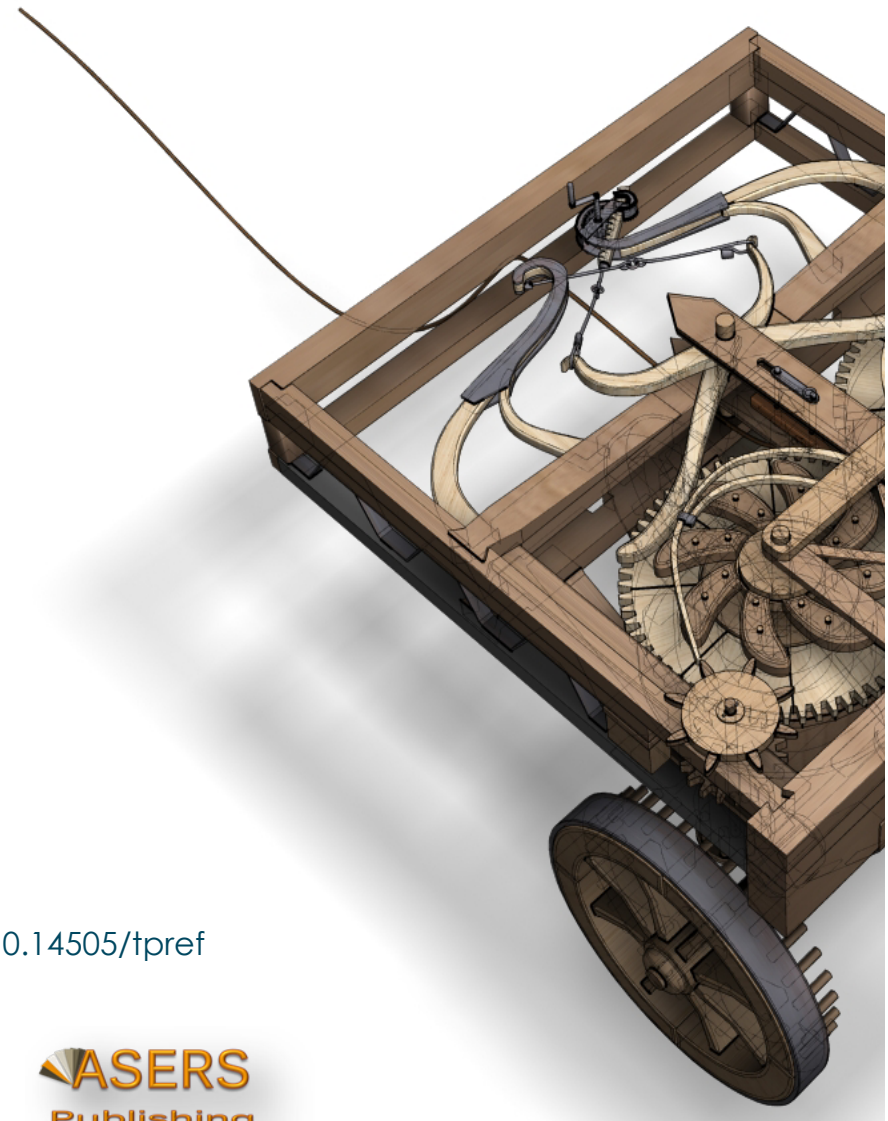
Theoretical and Practical Research in Economic Fields



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Theoretical and Practical Research in Economic Fields

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Financial Factors and Beyond: A Survey of Credit Risk Assessment for VSBs by Moroccan Banks

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Abstract: This article analyzes the extent to which Moroccan banks adopt a holistic approach to credit risk assessment, incorporating criteria that go beyond simple balance sheets and financial ratios. To this end, Multiple Correspondence Analysis and advanced statistical techniques were employed using R software. A detailed questionnaire comprising 14 questions, was distributed to a sample of Moroccan bankers. The results of this analysis reliably confirm our initial hypotheses. They reveal a growing trend among Moroccan banks towards a more complex and nuanced assessment of credit risk. In addition to traditional financial aspects such as financial statement analysis, banks are increasingly considering non-financial criteria such as collateral requirements, quality of corporate governance, sustainability of business practices, and technological positioning. This diversified approach gives banks a more accurate and comprehensive view of a company's risk profile. It also enables them to make better-informed and more balanced lending decisions, considering the multitude of factors that can influence a company's ability to repay.

Keywords: credit risk management; very small businesses; statistical analysis.

JEL Classification: C52; G21; G32; C10.

Introduction

The heart of banking lies in its role as a financial intermediary, acting between those who have funds and those who need them. This function, according to the theory of financial intermediation, implies that banks play a specialized supervisory role, delegated by lenders to guarantee the proper management of the credits granted (Diamond 1984, 1991).

However, this function is not without risk. Banks are exposed to a wide range of risks, from financial to operational and business risks (Greuning and Bratanovic, 2004). Among these, credit risk, considered the main risk for a bank, arises when borrowers fail to meet their repayment obligations, leading to an increase in bad debts (Godlewski, 2005; Louzis *et al.* 2012).

According to the Bank for International Settlements (2011), credit risk lies in the fact that the counterparty may not fulfill its obligations in accordance with the agreed contractual terms. A financial asset is considered unpaid when a counterparty has failed to make the payment due on the contractual due date. In the same vein, Bank Al-Maghrib (2023) has defined credit risk as the risk incurred in the event of a counterparty default, *i.e.*, the borrower's inability to repay its debts and honor its commitments to the banking institution.

