

From Data to Financial Decision: Development and Implementation of a Credit Risk Scoring Model in the Moroccan Context

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Abstract: At the dawn of a silent revolution in the prudential management of banking risks in Morocco, this report aims to examine the various international advances in prudential standards and their transposition to the Moroccan context, more specifically in terms of credit risk management. Using raw, real, but non-nominative data, we work together to build a scoring model to assess the credit risk of Moroccan companies. The ultimate goal is to understand how credit risk management forms the basis for effective decision-making, as well as the methodological approach to building a credit scoring model that combines theoretical rigor with the evolution of a rapidly changing regulatory environment.

Keywords: Credit Risk, Credit Scoring Model, Probability of Default, Basel Committee, Bank Al-Maghrib, Logistic Regression, Regulatory Framework

Introduction

The Moroccan banking system has undergone several changes since the creation of the National Bank in 1906 to the present day, with the aim of improving the functioning of banks and creating an environment conducive to Morocco's economic development. The main change was the introduction of the first legislation governing banks and professions related to banking in 1943. Thus, a situation of compartmentalization began to take shape, differentiating between banks controlled by the central bank and specialized banking institutions subject to specific regulations outside the 1943 legislation. Later, in the wake of independence, banks were reorganized into a centralized system under state control. This allowed banks to prosper with comfortable margins and minimal risk in a government-controlled system. This included banking monopolies, credit supervision, interest rate pricing for debtors and creditors, preferential refinancing, etc.

It was not until the end of the 1970s that the barriers began to come down, when the monetary authorities decided to encourage banks to finance investments considered to be priorities for economic development. This period was also marked by the enactment of the first banking law. Then, the 1990s saw the implementation of the SAP (Structural Adjustment Program) and the initiation of major banking and financial reforms, the main purpose of which was “the management of national public debt.” Finally, since the 2008 crisis, Morocco has been fully committed to adapting to international standards while responding to national challenges through the 2014 Banking Law, which broadens the regulatory framework to include participatory (Islamic) banking, and several prudential measures from the Basel Committee, demonstrating responsiveness to market diversification and financial inclusion objectives. Furthermore, new regulations relating to the supervision of financial conglomerates and recovery plans for systemically important financial institutions (SIFIs) were put in place at the end of 2016.

In addition, this development automatically entails an increase in banking risks, particularly credit risk. The significance of this risk stems from the fact that one of the main functions of banks is to collect savings from economic agents, households, or businesses that have surplus of funds, in order to distribute them to agents with financing needs who will be granted credit. This risk depends on mutual trust between borrowers and lenders, but also on

the fact that it constitutes the primary source of funding for banks, which may ultimately impact the financial results of credit institutions. It is in this context that banking supervision, led by Bank Al-Maghrib and more specifically managed by the Banking Supervision Department, intervenes to mitigate banking risks and preserve stability in the banking sector. The BSD closely monitors all credit institutions, continuously tracking all types of risks on a social and consolidated basis, as well as internal control and governance mechanisms. To this end, Morocco has strengthened its regulatory framework to incorporate the recommendations of the Basel norms. In light of these circumstances, the development and implementation of a credit risk scoring model becomes essential. Such a model aims to provide banks, on the one hand, and supervisory authorities, on the other, with an objective and dynamic tool to anticipate borrower default, optimize capital allocation, and reinforce the stability of the banking system.

This raises the following question: *How can we build and implement a relevant, robust scoring model adapted to the Moroccan context to assess the credit risk of Moroccan companies, and to what extent does this model improve risk discrimination and banking decision-making?*

We will address this topic in three distinct parts. The first part is the literature review, which will enable us to understand and assimilate all the essential concepts related to credit scoring. The second part then discusses the detailed methodology of our approach to building the scoring model. In addition, part three will be a practical section, where we will use a database provided by BAM containing real but non-nominative data, due to the confidentiality and sensitivity of banking data, to create our scoring function and test it. Then, we will move on to discuss the results and recommendations.

