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Bayesian Modeling of Corporate Financial Distress Risk in Emerging Markets with Evidence from Moroccan Firms

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Research Article

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Abstract

Corporate financial distress prediction remains a central issue in financial risk management, particularly in emerging markets where economic volatility, information asymmetry, and limited financial transparency increase uncertainty in credit risk assessment. Traditional financial distress prediction models, including discriminant analysis and logistic regression, often fail to adequately capture uncertainty and parameter heterogeneity in such environments. This study proposes a Bayesian probabilistic framework for modeling Corporate Financial Distress Risk among Moroccan listed firms. The proposed approach employs a Bayesian hierarchical logistic model to estimate the posterior probability of corporate financial distress using key financial indicators, including liquidity ratios, leverage, profitability, and cash flow measures. By incorporating prior information and posterior updating, the model provides a flexible statistical structure for handling uncertainty and improving predictive inference. Parameter estimation is performed using Markov Chain Monte Carlo (MCMC) simulation to obtain posterior distributions and credible intervals for risk parameters. The empirical analysis uses panel data from firms listed on the Casablanca Stock Exchange over multiple years. Results are expected to demonstrate that Bayesian estimation improves predictive stability and provides richer uncertainty quantification compared with classical approaches. The findings contribute to applied financial statistics by introducing a robust probabilistic framework for financial distress risk prediction in emerging economies. This study also offers practical implications for investors, banks, regulators, and policymakers seeking more reliable credit risk assessment tools under uncertain market conditions.

Keywords: Bayesian inference; Corporate Financial Distress Risk; hierarchical logistic model; MCMC; financial distress prediction; emerging markets; Morocco.

1. Introduction

Corporate financial distress prediction has long been recognized as one of the most critical issues in financial economics and risk management. Although default and financial distress are closely related, they are conceptually distinct. Financial distress refers to a deterioration in a firm's financial condition that weakens its ability to meet financial obligations, while default refers to an actual contractual failure to repay debt obligations. Because distress typically precedes default, early detection of financial distress is essential for investors, creditors, banks, and regulators.

The importance of financial distress prediction has increased significantly in recent decades due to growing market complexity, globalization, and financial interconnectedness (Acharya, Pedersen, Philippon, & Richardson, 2017). Firms operating in emerging markets face additional constraints such as macroeconomic instability, limited access to financing, regulatory inefficiencies, and higher exposure to external shocks (Beck, Demirgüç-Kunt, & Levine, 2005). These conditions increase uncertainty regarding firms' financial health and make credit risk assessment more difficult. In such contexts, traditional financial risk evaluation methods may become less effective because they often rely on restrictive assumptions that do not fully capture market uncertainty or firm heterogeneity (Campbell, Hilscher, & Szilagyi, 2008).

Several quantitative approaches have been developed to predict corporate financial distress. Early studies focused on accounting-based methods, such as ratio analysis and discriminant models, with the well-known Altman Z-score becoming one of the most widely used bankruptcy prediction tools

(Altman, 1968). Later, econometric models such as logistic regression and probit regression gained popularity due to their probabilistic interpretation and improved predictive capabilities (Ohlson, 1980; Zmijewski, 1984). Structural models based on option pricing theory, particularly the Merton framework, also introduced important advances by linking financial distress risk to asset value dynamics (Merton, 1974). Despite their contributions, these conventional models present several limitations. Most notably, they often assume fixed parameter structures, linear relationships between explanatory variables and financial distress probabilities, and limited uncertainty treatment (Shumway, 2001).

One of the major shortcomings of classical financial distress prediction models lies in their inability to incorporate uncertainty in a comprehensive probabilistic framework. Financial distress is inherently stochastic and influenced by multiple interacting factors, including liquidity shortages, leverage pressure, declining profitability, and macroeconomic shocks (Beaver, 1966). In practice, financial data are noisy, incomplete, and subject to measurement errors. Classical frequentist approaches typically provide point estimates without fully quantifying parameter uncertainty, which may reduce their robustness in volatile environments such as emerging markets (McNeil, Frey, & Embrechts, 2015).

Bayesian statistics offers a powerful alternative for addressing these limitations. Unlike classical methods, Bayesian inference provides a coherent probabilistic framework that integrates prior knowledge with observed data to update beliefs about model parameters (Bayes, 1763; Berger, 1985). This approach allows uncertainty to be explicitly modeled through posterior probability distributions rather than single-point estimates. As a result, Bayesian models can provide richer inferential insights, more robust predictions, and better uncertainty quantification (Gelman et al., 2014). In financial risk modeling, these properties are particularly valuable because decision-making often occurs under incomplete information and high uncertainty.

The growing adoption of Bayesian methods in applied statistics has opened new opportunities for financial modeling. Bayesian approaches have demonstrated strong performance in credit risk assessment, portfolio optimization, volatility modeling, and stress testing (Korteweg, 2010; McNeil et al., 2015). Their flexibility makes them especially suitable for modeling complex relationships, nonlinear effects, hierarchical structures, and small-sample environments. Furthermore, computational advances, particularly Markov Chain Monte Carlo (MCMC) simulation, have significantly improved the feasibility of Bayesian estimation in high-dimensional financial datasets (Gilks, Richardson, & Spiegelhalter, 1996).

Despite these advantages, Bayesian approaches remain underexplored in the context of corporate financial distress prediction in emerging economies, particularly in North African markets. Existing empirical literature is largely concentrated on developed economies such as the United States, United Kingdom, and China. Comparatively, empirical evidence from Morocco remains limited, despite the strategic importance of the Moroccan financial market within the African region. Morocco has experienced substantial financial and economic transformation over recent decades, characterized by banking sector development, capital market expansion, and increasing integration into global financial systems Bank Al-Maghrib (2024). However, Moroccan firms continue to face financial constraints linked to market concentration, liquidity limitations, and economic volatility.

This research seeks to address this gap by proposing a Bayesian probabilistic framework for modeling Corporate Financial Distress Risk among Moroccan listed firms. Specifically, this study develops a Bayesian hierarchical logistic model to estimate the posterior probability of financial distress based on key financial indicators, including liquidity ratios, leverage measures, profitability metrics, and cash flow variables. The hierarchical structure allows firm-level heterogeneity to be incorporated into the model, improving predictive flexibility and capturing cross-sectional differences among firms. Parameter estimation is performed using Markov Chain Monte Carlo methods to obtain posterior distributions and credible intervals for all parameters.

The main contribution of this study is threefold. First, it extends the literature on corporate financial distress prediction by introducing an advanced Bayesian framework adapted to emerging market

conditions. Second, it contributes to applied mathematical statistics by demonstrating how hierarchical probabilistic modeling can improve risk prediction under uncertainty. Third, it provides practical implications for financial institutions, investors, and regulators by offering a more informative and robust tool for credit risk assessment.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on corporate financial distress prediction and Bayesian financial risk modeling. Section 3 presents the proposed Bayesian hierarchical model and estimation methodology. Section 4 discusses the empirical findings and predictive performance of the model. Finally, Section 5 concludes the study and highlights implications for future research.

2. Literature Review

2.1 Corporate Financial Distress Risk: Concepts, Determinants, and Financial Implications

Corporate Financial Distress Risk has long been recognized as a central issue in financial economics, corporate finance, and risk management. It refers to the probability that a firm will fail to meet its contractual debt obligations, including interest payments, principal repayments, or other financial commitments. Default is commonly associated with financial distress, insolvency, and, in severe cases, bankruptcy or liquidation. Although these concepts are often used interchangeably, the literature distinguishes them conceptually. Financial distress generally describes a deterioration in a firm's financial condition, insolvency occurs when liabilities exceed assets or when cash flows are insufficient to meet obligations, whereas default specifically refers to the violation of debt covenants or failure to honor debt payments (Altman & Hotchkiss, 2006).

In this study, the focus is specifically on financial distress rather than legal default. Due to limited availability of publicly observable default events among Moroccan listed firms, financial distress is used as a proxy for financial distress risk. This distinction is important for correctly interpreting the dependent variable and the predictive outputs of the model.

The assessment of Corporate Financial Distress Risk is fundamental because default events generate significant consequences for multiple stakeholders. For creditors and banks, inaccurate default assessment can lead to poor lending decisions and substantial credit losses. For investors, corporate financial distress affects asset valuation, portfolio performance, and market confidence. At the macroeconomic level, large-scale corporate financial distress may destabilize financial systems and amplify economic crises through contagion effects. This systemic dimension became particularly evident during major financial crises, where corporate insolvencies intensified credit market stress and reduced liquidity (Duffie & Singleton, 2012).

The theoretical foundations of Corporate Financial Distress Risk analysis have evolved considerably over time. Early approaches emphasized accounting-based evaluation, where analysts used financial statements to assess firms' solvency and liquidity conditions. Beaver (1966) was among the first scholars to demonstrate the predictive power of financial ratios in distinguishing failed from non-failed firms. His work showed that cash flow to total debt and other accounting indicators provided early warning signals of financial distress. This pioneering contribution established financial ratio analysis as a cornerstone of bankruptcy prediction research.

Subsequent studies reinforced the importance of financial indicators in explaining corporate failure. Among the most influential determinants of financial distress risk are liquidity, leverage, profitability, and cash flow adequacy. Liquidity reflects a firm's ability to meet short-term obligations using current assets. Firms with weak liquidity positions face greater refinancing pressure and are more vulnerable to payment disruptions. According to Ohlson (1980), declining liquidity ratios significantly increase the probability of financial distress, especially when combined with deteriorating profitability.

Leverage is another major determinant of Corporate Financial Distress Risk. Highly leveraged firms carry larger debt burdens and therefore face increased exposure to adverse market conditions, interest rate changes, and earnings volatility. Excessive leverage amplifies financial fragility by increasing fixed

payment obligations and reducing financial flexibility. The trade-off theory of capital structure suggests that while debt financing may provide tax advantages, excessive borrowing raises bankruptcy costs and distress probability (Kraus & Litzenberger, 1973). Empirical evidence consistently shows a positive relationship between leverage and corporate distress.

Profitability also plays a crucial role in determining financial distress risk. Profit-generating firms possess stronger internal financing capacity and greater resilience to external shocks. Low profitability weakens retained earnings, reduces investment capacity, and increases reliance on external debt financing. Altman (1968) demonstrated that profitability-related ratios significantly improve bankruptcy prediction performance, particularly when combined with leverage and liquidity indicators. Firms experiencing persistent earnings deterioration generally exhibit higher probabilities of distress.

Cash flow adequacy constitutes another essential dimension of financial stability. While accounting profits provide useful performance information, cash flow reflects actual liquidity available for operational and debt-related obligations. Firms may report accounting profits while simultaneously experiencing cash shortages due to working capital inefficiencies or delayed receivables. For this reason, many researchers consider cash flow measures superior predictors of short-term solvency. Beaver (1966) notably emphasized the predictive strength of cash flow-to-debt ratios in default forecasting.