The banking sector is deeply regulated and often considered a barometer of the economy as a whole (Sumna, P. 2013). In order to prevent crises, regulatory authorities, such as the Basel Committee, have put in place arrangements to strengthen the financial stability of banks, notably by imposing capital requirements and prudential supervision standards (Pierandrei, L. 2015).

In the Moroccan context, non-performing-loans in Morocco have reached 88.8 billion of dirhams. Additionally, Business failures in Morocco have risen by 15% in 2023. Most of these failures are among Very Small Businesses (VSBs), which account for 98.7% of the total.

Faced with rising levels of non-performing loans and business failures, our article aims to answer the following question: How do Moroccan banks integrate non-financial factors, such as sustainability, governance, technology and market positioning, into their assessment processes to refine their credit risk management? In other words, can credit risk assessment based solely on financial data be considered sufficient to assess the solvency of Moroccan VSBs, or do Moroccan banks need to adopt a more complementary approach that includes non-financial data as well?

This questioning raises the hypothesis that, faced with the inadequacy of financial information alone for a complete risk assessment, banks need to extend their analysis to additional dimensions to improve their prediction of the future performance and repayment capacity of VSBs. The aim is to examine the extent to which Moroccan banks adopt a holistic approach to credit risk assessment, incorporating criteria beyond balance sheets and financial ratios, and to identify the main non-financial factors taken into account in their decision-making process.

To answer our research question, we adopt a methodology based on a questionnaire distributed to 44 corporate relationship managers in the Fez-Meknes region. To analyze the data collected, we use Multiple Correspondence Analysis (MCA) and advanced statistical tests, such as the G6 coefficient (SMC) and the RMSR.

The choice of the Fez-Meknes region is justified by its unique characteristics. According to the HCP (2018), among the twelve Moroccan regions, it ranks second with a contribution of 14.5% in the primary sector. This region is also characterized by a high concentration of VSBs operating in the construction sector (HCP, 2019). Construction and trade are the two sectors most affected by business failure in Morocco (Inforisk, 2024).

The novelty of this article is twofold. Firstly, to the best of our knowledge, this is the first study to take a holistic approach to credit risk in the Fez-Meknes region. Secondly, our scientific article highlights the importance of non-financial data in the assessment of VSBs credit risk by Moroccan banks.

To explore this issue further, our research is divided into two parts. The first is a literature review and methodology. The second part presents an in-depth case study. It aims to address our problem and gain a better understanding of credit risk assessment for VSBs by identifying the key factors that predict this specific risk.

1. Literature Review

Over the past few decades, numerous scientific studies have assessed the credit risk of banks. Commercial banks generate income by distributing credit to their customers. Nevertheless, this credit-granting activity involves credit risk when borrowers fail to meet their commitments to creditor banks (Accornero *et al.* 2018).

The inability of banks to accurately assess credit risk and predict financial distress can have detrimental effects on the financial system in particular and on economic activity in general. As a result, the assessment of credit risk and the prediction of financial distress before it occurs are considered major global challenges in the world of finance. Several articles have pointed out that excessive credit growth combined with poor risk management are the main causes of global financial crises (Chaplinska, 2012; Mileris, 2012).

To assess credit risk, operating and investment credit analysts consider the company's situation. Credit risk is generally assessed based on financial ratios. However, it is necessary to supplement this assessment with additional data such as the company's age, size, competition, and sector of activity (Alfaro *et al.* 2008; Ali *et al.* 2023). By using ordered probit analysis in cross-sectional and panel data, Gupta (2023) showed that size has the most significant influence on the credit ratings of Indian firms.

In the literature on predicting financial distress, financial ratios derived from the financial records of borrowing companies are most often used to predict credit risk using predictive models developed by researchers

(Altman, 1968; Beaver, 1966; Mehmood and De Luca, 2023; Khemakhem and Boujelbene, 2018; Zizi *et al.* 2020, 2021).

Siddique *et al.* (2021)used panel data from 19 commercial banks in India and Pakistan between 2009 and 2018 to assess the impact of credit risk management by including non-performing loans and the capital adequacy ratio, along with the bank-specific factors. The results of the study showed that the capital adequacy ratio (CAR) has a positive impact on the financial performance of South Asian commercial banks, while non-performing loans (NPLs) have negatively affect this performance.

Several studies have identified that high levels of non-performing loans indicate potential weaknesses in risk management and lending practices, thereby impacting financial indicators and overall financial stability (Cucinelli *et al.* 2018; Partovi and Matousek, 2019; Tarchouna *et al.* 2017). In addition, other studies have highlighted the importance of diversifying banking portfolios, as diversification spreads the risks incurred by banks over various assets (Naili and Lahrichi, 2022; Rossi *et al.* 2009; Zhou, 2014).

Ghanem (2016) employed a cross-national Basel II adoption database to examine the impact of capital ratios (the loan-to-assets ratio, banks' total assets, government securities holding, and equity) across five MENA countries (Morocco, Tunisia, Egypt, Jordan, and Lebanon) from 1997 to 2013. The results confirmed an increase in bank loans and assets following the introduction of capital regulations, particularly higher capital adequacy ratios.

On the other hand, the risk management literature has emphasized the usefulness of including non-financial variables, such as sector of activity and company age, in combination with financial ratios. Based on these variables, several business failure prediction models have been developed (Altman *et al.* 2008).

Altman *et al.* (2008) developed default prediction models for UK SMEs, including more than 5.8 million SMEs over the period of 2000-2007. The results reveal that firm-specific characteristics, company filing histories, and comprehensive audit report/opinion data significantly enhance the default prediction power of risk models developed for SMES. In Tunisia, Khemakhem and Boujelbene (2018) combined financial ratios with non-financial factors in a sample of 480 companies from 2011 to 2012. The findings demonstrated that guarantees, the duration of credit report, ownership structure, and corporate banking relationship duration are important in evaluating credit risk. Bhatt *et al.* (2023) revealed that market risk analysis significantly affects credit risk management in Nepal.

