Companies are followed over 6 years, between T-3 and T+2 for the first cohort and over 5 years, between T-3 and T+1 for the second cohort.

The propensity scores which serve as a matching measure are estimated from a logistic regression which models the probability of benefiting from fund support at period T as a function of a certain number of observable variables which are likely to have influenced the selection of beneficiaries. These variables are essentially the demographic characteristics of the company and certain indicators of its financial health in T-1 (before support from the fund). To these variables, we have attached a certain number of indicators which provide information on the dynamics of the company between T-2 and T. The choice of introducing the ex-ante dynamics of the company in the modeling of the selection process allows us to take into account the extent of the pandemic on the overall state of health of the company before support from the fund.

- ❖ **Choice of variables to retain**

Modeling the propensity to benefit from the support granted by the FSGE must make it possible to explain several facts: the fact of having decided to apply to benefit from the support of the fund and the fact of having been selected by the management committee to actually benefit from the support. Thus, we retained a certain number of variables in relation to the eligibility criteria in support of the fund, the selection criteria retained by the management committee and indicators of the state of financial health and ex -ante of the company.

Drawing on the review by **Teefalen et al. (2009)** on the modeling of the use of external financing by companies, we retained the following variables:

- The company's sector of activity

- Company size measured by number of employees
- Legal status
- The age of the company on the national territory
- The level of tangible assets
- The Body Investment Flow
- The wear rate is measured as the level of net tangible assets compared to the level of gross tangible assets. This ratio makes it possible to measure the degree of wear of the company's production tools.
- The level of employment productivity measured as the ratio between the level of value added and the number of employees
- The level and dynamics of the company's turnover
- The level and dynamics of the company's gross operating surplus
- The level and dynamics of the company's financial debt
- The economic profitability of the company
- Financial profitability of the company
- Certain ratios linked to the financial structure of the company (EBE/VA ratio, equity/balance sheet ratios, financial debt/EBE ratio, liquidity ratio)

❖ **Impact indicators**

In accordance with the objectives pursued by the FSGE, in this case to provide financial support to all Large Companies established throughout the Ivorian territory, particularly with regard to the preservation of their production tools and jobs, we have, in the light of a literature review, retained a certain number of impact indicators. It is :

- **The employment indicator** which corresponds to the absolute variation in the number of employees between T and T+2 for the first cohort and between T and T+1 for the second.

- **Two performance indicators** : This is the variation in turnover and gross operating surplus between T and T+2 for the first cohort and between T and T+1 for the second.
- **The labor productivity indicator** which corresponds to the added value of the company compared to its number of FTE employees
- **The survival indicator:** This is an indicator which checks whether the company remained active at T+2 for the first cohort and at T+1 for the second.

Furthermore, an approach based on the Evidence-Based Policy Making (EBPM) method will be used to improve the support policy initiated by the Ivorian government. This approach will examine time horizons, sources of uncertainty, the economic aspect and the flexibility of public policies. By studying these characteristics, it will focus on normative instruments such as:

- Cost-benefit analysis;
- Decision theory;
- Expected utility;
- Real options theory.

However, it appears that these instruments are incomplete to adequately evaluate public policie s, which will require the construction of a new ad hoc decision tree for public policies. This temporal decision tree will integrate the temporal dimension, the notion of economic costs and benefits, as well as ideas linked to managerial flexibility from the theory of real options, making it possible to respond to the specific requirements of the supporting public decision.

2- Modeling the construction of an optimal econometric model for the collection portfolio

The objective of the credit scoring model is to classify the risks of new or existing customers based on the assumption that the future will be similar to the past. Indeed, we start from the hypothesis that the behavior of old or new customers is linked in the same way to a certain number of their characteristics. Thus, if an existing candidate or client had a certain behavior in the past (e.g., was in arrears or not), it is likely that a new candidate or client, with similar characteristics, would display the same behavior (**Sabato, 2008)** .

Thanks to the sample of clients who received credit from the fund between 2020 and 2022, we can observe their performance and explain it by their characteristics at the start of the period. For this purpose, the conditional probability (logistic) model is widely used in the literature.

The population we study is divided into two categories (good debtors and bad debtors). We have a sample of 120 individuals indexed by i, representing large companies that have benefited from the fund's support. We know a certain number of characteristics of these companies.