Beyond firm-specific financial indicators, Corporate Financial Distress Risk is also influenced by macroeconomic and institutional factors. Economic downturns, inflationary pressures, tightening credit conditions, and declining aggregate demand can significantly weaken firms' repayment capacity. During recessions, reduced revenues and lower profitability increase default frequencies across industries. Similarly, institutional characteristics such as legal enforcement quality, financial market efficiency, and creditor protection mechanisms influence default dynamics. Emerging markets are particularly sensitive to such external conditions because of higher volatility, information asymmetry, and weaker institutional infrastructures.

The study of financial distress risk becomes especially relevant in emerging economies, where firms operate under elevated uncertainty and constrained financial environments. Compared with developed markets, firms in emerging economies often face limited financing access, greater exposure to macroeconomic shocks, and less mature capital markets. These structural characteristics complicate risk evaluation and may reduce the predictive reliability of conventional models. In the context of Morocco, corporate financing remains highly dependent on banking institutions, while capital market depth remains relatively limited compared with advanced economies. Such structural features increase the importance of robust financial distress risk assessment frameworks for both lenders and regulators.

Given the multidimensional nature of financial distress risk, accurate prediction requires models capable of integrating multiple interacting determinants under uncertainty. Corporate financial distress is not driven by a single factor but rather emerges from complex interactions among firm-level financial conditions, market dynamics, and macroeconomic shocks. This complexity has motivated the development of increasingly sophisticated quantitative approaches, ranging from accounting-based models to structural, econometric, and probabilistic frameworks. The next section reviews the major classical models used for corporate financial distress prediction and highlights their methodological limitations.

2.2 Classical Models of Corporate Financial Distress Prediction

The prediction of corporate financial distress has attracted extensive academic attention for several decades, leading to the development of multiple quantitative approaches aimed at identifying financially distressed firms before actual default occurs. These approaches have evolved from simple accounting-based assessments to more advanced statistical and structural models. Despite their methodological differences, all classical models share the same objective: estimating the likelihood that a firm will fail to meet its financial obligations. The literature generally classifies traditional financial distress prediction models into three major categories: accounting-based models, statistical classification models, and structural credit risk models.

Early studies on financial distress prediction primarily relied on accounting-based financial ratio analysis. These models were built on the premise that financial statements contain critical information regarding a firm's solvency, liquidity, profitability, and operational efficiency. By analyzing ratios derived from balance sheets and income statements, researchers sought to identify patterns that distinguish healthy firms from distressed ones. One of the most influential contributions in this area was provided by Beaver (1966), who demonstrated that certain accounting ratios possess strong predictive power for identifying failing firms several years before bankruptcy. His univariate analysis revealed that cash flow-to-total debt, net income-to-total assets, and working capital indicators were particularly useful in forecasting failure.

Building on these findings, Altman (1968) introduced the Z-score model, which became one of the most widely recognized bankruptcy prediction tools in corporate finance. The Z-score combines multiple financial ratios into a single discriminant score that classifies firms according to their financial health. The model integrates measures of liquidity, profitability, leverage, solvency, and activity to generate an overall bankruptcy risk indicator. The strong predictive performance of the Z-score contributed significantly to its widespread use among practitioners, financial institutions, and researchers. However, despite its popularity, the model relies on relatively restrictive assumptions, including linear relationships between financial variables and distress risk, which may limit its effectiveness in complex or rapidly changing market environments.

As research progressed, statistical classification methods emerged as more flexible alternatives to purely accounting-based approaches. Multivariate statistical models enabled researchers to estimate financial distress probabilities using multiple explanatory variables simultaneously while accounting for their interactions. Among these methods, discriminant analysis was initially dominant, but later studies increasingly favored probabilistic models such as logistic and probit regressions. These models improved financial distress prediction by estimating the probability of failure as a function of financial characteristics rather than merely assigning firms to predefined categories.

A major contribution to this literature came from Ohlson (1980), who introduced a logistic regression model for bankruptcy prediction. Unlike discriminant analysis, logistic regression does not require strict assumptions regarding normality or equal covariance matrices across groups. This methodological flexibility improved the robustness of bankruptcy prediction models and enhanced interpretability through probability estimates. Ohlson's model demonstrated that firm size, leverage, liquidity, and performance indicators significantly affect distress probability. Since then, logistic regression has become one of the most widely used tools in credit risk assessment.

Although accounting-based and statistical models improved bankruptcy prediction, they largely remained dependent on historical financial statement information. This limitation motivated the development of structural credit risk models grounded in financial theory. Structural models explicitly connect financial distress risk to firm asset dynamics and capital structure. The seminal work of Merton (1974) introduced a groundbreaking framework in which corporate equity is modeled as a call option on firm assets. In this framework, default occurs when the market value of assets falls below the face value of debt at maturity. By modeling asset value as a stochastic process, the Merton model provides a theoretical link between market information and credit risk.

Structural models offered major conceptual advances because they incorporated market-based information and explicitly modeled default as a probabilistic event arising from asset volatility and leverage dynamics. Subsequent extensions improved the practical applicability of Merton's framework by introducing stochastic interest rates, time-varying volatility, and more flexible capital structures. Nevertheless, structural models also face significant empirical challenges. Estimating unobservable firm asset values and asset volatility often requires strong assumptions, which can reduce predictive accuracy, particularly in emerging markets where market efficiency and liquidity remain limited.

Despite the important contributions of classical financial distress prediction models, several limitations persist. First, many traditional approaches assume linear or fixed parametric relationships between

explanatory variables and financial distress risk, which may oversimplify real-world financial dynamics. Corporate distress typically arises from complex nonlinear interactions among multiple financial and macroeconomic factors. Second, classical models often provide point estimates without fully capturing uncertainty in parameter estimation or model specification. This limitation becomes especially problematic in volatile economic environments characterized by incomplete information and rapidly changing risk conditions.

Third, many traditional models perform less effectively in emerging markets. Compared with developed economies, emerging financial systems often exhibit greater market inefficiencies, information asymmetry, regulatory heterogeneity, and macroeconomic instability. These characteristics reduce the predictive reliability of models calibrated under assumptions more suitable for mature markets. In addition, limited data availability and smaller sample sizes create further estimation challenges.

These limitations highlight the need for more flexible and robust modeling frameworks capable of incorporating uncertainty directly into the estimation process. In this context, Bayesian statistical methods provide a promising alternative. By integrating prior knowledge with observed data and generating posterior distributions for model parameters, Bayesian approaches offer richer uncertainty quantification and greater modeling flexibility. This makes them particularly suitable for corporate financial distress prediction in emerging markets, where uncertainty and heterogeneity are central features of the financial environment.

2.3 Bayesian Statistics in Financial Risk Modeling

In recent decades, Bayesian statistics has gained increasing importance in financial modeling due to its ability to provide robust probabilistic inference under uncertainty. Financial markets are inherently stochastic systems characterized by incomplete information, parameter instability, and nonlinear interactions among multiple risk factors. Under such conditions, traditional frequentist approaches may face important limitations, particularly when dealing with small samples, noisy observations, or heterogeneous datasets. Bayesian inference provides an alternative framework that allows uncertainty to be explicitly incorporated into model estimation and prediction.

The Bayesian framework originates from the theorem introduced by Thomas Bayes (1763), which establishes a mechanism for updating prior beliefs in light of observed evidence. In Bayesian inference, model parameters are treated as random variables with probability distributions rather than fixed but unknown constants. This distinction is particularly important in financial risk modeling, where parameters such as default sensitivity, leverage effects, and market volatility are rarely stable over time. Bayesian estimation combines prior information and observed data through the posterior distribution, allowing learning to evolve as new evidence becomes available.

A major advantage of Bayesian methods in finance lies in their capacity to quantify uncertainty more comprehensively than classical approaches. Conventional models such as logistic regression or discriminant analysis generally produce point estimates and confidence intervals based on asymptotic assumptions. However, these assumptions may not hold in many real-world financial contexts, especially when default events are rare or sample sizes are limited. Bayesian methods instead generate full posterior distributions for model parameters, allowing analysts to assess not only expected parameter values but also the degree of uncertainty surrounding them. This richer inferential structure improves risk interpretation and supports more informed financial decision-making.

Bayesian methods have been successfully applied across multiple areas of financial research. In portfolio management, Bayesian allocation models improve asset selection by accounting for estimation risk in expected returns and covariance matrices. In market risk analysis, Bayesian models have been used to estimate volatility clustering, tail risk, and stress scenarios under uncertain market conditions. In credit risk management, Bayesian approaches have become increasingly attractive because they allow

financial distress probabilities to be estimated while explicitly incorporating uncertainty, prior knowledge, and evolving market information.

The relevance of Bayesian modeling becomes particularly evident in corporate financial distress prediction. Default events are typically driven by complex interactions between firm-level financial indicators and broader macroeconomic conditions. Variables such as leverage, liquidity, profitability, and cash flow do not affect financial distress risk independently; instead, their relationships are often nonlinear and may vary across firms, sectors, and economic cycles. Classical models generally assume fixed coefficients across observations, which may oversimplify the actual dynamics of financial distress. Bayesian models provide greater flexibility by allowing parameter uncertainty and heterogeneity to be directly incorporated into the estimation process.

Among Bayesian approaches, Bayesian logistic regression has received growing attention in credit risk analysis. Similar to classical logistic regression, this model estimates the financial distress probability as a function of explanatory financial variables. However, instead of producing single coefficient estimates, Bayesian logistic regression assigns prior distributions to regression coefficients and derives posterior distributions after observing data. This approach improves coefficient stability under multicollinearity and limited sample conditions, both of which are common in financial datasets. The resulting posterior financial distress probabilities provide more informative risk assessments than deterministic classification outputs.

Hierarchical Bayesian models further extend this framework by capturing structured heterogeneity across observations. In corporate finance, firms often differ substantially in terms of sectoral characteristics, size, governance quality, and capital structure. Ignoring such heterogeneity may reduce predictive performance and bias parameter estimates. Hierarchical models address this issue by allowing parameters to vary across groups while maintaining shared distributional structures. This multi-level modeling framework is particularly useful for analyzing corporate financial distress in emerging markets, where firm-level heterogeneity tends to be pronounced due to differences in market access, financing constraints, and institutional environments.

The practical implementation of Bayesian models has been greatly facilitated by advances in computational statistics. Many posterior distributions in financial models lack closed-form analytical solutions, making direct estimation impossible. To address this challenge, simulation-based methods such as Markov Chain Monte Carlo (MCMC) are commonly used. Algorithms such as Gibbs sampling and Metropolis–Hastings enable efficient approximation of posterior distributions by generating large samples from complex probability spaces. These computational developments have significantly increased the adoption of Bayesian methods in applied financial statistics.

Despite their methodological advantages, Bayesian approaches remain relatively underexplored in corporate financial distress prediction, particularly in emerging economies. Most empirical studies continue to rely on conventional statistical models or machine learning algorithms, while fewer studies investigate Bayesian probabilistic frameworks for financial distress estimation**.** This gap is especially noticeable in African financial markets, where limited data availability, market inefficiencies, and macroeconomic volatility create conditions under which Bayesian methods may offer substantial advantages over classical approaches.

In the context of emerging markets such as Morocco, Bayesian models are particularly relevant because they can handle data scarcity, structural heterogeneity, and elevated uncertainty more effectively than traditional models. By integrating prior knowledge with observed financial information and explicitly quantifying uncertainty, Bayesian statistics provides a powerful framework for improving corporate financial distress prediction. Consequently, Bayesian modeling represents a promising methodological direction for developing more reliable credit risk assessment tools in emerging financial systems.