Du *et al.* (2021) aimed to determine the level of credit risk on the internet for early warning assessment using the BP neural network algorithm on a sample from 90 companies over a five-year period. The trained model consists of the input's variables, namely non-financial index, enterprise profitability index, enterprise operating capability index, and enterprise-scale potential index. The accuracy rate of the trained model can reach 97%.

Using Chinese commercial bank data from 2008 to 2017, Chen and Tsai (2020) explored how credit risk is affected by banking FinTech. The results indicated that banking FinTechs significantly reduce credit risk among commercial banks in China. However, further analysis showed that the negative impact of banking FinTechs on credit risk is moderately low among state-owned banks, large banks, and listed banks.

Finally, Donovan *et al.* (2021) analyzed qualitative information from disclosed in conference calls and the management's discussion and analysis (MDandA) section of the 10-K filings. The researchers gathered a sample of these fillings and transcripts spanning from 2002 to 2016. The machine learning methods employed identified significant key categories in predicting credit events and assessing credit risk, particularly industry-specific information, firm performance, and liquidity debt.

2. Methodology

To gain a rigorous understanding of banks' assessment of credit risk, our methodology is sructured and systematic. This section details the methods used to collect and analyze the data, illustrating the rigor and precision of our approach.

The survey was carried out using a designed questionnaire consisting of 14-targeted questions. These questions aim to explore banking practices in credit risk assessment. Each question was formulated to induce responses that reveal the nuances and complexities of the assessment strategies used in the banking sector.

Our study population consists of 44 corporate relations managers[15], each offering a unique and informed perspective on credit risk assessment practices. The sample was selected to reflect the diversity of strategies

[15] Our sample is made up of corporate relations managers in the Fez-Meknes region. Corporate relations managers are responsible for managing portfolios of SMEs, including VSBs.

within the banking community, and each participant was chosen for their knowledge and experience in the credit field.

Regarding the selected measurement variables, the items chosen for this study are mainly qualitative, with a variety of response modalities that capture the breadth of evaluative practices. These variables include, but are not limited to, balance sheet analysis, cash flow assessment, collateral review, and the incorporation of qualitative criteria such as entrepreneurial competence. The qualitative nature of the data enabled us to grasp the complexity of credit risk decision-making processes.

Table 1. Summary of selected variables

	Variables	Meanings
Evaluation based on traditional financial data	H3_UB	Use of balance sheets
	H3_AFT	Cash flow analysis
	H3_DH	Impact of historical financial data
	H3_IPP	The importance of past financial performance
	H3_IPF	The importance of financial planning and forecasting
	H3_IRF	The importance of financial ratios
Integration of non-financial factors	H3_CIM	Consideration of market information
	H3_IINF	The importance of non-financial information (sustainability, governance)
	H3_ISC	The importance of capital structure
	H3_ITI	Integration of information technologies
Complementary approaches and collateral requirements	H3_RCE	External credit reporting
	H3_TES	Application of solvency assessment techniques
	H3_EGR	Consideration of real collateral requirements even in the presence of positive financial performance
	H3_CEG	Comparison of guarantee policies applied to Very Small Businesses (VSB), Small and Medium Enterprises (SME) and Large Enterprises (LE)

Source: Compiled by the author

To analyze the data, we employ advanced statistical techniques using R software, recognized for its power and flexibility in statistical processing. We used Multiple Correspondence Analysis (MCA) to explore associations between qualitative variables. Additionally, advanced statistical tests such as Cronbach's alpha, the G6 coefficient (SMC), and the RMSR measure are used to assess the reliability and internal consistency of the data. The chi-square test is employed to determine the significance of observed relationships.

Together, these methods enabled us to identify precise outputs and confirm the research hypotheses with a high degree of reliability. The results obtained offer a significant contribution to the existing literature and can guide banks in optimizing their credit risk assessment strategies.

3. Results and Discussion

Based on our cleaned and structured[16] database, we then turned to the reliability analysis of the collected data. The importance of this step cannot be underestimated, as it aims to verify the internal consistency of our questionnaire items, which is essential to ensure the validity of our conclusions. To do this, we used Cronbach's alpha coefficient, a classic indicator of reliability introduced by Lee Cronbach in 1951. This index enables us to assess the extent to which a set of items measures the same concept or dimension, thus providing an estimate of the reliability of the scale used.

[16] Before delving into the heart of our reliability analysis, it is essential to acknowledge the rigorous statistical groundwork that was undertaken to prepare our database. This initial process included the meticulous cleaning of the collected base, ensuring the elimination of outliers and missing values, as well as the proper coding of quantitative data, in line with best practices in data management using R software. This preparatory work is fundamental, as it establishes the solidity of our analytical foundation, enabling reliable and accurate subsequent analyses.

Table 2. Summary of significant results

Statistic	Value
Alpha de Cronbach (Raw_Alpha)	0.25
Alpha de Cronbach standardisé	0.76
G6 (SMC)	0.84
Corrélation moyenne (Average_R)	0.19
Signal sur bruit (S/N)	3.2
Erreur standard (ASE)	0.067
Écart-type (SD)	1
Médiane de la corrélation (Median_R)	0.21

Source: Compiled by the author

Our statistical investigation of the reliability of the data collected to study banks' assessment of credit risk highlights internal consistency, which, upon closer examination, reveals promising aspects of instrumental precision. Initially, Cronbach's alpha for our raw scale stands at a modest 0.25, suggesting moderate initial consistency within the sample. However, a more favorable picture emerges when we consider the standardized Cronbach's alpha, which rises to 0.76. This value, well above the threshold of 0.7[17], reflects reliable internal consistency after standardization, attesting to the robustness of the survey items when assessed on a common ground[18].