These include qualitative criteria that we note $X_1, X_2, \ldots, X_k$ and the financial ratios which we note $R_1, R_2, \ldots, R_s$.

For the company i, the values taken by these variables are noted $x_{i1}, x_{i2}, \ldots, x_{ik}$ And $r_{i1}, r_{i2}, \ldots, r_{is}$. We assume that the probability P that the company i defaults depends on a linear combination of $x_{i1}, x_{i2}, \ldots, x_{ik}$ And $r_{i1}, r_{i2}, \ldots, r_{is}$. Which is written:

$$P(i \text{ soit en défaut}) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik}+\alpha_1 r_{i1}+\alpha_2 r_{i2}+\cdots+\alpha_s r_{is})}}$$

Where β_i et α_i the model parameters are estimated by **Gujarati (2003)** . The procedure used to obtain the parameter estimates consists of maximizing the log-likelihood function of the previous model.

3- Model validation

The evaluation of the stability and performance of the obtained model is essential. The literature presents several criteria used to evaluate models, such as the average correct classification rate (ACC), type I and type II error rates which measure the accuracy of classifying "good" and

“bad” customers. It is important to note that there is a “gray” area where credit scoring models fail to reliably distinguish “good” from “bad” customers. This leads to two types of prediction errors: Type I errors, which incorrectly classify good credit as bad, and Type II errors, which classify bad credit as good. Type I and Type II error rates are used to evaluate the accuracy of the model.

Error rates depend on the score threshold (threshold) used to classify customers as "good" or "bad". The challenge for credit risk managers is therefore to define the most appropriate and effective solutions. Maximizing the effectiveness of the model requires setting a threshold that takes into account the costs associated with type I and type II classification errors **(Altman, 1977; Abdou, 2009b ; Abdou & Pointon, 2009)** . There is no ideal procedure for determining the cutoff score in the literature (**Abdou and Pointon (2011))** .

However, it is recommended to carry out a careful analysis and take into account the specificities of the credit provider (risk tolerance, profitability, financial objectives, costs, efficiency of the recovery process) to find the optimal threshold. The idea is to minimize the costs of accepting questionable loan applications (Type II) or rejecting loan applications that are profitable for the lender (Type I). The Support Fund for Large Ivorian Enterprises (FSGE) has adopted procedures and a mode of operation which make it possible to determine the threshold minimizing the costs linked to poor classifications.

IV- RESULT OF THE RESEARCH

The objective of this part is to implement the methodology presented in the previous chapter. We will first provide a description of the sample of selected companies, then we will present the results of the estimation of the rating model, finally the model will be validated using the different criteria mentioned in the previous chapter.

I- Description of the large companies selected

We selected a random sample of 120 large companies that had benefited from credits granted by the fund. The sample thus constituted benefited from **27,671,159,330** FCFA, or **84.61%** of the total amount granted by the fund.

- Activity area

The construction sector is the most represented in the FSGE portfolio. It represents 21.67% of the number of companies selected and represents 19.11% of the total amount of credits granted by the fund. It is closely followed by the commerce sector which represents 20% of the companies in the portfolio and accounts for 16.17% of the total loans granted. The industrial sector comes in third position in terms of number of companies (15%) but represents the second sector having benefited the most from the fund's support with 18.52% of the total amount of credits granted.

Furthermore, the tourism, hotel and import-export sectors are the least represented in the sample of large companies with importance levels below 5% both in number and in proportion to the amount of credits granted.