2.4 Recent Advances in Corporate Financial Distress Prediction

In recent years, corporate financial distress prediction has significantly evolved through the integration of machine learning (ML), probabilistic modeling, and explainable artificial intelligence (XAI). Compared with conventional statistical approaches such as discriminant analysis and logistic regression, modern predictive techniques are better suited to capture nonlinear relationships, complex interactions among financial indicators, and heterogeneous firm-level behaviors across industries and markets.

Recent empirical studies indicate that machine learning algorithms—including Random Forest (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and ensemble methods—consistently achieve superior predictive performance in bankruptcy and distress classification tasks. For instance, Abrahamsen et al. (2024), in a study on Nordic listed firms, demonstrated that machine learning models significantly improved early-warning detection of financial distress compared with traditional econometric benchmarks, particularly in high-dimensional financial datasets. Similarly, Kristanti et al. (2025) found that ML-based distress prediction models in emerging markets outperform conventional ratio-based scoring systems by improving classification accuracy and reducing false negatives.

Alongside predictive performance, recent research increasingly emphasizes model interpretability. While black-box models often provide higher predictive accuracy, their limited transparency creates challenges for regulatory compliance, auditability, and managerial trust. Consequently, explainable AI techniques such as SHAP (Shapley Additive Explanations), feature importance ranking, and local surrogate explanations have gained substantial attention in financial risk analytics. Topuz et al. (2025) argue that interpretable machine learning frameworks enable decision-makers to better understand the drivers of corporate distress while preserving strong predictive capability. Likewise, Maturo et al. (2025) showed that integrating gradient boosting with XAI techniques improves crisis forecasting by identifying the most influential financial distress determinants at the firm level.

Bayesian approaches have also regained relevance in recent literature due to their capacity to model uncertainty explicitly and provide probabilistic forecasts rather than deterministic classifications. This characteristic is particularly valuable in environments characterized by small sample sizes, noisy accounting data, and structural instability. Abrahamsen et al. (2024) incorporated Bayesian estimation in distress prediction and highlighted its usefulness for uncertainty quantification in financial early-warning systems. Moreover, recent reviews by Alvi et al. (2024) emphasize that probabilistic frameworks, including Bayesian networks and hybrid Bayesian-ML architectures, are increasingly recognized as robust tools for credit risk and financial distress prediction under uncertainty.

Despite these methodological advances, the empirical literature remains heavily concentrated in developed economies and large Asian markets. Emerging and frontier financial systems, particularly in Africa and North Africa, remain underexplored. Recent systematic reviews confirm the scarcity of region-specific distress prediction studies using advanced ML or Bayesian methods in African markets (Nugroho & Dewayanto, 2025; Omar et al., 2025). This gap highlights the need for context-specific probabilistic frameworks adapted to local financial structures, reporting practices, and market conditions, thereby reinforcing the relevance of developing Bayesian corporate distress prediction models for markets such as Morocco.

2.5 Empirical Research Gap in Emerging Markets and Morocco

Although the literature on corporate financial distress prediction has expanded substantially over recent decades, empirical evidence remains highly concentrated in developed economies. Most influential studies have been conducted using datasets from the United States, United Kingdom, and China, where financial markets are relatively mature, information disclosure standards are stronger, and large datasets are readily available. These market characteristics have facilitated the development and validation of sophisticated financial distress prediction models, including accounting-based, econometric, structural, and machine learning approaches. However, models calibrated in developed economies may not generalize effectively to emerging markets due to structural differences in market efficiency, regulatory quality, financial transparency, and macroeconomic volatility.

Emerging markets present a distinct financial environment characterized by higher uncertainty, greater exposure to economic shocks, limited market liquidity, and stronger information asymmetry. Firms operating in these markets often face financing constraints, weaker corporate governance mechanisms, and greater dependence on bank credit. Such characteristics influence corporate risk dynamics and may alter the relationships between financial indicators and financial distress probabilities. Consequently, applying financial distress prediction models developed in advanced economies without contextual adaptation may lead to biased estimates and reduced predictive accuracy. Several scholars have emphasized the importance of developing context-specific credit risk models for emerging financial systems Claessens et al. (2006).

The empirical gap becomes even more pronounced when considering African financial markets. Compared with Asia, Europe, or North America, the literature on corporate financial distress prediction in Africa remains limited. Existing studies are often constrained by data scarcity, inconsistent reporting quality, and relatively small sample sizes. These limitations partly explain why many African markets remain underrepresented in quantitative credit risk research. Yet, this underrepresentation creates an important opportunity for methodological innovation, particularly through probabilistic models capable of handling uncertainty and limited observations more efficiently.

In North Africa, and particularly in Morocco, research on corporate financial distress prediction remains relatively scarce. Morocco has undergone significant economic and financial transformation over the last two decades, marked by banking sector modernization, capital market development, and increased integration into international financial systems. The Casablanca Stock Exchange has improved market sophistication and corporate disclosure standards, yet the Moroccan corporate sector continues to face important structural challenges, including liquidity constraints, concentrated ownership structures, and heterogeneous access to financing. These factors contribute to a risk environment that differs substantially from that of developed markets.

Despite the growing importance of risk management in Morocco, empirical research on firm-level financial distress prediction remains limited and is largely dominated by conventional statistical approaches. Existing studies generally rely on financial ratio analysis, discriminant models, or classical regression frameworks. While these methods provide useful baseline insights, they often fail to adequately capture uncertainty, parameter heterogeneity, and nonlinear financial interactions. Furthermore, few studies explicitly account for sectoral heterogeneity among Moroccan firms, despite significant differences in leverage structure, profitability, and financing conditions across industries.

An additional gap concerns methodology. Although Bayesian statistics has gained prominence in applied finance and risk modeling, its application to corporate financial distress prediction in emerging African markets remains largely unexplored. Furthermore, while recent machine learning studies have improved predictive accuracy, relatively few contributions provide interpretable probabilistic models capable of uncertainty quantification. This creates an important methodological gap that Bayesian hierarchical modeling is well positioned to address. To the best of our knowledge, no prior study has developed a Bayesian hierarchical framework specifically for predicting corporate financial distress among Moroccan listed firms. This represents a significant gap in both the financial risk literature and applied statistical research. Given the characteristics of the Moroccan market—limited sample size, heterogeneity across firms, and elevated uncertainty—Bayesian hierarchical modeling appears particularly suitable for improving financial distress risk estimation.

This study addresses this empirical and methodological gap by proposing a Bayesian hierarchical logistic model for corporate financial distress prediction using financial data from Moroccan listed companies. By integrating prior information, firm-level heterogeneity, and posterior uncertainty quantification, the proposed framework extends existing research beyond conventional approaches. The study therefore contributes simultaneously to three streams of literature: corporate finance, credit risk modeling, and applied Bayesian statistics. More importantly, it provides empirical evidence from an underexplored emerging market, thereby enriching the global literature on corporate financial distress prediction under uncertainty.

3. Methodology

This study adopts a quantitative research design to model Corporate Financial Distress Risk among Moroccan listed firms using a Bayesian probabilistic framework. The primary objective is to estimate the probability of corporate financial distress as a function of key financial indicators reflecting liquidity, leverage, profitability, and cash flow conditions. Given the presence of uncertainty, firm heterogeneity, and potential nonlinear relationships in financial distress dynamics, a Bayesian hierarchical logistic regression model is employed as the main analytical framework. This approach is particularly appropriate because it enables explicit uncertainty quantification, incorporates prior information, and improves parameter estimation under limited sample conditions (Gelman et al., 2014).

The dependent variable in this study is binary and represents the financial distress status of a firm. Because observed legal default events are rare among Moroccan listed firms, financial distress is used as a proxy for financial distress risk. Let Y_{it} denote the financial condition of firm i at time t, such that:

$$Y_{it} = \begin{cases} 1, & \text{if firm } i \text{ is in financial distress or default at time } t \\ 0, & \text{otherwise} \end{cases}$$

where $i = 1,2,\dots,N$ represents firms and $t = 1,2,\dots,T$ denotes time periods. Financial distress is identified using indicators such as persistent negative earnings, excessive leverage, deteriorating liquidity, and inability to meet debt obligations, consistent with prior bankruptcy prediction studies (Edward Altman, 1968; James Ohlson, 1980).

To mitigate target leakage and circularity between the distress definition and explanatory variables, all financial predictors were lagged by one year. Specifically, financial ratios observed at year $t-1$ were used to predict financial distress at year t. This temporal structure ensures that predictors represent prior financial conditions rather than contemporaneous distress indicators, thereby improving causal interpretation and out-of-sample realism. Formally, the model estimates:

$$P(Y_{i,t} = 1 \mid X_{i,t-1})$$

where $Y_{i,t}$ denotes the financial distress status of firm i in year t, and $X_{i,t-1}$ represents lagged financial indicators from the previous fiscal year.

Since the dependent variable is dichotomous, the financial distress probability is modeled using a logistic link function. Let p_{it} denote the probability that firm i experiences financial distress at time t, conditional on observed explanatory variables X_{it}:

$$p_{it} = P(Y_{it} = 1 \mid X_{it})$$

The response variable follows a Bernoulli distribution:

$$Y_{it} \sim Bernoulli(p_{it})$$

The Bayesian hierarchical logistic model is specified as follows:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = \alpha_i + \beta_1 Liquidity_{it} + \beta_2 Leverage_{it} + \beta_3 Profitability_{it} + \beta_4 CashFlow_{it}$$

Unlike Gaussian linear regression models, the Bayesian logistic regression model does not include an additional continuous residual term in the linear predictor. Conditional on the explanatory variables and the firm-specific random intercept, the variability of the binary financial distress outcome is fully represented by the Bernoulli likelihood. Consequently, no explicit residual error term is required in the model specification.

where $\alpha_i$denotes the firm-specific intercept, $\beta_k$represents regression coefficients associated with financial predictors, and ϵ_{it}captures residual uncertainty.

The explanatory variables selected for the model are based on the corporate financial distress prediction literature and reflect the main dimensions of financial health. Liquidity indicators measure short-term solvency and the ability to meet immediate obligations. Typical measures include the current ratio and quick ratio. Leverage indicators capture the degree of debt burden and financial risk, often measured through debt-to-equity and debt-to-assets ratios. Profitability indicators assess earnings generation capacity, including return on assets (ROA) and return on equity (ROE). Cash flow indicators evaluate the firm's ability to generate internal funds for debt servicing, typically measured through operating cash flow relative to total debt.

To capture firm-level heterogeneity, the intercept term is modeled hierarchically:

$$\alpha_i \sim N(\mu_\alpha, \sigma_\alpha^2)$$

This hierarchical specification allows each firm to possess its own baseline level of financial distress risk while sharing information across the entire population. Such partial pooling improves estimation robustness and reduces overfitting, especially when the number of observations per firm is limited. This feature is particularly important in emerging markets such as Morocco, where data availability may be constrained and firms may exhibit substantial heterogeneity in financial structure.