Literature Review

Risk is a complex and multidimensional concept referring to the possibility that a future event, by its very nature uncertain, may result in adverse consequences. It is commonly understood as the interaction between a *hazard* (the uncertainty) and a *stake* (the severity of the outcome) (Zolla, 2013). In the financial sector, risk is often formalized as the product of the probability of occurrence of an event and the magnitude of its consequences, as follows: $R = f(P, C)$, where P denotes probability and C denotes consequence (Therrien & Normandin, 2012). A distinction is generally made between **Specific risk**, which relates to an individual borrower or a particular transaction, and **Systemic risk**, which affects the financial system as a whole, with a potential domino effect capable of triggering widespread defaults (Brunel, 2009).

Financial institutions may face various categories of risk, including:

- **Operational risk:** The risk of loss resulting from inadequate or failed internal processes, people, and systems.
- **Credit risk:** The risk that a borrower will fail to fulfill their financial obligations.
- **Market risk:** The risk of losses in on- and off-balance-sheet positions arising from movements in market prices.

Credit, in its most common definition, refers to a financial arrangement in which one party (the lender or creditor) provides funds to another (the borrower or debtor), on the trust that the borrower will repay the funds at a future date (Gouriéroux & Tiomo, 2007). Three fundamental components define credit operation: first, the lender's confidence in the borrower's ability and willingness to repay. Second, a defined time period during which the borrower has access to the funds, and a promise of repayment, typically accompanied by interest payments as compensation for the credit risk assumed.

Credit risk is historically the oldest and remains the most significant type of risk faced by banking institutions. It is inherently linked to the core banking activity of financial intermediation: collecting funds from surplus economic agents and reallocating them, through loans, to agents in need of financing. Credit risk is composed of several elements, including

default or delinquency, exposure at the time of default, expected and unexpected losses, and the time horizon of the exposure (Lobez, 1997).

Importantly, credit transactions are governed by the “**golden rule of banking**,” also known as the *principle of maturity matching*, which stipulates that banks should finance short-term loans with short-term liabilities and long-term loans with long-term liabilities. Failure to respect this principle exposes banks to significant risks, particularly credit risk in its multiple manifestations.

According to Dietsch and Petey (2008), credit risk can be decomposed into three major categories:

1. **Default Risk:** This refers to the probability that the borrower will fail to meet their contractual repayment obligations, whether in terms of principal or interest payments. This probability of default (PD) can be estimated using either a binary (default vs. non-default) or a continuous (graded) approach.
2. **Recovery Risk (Loss Given Default - LGD):** This relates to the portion of the exposure that is not recovered following a default event. It depends on several factors, including the value and enforceability of collateral, the length of the recovery process, and the seniority of the claims (e.g., debt subordination).
3. **Exposure Risk (Exposure at Default - EAD):** This reflects the uncertainty surrounding the total value of the exposure at the time the default occurs. It encompasses the potential increase in credit lines drawn or other forms of contingent exposure leading up to the default event.

The Basel Committee was established in 1974 by the central bank governors of the G10 countries. Its creation was triggered by the failure of the German Herstatt Bank, which had a domino effect on other financial institutions (Lameta, 2008; Rochet, 2008). The Committee's overarching objective is to strengthen the regulation and supervision of banks worldwide in order to promote global financial stability. The successive Basel Accords reflect an increasing complexity and sophistication of banking regulations, in response to the structural weaknesses exposed by successive financial crises. To date, four successive frameworks, Basel I, II, III, and IV, constitute the core of the international prudential architecture. Their progressive evolution is summarized in Table 1.