Figure 1: Distribution of the number of companies by sector

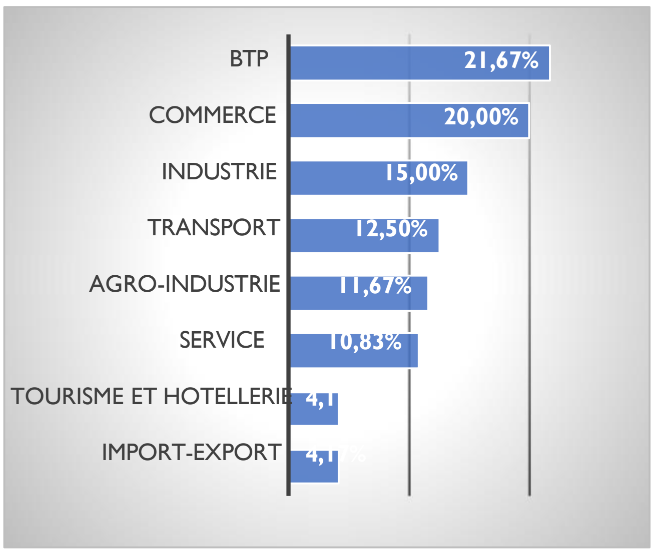
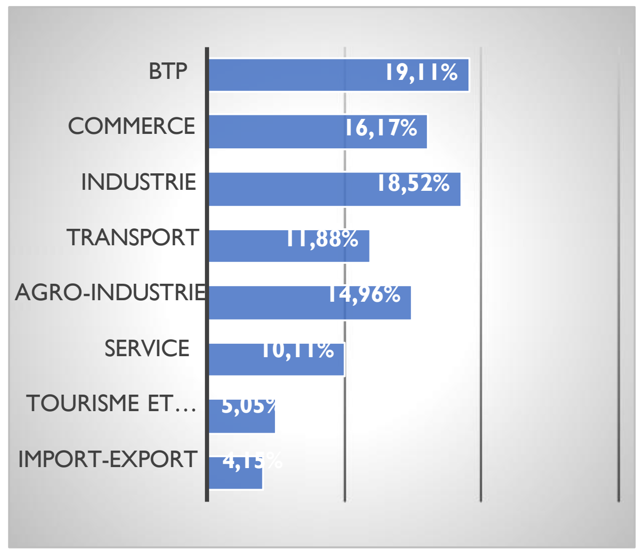


Figure 2: Distribution of credits granted to each sector



Source: Author's analyses.

- Legal form of sample companies

Limited companies (SA) are the most important in the fund's credit portfolio. They represent almost 43% of the number of large companies selected and weigh almost as much in terms of total credit granted. They are closely followed by limited liability companies (SARL) which number around forty both in terms of staff and in terms of the amount granted by the fund. SAS and cooperatives are the least represented since they represent respectively 10% and 7.5% of the company workforce and represent respectively 7.95% and 8.49% in the amounts granted by the fund.

Figure 3: Distribution of the number of companies by legal form

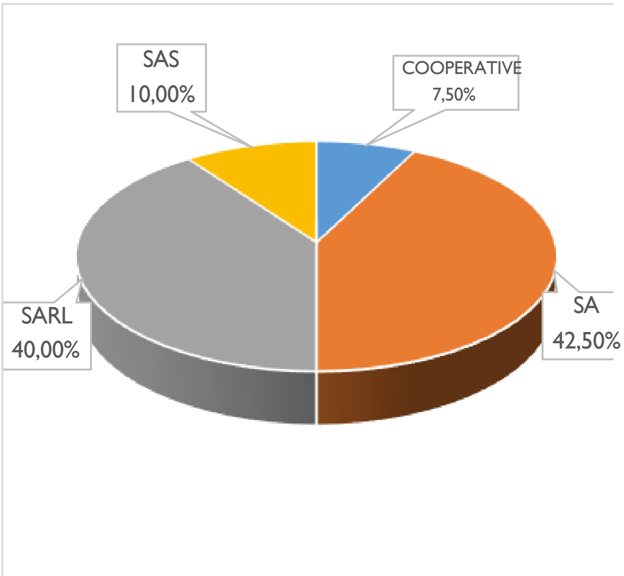
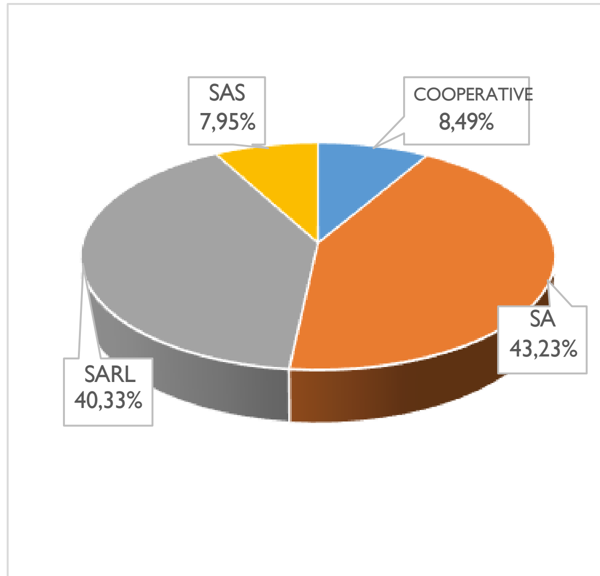


Figure 4: Distribution of credits granted to each type of business (legal form)



Source: Author's analyses.

