

Credit scoring in risk intelligence of non-bank financial institutions in the Province of Laguna**Edraleen P. Gonzales***

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Abstract: Credit scoring has become a crucial tool for modern financial risk assessment, affecting loan choices at both conventional and non-bank financial institutions (NBFIs). This study looks at the connection between credit scoring and risk intelligence in Laguna Province's non-bank financial institutions (NBFIs). This study uses the FICO model to examine key aspects of credit scoring, such as payment history, amount due, duration of credit history, new credit, and credit mix. This study examines how these elements relate to risk intelligence, which encompasses how much risk a person is willing to accept, how they perceive hazards, what they learn, how they adapt, ambiguity, decision-making quality, and risk prediction accuracy. Statistical approaches such as mean frequency, standard deviation, and Pearson's Correlation Coefficient were used to study the relationship between credit rating and risk intelligence. Data were obtained from 114 respondents, including credit assessors from several NBFIs, using a standardized survey questionnaire as the major study tool. The research used purposive sampling to ensure that participants had appropriate knowledge and operational experience in credit risk assessment inside NBFIs. The findings show a substantial correlation between credit score components and risk intelligence, implying that thorough credit evaluations might help NBFIs make better choices and become more resilient. This research provides empirical data that supports improving credit assessment systems, with important consequences for credit evaluators, financial institutions, regulators, and borrowers.

Keywords: Credit Scoring, Risk Intelligence, FICO Model, Non-Bank Financial Institutions, Credit Score

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Date Submitted: June 5, 2025

Date Accepted: June 15, 2025

Date Published: June 30, 2025

INTRODUCTION

Non-bank financial institutions (NBFIs) have changed the manner in which they view credit risk due to increasing reliance on credit scoring systems. This was reported by Mangura (2023), who later observed the fact that these models heavily determine how institutions approach their risk management policies. Credit scoring serves as a critical mechanism for assessing borrowers' creditworthiness and enabling institutions to make informed lending decisions relatively free from the risk of default Malhotra, et al. (2025).

Effective credit risk management is a vital factor in sustaining financial operations in this region of Laguna where lending companies, microfinance providers, and other NBFIs play an important role in local economic activities and sustained growth. Risk intelligence, which is the ability of financial institutions to identify, manage, and respond to different risk factors, forms the basis of operational effectiveness of the NBFIs. By incorporating credit scoring into the risk

management strategies, more accurate and efficient decision-making is made possible through the logic of measurable data on borrowers' financial behavior. It assists institutions in identifying loan applicants, determining how much to lend, and executing operational strategies that will enhance borrower performance and the profitability of the institution (Lyn Thomas, 2022).

Inevitably, in spite of these advantages, credit scoring comes with some drawbacks. It is the application of algorithmic discrimination, the misinterpretation of data, and most notably dependence on historical credit behavior that proves to be some of the detriments (Cindik & Armutlulu, 2021). The credit scoring boom among financial institutions in the Philippines could be attributed to regulation and initiative for expanded financial inclusion. As stated by the Bangko Sentral ng Pilipinas (BSP), credit scoring is very important for unlocking credit access for microenterprises and previously unbanked segments of the population (Bangko Sentral ng Pilipinas, 2020). Nevertheless, studies have shown that these models do increase accessibility to finance, yet the upfront lack of files about the majority of applicants remains a big hindrance (Castillo, 2020).

Banks and other lenders lend money or provide credit facilities to businesses and entrepreneurs to invest and increase the productive capacity of the economy (Francisco & Flaminiano, 2021). According to Agu et al. (2024), credit scoring for risk intelligence offers insight into whether credit risk management can be improved, loan default reduced, and increased financial inclusivity in the region.

This study aims to contribute to the growing body of literature by examining how credit scoring influences the risk intelligence of NBFIs in Laguna, providing empirical evidence on its effectiveness in mitigating financial risks and improving lending strategies focusing on financing companies in the Province of Laguna that offers motor vehicle, equipment and real estate financing, personal loans, and SME financing that uses credit bureau as their tool in credit assessment and risk management processes.

Given the dynamic nature of financial risks the objective of this study is to examine the relationship between credit scoring and risk intelligence particularly on how credit scores influence the risk intelligence and decision-making of NBFIs in Province of Laguna. Additionally, the study seeks help to forecast potential default risks, allowing institutions to price loans accordingly and set appropriate lending limits (Tang & Luo, 2022).