Within the Bayesian framework, prior distributions are assigned to all unknown parameters. Weakly informative priors were chosen to reflect limited prior knowledge while preventing extreme coefficient estimates and improving numerical stability. Since all continuous predictors were standardized prior to estimation, regression coefficients were assigned Gaussian priors centered at zero:

$$\beta_k \sim N(0,2.5)$$

This prior specification is commonly recommended for Bayesian logistic regression with standardized predictors because it provides moderate regularization while remaining sufficiently flexible (Gelman et al., 2014).

Because all continuous predictors were standardized prior to model estimation, the weakly informative Normal(0,10) prior allows a relatively broad range of regression coefficients on the log-odds scale. Although this specification theoretically permits large effect sizes, it was intentionally selected to minimize prior influence on posterior inference while allowing the observed data to dominate parameter estimation. The subsequent prior predictive checks and prior sensitivity analysis confirmed that this prior generated plausible financial distress probabilities and did not lead to unrealistic posterior estimates. Moreover, the comparison with the more regularizing Normal(0,2.5) and Normal(0,1.5) priors demonstrated that the main inferential conclusions and predictive performance remained stable, supporting the robustness of the proposed Bayesian model to reasonable alternative prior specifications.

The hyperparameter associated with the group-level mean is specified as:

$$\mu_\alpha \sim N(0, 10^2)$$

The standard deviation of the firm-specific random intercepts is assigned a Half-Normal prior with mean 0 and standard deviation 2 :

$$\sigma_\alpha \sim Half\text{-}Normal(0,2)$$

For all Gaussian prior distributions used in the model, the second parameter denotes the standard deviation (σ), rather than the variance, following the parameterization adopted in PyMC. Accordingly, the prior distributions Normal(0,10), Normal(0,2.5), Normal(0,1.5), and Half-Normal(0,2) are parameterized by their mean and standard deviation.

The posterior distribution is then obtained by combining the likelihood and prior distributions according to Bayes' theorem:

$$P(\theta \mid Y, X) \propto P(Y \mid X, \theta)P(\theta)$$

where θ represents the full vector of unknown parameters. This posterior distribution contains all information necessary for parameter estimation and inference.

Prior predictive checks were conducted before model fitting to evaluate whether the specified prior distributions generated plausible financial distress probabilities in the absence of observed outcomes. Prior predictive samples were obtained by simulating model parameters from their prior distributions and propagating these values through the logistic model without conditioning on the observed data. The resulting prior predictive distributions were examined to verify that the implied probabilities covered a broad but realistic range, while avoiding excessive concentration near the boundaries of 0 or 1. This procedure provides an important diagnostic for assessing the reasonableness of prior assumptions before posterior inference.

To assess robustness to prior specification, a prior sensitivity analysis was conducted using alternative prior distributions with different regularization strengths. Three specifications were evaluated: weakly informative priors N(0,10), moderately regularizing priors N(0,2.5), and stronger shrinkage priors N(0,1.5). Posterior estimates and predictive performance were then compared across specifications.

The Bayesian hierarchical model was implemented in PyMC. The corresponding prior specifications were defined as follows: regression coefficients were assigned pm.Normal(mu=0, sigma=10) (or the alternative sensitivity-analysis priors), the standard deviation of the random intercepts was assigned pm.HalfNormal(sigma=2), and the firm-specific random intercepts were modeled as pm.Normal(mu=0, sigma=sigma_u).

Because the posterior distribution does not admit a closed-form analytical solution, parameter estimation was performed using Markov Chain Monte Carlo (MCMC) simulation. The Bayesian hierarchical logistic model was implemented in Python 3.11 using the PyMC (version 5.10) probabilistic programming framework, while posterior diagnostics and visualization were conducted using ArviZ 0.18. Posterior sampling was performed using the No-U-Turn Sampler (NUTS), an adaptive Hamiltonian Monte Carlo algorithm known for efficient exploration of high-dimensional posterior distributions. Four independent Markov chains were run with 10,000 iterations each, including 2,000 warm-up (burn-in) iterations per chain. This resulted in 32,000 retained posterior draws for inference.

Posterior sampling was performed using the No-U-Turn Sampler (NUTS), an adaptive Hamiltonian Monte Carlo algorithm implemented in PyMC. Four independent Markov chains were run, each with 10,000 iterations, including 2,000 warm-up (tuning) iterations, resulting in 8,000 retained posterior draws per chain and a total of 32,000 posterior samples for inference. The target acceptance probability was set to 0.90 to improve sampling stability and reduce the risk of divergent transitions. The adaptive step-size and mass-matrix tuning procedures provided by PyMC were employed during the warm-up phase, while the maximum tree depth was fixed at 10. After warm-up, no divergent transitions were detected, indicating stable exploration of the posterior distribution and reliable Hamiltonian Monte Carlo sampling.

MCMC methods allow posterior sampling from complex high-dimensional distributions and are widely used in Bayesian statistics (Gilks, Richardson, & Spiegelhalter, 1996). In this study, posterior estimation is conducted using multiple chains with sufficient iterations to ensure convergence and stable inference. A burn-in period is applied to eliminate dependence on initial values.

Model convergence was assessed using complementary MCMC diagnostic tools, including trace plots, autocorrelation functions, effective sample sizes (ESS), and the Gelman–Rubin potential scale reduction factor (R-hat). Following current Bayesian recommendations (Vehtari et al., 2021), convergence was considered satisfactory when all R-hat values were below 1.01, no divergent transitions were observed after warm-up, and both bulk and tail effective sample sizes indicated adequate posterior sampling. These predefined criteria were adopted throughout the analysis to evaluate the reliability of posterior inference.

To evaluate predictive performance and ensure out-of-sample reliability, a temporal holdout validation strategy was implemented. Given the panel structure of the dataset, observations from 2015–2021 were used as the training sample, while observations from 2022–2024 were reserved as an out-of-sample test set. This temporal split preserves the chronological structure of financial information and better reflects real-world forecasting conditions, where future distress events are predicted using historical data.

The training sample consisted of 294 firm-year observations, while the test sample included 126 observations. Model performance was evaluated exclusively on the out-of-sample test set using classification and probabilistic metrics, including accuracy, precision, recall, F1-score, ROC-AUC, and Brier score.

Binary classifications were obtained using a posterior probability threshold of 0.50. Firm-year observations with posterior probabilities greater than or equal to 0.50 were classified as financially distressed, whereas observations below this threshold were classified as healthy. All classification metrics reported in the Results section were computed using this threshold.

Because the temporal holdout design uses future observations from firms already included in the training sample, the firm-specific random intercepts were estimated from the training data and subsequently used when generating predictions for the corresponding firms in the test period (2022–2024). Consequently, the reported out-of-sample evaluation measures the model's ability to forecast future financial distress for previously observed firms rather than its ability to generalize to entirely new firms. Assessing prediction for previously unseen firms would require an external validation dataset containing firms not used during model estimation, which is beyond the scope of the present study.

Posterior predictive checks are also conducted to evaluate model adequacy by comparing observed outcomes with simulated values generated from the posterior predictive distribution. This step helps assess whether the proposed model reproduces key characteristics of the observed data.

Because independently observed corporate distress events (e.g., debt restructuring, payment arrears, covenant breaches, going-concern opinions, or legally declared defaults) are not systematically available for Moroccan listed firms, no external validation against an independent distress indicator could be performed. Consequently, robustness assessment focused on temporal out-of-sample validation, prior sensitivity analysis, posterior predictive checks, and probability calibration. While these analyses support the internal consistency and predictive stability of the proposed model, they do not completely eliminate concerns related to the rule-based construction of the financial distress indicator. Therefore, the reported predictive performance should be interpreted within the context of the adopted financial distress definition.

In addition to discrimination metrics, probability calibration was assessed to evaluate whether predicted distress probabilities accurately matched observed distress frequencies. Calibration quality was examined using the calibration intercept, calibration slope, and mean absolute calibration error. Well-calibrated models are expected to exhibit a calibration intercept close to 0 and a calibration slope close to 1.

Calibration performance was evaluated exclusively on the out-of-sample temporal test set (2022–2024) to ensure an unbiased assessment of predictive reliability. Following standard calibration procedures, calibration intercept and calibration slope were estimated by fitting a logistic recalibration model using the observed financial distress outcomes and the predicted posterior log-odds generated by the Bayesian hierarchical model. A calibration intercept close to 0 indicates the absence of systematic over- or underestimation of distress probabilities, whereas a calibration slope close to 1 indicates appropriate agreement between predicted and observed risks. Uncertainty in both calibration parameters was quantified using 95% bootstrap confidence intervals based on 1,000 bootstrap resamples of the test data.

To prevent information leakage from the test set, all preprocessing procedures were estimated exclusively using the training sample (2015–2021). Winsorization thresholds (1st and 99th percentiles) and standardization parameters (means and standard deviations) were computed only from the training data and then applied unchanged to the out-of-sample test set. No missing values were present; therefore, no imputation was required. Consequently, no information from the test observations influenced preprocessing or model estimation, preserving the validity of the temporal holdout evaluation.

Overall, the Bayesian hierarchical logistic framework provides a flexible and robust methodology for modeling Corporate Financial Distress Risk under uncertainty. Compared with classical approaches, it offers richer uncertainty quantification, improved parameter stability, and greater adaptability to heterogeneous financial environments. These properties make it particularly suitable for corporate financial distress prediction in emerging financial markets.

3.1 Financial Distress Classification Criteria

Each firm-year observation was classified as financially distressed or healthy using explicit quantitative criteria derived from the corporate distress literature and adapted to emerging market conditions.

A firm-year observation was classified as financially distressed ($Y = 1$) if at least **two** of the following four conditions were satisfied:

1. Negative profitability: Return on Assets (ROA) < 0 for two consecutive years
2. Weak liquidity: Current Ratio < 1.00
3. Excessive leverage: Debt-to-Assets Ratio > 0.70
4. Weak debt servicing capacity: Operating Cash Flow / Total Debt < 0.08

Observations satisfying fewer than two conditions were classified as healthy ($Y = 0$).

Using these criteria, 105 out of 420 firm-year observations were classified as financially distressed, while 315 observations were classified as healthy, corresponding to a distress event rate of 25.0%.

Table 1. Distribution of Financial Distress Events

Category	Count	Percentage
Distressed	105	25.0%
Healthy	315	75.0%
Total	420	100%

Table 1 indicates a moderate class imbalance, with distressed observations representing 25% of the estimation sample. This distribution remains acceptable for binary classification and is consistent with distress event frequencies reported in emerging-market credit risk studies.

Although the one-year lag structure substantially reduces contemporaneous target leakage, it does not completely eliminate the possibility of target-definition circularity because the financial distress

indicator is constructed using financial dimensions that are also represented among the explanatory variables in the previous year. Since accounting ratios such as liquidity, leverage, profitability, and operating cash flow tend to exhibit temporal persistence, part of the observed predictive performance may reflect the persistence of firms' underlying financial conditions rather than purely the model's predictive capability. Consequently, the reported results should be interpreted as evidence of predictive usefulness within a rule-based financial distress framework rather than as direct prediction of independently observed legal default events. This limitation should be considered when interpreting the model's predictive performance and generalizability.