Table 1. Summary of Basel I, II, III, IV

Characteristic	Basel I (1988)	Basel II (2004)	Basel III (2010)	Basel IV (2017)
Minimum capital requirements	Cooke ratio: 8% (credit risk only)	McDonough ratio: 8% (credit, market, and operational risks)	Strengthening of Tier 1, counter-cyclical buffer	Output floor at 72.5%, restrictions on internal models
Risk approach	Standardized risk weights	Standardized approach and IRB internal models	Integration of liquidity and leverage ratios	Revised standard approach, SMA for operational risk
Pillar 2 (supervision)	Weak	Strengthened prudential oversight	Enhanced supervision and mandatory stress testing	Stricter control of internal models
Pillar 3 (market discipline)	Limited	Greater disclosure requirements	Further enhanced transparency	Harmonization and reduced RWA variability
Liquidity risk management	Not addressed	Minimal consideration	Mandatory LCR and NSFR ratios	Reinforcement and preservation of liquidity standards

Sources: Authors

Morocco's adoption of international prudential standards reflects a gradual alignment with the Basel framework, while simultaneously accounting for the specific characteristics of the national

economic environment. Bank Al-Maghrib (BAM) has implemented a regulatory framework that is both coherent and proactive. This framework includes a prudentially reinforced solvency ratio (12% versus 8% internationally), a rigorously structured capital base, and an integrated risk management system, most notably, through Circular 26/G/2006, which forms the cornerstone of Pillar II implementation in Morocco (Bank Al-Maghrib, 2007; Bendhaiba, 2019).

Beyond formal transposition, the Moroccan regulator has adopted a deliberately overcompensating approach. This regulatory rigor is evidenced by stricter capital requirements particularly for Common Equity Tier 1 ($CET1 \geq 8\%$) and a structurally elevated liquidity coverage ratio ($LCR > 135\%$), and significant reinforcement of governance, transparency, and internal control mechanisms. A comparative analysis between the Basel Accords and the Moroccan prudential framework reveals both convergence on the foundational pillars: capital requirements, supervisory oversight, and market discipline and a nationally specific intensity in the thresholds imposed.

Moreover, the Moroccan framework anticipates and integrates emerging risks, particularly those linked to digitalization, cybersecurity, and environmental, social, and governance (ESG) factors. Nevertheless, the use of advanced risk assessment approaches such as Internal Ratings-Based (IRB) models for capital requirement calculations remains limited and is still under development.

Ultimately, Morocco's prudential framework is characterized by a rigorous and often anticipatory implementation of international norms, thereby enhancing the resilience of its banking system to exogenous shocks.

Credit risk management has traditionally relied on two complementary approaches: qualitative expert analysis based on financial and contextual criteria and quantitative analysis, grounded in predictive statistical models. Credit scoring falls squarely within the latter domain and has become central to the architecture of modern prudential regulation.

Originally developed by Altman (1968) and enriched through successive academic and industry contributions, credit scoring estimates the probability of default using a set of discriminative variables (e.g., financial ratios, payment history). These variables are aggregated into a single score via statistical or machine learning techniques such as logistic regression, decision trees, or neural networks. Credit scoring offers multiple advantages for lending institutions. It enables rapid, consistent, and decentralized decision-making, thereby enhancing productivity and reducing delinquency rates (Verdier, 1986; Ramage, 2001).

The general scoring formula takes the form: $Z = \alpha_1 R_1 + \alpha_2 R_2 + \dots + \alpha_n R_n + b$; where R_i represents the explanatory variables, α_i the estimated coefficients, and b a constant.

Importantly, credit scoring differs fundamentally from rating systems. While ratings rely on expert judgment, scoring is based on algorithms and objective data, making it especially suitable for high-volume assessments, such as those involving SMEs or individual borrowers. In metaphorical terms, rating resembles artisanal craftsmanship, whereas scoring functions more like a standardized, automated factory process.