The G6 coefficient (SMC) of 0.84 confirms the reliability of our instruments, revealing significant convergence in the answers provided by respondents. This convergence is crucial, as it indicates that our items do indeed capture a shared essence of the concept under study. Despite this, the average correlation between items is 0.19, a value that warrants further analysis. Although this correlation may seem modest, it nevertheless reflects significant overall consistency, suggesting that the items are significantly interconnected, even though they may measure slightly divergent facets of our central concept.

The real strength of our assessment lies in the signal-to-noise ratio of 3.2, which underlines that the observed variance is mainly due to real differences rather than random variations, thus reinforcing the quality of our collected data. The accuracy of the reliability estimate is corroborated by a low alpha standard error (0.067), guaranteeing the stability of our results across the sample examined.

Having examined the reliability of the data, the next step is to explore the relationships between selected variables to confirm the hypotheses of our research on banks' assessment of credit risk among VSBs in Morocco. Validating reliability strengthens our confidence in future analyses, which will use advanced statistical methods to investigate banks' assessment practices and the effectiveness of these methods for VSBs. We aim to understand the impact of non-financial factors on credit decisions and offer recommendations for optimizing credit risk assessment in a complex economic context, emphasizing the importance of a more holistic approach.

3.1. Valuation Based on Traditional Financial Data

Here, we focus on a confirmatory factor analysis of responses[19] related to the use of traditional financial assessment methods by banks. Our aim is to determine whether the assessment of credit risk by these institutions is based primarily on financial information. Specific variables examined include the use of balance sheets (H3_UB), cash flow analysis (H3_AFT), the impact of historical financial data (H3_DH), the importance of

[17] Interpretation:
- Alpha > 0.9: Excellent reliability.
- Alpha > 0.8: Good reliability.
- Alpha > 0.7: Acceptable reliability in most situations.
- Alpha < 0.7: Questionable item consistency.

[18] This value is considered acceptable and even good for studies in the social sciences, testifying to a reliable measure (Kuh, G. D., & Whitt, E. J. 1988). Furthermore, the difference between raw and standardized alpha suggests that standardizing items (e.g., bringing them all to the same scale) considerably improves the internal consistency of the scale, which could be due to variations in response scales or in the dispersion of responses between items.

[19] Confirmatory analysis, an advanced statistical method used to test whether a set of variables adheres to a certain hypothetical structure, is particularly well-suited to examining the complex relationships between these financial variables and their contributions to credit risk assessment. This technique enables us to confirm the validity of our research hypotheses and provide a solid basis for accurate and reliable conclusions (Jöreskog, K. G. 1969).

past financial performance (H3_IPP), the importance of financial planning and forecasting (H3_IPF), and the importance of financial ratios (H3_IRF).

Table 3. Results summary table

Tranche	Chargement sur Facteur 1 (MR1)	Chargement sur Facteur 2 (MR2)	Communauté (h2)	Unicité (u2)	Complexité
H3_UB	0.42	0.23	0.23	0.77	1.5
H3_AFT	0.64	-0.28	0.49	0.51	1.4
H3_DH	0.35	-0.24	0.18	0.82	1.8
H3_IPP	0.72	-0.27	0.59	0.41	1.3
H3_IPF	0.58	0.09	0.35	0.65	1.0
H3_IRF	0.51	0.61	0.63	0.37	1.9

Source: Compiled by the author, R

Turning to factor loadings, it is clear that the variables H3_IPP (Importance of past financial performance) and H3_IPF (Importance of financial planning and forecasting) show the strongest loadings on Factor 1 (MR1), indicating a strong association with what could be interpreted as key aspects of traditional financial assessment. Factor 2 (MR2) is strongly associated with H3_IRF (Importance of financial ratios), suggesting a distinct dimension in credit risk assessment.

As for communality and uniqueness, communality scores (h2) vary, indicating that some variables are better explained by the extracted factors than others. For example, H3_IRF has a high communality score (0.63), suggesting that this variable is well represented by the factors. The high uniqueness (u2) of some variables, such as H3_DH (0.82), suggests that these variables have features not captured by the two factors[20].

Factor analysis has highlighted two main dimensions in the credit risk assessment methods used by banks for Very Small Enterprises (VSBs). On the one hand, the emphasis on past financial performance and financial planning reveals a traditional component of financial assessment. This observation corroborates the work of Berger and Udell (2006), who discussed the importance of historical financial information in access to credit for small businesses.

On the other hand, the significant valuation of financial ratios underlines an analytical approach that goes beyond the simple consideration of raw financial data. This finding is in line with the studies of Altman (1968), notably his model for predicting business failures, which illustrates the usefulness of financial ratios in assessing credit risk.

The duality of these dimensions reflects the complexity and sophistication of credit risk assessment processes, a thesis supported by the research of Frame, Srinivasan, and Woosley (2001), who examined the impact of information technology on credit risk assessment methods for small businesses. These authors highlighted the emergence of innovative assessment techniques, complementing traditional methods.

Our results encourage banks to adopt an integrated approach to credit risk assessment for VSBs, recognizing the value of traditional financial data while exploring the benefits of complementary indicators, such as financial ratios. This conclusion is in line with the recommendations of DeYoung, Glennon, and Nigro (2008), who stressed the importance of accurate risk assessment for the financial stability and access to finance of small businesses.