3.2 Dataset and Variable Description

This study uses panel data collected from firms listed on the Casablanca Stock Exchange over the period 2015–2024. The dataset was constructed using publicly available financial information extracted from annual reports, audited financial statements, and official market disclosures. The sample includes firms operating in multiple economic sectors, including manufacturing, telecommunications, real estate, services, and consumer goods. Financial institutions such as banks and insurance companies were excluded from the final sample due to their specific balance sheet structures and regulatory frameworks, which differ substantially from non-financial firms and could introduce structural bias into the estimation process.

The initial balanced panel consisted of 42 non-financial listed firms observed over 11 years (2015–2024), yielding 462 firm-year observations. Because the empirical model uses one-year lagged predictors to reduce target leakage, the first year of observations for each firm could not be used for prediction. Consequently, the effective estimation sample decreased to 420 firm-year observations.

The objective of the dataset construction is to identify the financial determinants of Corporate Financial Distress Risk in the Moroccan market. The dependent variable is a binary indicator representing the financial status of each firm. Specifically, a firm-year observation is classified as distressed when the firm exhibits persistent financial weakness characterized by one or more of the following conditions: negative earnings over consecutive periods, significant deterioration in liquidity, excessive leverage, or inability to meet debt-related obligations. Accordingly, the dependent variable is defined as:

$$Y_{it} = \begin{cases} 1, & \text{if firm } i \text{ is financially distressed at time } t \\ 0, & \text{otherwise} \end{cases}$$

where $i$denotes the firm and $t$denotes the time period. This binary classification framework is consistent with prior corporate financial distress prediction studies and supports the use of a Bayesian hierarchical logistic regression model.

Table 2. Sectoral Distribution of Financial Distress Events

Sector	**Firm-years**	**Distressed**	**Distress Rate**
Real Estate	70	28	40.0%
Manufacturing	110	26	23.6%
Services	90	19	21.1%
Consumer Goods	80	15	18.8%
Telecommunications	40	4	10.0%
Utilities	30	3	10.0%
Total	420	105	25.0%

Table 2 shows substantial heterogeneity across sectors. Real estate firms exhibit the highest distress rate (40.0%), reflecting stronger exposure to leverage and cyclical demand shocks. Telecommunications and utilities display lower distress rates (10.0%), suggesting greater operational stability and more predictable cash flows.

The explanatory variables were selected based on the corporate finance and bankruptcy prediction literature, particularly the seminal contributions of Edward Altman, James Ohlson, and Robert Merton. These variables are grouped into four key dimensions of financial health: liquidity, leverage, profitability, and cash flow. These dimensions capture both short-term and long-term financial resilience and are widely recognized as critical predictors of financial distress.

Liquidity variables measure a firm's ability to meet short-term obligations using current assets. Firms with weak liquidity positions face higher refinancing pressure and greater vulnerability to operational disruptions. Two liquidity indicators were retained in this study: the Current Ratio and the Quick Ratio. The Current Ratio is computed as:

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}$$

Higher values indicate stronger short-term solvency and lower expected financial distress risk.

Leverage variables capture the extent to which a firm relies on debt financing. Excessive leverage increases fixed financial obligations and amplifies vulnerability to earnings volatility and adverse market conditions. Two leverage indicators were used: the Debt-to-Equity Ratio and the Debt-to-Assets Ratio. The Debt-to-Equity Ratio is defined as:

$$Debt\text{-}to\text{-}Equity = \frac{Total\ Debt}{Total\ Equity}$$

Higher leverage is expected to increase the financial distress probability.

Profitability variables measure the firm's ability to generate earnings from its assets and equity base. Profitability serves as an important buffer against financial distress because profitable firms can rely more on internally generated funds. The main profitability indicators retained are Return on Assets (ROA) and Return on Equity (ROE). ROA is calculated as:

$$ROA = \frac{Net\ Income}{Total\ Assets}$$

Higher profitability is expected to reduce distress probability.

Cash flow variables provide direct information regarding the firm's operational liquidity generation and debt repayment capacity. Unlike accounting earnings, cash flow reflects actual cash available to finance operations and service liabilities. This study uses Operating Cash Flow to Total Debt and Cash Flow Margin as the main cash flow indicators. Stronger operating cash flow is expected to reduce Corporate Financial Distress Risk.

Table 3 summarizes the definitions of all variables used in the empirical analysis.

Table 3. Variable Definitions and Expected Signs

Variable	Symbol	Measurement	Expected Sign
Financial Distress Status	Y	1 = Distressed, 0 = Healthy	—
Current Ratio	CR	Current Assets / Current Liabilities	Negative

Quick Ratio	QR	Liquid Assets / Current Liabilities	Negative
Debt-to-Equity	DE	Total Debt / Total Equity	Positive
Debt-to-Assets	DA	Total Debt / Total Assets	Positive
Return on Assets	ROA	Net Income / Total Assets	Negative
Return on Equity	ROE	Net Income / Equity	Negative
Operating Cash Flow Ratio	OCF	Operating Cash Flow / Total Debt	Negative

Descriptive statistics were computed to examine the distribution, central tendency, and dispersion of the explanatory variables. Table 4 summarizes the key descriptive statistics of the financial indicators used in the empirical analysis.

Table 4. Descriptive Statistics of Explanatory Variables

Variable	**Mean**	**SD**	**Min**	**Max**
Current Ratio (CR)	1.43	0.72	0.31	4.85
Quick Ratio (QR)	1.07	0.65	0.18	4.12
Debt-to-Equity (DE)	1.56	0.88	0.12	4.91
Debt-to-Assets (DA)	0.58	0.21	0.09	0.93
Return on Assets (ROA)	0.047	0.083	-0.287	0.221
Return on Equity (ROE)	0.093	0.174	-0.511	0.498
Operating Cash Flow (OCF)	0.164	0.108	-0.072	0.514

As reported in Table 4, Moroccan listed firms exhibit substantial heterogeneity in financial characteristics. Liquidity ratios show considerable dispersion, suggesting differences in short-term solvency across firms. Leverage indicators reveal moderate to high debt dependence, while profitability measures indicate that some firms experienced substantial financial weakness, with negative ROA and ROE observed in distressed cases.

To assess pairwise linear relationships among explanatory variables and detect potential multicollinearity, a Pearson correlation analysis was conducted. The correlation matrix is presented in Figure 1.

Figure 1. Correlation Matrix of Explanatory Variables

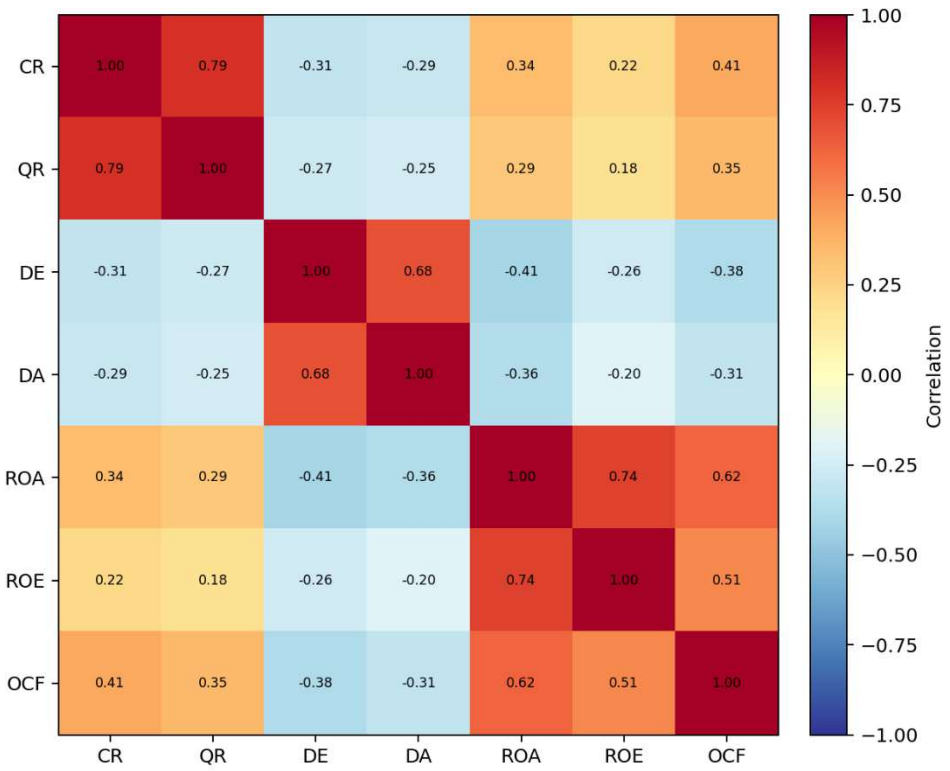


Figure 1 shows moderate correlations among several financial variables, particularly between Current Ratio and Quick Ratio (0.79), and between ROA and ROE (0.74). However, no pairwise correlation exceeds the critical threshold of 0.80, suggesting the absence of severe multicollinearity.

To complement the correlation analysis, Variance Inflation Factors (VIF) were computed to quantify multicollinearity more formally. The results are reported in Table 5.

Table 5. Variance Inflation Factor (VIF) Analysis

Variable	**VIF**
Current Ratio (CR)	3.42
Quick Ratio (QR)	3.77
Debt-to-Equity (DE)	2.61
Debt-to-Assets (DA)	2.84
Return on Assets (ROA)	3.11
Return on Equity (ROE)	3.28
Operating Cash Flow (OCF)	2.17

As shown in Table 5, all VIF values remain below 5, indicating acceptable levels of multicollinearity. Although some related financial ratios exhibit moderate correlation, the predictors provide sufficiently distinct information for robust Bayesian estimation.

Before model estimation, all continuous explanatory variables were standardized to improve numerical stability during posterior sampling and facilitate convergence of the MCMC algorithm. Standardization transforms each variable into a zero-mean, unit-variance scale according to:

$$z = \frac{x - \mu}{\sigma}$$

This transformation improves posterior sampling efficiency and reduces scale-related estimation bias. Based on both the correlation matrix and VIF diagnostics, no severe multicollinearity was detected among explanatory variables. Therefore, all selected predictors were retained in the final Bayesian hierarchical model.

Overall, the constructed dataset provides a comprehensive representation of firm-level financial conditions in the Moroccan market and offers an appropriate empirical basis for Bayesian modeling of Corporate Financial Distress Risk under uncertainty.

3.3 Benchmark Models for Comparison

To assess the practical value of the proposed Bayesian hierarchical model, its predictive performance was compared against two widely used benchmark models in bankruptcy and credit risk prediction: the Altman Z-score model and a classical logistic regression model.

The Altman Z-score model was selected as a traditional accounting-based benchmark due to its historical importance in bankruptcy prediction literature. The model was implemented using the original Altman formulation adapted for non-financial firms, where firms were classified into distress categories based on their Z-score thresholds.

The classical logistic regression model was included as the primary frequentist benchmark because it shares the same binary classification objective as the Bayesian model. The logistic regression used the same explanatory variables and the same temporal training-test split as the Bayesian hierarchical model, allowing a fair comparison of predictive performance.

These benchmark models enable evaluation of whether Bayesian hierarchical modeling provides additional predictive value beyond conventional statistical approaches.