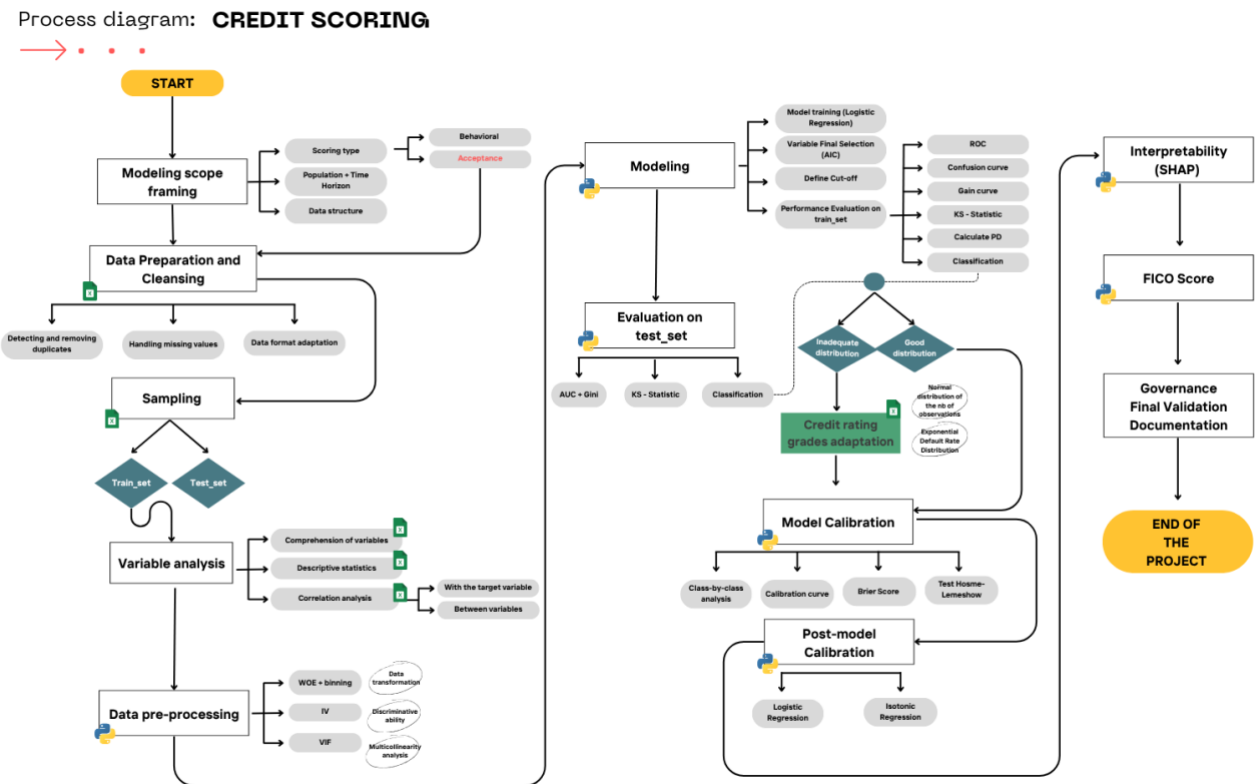
However, credit scoring is not without limitations. Its predictive power is never absolute and inevitably produces classification errors (false positives and false negatives). Furthermore, its effectiveness depends heavily on data quality, and it does not account for qualitative dimensions of borrower profiles. Robust calibration is thus essential for scoring models to remain relevant.

In conclusion, credit scoring constitutes a powerful yet non-autonomous tool. Its optimal use lies in integration within a holistic risk management approach, combining quantitative modeling, expert analysis, and a nuanced understanding of the local economic context.