3.2. Integration of Non-Financial Factors

Confirmatory Factor Analysis (CFA) explored the importance and integration of non-financial factors in banks' assessment of credit risk. This process highlighted how banks consider aspects beyond simple financial data, such as the consideration of market information (H3_CIM), the importance of non-financial information (sustainability, governance) (H3_IINF), the importance of capital structure (H3_ISC), and the integration of information technology (H3_ITI). The results obtained align and enrich our understanding of these dynamics, offering valuable insights into current practices in the banking sector.

[20] In addition, reliability indices such as the Tucker Lewis Index (1.239) and RMSEA (0 with a 90% confidence interval of 0 to 0.184) indicate a good model fit. The Fit based upon off-diagonal values of 0.98 reinforces this interpretation.

Table 4. Summary of AFC results

Indicator	Quality of fit Value	Interpretation
Test statistique (Chi-square)	0.170	Indicates a very good fit of the model to the data.
P-value (Chi-square)	0.919	A value greater than 0.05 suggests a good model fit.
Comparative Fit Index (CFI)	1.000	Perfect fit; values close to 1 indicate a good fit.
Tucker-Lewis Index (TLI)	1.608	Unusually high value: in general, values > 0.95 indicate a good fit.
RMSEA	0.000	The mean square error of the approximation is very low, indicating a good fit. Confidence intervals support this conclusion.
SRMR	0.017	The standardized mean square deviation of the residuals is very low, indicating a good fit.
Variable	**Factor loadings** **Factorial loading**	**P-value** **Interpretation**
H3_CIM	0.205	0.016 Statistically significant, but low contribution to factor.
H3_IINF	0.719	0.002 Strong contribution to the factor and statistically significant.
H3_ISC	0.391	0.008 Moderate contribution and statistically significant.
H3_ITI	-0.017	0.945 Not significant and negligible/negative contribution to the factor.
Variable	**Variance factor loadings** **Estimate**	**P-value** **Interpretation**
H3_CIM	0.151	0.000 Significant variance explained by the model.
H3_IINF	0.338	0.244 Not significant, suggesting less well explained variance.
H3_ISC	0.362	0.002 Significant variance explained by the model.
H3_ITI	1.800	0.000 Significant variance, but negative/non-significant load raises questions.

Source: Compiled by the author, R

Statistically, indicators of model fit, such as the Chi-square statistical test (0.170) with a P-value of 0.919, the Comparative Fit Index (CFI) of 1,000, and the unusually high Tucker-Lewis Index (TLI) of 1,608, reveal an exceptional fit of the model to the data. These outputs suggest that the proposed model faithfully captures the relationships between observed variables. In addition, measures such as RMSEA (0.000) and SRMR (0.017) confirm the goodness of fit, indicating that the model is well specified.

Furthermore, the factor loadings of each variable on the latent factor "Non-Financial Factors" reveal varying degrees of contribution. In particular, H3_IINF shows a strong contribution and statistical significance, underlining the importance of non-financial information in credit risk assessment. H3_ISC also offers a moderate and significant contribution, highlighting the role of capital structure. On the other hand, H3_CIM shows a weaker, albeit statistically significant, contribution, and H3_ITI appears to have a negligible and insignificant contribution.

The results confirm the sub-hypothesis that banks consider a range of non-financial information when assessing credit risk. The strong association of H3_IINF with the latent factor underlines the emergence of a sophisticated approach to risk assessment, aligned with the findings of researchers such as Levine (2005), who noted the growing importance of non-financial factors in financial decision-making. Similarly, H3_ISC's significant contribution recalls the work of Modigliani and Miller (1958) on capital structure, reaffirming the importance of companies' internal financial structures in risk assessment.

In the same vein, the less pronounced impact of H3_CIM and the negative/non-significant contribution of H3_ITI invite further reflection. This might suggest that, despite recognition of their potential, the way in which market information and information technologies are integrated into risk assessment processes requires more

detailed exploration. These observations are in line with Bharadwaj *et al.* (2007) recommendations on the strategic role of IT in risk management.

The analysis confirms the growing importance of non-financial factors in banks' assessment of credit risk. It underlines an evolution towards more nuanced assessment practices, integrating a diversity of information beyond financial data alone. The results invite financial institutions to continue exploring and integrating these non-financial dimensions to refine their credit risk assessment methods, in line with modern trends in sustainable and responsible finance.

3.3. Complementary Approaches and Warranty Requirements

In the third sub-hypothesis that orchestrates our exploration, we look at the nuances of banking approaches to collateral requirements and the use of specific methods for assessing creditworthiness. This exploration aims to unveil a richer and more diversified perspective on how banks apprehend and manage credit risk. Specifically, we examine the influence of external credit reports (H3_RCE), the application of creditworthiness assessment techniques (H3_TES), the consideration of real collateral requirements even in the presence of positive financial performance (H3_EGR), and finally, the comparison of collateral policies applied to Very Small Enterprises (VSBs), Small and Medium Enterprises (SMEs) and Large Enterprises (GEs) (H3_CEG). In doing so, we hope to offer an insight into the concise and nuanced approach adopted by banks in their risk assessment, revealing the importance attached to factors that go beyond simple financial measures.