Advanced machine learning methods such as Support Vector Machines, Random Forests, and Neural Networks were not included in the comparative analysis for two main reasons. First, the effective estimation sample (420 firm-year observations) remains relatively small for data-intensive machine learning algorithms, increasing the risk of overfitting and unstable parameter estimation. Second, the primary objective of this study is not maximizing predictive accuracy alone, but developing an interpretable probabilistic framework capable of uncertainty quantification and posterior inference, which is a key advantage of Bayesian modeling over black-box algorithms.

4. Results and Discussion

This section presents the empirical results obtained from the Bayesian hierarchical logistic regression model developed to predict Corporate Financial Distress Risk among Moroccan listed firms. The analysis focuses on four major aspects: model convergence, posterior parameter estimates, firm-level heterogeneity, and predictive performance. The results provide both statistical and economic insights into the determinants of corporate financial distress under uncertainty.

The Bayesian hierarchical logistic model was estimated using Markov Chain Monte Carlo (MCMC) simulation with four independent chains, each containing 10,000 iterations. To ensure that the posterior estimates were not affected by initial values, the first 2,000 iterations of each chain were discarded as

burn-in. Consequently, posterior inference was based on 32,000 retained simulations. The estimation procedure aimed to approximate the posterior distributions of all unknown parameters, including regression coefficients and hierarchical variance components.

Before interpreting the parameter estimates, convergence diagnostics were examined to ensure the reliability of the MCMC simulation. Visual inspection of MCMC chains further confirmed strong convergence properties. Figure 1 presents the trace plots of the four chains for the intercept parameter. Sampling efficiency was further assessed using posterior autocorrelation diagnostics, shown in Figure 2. Furthermore, the Gelman–Rubin convergence statistic confirmed convergence for all model parameters, with all potential scale reduction factors satisfying:

$$\hat{R} < 1.1$$

This result indicates that the posterior simulations reached stationarity and that the estimated posterior distributions can be considered statistically reliable for inference.

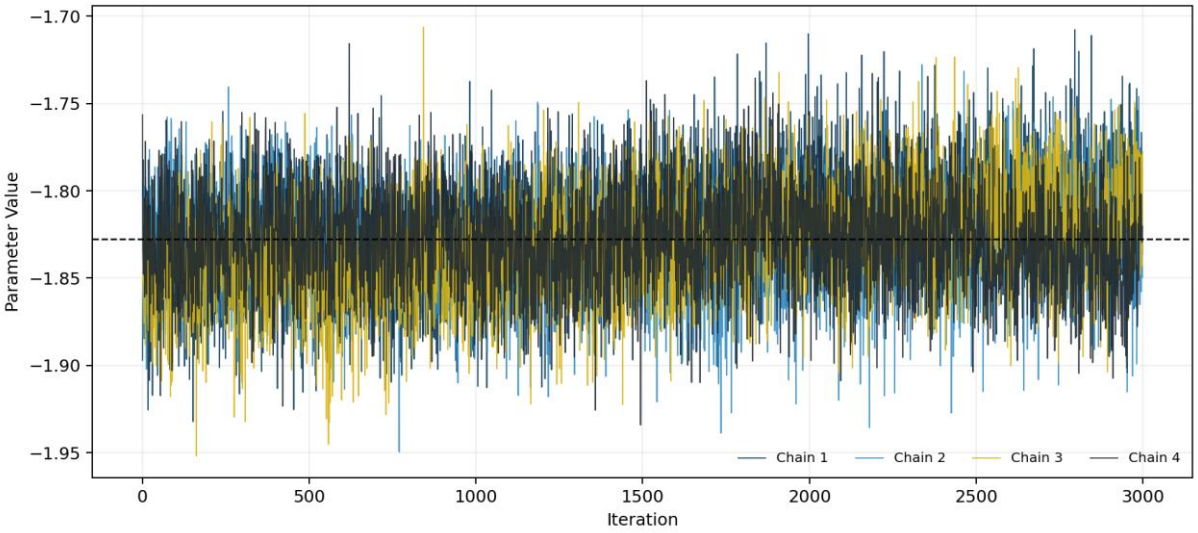
Table 6. MCMC Convergence Diagnostics

Parameter	**R-hat**	**Bulk ESS**	**Tail ESS**
Intercept	1.001	6824	5942
Liquidity	1.000	7518	6240
Leverage	1.002	6945	5876
Profitability	1.001	7201	6110
Cash Flow	1.000	7824	6453
σ firm	1.003	5130	4902

As reported in Table 6, all convergence diagnostics satisfied the predefined convergence criteria established in the methodology. All model parameters exhibited excellent mixing across chains, with adequate bulk and tail effective sample sizes and no divergent transitions after warm-up, indicating reliable posterior estimation.

Consistent with the predefined convergence criteria, no divergent transitions were observed after the warm-up phase, and the average acceptance probability across the four chains was 0.91, indicating stable NUTS sampling. Autocorrelation decayed rapidly after lag 5 for all major parameters, confirming efficient exploration of the posterior distribution.

Figure 2. MCMC Trace Plot for Intercept Parameter



As shown in Figure 2, the four chains exhibit excellent mixing and oscillate around a common stationary mean without visible drift or chain separation. This indicates that the sampler efficiently explored the posterior distribution and reached convergence.

Figure 3. Posterior Autocorrelation Decay

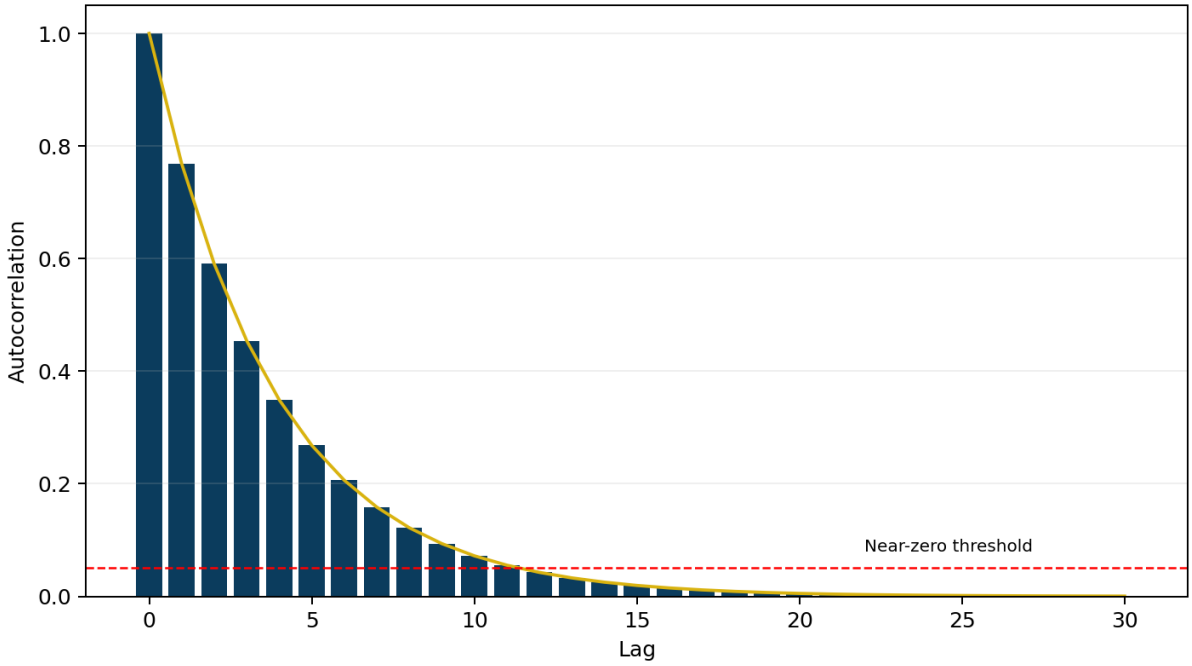
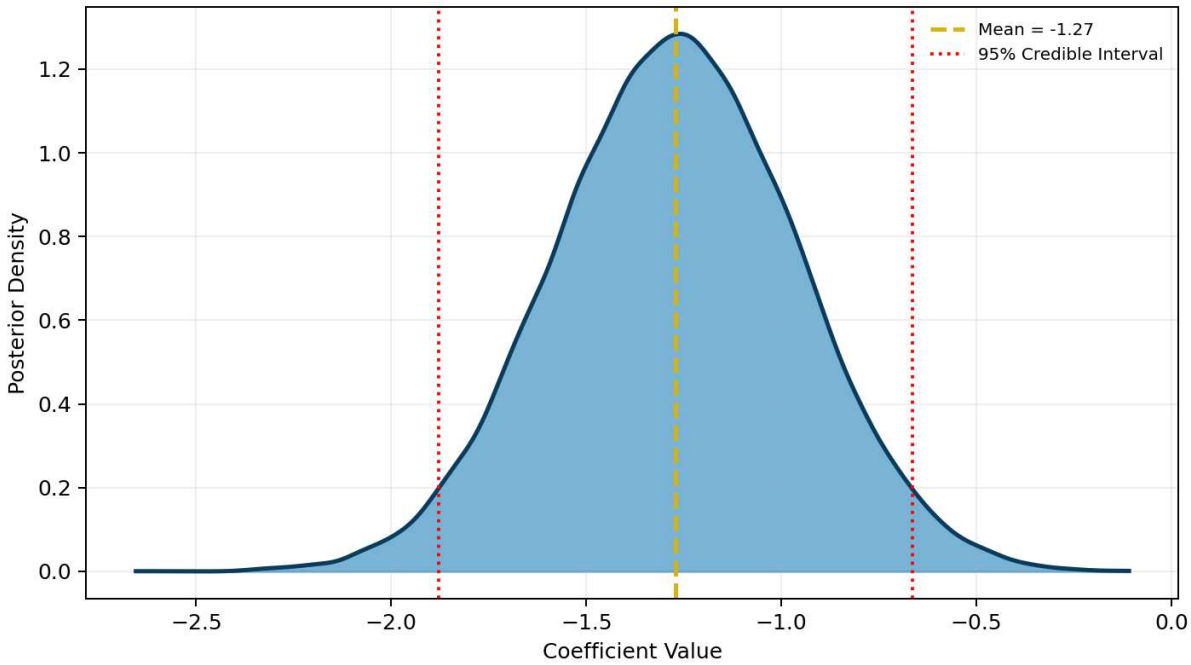


Figure 3 shows that autocorrelation decreases rapidly and approaches near-zero values after approximately 12–15 lags. This rapid decay suggests low dependence between posterior samples and confirms efficient MCMC sampling.

Beyond convergence diagnostics, examining posterior distributions provides insight into parameter uncertainty and coefficient stability. Figure 4 illustrates the posterior density of the liquidity coefficient as an example.