Methodology

The construction of the scoring model follows a rigorous 13-step methodology, combining academic rigor, regulatory compliance (Bank Al-Maghrib), and operational applicability. The initial framework defines an *acceptance scoring* approach (static historical data), delineates the target population, time horizon, and data structure. Preprocessing steps include data cleaning (duplicates, missing values), sampling (train/validation split), and exploratory analysis (descriptive statistics, Pearson correlations, Weight of Evidence (WOE), Information Value (IV), and Variance Inflation Factor (VIF)). The modeling, based on logistic regression, is optimized using the Akaike Information Criterion (AIC) and evaluated via ROC curves, confusion matrices, and gain curves. Out-of-sample validation ensures robustness, followed by discretization into five risk classes (normal distribution of observations, exponential distribution of defaults). Calibration (Brier Score, Hosmer-Lemeshow test, empirical calibration curve) and recalibration (Platt Scaling, isotonic regression) ensure probabilistic accuracy. Interpretability is achieved through SHAP (SHapley Additive exPlanations), while score standardization aligns with the FICO scale for universal interpretability. Finally, regulatory documentation and a monitoring framework (drift detection, backtesting) ensure long-term model stability in a constrained banking environment.

Figure 1. Process diagram for building a credit scoring model



Sources: Authors

Empirical Results, Analysis and Discussion

The comprehensive methodological framework we developed culminates in this section, where we present empirical results. The study's objective is to predict corporate default probability, whether for large firms or SMEs, using objective accounting data. To achieve this, we utilized a

real but anonymized data set provided by Bank Al-Maghrib, comprising 1,063 firms, of which 74 experienced a default event according to internal criteria. The analysis adopts a 12-month forward-looking horizon over a three-year consecutive window, ensuring robust calibration of estimated probabilities.

The dataset underwent rigorous cleaning to address missing values, outliers, and inconsistencies. Subsequently, we applied stratified sampling to preserve the representativeness of the minority class (defaults): 80% for training (including 60 defaulted firms) and 20% for testing (14 defaults), ensuring both data independence and class balance.

Candidate variables were selected based on three key financial dimensions:

1. Activity & Performance: Revenue (CA), revenue growth, EBITDA/Revenue, Operating Cash Flow / Total Balance Sheet, NetIncome/Revenue.
2. Financial Structure: Net Equity/Total Balance Sheet, bank debt, Current Liabilities/Current Assets, capitalization.
3. Operational Metrics: Average client and supplier payment delays.

These variables were rigorously tested for predictive power, multicollinearity, and economic interpretability before final model inclusion. Following the rigorous selection phase and many model training. The final model retains five significant explanatory variables, demonstrating enhanced parsimony without compromising predictive power. A comparative assessment of global performance metrics between initial training and the AIC method reveals a systematic improvement:

- **AIC** decreased from 404.42 to 402.18 ($\Delta = +2.24$),
- **BIC** from 444.03 to 438.22 ($\Delta = +5.81$),
- **Log-Likelihood** increased from -195.21 to -194.09 ($\Delta = +1.12$),
- **McFadden's Pseudo R²** improved marginally from 0.2849 to 0.2893 ($\Delta = +0.0044$).

Though these gains appear modest, they statistically validate the **AIC-driven pruning strategy**, confirming that the final model achieves superior efficiency with fewer parameters.

The estimated coefficients exhibit statistically significant relationships ($p < 0.05$) with the target variable, underscoring their economic and predictive relevance:

Table 2. Estimated Coefficients – Final Model

Variable	Coeff. (β)	Std. Error	z-value	p-value	95% CI
const	-3.5965	0.191	-18.811	0.000	[-3.971 ; -3.222]
dyn_Revenue_WOE	-0.4675	0.188	-2.492	0.013	[-0.835 ; -0.100]
CurrLiabilities_CurrAssets_WOE	-0.4833	0.154	-3.132	0.002	[-0.786 ; -0.181]
IntExpenses_Revenue_WOE	-0.6683	0.144	-4.648	0.000	[-0.950 ; -0.386]
NetIncome_Revenue_WOE	-0.4726	0.189	-2.505	0.012	[-0.842 ; -0.103]
OCF_TBS_WOE	-0.4802	0.174	-2.752	0.006	[-0.822 ; -0.138]