- Type of control to which the company is subject

The majority (87.50%) of the companies in the sample that benefited from support from the fund are under national control. To this end, 85.31% of the credits granted by the fund are for the benefit of companies under national control.

Figure 5: Type of control to which companies are subject

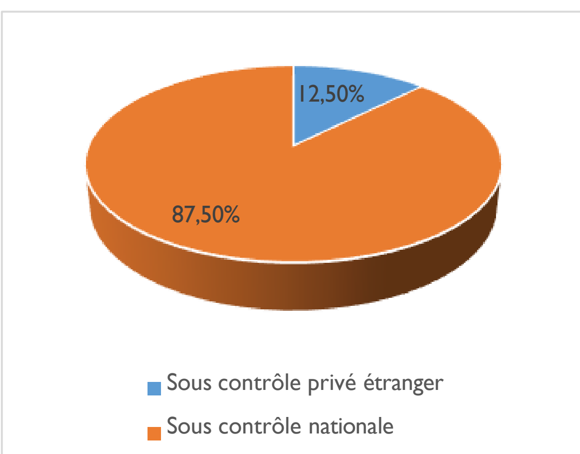
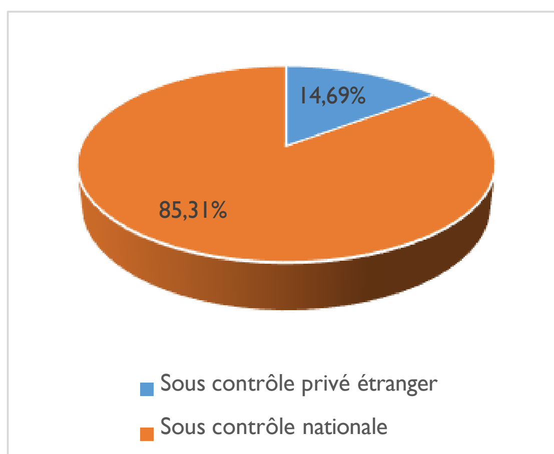


Figure 6: Share of credit granted by type of control



Source: Author's analyses.

- Gender of manager

For the companies in the sample, only 5% of them are managed by women and they were entitled to 5.64% of the total amount of credits granted by the fund.

Figure 7: distribution of men/women among business leaders

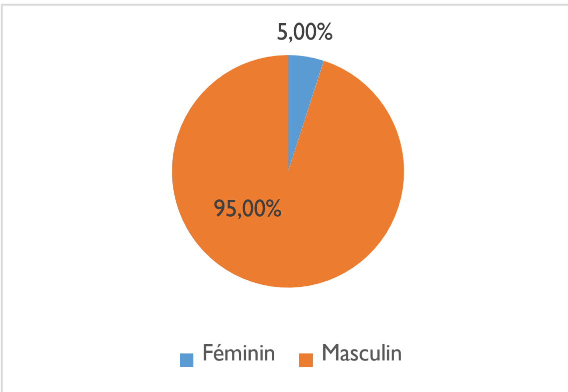
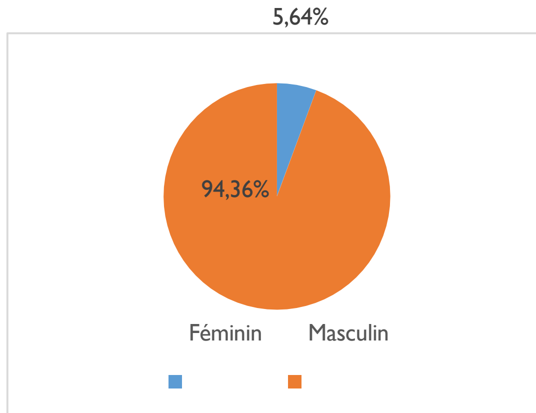


Figure 8: Amount granted by type of manager (Sex)



Source: Author's analyses.

- Age of businesses on the national territory

Overall, the large companies that have benefited from the fund's support have been operating on Ivorian territory for a certain number of years, ranging from 5 years for the youngest to 72 years for the oldest. They have an average age of 17 years and the oldest among them work in the commerce, industry and services sector. Those in the import-export sector are the youngest in that the oldest of them has only been operating in the country for 18 years.