Table 5. Quality of results adjustment

Indicator	Value	Interpretation
Test statistique (Chi-square)	1.669	Indicates a good fit of the model to the data, suggesting that the specified model is appropriate.
P-value (Chi-square)	0.434	A value greater than 0.05 confirms adequate model fit.
Comparative Fit Index (CFI)	1.000	A perfect fit, indicating a very good model fit.
Tucker-Lewis Index (TLI)	2.357	An unusually high value: generally, values above 0.95 indicate a good fit. This high value requires re-evaluation to understand its significance in this context.
RMSEA	0.000 (90% CI: 0.000 - 0.286)	The mean square error of the approximation is very low, indicating a good fit. However, the wide confidence interval suggests that this estimate should be treated with caution.
SRMR	0.059	The standardized mean square deviation of the residuals is low, indicating a good model fit.

Source: Compiled by the author, R

Factor loadings for observed variables on the latent factor "Approches_Complementaires" are relatively low and insignificant for H3_RCE, H3_TES, H3_EGR, and H3_CEG, suggesting that these variables make a limited contribution to the construction of the latent factor based on current data. The variable H3_CEG (Comparison of collateral requirements between VSBs, SMEs, and GEs) shows the highest loading, although it is not statistically significant.

Table 6. Combined summary table of factor[21] loadings and variances

Variable	Factorial loading	P-value	Estimate of Variance	P-value of Variance
H3_RCE	0.088	0.335	0.112	< 0.001
H3_TES	0.295	0.760	25.705	< 0.001
H3_EGR	0.292	0.300	0.715	0.001
H3_CEG	0.556	0.247	0.168	0.750

Source: Compiled by the author, R

The integration of non-financial factors and collateral requirements in the assessment of credit risk illustrates a complex and nuanced approach by banks. The results of the Confirmatory Factor Analysis (CFA) suggest a varied interaction between the variables considered, reflecting distinct degrees of association with the

[21] It is important to note that the lack of statistical significance for some loadings may reflect limitations in sample size, variability in responses, or nuances in how these variables are measured or perceived by respondents.

latent factor "Approches_Complementaires". Although the factor loadings indicate a limited association between these variables and the latent factor, the significant variance for some variables underlines the importance of considering the diversity of responses. These observations offer an important perspective on banks' multifaceted approach to credit risk assessment, in line with existing studies in the field.

The moderate factor loading of H3_EGR (Requirement of real collateral despite positive financial performance) with significant variance suggests a recognition of the importance of collateral in risk assessment, in line with the findings of Berger and Frame (2006), who found that collateral plays a determinant role in lending decisions, especially for new businesses or those with less established credit histories.

The significance of the variance for H3_TES (Techniques for assessing creditworthiness), although the factor loading is low, could reflect the complexity and diversity of the techniques used by banks, echoing Altman's (1968) analysis of bankruptcy prediction models and recognition of the usefulness of financial ratios in assessing credit risk.

The comparison of collateral requirements between VSBs, SMEs, and GEs (H3_CEG) with the highest factor loading suggests a differentiation in risk management strategies according to company size, aligned with the observations of DeYoung, Glennon, and Nigro (2008), who highlighted how banks adjust their lending criteria according to company size and perceived risk.

As for the high variance observed for H3_TES (Solvency assessment techniques), this suggests an inherent complexity and considerable diversification in the approaches adopted by banks to assess solvency. This complexity is reflected in the range of answers given by respondents, which include not only assessments of financial statements, such as balance sheets and income statements, but also a forward-looking appraisal of future cash flows. In addition, the responses highlight the inclusion of procedures such as field surveys - company visits and interviews - which provide essential qualitative insights into a company's management and operational potential.

Credit scoring based on statistical models, also cited by respondents, aligns with the foundations laid by Altman, who argued for the integration of multiple financial and non-financial variables into predictive models. The emphasis on qualitative criteria, such as company size, loan purpose, industry and entrepreneurial competence, reflects a contemporary tendency to recognize factors that go beyond traditional financial measures in risk assessment.

This nuance and depth in assessment techniques, as reported by respondents, points to an evolving risk assessment landscape. This is in line with the observations of researchers such as Berger and Udell (2006), who found that the combination of qualitative and quantitative methods leads to a more accurate and comprehensive assessment of credit risk and suggests a growing recognition of the need to adapt assessment methods to meet the complex realities of the modern financial landscape.

The statistical significance of the variance for H3_TES, despite its relatively low factor loading, therefore testifies to the wide range and relevance of the different valuation techniques used. It underlines the importance of a multidimensional assessment that integrates both robust financial data and qualitative evaluations for a comprehensive assessment of credit risk.

In summary, although the CFA indicates a good overall fit of the model, the analysis reveals that the specific contributions of the variables considered in the complementary approach to credit risk assessment require more careful consideration. These various assessment techniques reflect a recognition by banks of the complexity of credit risk assessment and the need to adopt a multifactorial approach. Research by Altman (1968) highlighted the importance of financial information in predicting bankruptcy, while Berger and Udell (2006) highlighted the value of qualitative information and relationships in risk assessment. Modern assessment methods, such as credit scoring, are based on work such as that of Poon (2009), who examined scoring methods and their application in different lending contexts.

3.4. Integrated Banking Strategies: A Multidimensional Analysis of Credit Risk

The growing complexity of the financial landscape has led banking institutions to seek credit risk assessment methods that transcend traditional approaches. The current trend is towards an integrated strategy that encompasses not only financial indicators but also a multitude of non-financial factors. These diversified strategies, considering variables such as financial statement analysis, the impact of historical data, and even collateral requirements, offer a more sophisticated view of a company's risk profile.