Sources: Authors

The final scoring function is expressed as:

$$\begin{aligned} \text{Final Score} = & -3.5965 - 0.4675 \cdot \text{dyn_Revenue_WOE} - 0.4833 \\ & \cdot \text{CurrLiabilities_CurrAssets_WOE} - 0.6683 \cdot \text{IntExpenses_Revenue_WOE} \\ & - 0.4726 \cdot \text{NetIncome_Revenue_WOE} - 0.4802 \cdot \text{OCF_TBS_WOE} \end{aligned}$$

The model's out-of-sample performance (Train vs. Test) confirms robustness, with minimal degradation in key metrics:

Table 3. Model Performance Comparison: Training vs. Test Samples

Metric	Training	Test	Difference (Δ)
AUC	0.8861	0.8755	-0.0106
Gini	0.7721	0.7510	-0.0211
KS-statistic	0.6336	0.6329	-0.0007
Sensitivity (Recall)	0.8333	0.7857	-0.0476
Specificity	0.8003	0.8194	+0.0192
Precision	0.1085	0.1078	-0.0006
Accuracy	0.8012	0.8185	+0.0173

Sources: Authors

The final model demonstrates outstanding statistical performance, validated by robust key indicators that meet both academic and regulatory standards. The AUC of 0.886, significantly exceeding the 0.75 threshold established in the literature (Hand & Till, 2001), reflects strong discriminatory power. The elevated KS statistic of 0.633 confirms a clear separation between defaulting and non-defaulting firms, well above the regulatory minimum of 0.3 (Anderson, 2007).

The selection of a cut-off at 0.030 optimizes the trade-off between sensitivity (83.3%) and specificity (80.0%), ensuring reliable default detection while minimizing false positives, in line with prudential recommendations (Bellotti & Crook, 2009). The overall accuracy of 80.1% underscores the model's robustness, even under low default rate conditions, thereby satisfying Pillar 1 requirements of Basel II as implemented by Bank Al-Maghrib (BCBS, 2006).

Thus, this model meets rigorous criteria for discrimination, stability, and applicability in credit risk management, aligning with international best practices.

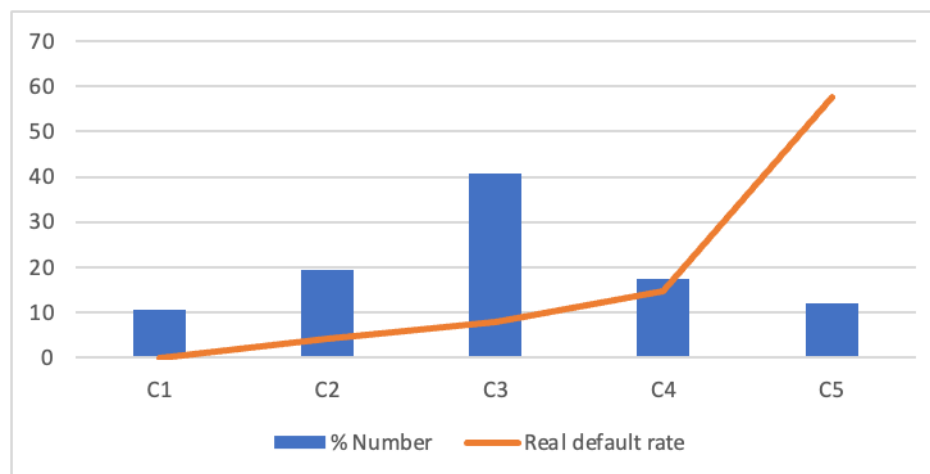
Furthermore, the development of risk classes serves to transform continuous default probabilities into discrete categories, thereby facilitating their integration into banking decision-making processes. This segmentation into five ordinal classes (C1 to C5) is grounded in two fundamental methodological requirements. First, the distribution of observations approximates a normal distribution, ensuring statistical representativeness (Hand & Henley, 1997). Second, the exponential progression of observed default rates across classes demonstrates the model's discriminatory power, consistent with theoretical expectations in advanced credit scoring (Crook, Edelman, & Thomas, 2007).