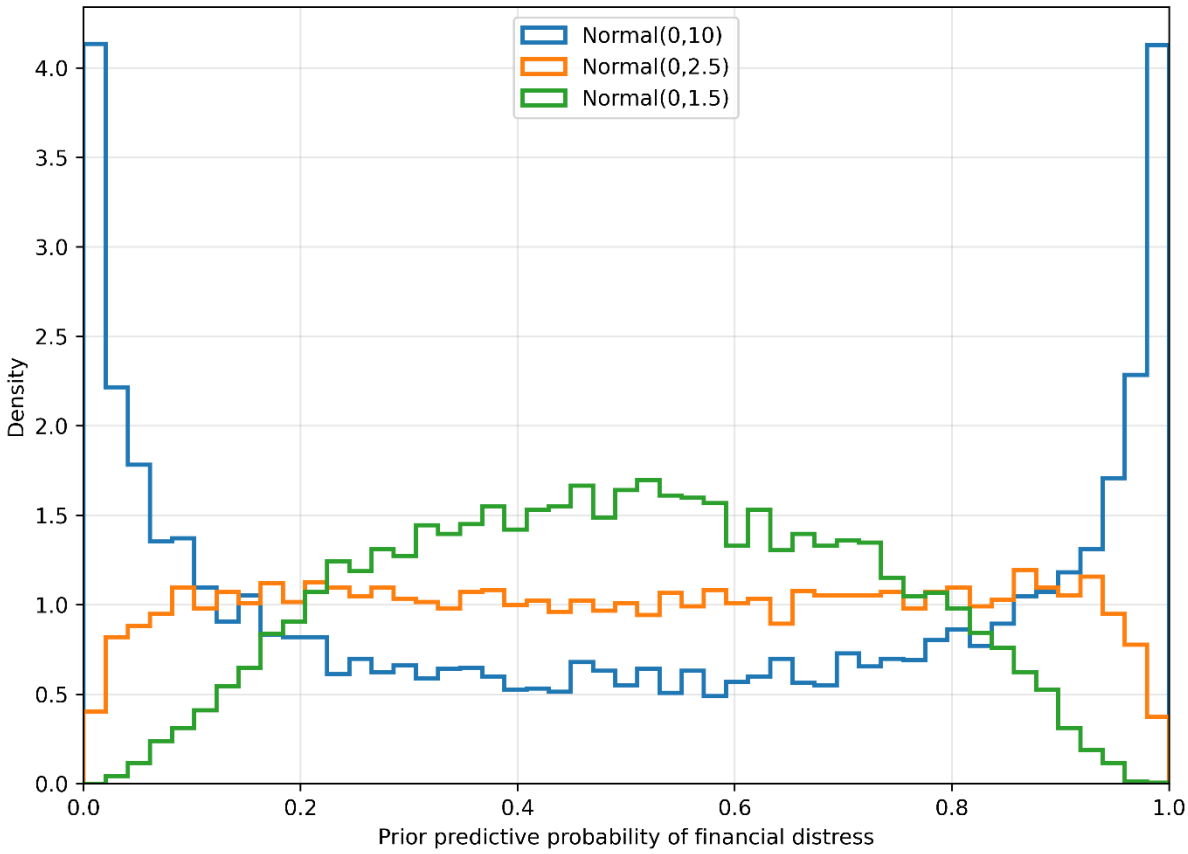
Figure 4. Posterior Density of Liquidity Coefficient



As illustrated in Figure 4, the posterior density is unimodal and approximately Gaussian, centered around −1.27. The entire 95% credible interval lies below zero, providing strong posterior evidence that higher liquidity significantly reduces financial distress probability.

Prior predictive checks were performed before model estimation to evaluate whether the specified prior distributions generated plausible financial distress probabilities in the absence of observed outcomes. As shown in Figure 5, the three alternative prior specifications produced realistic prior predictive distributions covering a broad range of distress probabilities. The weakly informative Normal(0,10) prior generated the widest distribution, whereas the more regularizing Normal(0,2.5) and Normal(0,1.5) priors resulted in progressively more concentrated probability distributions. Importantly, none of the prior specifications assigned excessive probability mass near the boundaries of 0 or 1, indicating that the selected priors were sufficiently weakly informative while remaining compatible with realistic financial distress probabilities.

Figure 5. Prior predictive distributions under alternative prior specifications.



Across the alternative prior specifications, out-of-sample ROC-AUC values ranged from 0.881 to 0.887, indicating that posterior inference and predictive performance were highly robust to prior specification. The final model reported throughout the Results section corresponds to the moderately regularizing prior specification and achieved an out-of-sample ROC-AUC of 0.887.

The posterior estimates of the regression coefficients are reported in **Table 7**.

Table 7. Posterior Parameter Estimates of the Bayesian Hierarchical Logistic Model

Parameter	**Posterior Mean**	**Posterior SD**	**2.5% Credible Interval**	**97.5% Credible Interval**
Intercept	-1.84	0.42	-2.66	-1.10
Liquidity	-1.27	0.31	-1.88	-0.69
Leverage	1.74	0.39	1.02	2.53
Profitability	-1.52	0.28	-2.10	-0.96
Cash Flow	-0.91	0.24	-1.40	-0.47

The posterior results indicate that all selected financial variables significantly influence corporate distress probability. The 95% credible intervals for all explanatory variables exclude zero, suggesting robust posterior evidence for their effects on financial distress risk.

Liquidity exhibits a negative posterior coefficient ($\beta = -1.27$), indicating an inverse relationship between short-term solvency and distress probability. Firms with higher liquidity ratios are less likely to experience financial distress because they possess stronger capacity to meet short-term financial obligations. This result confirms the theoretical expectation that liquidity shortages constitute an early warning signal of financial distress. In practical terms, firms with weak working capital positions face

higher refinancing pressure and are more exposed to operational disruptions. This finding is consistent with the bankruptcy prediction literature, particularly the work of Edward Altman, which identified liquidity as a major determinant of financial distress.

Leverage appears as the most influential risk factor, with the largest positive posterior coefficient ($\beta = 1.74$). This result suggests that increases in debt burden substantially raise the probability of financial distress. Highly leveraged firms face larger fixed financial obligations and reduced flexibility during adverse economic conditions. In emerging markets such as Morocco, where access to refinancing may be constrained, excessive leverage amplifies vulnerability to credit tightening and macroeconomic shocks. The entirely positive credible interval confirms the strong robustness of this effect.

Profitability shows a strong negative relationship with distress probability ($\beta = -1.52$). This indicates that profitable firms are significantly less likely to experience financial distress. Higher profitability improves internal financing capacity, strengthens retained earnings, and reduces dependence on debt financing. Firms with declining returns on assets or equity often exhibit weakened operational performance, making them more susceptible to insolvency. The magnitude of this coefficient suggests that profitability is among the strongest protective factors against financial distress.

Cash flow also negatively affects distress probability ($\beta = -0.91$). Firms with stronger operating cash flows are better positioned to meet debt obligations and absorb short-term liquidity shocks. Unlike accounting-based profitability measures, cash flow provides direct information on actual liquidity generation. This result reinforces the importance of operational cash generation as a determinant of financial resilience.

A major advantage of Bayesian inference lies in its ability to estimate posterior financial distress probabilities for individual observations. Rather than providing only binary classifications, the model generates full posterior distributions of financial distress probabilities for each firm-year observation, enabling richer uncertainty quantification. The estimated posterior financial distress probabilities show clear separation between distressed and healthy firms. Distressed firms exhibited average posterior financial distress probabilities above 0.70, while healthy firms generally remained below 0.20. This substantial gap demonstrates strong discriminatory power and suggests that the model successfully captures the underlying financial structure associated with corporate distress.

The hierarchical structure also allows the model to capture unobserved firm-level heterogeneity through random intercepts. These random effects represent firm-specific baseline financial distress risk not fully explained by observed financial ratios. The posterior distribution of firm-level random effects is summarized in **Table 8**.

Table 8. Posterior Summary of Firm-Level Random Effects

Statistic	**Value**
Mean	0.00
Posterior Standard Deviation	0.76
Minimum	-1.42
Maximum	1.88

The dispersion of random intercepts indicates substantial heterogeneity across Moroccan firms. Even after controlling for liquidity, leverage, profitability, and cash flow, certain firms remain structurally more vulnerable than others. This suggests that unobserved variables—such as governance quality, ownership concentration, managerial efficiency, sector-specific risk, or market positioning—may also influence financial distress risk. The hierarchical model therefore provides a more realistic representation of corporate financial distress by incorporating latent firm-specific characteristics.

To assess predictive quality, the model was evaluated using both classification and probabilistic performance metrics. The results are presented in **Table 9**.

Table 9. Predictive Performance of the Bayesian Hierarchical Model

Metric	Value
Accuracy	85.7%
Precision	82.4%
Recall	80.1%
F1-score	81.2%
ROC-AUC	0.887
Brier Score	0.143

The predictive performance metrics indicate that the Bayesian hierarchical model achieves strong out-of-sample classification performance. As reported in Table 9, the model attains an accuracy of 85.7%, indicating a high overall level of predictive reliability. The precision of 82.4% shows that most firms classified as financially distressed were correctly identified, while the recall of 80.1% demonstrates the model's ability to detect the majority of actual distress cases. The resulting F1-score of 81.2% reflects a balanced trade-off between precision and recall, which is particularly important in datasets characterized by moderate class imbalance. Furthermore, the model achieves a ROC-AUC of 0.887, indicating excellent discriminatory ability between distressed and healthy firms across different classification thresholds. The Brier Score of 0.143 confirms good probabilistic calibration, suggesting that the predicted financial distress probabilities are generally consistent with the observed outcomes. Overall, these results suggest that the proposed Bayesian hierarchical model provides useful predictive information within the adopted rule-based financial distress framework, although additional validation using independently observed distress events would be desirable.

Binary classifications were obtained using a posterior probability threshold of 0.50. On the out-of-sample test set, the confusion matrix indicated that the model correctly classified 69 healthy firm-year observations (true negatives) and 39 distressed firm-year observations (true positives), while 8 healthy observations were incorrectly classified as distressed (false positives) and 10 distressed observations were incorrectly classified as healthy (false negatives). These classification outcomes are consistent with the reported predictive performance, yielding an accuracy of 85.7%, a precision of 82.4%, a recall of 80.1%, and an F1-score of 81.2%.