Table 3: Age of companies on the national territory

Activity area	**Minimum age**	**Maximum age**	**Middle age**	**Standard deviation**
AGRO INDUSTRY	6	29	14.93	8.41
BUILDING BTP	6	25	13.12	5.78
TRADE	6	72	21.13	20.06
IMPORT EXPORT	6	18	10.20	4.92
INDUSTRY	5	54	20.44	15.05
SERVICE	5	49	21.46	13.77
TOURISM AND HOSPITALITY	9	36	17.40	10.71
TRANSPORTATION	8	39	18.53	9.13
Grand total	**5**	**72**	**17.67**	**13.09**

Source: Author's analyses.

- Size of companies in number of employees

The sampled companies employ 16,143 employees. The number of employees varies between 6 and 890 for an average of approximately 134 employees per company. It should be noted that the number of employees can vary enormously from one company to another. The industrial sector is the one that employs the most to the extent that it alone employs 3,387 people. Furthermore, the company that employs the least has 12 employees and some employ up to 890 people. This sector is closely followed by the transport sector which employs 2904 people with at least 76 employees per company. The table below allows you to assess the sizes of each of the sectors of activity in terms of number of employees.

Table 4: Number of company employees by sector of activity

Activity area	Minimum size	Maximum size	Midsized	Total employees
AGRO INDUSTRY	17	680	177.07	2479
BUILDING BTP	19	365	97.42	2533
TRADE	6	503	88.29	2119
IMPORT EXPORT	6	42	24.20	121
INDUSTRY	12	890	188.17	3387
SERVICE	8	501	141.54	1840
TOURISM AND HOSPITALITY	93	266	152.00	760
TRANSPORTATION	76	630	193.60	2904
Grand total	**6**	**890**	**134,525**	**16143**

Source: Author's analyses.

II- Credit Default Distributions

Among the 120 companies studied, 77 have a credit default, which represents a proportion of overdue debt estimated at 64.17%. As shown in the table below, the tourism and hospitality sectors, as well as import-export, seem to be the most affected by the phenomenon of unpaid debts. In these sectors, eight out of ten companies have not honored their debt repayment commitments. The services sector shows similar behavior, but less significantly since only seven out of ten companies are unable to pay their debt.

Table 5: Default rate by sector

Activity area	Good credit (%)	Bad credit (%)	Total (%)
AGRO INDUSTRY	42.86	57.14	100
BUILDING BTP	42.31	57.69	100
TRADE	37.50	62.50	100
IMPORT EXPORT	20.00	80.00	100
INDUSTRY	50.00	50.00	100
SERVICE	30.77	69.23	100
TOURISM AND HOSPITALITY	20.00	80.00	100
TRANSPORTATION	40.00	60.00	100
Grand total	**35.83**	**64.17**	**100**

Source: Author's analyses.

Additionally, co-ops seem to be the type of business that offers the greatest share of bad credit. Out of ten companies of this form, nearly nine record unpaid bills. The situation is less alarming on the side of SARLs, of which a little more than six out of ten do not pay their debt. SAS and SA seem to have less difficulty than the others in repaying their debt since for the latter, only one company in two defaults.

Table 6: Default rate by type of business

Legal status	Good credit (%)	Bad credit (%)	Total (%)
COOPERATIVE	11.11	88.89	100
SA	49.02	50.98	100
SARL	33.33	66.67	100
SAS	41.67	58.33	100
Grand total	**35.83**	**64.17**	**100**

Source: Author's analyses.

On the other hand, payment defaults appear to be a phenomenon mainly fueled by large companies under national control. As we can see in the table below, 63.81% of them do not honor their commitments.

Table 7: Delinquency rate by type of control

Type of control	Good credit (%)	Bad credit (%)	Total (%)
Under foreign private control	60.00	40:00	100
Under national control	36.19	63.81	100
total	35.83	64.17	100

Source: Author's analyses.

III- Estimated credit rating model granted by the FSGE

The estimates of the logistic model to explain the arrears of the FSGE credit portfolio can be seen in the table below. The model is overall significant **(P-value = 0.02)** with a Log likelihood, provided by the STATA software, which follows **a Chi-square law and is worth 47.57 with 31 degrees of freedom** . The analysis of the results reveals the main characteristics of companies explaining their propensity to default on payments.