Table 4. Final Rating Classes

Classes	Risk level	% Number	Number	PD min	PD max	Real default rate (%)
C1	Very low	10,70 %	282	0,0002	0,0004	0,00
C2	Low	19,35 %	510	0,0004	0,0017	4,22
C3	Moderate	40,59 %	1 070	0,0017	0,0173	7,90
C4	High	17,30 %	456	0,0174	0,0565	14,75
C5	Critical	12,06 %	318	0,0565	0,5356	57,71

Sources: Authors

Figure 2. Global Rating Scale and Risk Class Distribution



Sources: Authors

Empirical results highlight the model's strong performance, particularly in the extreme risk classes. Class C1, comprising the lowest-risk profiles (default probability < 0.04%), exhibits an observed default rate of 0%, while Class C5, containing the highest-risk exposures (default probability > 53%), shows an actual default rate of 57.7%. The intermediate classes (C2 to C4) display a consistent and monotonic increase in default rates, ensuring both operational clarity in risk assessment and strong alignment with model predictions.

From an operational perspective, this classification framework enhances risk transparency for banking professionals, enables differentiated calibration of prudential measures (including provisioning, collateral requirements, and risk-based pricing), and provides a robust foundation for developing adaptive credit policies and portfolio management strategies. The approach fully complies with international academic standards and regulatory requirements, particularly those outlined in the Basel II and III accords (BCBS, 2006), while simultaneously reflecting best practices among financial institutions that incorporate risk segmentation into their risk management frameworks.

Following the various stages of modeling, evaluation, and calibration, the developed model demonstrates a remarkable capacity to rigorously and operationally quantify and classify default risk. Its parsimonious structure, precise probabilistic calibration, and integration into a legible rating framework render it both statistically robust and directly deployable within banking decision-making processes. The model does not merely predict, it explains, discriminates, and aligns risk scores with empirical risk realities, thereby paving the way for concrete, responsible, and prudentially compliant implementation.

The development and implementation of the credit risk scoring model within the Moroccan banking context reveal a complex balance between methodological rigor, data limitations, and the practical demands of regulatory compliance. Notably, the use of a three-year observation window, while constrained by data availability, represents a strategically justified compromise in an exploratory setting but remains below the five-year horizon recommended by Basel's Advanced Internal Ratings-Based (IRB) approaches (BCBS, 2006). Such temporal truncation risks undermining the model's robustness to economic cycles and its capacity to fully capture the latent dynamics of default behavior (Crook et al., 2007), thereby necessitating future extensions to enhance longitudinal stability and predictive accuracy.

The preprocessing phase and variable selection methodology underscore the dual challenge of harnessing model interpretability while maintaining predictive strength. Techniques including Weight of Evidence transformations (Hand & Henley, 1997),

Information Value assessments, and multicollinearity diagnostics proved effective in fostering model transparency and parsimony, yet they inherently induce information loss and remain sensitive to sample specificity (Bellotti & Crook, 2009). Emerging interpretability tools such as SHAP (Lundberg & Lee, 2017) enrich this framework by unveiling nonlinear and interaction effects otherwise obscured in classical logistic regression, bridging academic sophistication with practical transparency demands. The reconciliation of increasingly complex data patterns with the imperative for regulatory explainability thus emerges as a critical frontier in credit risk modeling research (Doshi-Velez & Kim, 2017).

Model evaluation evidenced strong discriminatory power and operational performance characteristics, particularly when assessed on independent test data, signaling commendable generalization and minimal overfitting despite the endemic challenge of class imbalance (Hand & Till, 2001). Nonetheless, persistent low precision for default predictions illuminates ongoing difficulties in rare event classification prevalent in credit risk contexts. Adaptive threshold optimization, augmentation of default case representation, and exploration of ensemble or resampling techniques offer promising asymptotic improvements (Chen et al., 2015). Simultaneously, the rigorous calibration procedures, especially with isotonic regression recalibration (Niculescu-Mizil & Caruana, 2005), affirm the model's capability to deliver probabilistically sound predictions crucial for economic interpretation and regulatory compliance under frameworks such as IFRS 9.