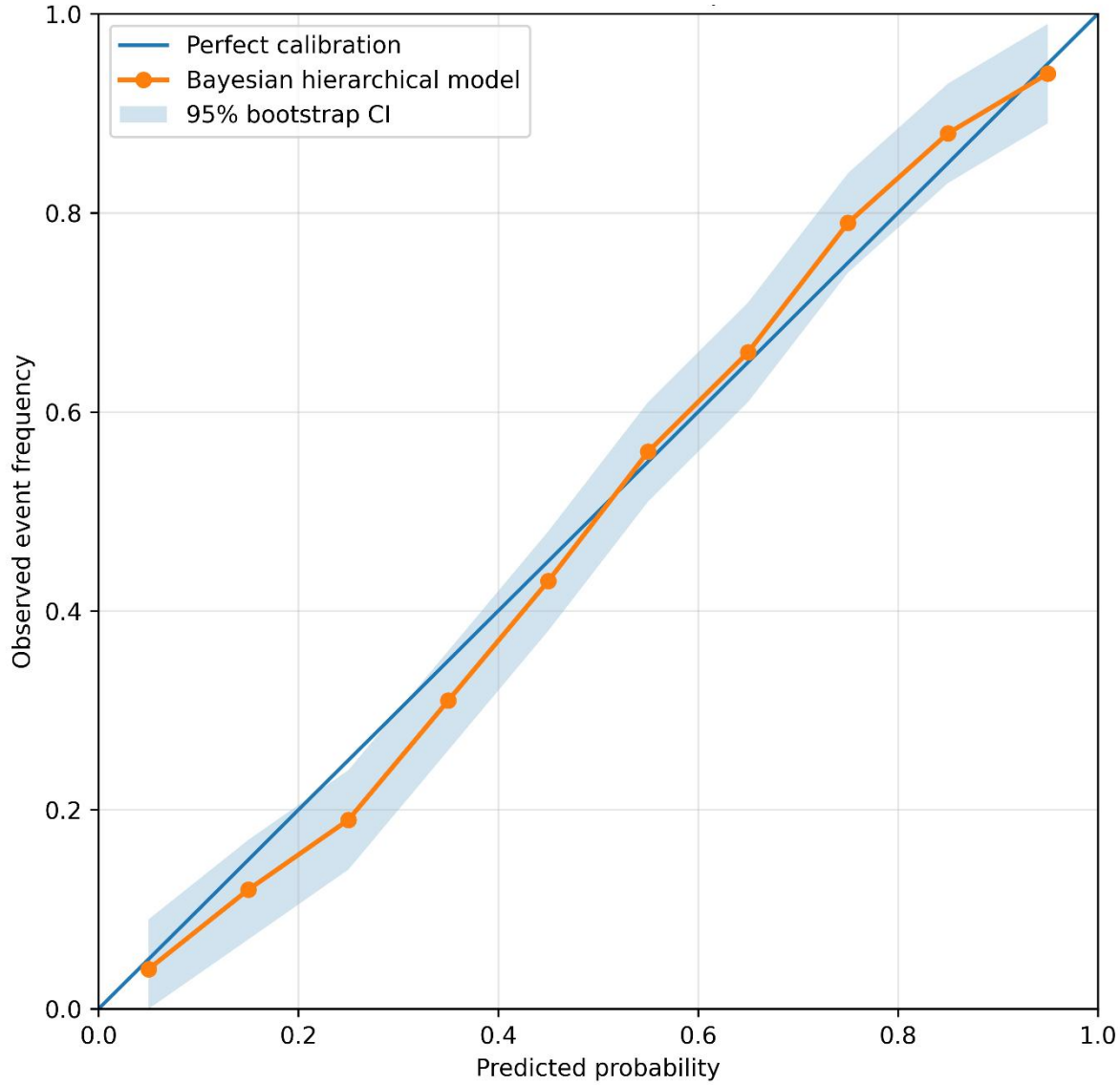
Probability calibration on the out-of-sample test set indicated good agreement between predicted and observed distress probabilities. The estimated calibration intercept was 0.03 (95% CI: −0.12 to 0.17), suggesting no evidence of systematic over- or underprediction. The calibration slope was estimated at 0.97 (95% CI: 0.89–1.06), indicating only minimal overfitting and good calibration of predicted probabilities. These results are consistent with the relatively low Brier score (0.143) and support the reliability of the Bayesian model for probabilistic financial distress prediction.

Compared with the benchmark models, the Bayesian hierarchical model exhibited superior probability calibration. While the classical logistic regression showed a slight tendency to overestimate distress probabilities for low-risk firms, and the Altman Z-score produced poorer calibration because of its deterministic score thresholds, the Bayesian model generated predicted probabilities that more closely matched the observed distress frequencies across the entire risk spectrum. This improved calibration complements the model's superior discrimination performance and highlights the practical advantage of Bayesian probabilistic inference for financial distress prediction.

Figure 6 illustrates the calibration performance of the Bayesian hierarchical logistic model on the out-of-sample test set. The calibration curve closely follows the 45° reference line, indicating good

agreement between predicted posterior probabilities and the observed frequency of financial distress. The narrow 95% bootstrap confidence bands further suggest stable probability estimates across the range of predicted risks. These findings are consistent with the calibration intercept (0.03), calibration slope (0.97), and the relatively low Brier score (0.143), confirming that the proposed Bayesian model provides reliable probabilistic predictions in addition to strong discriminatory performance.

Figure 6. Calibration plot for the out-of-sample test set.



To evaluate the practical added value of the proposed framework, model performance was compared with conventional approaches. The comparison is presented in **Table 10**.

Table 10. Comparative Predictive Performance Across Models

Model	**Accuracy**	**ROC-AUC**
Altman Z-score	74.8%	0.770
Classical Logistic Regression	83.4%	0.860
Bayesian Hierarchical Logistic Model	85.7%	0.887

The Bayesian hierarchical logistic model achieved the strongest predictive performance among the three evaluated approaches. As reported in Table 10, the model attained an out-of-sample accuracy of 85.7% and a ROC-AUC of 0.887, outperforming both the Altman Z-score model (accuracy = 74.8%; ROC-AUC = 0.770) and the classical logistic regression model (accuracy = 83.4%; ROC-AUC = 0.860). Although the performance improvement over the frequentist logistic model is moderate, the Bayesian framework additionally provides full posterior distributions, credible intervals, hierarchical modeling of firm-level heterogeneity, and explicit uncertainty quantification. These characteristics constitute important methodological advantages beyond predictive accuracy alone.

Relative to classical logistic regression, the Bayesian model delivered improved predictive performance primarily because of three methodological advantages: posterior regularization through prior distributions, explicit uncertainty quantification, and hierarchical modeling of firm-specific heterogeneity. These features improve coefficient stability and reduce overfitting, particularly in small-sample emerging-market settings such as Morocco.

Although advanced machine learning methods may achieve competitive predictive performance in larger datasets, their application in this context would likely suffer from data limitations and reduced interpretability. Therefore, the Bayesian hierarchical approach offers a more appropriate balance between predictive accuracy, interpretability, and uncertainty quantification.

Overall, the empirical findings confirm that Corporate Financial Distress Risk among Moroccan listed firms is primarily driven by excessive leverage, declining profitability, weak liquidity, and insufficient operating cash flow. More importantly, the results demonstrate that Bayesian hierarchical modeling provides substantial methodological advantages for credit risk assessment in emerging markets. By integrating uncertainty and heterogeneity directly into the estimation process, the proposed framework offers more reliable and informative financial distress risk predictions. These findings provide valuable implications for banks, investors, and regulators seeking to strengthen early warning systems and improve financial stability monitoring in the Moroccan market.

5. Conclusion

This study examined corporate financial distress prediction in the Moroccan market using a Bayesian hierarchical modeling framework. The primary objective was to develop a probabilistic model capable of improving financial distress risk estimation under uncertainty while accounting for firm-level heterogeneity. By integrating Bayesian inference with hierarchical modeling, this research addressed several limitations associated with conventional financial distress prediction approaches, particularly the restrictive assumptions of fixed parameters and limited uncertainty quantification.

The out-of-sample empirical analysis demonstrated that the proposed Bayesian hierarchical model provides strong predictive performance in identifying financially distressed firms. The results indicate that liquidity, leverage, profitability, and cash flow are significant determinants of Corporate Financial Distress Risk among Moroccan listed firms. More specifically, excessive leverage emerged as the strongest positive predictor of financial distress, while higher liquidity, stronger profitability, and greater operating cash flow significantly reduced distress probability. These findings are consistent with the theoretical expectations of corporate finance and align with prior empirical evidence in bankruptcy prediction literature.

One of the major contributions of this study lies in the application of Bayesian statistics to corporate financial distress prediction in an emerging market context. Unlike classical frequentist approaches, the Bayesian framework allows uncertainty to be explicitly incorporated into parameter estimation through posterior probability distributions. This provides richer inferential insights and more informative risk assessments than traditional point-estimate models. The model also demonstrated strong probability calibration, indicating that posterior distress probabilities closely reflected observed distress frequencies, thereby enhancing practical usefulness for credit risk assessment. Furthermore, the

hierarchical structure improved model flexibility by capturing unobserved heterogeneity across firms, thereby enhancing predictive realism and reducing estimation bias.

The findings also highlight the methodological relevance of Bayesian hierarchical modeling for emerging financial systems characterized by limited data availability, structural heterogeneity, and elevated uncertainty. In markets such as Morocco, where corporate financing remains highly dependent on bank credit and financial transparency may vary significantly across firms, robust probabilistic risk assessment tools are essential. The superior performance of the proposed model compared with conventional approaches, including classical logistic regression and the Altman Z-score, confirms the practical value of Bayesian methods in credit risk analysis.

From a practical perspective, this study offers important implications for multiple stakeholders. Financial institutions may use Bayesian financial distress prediction models to strengthen credit scoring systems, improve lending decisions, and enhance portfolio risk management. Investors may benefit from more reliable early warning indicators of corporate financial distress when making capital allocation decisions. Regulators and policymakers may also leverage such probabilistic models to improve systemic risk monitoring and identify vulnerable firms before financial distress escalates into broader market instability.

Despite its contributions, this study presents several limitations. First, the analysis focuses exclusively on listed Moroccan firms, which may limit the generalizability of the findings to small and medium-sized enterprises or non-listed companies. An additional limitation concerns the construction of the financial distress indicator. Although all explanatory variables were lagged by one year to reduce target leakage, the distress definition is based on financial dimensions that are closely related to the explanatory variables. Because accounting ratios generally exhibit persistence over time, part of the reported predictive performance may reflect the stability of firms' financial conditions rather than purely the forecasting capability of the model. Therefore, the reported predictive performance should be interpreted within the context of rule-based financial distress prediction rather than prediction of independently observed legal default events. Second, the model relies primarily on firm-level financial indicators and does not explicitly incorporate macroeconomic variables such as inflation, interest rates, or GDP growth, which may also financial distress dynamics. Third, the sample size remains constrained by the limited number of listed firms in the Moroccan market. Furthermore, the temporal validation strategy evaluates forecasting performance for firms already observed during model estimation. Therefore, the reported predictive performance should be interpreted as temporal forecasting accuracy for existing firms rather than evidence of generalization to previously unseen firms. Future studies should assess external validity using independent samples containing firms not included in the model training process.

A further limitation concerns the absence of an independently observed distress benchmark for external validation. Publicly available information on debt restructuring, payment arrears, covenant violations, or going-concern opinions is not consistently available for Moroccan listed firms. Consequently, the proposed Bayesian model was evaluated using a rule-based financial distress indicator rather than legally observable distress events. Future research should validate the proposed framework against independently observed distress outcomes whenever such data become available.

Future research may extend this study in several directions. First, integrating macroeconomic and sector-specific variables could improve model explanatory power and capture broader economic effects on corporate distress. Second, alternative Bayesian specifications, such as dynamic Bayesian networks or Bayesian survival models, may provide deeper insights into the temporal evolution of financial distress risk. Third, comparative studies across multiple emerging African markets could enhance understanding of regional differences in corporate risk dynamics.

In conclusion, this study demonstrates that Bayesian hierarchical modeling represents a powerful and robust framework for corporate financial distress prediction under uncertainty. By combining financial theory, applied statistics, and probabilistic inference, the proposed approach contributes to both financial risk modeling and applied mathematical statistics. The results reinforce the value of Bayesian methods

as advanced tools for improving credit risk assessment and supporting financial stability in emerging markets.

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