The retail, tourism and hospitality sectors have the highest risks, with 6 and 4 times more default risk than agribusiness, respectively.

Foreign privately controlled firms are less likely to default. Additionally, the gender of the manager plays a role, with companies led by men less likely to honor their commitments.

Certain financial ratios such as the liquidity ratio, the structural balance ratio, the working capital ratio and the turnover ratio also influence the propensity of companies to honor their commitments. Finally, it is interesting to note that the higher the amount granted by the fund, the more the company runs the risk of default.

Table 8: Logistic model results

	Failure to pay	Odd Ratio	St,Err,	t-value
Activity area	Agro industry	Ref	Ref	Ref,
	BUILDING BTP	1.75	1.76	0.55
	Trade	6.50	6.89	1.76*
	Import Export	8.65	14.48	1.29
	Industry	1.32	1.33	0.27
	Service	5.11	6.11	1.37
	Tourism and hospitality	4.48	377.40	2.06**
	Transportation	2,263	2,507	0.74

Legal status	Cooperative	Ref	Ref	Ref,
	SA	0.36	0.84	-0.44
	SARL	1.28	2.94	0.11
	SAS	0.41	0.91	-0.4
Entity Control	Under national control	Ref	Ref	Ref,
	Under foreign private control	0.07	0.06	-2.79***
Location	Abidjan	Ref	Ref	Ref,
	Outside Abidjan	0.425	0.37	-0.98
Gender_of_Leader	Feminine	Ref	Ref	Ref,
	Male	13.58	20.62	1.72*
Level of education	Primary	Ref	Ref	Ref,
	Secondary	7.16	12.83	1.1
	Superior	8.54	15.41	1.19
	Size	1.26	0.44	0.67
	Age	1.02	0.03	0.68
R1	Debt_coverage_ratio	1.35	0.28	1.46
R2	Liquidity ratio	0.19	0.16	-1.96*
R3	Economic profitability	1.06	0.41	0.16
R4	Financial_profitability	0.87	0.08	-1.46
R5	Gross margin	0.59	0.62	-0.5
R6	Profitability_of_assets	2.15	4.14	0.4
R7	Rotation_ratio	1.00	0.00	-1.59
R8	Financial autonomy	0.97	0.31	-0.11
R9	Structural_balance	14.85	21.35	1.88*
R10	Working_capital_ratio	1.24	0.13	2.02**
R11	Sales_ratio	1.86	0.54	2.13**
	Degree of rationing	1.10	0.07	1.38
	Amount	3.28	1.96	1.99**
	Constant	0.00	0.00	-2.41**

*, ** and *** mark significance levels at 10%, 5% and 1% respectively. Source: Author's analyses.

- **The predictive power of the model**

In the table below we can read the classification matrix which allows us to assess the accuracy of the predictions of our model.

Overall, the model displays an average correct classification rate of 83.33%. Among the 77 credits observed as actually defaulting, the model detected 70 as actually bad, i.e. a type II error rate estimated at 9.09%. On the other hand, the proportion of type I errors stands at 30.23%.

The good classification rates inherent in this model are close to the rates generally accepted in the credit rating literature, in particular the logistic model which for **Abdou (2009)** presents itself as the traditional model with the best prediction capacity. The model produced by this author displays an average correct classification rate of 82.81% for the prediction of credit default in Egyptian banks.

The same model produces average correct classification rates varying between 80% and 84% on different samples in the study by **Abdou and Pointon (2009)** .

Table 9: Characteristics matrix

		Predictions (threshold = 0.5)			
		Bad credit	**Good credit**	**Total**	**ACC (%)**
Comments	**Bad credit**	70	7	77	90.91
	Good credit	13	30	43	69.77
	Total			120	83.33

Source: Author's analyses.

As noted in particular by **Abdou and Pointon (2011)**, the average correct classification rate does not take into account the costs of misclassification for the credit provider. Indeed, each classification error, whatever its type, generates costs for the credit provider. A Type I error, which corresponds to misclassifying good credit as bad, refers only to the opportunity cost of lost interest, while a Type II error, which corresponds to misclassifying bad credit, refers only to the opportunity cost of lost interest. as being good (That is, recruiting it into the portfolio), the fund loses part or all of not only the interest but also the principal repayment.