To examine the effectiveness of these integrated strategies, Principal Component Analysis (PCA) can be used to reveal hidden patterns in the data, making it easier to understand the complex relationships between various risk indicators. This dimension reduction technique is particularly well-suited to identifying and interpreting

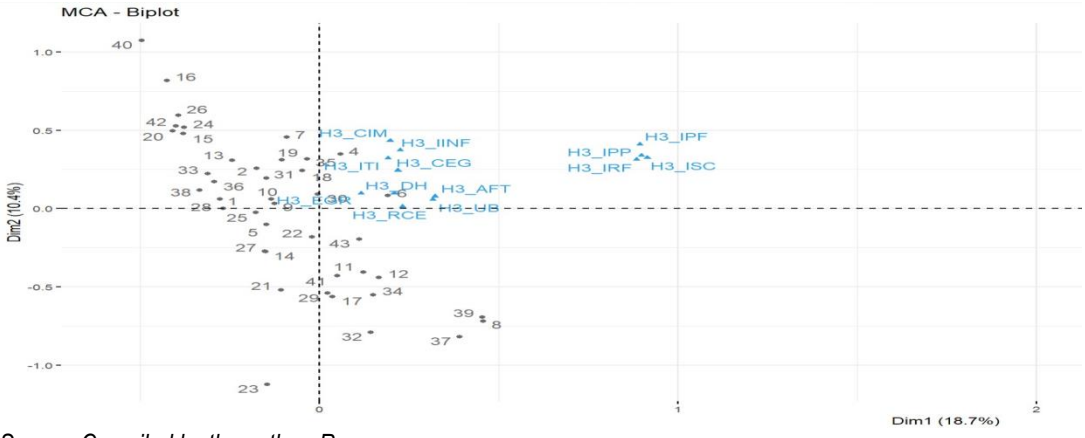
the underlying factors that influence lending decisions (Jolliffe, 2002). It allows us to determine whether a banking strategy that combines a multitude of variables can actually produce different and potentially more insightful results than those obtained by separate analyses (Abdi and Williams, 2010).

By analyzing a set of variables representative of credit risk assessment practices - ranging from market and non-financial information to collateral requirements - we can unveil whether banking strategies are truly multifaceted and whether they can be optimized for better risk prediction and management. The aim is to answer the question: can banks refine their risk assessment methods by integrating various measures into a unified approach, and how effective is this integration?

The Multiple Correspondence Analysis (MCA) we have carried out reveals some fascinating insights into bank strategy in credit risk assessment. The biplot obtained from our Multiple Correspondence Analysis (MCA) illustrates the relationships between the different variables used to assess credit risk by bankers. On the horizontal axis (Dim1, representing 18.7% of the variance), and on the vertical axis (Dim2, representing 14.6% of the variance), we observe how the variables and individuals (bankers) position themselves in relation to each other:

- The variables H3_IPF, H3_IPP, H3_IRF and H3_ISC are grouped together in the upper right quadrant, indicating that they are positively correlated with each other on these two dimensions.
- H3_UB, H3_AFT, H3_DH and H3_RCE appear to be located in the center, suggesting that they are less distinctive in relation to the two main dimensions of variance captured by the ACM…
- H3_CEG, H3_IINF, and H3_ITI are further apart on the horizontal axis but close to the center on the vertical axis, which might indicate that they are viewed differently along the first dimension but do not have a strong unique distinction along the second dimension.
- H3_CIM is a little more isolated on the left-hand side, suggesting that it represents a different facet of credit risk assessment from the other variables.

Figure 1. Biplot diagram. Multidimensional visualization of credit risk assessment strategies



Source: Compiled by the author, R

The centrality of variables such as balance sheet analysis and assessment of future cash flows indicates adherence to proven risk management methods, in line with the findings of Berger and Udell (2006), who identified solvency and liquidity as pillars of credit risk assessment. The variables at the center of the biplot suggest that these criteria are an integral part of standard risk assessment practices and are widely adopted by banks.

On the other hand, the move away from variables such as the integration of market information (H3_CIM) and the importance given to non-financial information (H3_IINF) on the horizontal axis suggests a growing recognition of the impact of external factors on risk assessments. This is consistent with the work of researchers such as Boot and Thakor (1994), who have highlighted the importance of contextual and environmental information in understanding financial risk.

The most striking strategy highlighted by our analysis is the emphasis placed on a detailed analysis of internal financial performance, while taking into account market information and governance. This observation is in line with the perspective of Boot, A. W. A., and Thakor, A. V. (2000), who suggest that effective credit risk assessment requires a combination of internal measures and external insights.

In practice, this analysis recommends that bankers adopt a balanced approach that integrates both robust financial data and qualitative assessments for comprehensive credit risk management. By doing so, financial

institutions can improve their competitiveness and efficiency, in line with Rajan and Zingales (1995) recommendations on the importance of innovation in financial management.

Overall, the ACM highlights the diversity of credit risk assessment practices and indicates areas where strategies could be refined for more accurate risk prediction. Banks are advised to continue integrating multidimensional approaches to remain competitive and efficient in credit risk management.

Conclusions and Further Research

In conclusion, credit risk models have evolved substantially since their introduction in the 1950s, becoming essential tools in the financial sector. Despite these advancements, challenges persist on both global and national scales, as evidenced by non-performing loans reaching 88.8 billion dirhams and a 15% increase in business failures in 2023, mainly affecting very small businesses (VSBs).

The lack of specific research in the Fez-Meknes region motivated us to undertake this study. It explored the challenges of credit risk assessment by identifying additional factors, particularly for VSBs, often perceived as high-risk due to asymmetric information and lack of sufficient collateral. Using a detailed questionnaire addressed to corporate relations managers in the Fez-Meknes region, this research delved deeper into credit risk assessment practices, revealing the diversity of strategies employed by the Moroccan banking sector.