Problem statement

The study aimed to determine the relationship between credit scoring and risk intelligence of non-bank financial institutions in the Province of Laguna. Specifically it sought answers to the following queries:

1. What is the business profile?
2. What is the level of credit scoring of non-bank financial institutions in the Province of Laguna?
3. What is the level of risk intelligence of financial institutions in the Province of Laguna?
4. Is there a significant relationship between credit scoring and risk intelligence?

METHODOLOGY

This research employed a predictive causal approach to examine the relationship between credit scoring and risk intelligence among non-bank financial institutions in Laguna, Philippines. Predictive causal research was chosen for its capacity to forecast outcomes with a high degree of

accuracy, especially in fields requiring informed decision-making. Specifically, the study sought to understand the credit evaluators' experiences in assessing loan applications, focusing on constructs such as risk appetite, perception, learning, feedback, adaptation, uncertainty, complexity, decision quality, and prediction accuracy. The researcher conducted a quantitative investigation, utilizing a descriptive correlational design to gather data from a purposively selected sample through a structured survey questionnaire.

Participants were selected using purposive sampling, leveraging the researcher's existing network and experience within the credit evaluation sector. The inclusion criteria required respondents to be of legal age and possess relevant expertise in assessing credit applications. These individuals were drawn from non-bank financial institutions across several key cities and municipalities in Laguna, including San Pedro, Biñan, Sta. Rosa, Cabuyao, Calamba, Los Baños, San Pablo, and Sta. Cruz. Laguna's dynamic mix of economic activity, encompassing SMEs, informal businesses, and a significant population of low-income borrowers, provided an ideal context for the study.

Data collection was conducted using a self-administered online survey disseminated via Google Forms. The survey instrument consisted of 51 items divided into three sections: demographic information (years of experience, services offered, and location), credit scoring practices (20 items), and institutional risk intelligence (28 items). Responses were recorded using a 4-point Likert scale ranging from strongly disagree to strongly agree. To ensure the instrument's validity, content and face validation were conducted by a panel of experts, while reliability was confirmed through a pilot test with 30 respondents, yielding a Cronbach's Alpha of 0.94—indicating excellent internal consistency.

Prior to data collection, the researcher obtained ethical clearance and secured formal approval from branch managers or relevant personnel of participating institutions. The study adhered strictly to ethical standards, including the principles outlined in the Data Privacy Act of 2012, which guaranteed the confidentiality of all personal information shared by respondents. The survey was distributed with clear instructions and assurances of anonymity and voluntary participation.

Upon collection, data were coded, tallied, and tabulated to facilitate statistical analysis. Descriptive statistics, including frequency counts and percentages, were used to profile the respondents and businesses. Mean and standard deviation were calculated to assess the levels of credit scoring and risk intelligence among institutions. To evaluate the relationship between credit scoring and risk intelligence, the Pearson Product-Moment Correlation Coefficient (Pearson r) was employed. The analysis was carried out with the assistance of a statistician to ensure the reliability and accuracy of the results, which were subsequently interpreted in relation to the study's objectives.

FINDINGS AND DISCUSSION

Business profile

The business profile of credit evaluators in non-bank financial institutions across Laguna Province reveals significant insights into experience, services offered, and geographic distribution. In terms of years of experience, the majority of respondents (30%) have one to three years of exposure in the field, followed closely by those with less than one year or four to six years of experience, each constituting 25% of the sample. Only a small portion of respondents

(8%) have more than ten years of experience. This suggests that most credit evaluators are relatively early in their careers and are likely dependent on standardized procedures and structured credit models, as novice decision-makers typically lack the intuitive judgment that more seasoned professionals develop over time (Schreiner, 2000). Andersson (2005) supports this by arguing that while experts may vary in their decision-making strategies, they often reach similar outcomes due to their deeper mental frameworks. In line with this, Harding and Vasconcelos (2022) emphasize the value of industry experience in enhancing evaluative judgment. Still, Cortés (2016) complicates the picture by introducing psychological dimensions—such as sentiment and mood attribution—that affect evaluators’ credit judgments, pointing to the critical role of human emotion even within structured decision-making processes.