Translating continuous default probabilities into a simplified five-class FICO-like scoring system effectively contextualizes complex model outputs for operational personnel and regulatory stakeholders alike. This segmentation facilitates nuanced decision-making, including differentiated loan approval and pricing strategies, while laying essential groundwork for future extensions involving stress testing and risk migration tracking (Crook et al., 2019). Importantly, this transformation balances statistical sophistication with communicative clarity, though it warrants ongoing refinement to mitigate subjectivity and better preserve underlying risk gradients through potential continuous scoring approaches (Thomas, 2009). Future research must thus pursue enhanced segmentation methodologies that sustain both analytical depth and practical applicability.

In summary, the constructed credit risk model exemplifies a robust, adaptable tool that operationalizes rigorous academic principles within Morocco's evolving regulatory environment. Nevertheless, its ongoing refinement through lengthened temporal horizons, improved minority class treatment, dynamic recalibration, and sector-sensitive segmentation remains imperative to maintain resilience amidst macroeconomic uncertainty and heterogeneous borrower profiles. These refinements will ensure adherence to international prudential standards and foster broader confidence among regulators, financial institutions, and stakeholders involved in the Moroccan credit ecosystem.

Conclusion

The assessment of the credit scoring model reveals a process characterized by statistical robustness, economic relevance, and operational adaptability. Nevertheless, several critical limitations temper its overall evaluative strength and highlight areas for improvement in alignment with advanced regulatory frameworks and best industry practices.

Firstly, the model's temporal scope is a notable constraint. It is constructed over a rolling horizon of three years, which falls short of the regulatory expectations under the Advanced Internal Ratings-Based (IRB) approaches, where a minimum observation period of five years is recommended. This extended horizon is imperative to adequately capture economic cyclicity and temporal variations in default behavior, thereby ensuring model stability and resilience across economic cycles (Basel Committee on Banking Supervision, 2006). The shorter horizon undermines the model's capacity to generalize beyond the immediate data window, potentially inducing temporal biases.

Secondly, the relatively low default incidence of approximately 7% introduces methodological challenges related to class imbalance. This disproportion elevates the likelihood of coefficient instability and overfitting within the predictive variables, especially for observations at the extremities of the score distribution. Such instability compromises the statistical reliability and interpretability of the risk scores (Bellotti & Crook, 2009). Consequently, caution is warranted when applying or extrapolating model predictions to marginal cases, where estimation variance may increase substantially.

Thirdly, the model's calibration is based on static historical data, which does not encompass periods of pronounced economic stress or crises. This exposes a fundamental vulnerability in the model's predictive validity under adverse macroeconomic conditions. Without the incorporation of stress-testing scenarios or dynamic recalibration mechanisms, the model risks significant deterioration in performance during recessions or systemic shocks (Crook et al., 2007). An adaptive framework incorporating forward-looking economic indicators and crisis-period observations would thus be essential to maintain predictive accuracy and regulatory compliance.

Finally, the model's aggregate application across heterogeneous counterparty segments disregards sector-specific idiosyncrasies and behavioral nuances. The lack of segmentation by industry, firm size, or economic profile constrains the model's discriminatory power and operational relevance. Sectoral and portfolio-specific modeling approaches, which tailor risk assessment methodologies to the unique risk drivers within subsets such as SMEs, large corporates, or distinct industries (manufacturing, retail, construction), have consistently demonstrated superior predictive performance and risk segmentation efficacy (Anderson, 2007).

In conclusion, while the existing model shows commendable performance metrics, its robustness would be markedly enhanced by adopting a segmented, longitudinal, and dynamically adaptive framework. Such enhancements, incorporating extended time horizons, sectoral specificity, behavioral variables, and stress-testing data, are not only consistent with the evolving regulatory landscape exemplified by Basel III/IV but also align with contemporary academic and practitioner standards for credit risk modeling.

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