The results obtained, using statistical techniques such as Multiple Correspondence Analysis, Cronbach's alpha, G6 coefficient (SMC), RMSR measure and chi-square test, reliably validated our initial hypotheses. They indicate a growing trend towards a more sophisticated and nuanced assessment of credit risk by Moroccan banks, incorporating non-financial criteria such as corporate governance, sustainability, business practices and technological position, as well as collateral requirement based on company size.

The practical implications of our study are significant for the banking sector, VSBs, and state institutions. To minimize counterparty risk and defaults by VSBs, it is essential that banks accurately assess the financial health of corporate borrowers, taking into account the specific non-financial factors identified in our research. For VSBs, variables identified will help strengthen their financial solidity, thereby facilitating access to the financing they need for sustainable growth. For state institutions, our results suggest the adoption of preventive measures aimed at anticipating bank financial crises, such as the creation of specific guarantees and the implementation of policies that support the VSB ecosystem, including tailored support programs and tax incentives.

The main limitation of this research is the limited sample, due to the limited number of corporate relations managers in the Fez-Meknes region. To improve the robustness of our findings, it would be advisable to include more qualitative and macroeconomic variables.

Credit Authorship Contribution Statement

Youssef Khanchaoui: Conceptualization; Software; Data curation; Investigation; Formal analysis; Methodology; Writing - original draft; Visualization.
Youssef Zizi: Conceptualization; Funding acquisition; Formal analysis; Validation; Writing - original draft; Writing - review and editing; Visualization; Project administration.
El Mouddem Abdeslam: Funding acquisition; Investigation; Validation; Project administration; Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Use of Generative AI and AI-assisted Technologies

The authors declare that they have not used generative AI and AI-assisted technologies during the preparation of this work.

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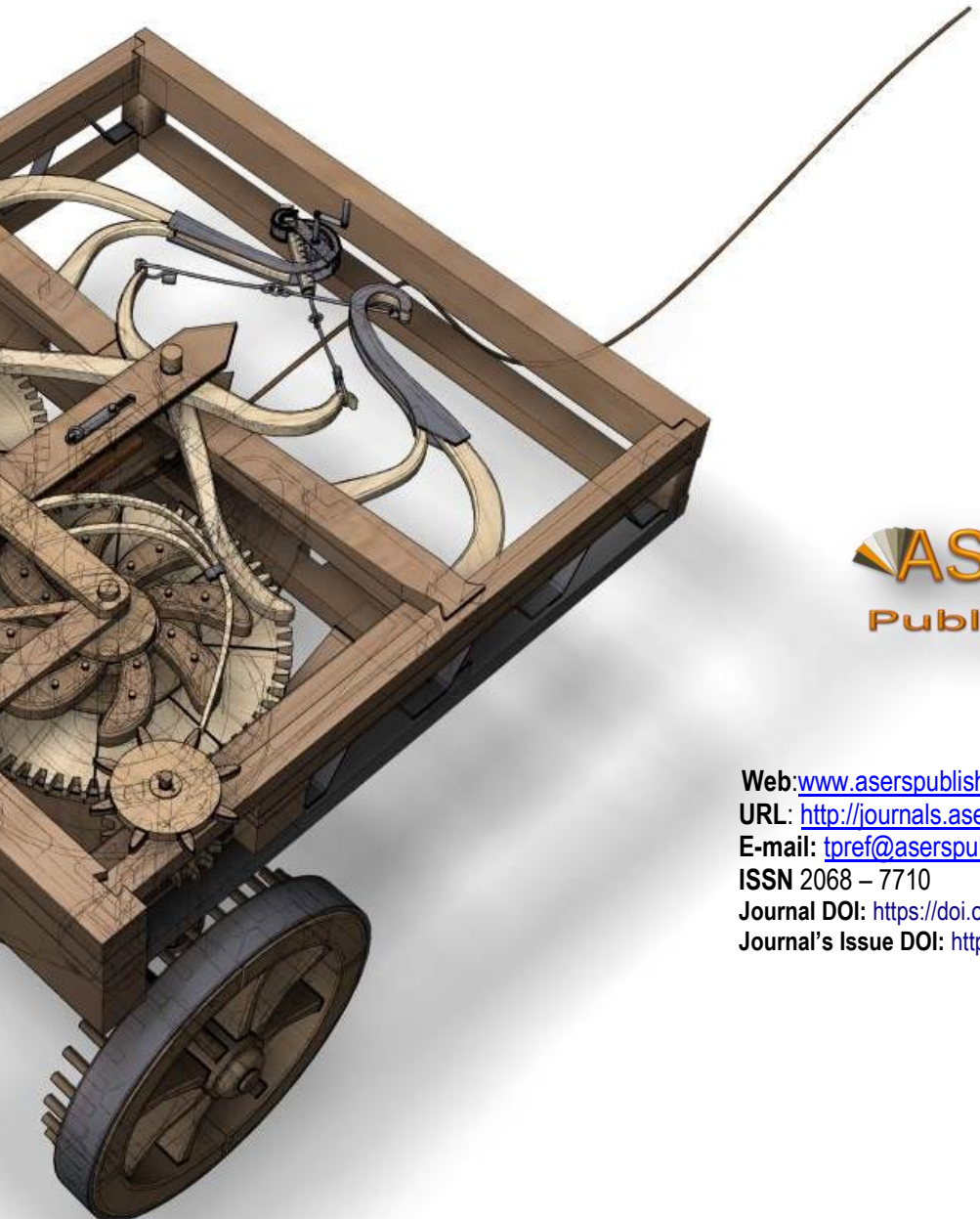

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