Thus, the optimal threshold for good classification can be considered as that which minimizes the estimated cost of a classification error. To this end, West (2000), taken up by Abdou (2009), proposes the formula below to estimate the cost of a classification error.

$$\boldsymbol{Co\hat{u}t} = \boldsymbol{C(B/M)P(B/M)\pi_1} + \boldsymbol{C(M/B)P(M/B)\pi_2}$$

Where $C(B/M)$and $C(M/B)$are respectively costs associated with Type I and II errors respectively, $P(B/M)$and $P(M/B)$respectively represent the Type I and II error rates committed by the model and depend on the chosen classification threshold. Finally, $\pi_1$and $\pi_2$represent the prior probabilities of good and bad credit in the context considered.

Certainly, the FSGE has solid skills for analyzing the health of companies wishing to use loans, but the existence of unpaid debts in the repayment situation indicates a flaw in the analysis system.

For the continuity of FSGE activities, the government will need to set cost measurement thresholds to determine acceptable levels for the selection of businesses eligible for the COVID- 19 loan when they submit an FSGE loan application.

The Fund's social support policy creates a potential deficit due to the lack of guarantees and ease of access. The econometric model found will allow managers to make more effective decisions by setting thresholds for costs. This will help exclude bad companies based on reality from the collection portfolio.

In addition, the government should define a fairly efficient regulatory framework for recovery in order to considerably reduce the rate of unpaid debts for this type of public policy.

CONCLUSION

In short, the level of deterioration of the credit portfolio of the Support Fund for Large Ivorian Enterprises (FSGE), observed through the default rate recorded by the fund, has raised questions about the tools and methods that could first assess the impact of the support provided by the fund to beneficiaries and then predict future defaults of the fund and optimize its credit portfolio at the same time. We have therefore proposed a method for evaluating the fund and a credit rating model. The latter is based on logistic regression and makes it possible to classify companies requesting credit based on a number of determining factors such as the sector of activity, the type of contro1 to which the company is subject and certain financial ratios that reflect its financial health before the support of the fund. The rating model records a level of performance close to those often mentioned in the literature, since it has a good classification rate of 83.33% with an excellent ability to predict bad credits (90.91%). The Fund's social support policy creates a potential deficit due to the lack of guarantees and ease of access. The econometric model found will allow managers to make more effective decisions. This will help exclude bad companies based on the reality of the recovery portfolio. In addition, the government should define a fairly efficient regulatory framework for recovery in order to significantly reduce the rate of defaults for this type of public policy.

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Table 10: Correlation matrix of qualitative variables

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15
(1) Size	1,000														
(2) Age	0.363	1,000													
(3) R1 Cover_ratio	0.150	-0.004	1,000												
(4) R2 liquid_value	-0.036	-0.112	-0.196	1,000											
(5) R3 Profitability_eco	-0.189	-0.181	-0.106	0.240	1,000										
(6) R4 Profitability_fi	-0.110	-0.063	-0.001	0.030	0.031	1,000									
(7) R5 gross_margin	0.085	-0.020	0.037	0.187	0.177	0.036	1,000								
(8) R6 Profitability_assets	-0.291	-0.307	-0.123	0.238	0.470	0.103	0.182	1,000							
(9) R7 Rotation_ratio	-0.062	-0.165	-0.071	0.113	0.144	0.059	-0.033	0.332	1,000						
(10) R8 autonomy_end	0.027	-0.099	-0.008	-0.213	-0.144	0.049	-0.032	0.076	0.000	1,000					
(11) R9 Balance_str	-0.057	-0.092	-0.290	0.076	0.185	0.036	0.071	0.320	0.129	-0.277	1,000				
(12) R10 Fund_ratio	-0.155	-0.019	-0.329	0.143	0.113	0.219	-0.097	0.224	0.109	-0.050	0.189	1,000			
(13) Degree_of_ratio	0.057	-0.005	-0.071	-0.022	-0.018	0.047	0.006	-0.046	-0.036	-0.055	0.027	0.064	1,000		
(14) R11 Sales_ratio	-0.336	-0.303	-0.198	0.177	0.194	0.080	-0.103	0.435	0.311	0.048	0.285	0.152	-0.017	1,000	
(15) Amount	0.176	0.086	0.160	0.076	0.019	-0.067	-0.072	-0.022	0.015	0.119	-0.070	-0.121	-0.464	-0.084	1,000