With regard to services offered, the data reflect a pronounced dominance of mortgage lending. Mortgage loans were identified by 83% of the respondents as the primary financial service they handle, far surpassing other offerings such as personal loans (29%) and finance leases (25%). This overwhelming focus on mortgages carries both strategic potential and inherent risk. Mari (2005) underscores that mortgage lending plays a crucial role in overall economic health but also introduces challenges in valuation due to interest rate volatility and borrower creditworthiness. Historically, the 2008 financial crisis—driven in part by the overextension of mortgage credit—demonstrated how misjudging credit risk in this sector could lead to systemic failure (Marian, 2008; Loo, 2008). Thus, while the strong emphasis on mortgages signals institutional alignment with consumer demand, it also necessitates a heightened degree of risk management rigor and analytical precision.

Geographic distribution of the respondents’ institutions also illustrates key structural dynamics in Laguna’s financial ecosystem. North Laguna, comprising cities such as Biñan, Santa Rosa, and Cabuyao, accounted for the highest respondent concentration (36%), followed by Central Laguna (31%) and South Laguna (29%). These areas differ not only demographically but also in their economic orientations. Bagarinao (2015) noted that North Laguna’s proximity to Metro Manila and rapid urbanization make it an attractive hub for financial operations. Central Laguna, particularly Calamba City, benefits from its industrial base and university presence, facilitating a stable economic environment conducive to lending. South Laguna, on the other hand, features more rural municipalities where lending may be more seasonal or agriculture-driven. According to Nugroho (2020), location is a pivotal determinant of business viability, affecting transaction volume and operational efficiency. Victor (2024) adds that location influences the accessibility of services and customer engagement, ultimately shaping credit performance. Empirical studies further support this: Levine (2007) found that businesses in economically dynamic areas exhibit stronger credit performance, while Brei (2019) warns that areas prone to natural disasters or economic instability may lead to restricted credit availability or higher collateral requirements.

Level of credit scoring of non-bank financial institutions

The level of credit scoring among non-bank financial institutions in Laguna reveals a consistent and structured understanding of the key dimensions used to assess borrower creditworthiness. Across all five core components—payment history, amount owed, length of credit history, new credit, and credit mix—respondents demonstrated a generally high level of awareness, with interpretations falling between “agree” and “strongly agree” in each domain. This pattern indicates that credit evaluators possess a solid foundation in the core mechanics of credit scoring

models, though with some variability in confidence and understanding, depending on the specific indicator evaluated.

In terms of payment history, evaluators strongly affirmed its critical importance, with an overall mean of 3.25 and a minimal standard deviation of 0.40. Respondents unanimously recognized that consistent repayment behavior—particularly on loans, mortgages, and credit cards—is the most significant factor in credit scoring. This is supported by Ahmed (2019), who identified payment history as the most influential determinant in predictive credit models. Thomas, Crook, and Edelman (2022) emphasized its role as a quantifiable proxy for financial responsibility, while Ebele (2024) stressed the reliability of historical repayment patterns in forecasting future behavior. However, greater variability in responses was noted concerning borrowers who make only minimum payments, reflecting uncertainty over how partial payments influence credit standing. Castillo (2020) warned that minimum payments, though technically compliant, may signal weak financial health due to increased credit utilization, while Demyanyk (2017) noted lingering penalties for late payments, even after they are corrected.

Regarding the amount owed, the results (overall mean = 3.18) suggest broad agreement that managing debt levels and credit utilization are vital in evaluating creditworthiness. Respondents strongly acknowledged that borrowers with fewer accounts holding balances are at reduced risk of financial overextension—a view supported by Jantsch (2021), who found that fewer active balances correlate with lower default rates. Likewise, keeping outstanding balances low was considered a sign of sound debt management (Mitchell, 2014). FICO (2023) reinforces this by stating that credit utilization makes up roughly 30% of a person's credit score, and maintaining it below 30% is optimal. While some variability existed in beliefs about utilization thresholds, the overall trend indicated that evaluators understand the importance of prudent debt usage. Agarwal et al. (2018) further supported this view by asserting that low balances minimize default risk and enhance financial stability.

In the area of credit history length, respondents showed solid agreement on its importance (mean = 3.23), though certain indicators—like maintaining old accounts—elicited more varied responses (SD = 0.73). Respondents largely recognized that long-standing credit relationships are valuable in predicting future repayment behavior, echoing Equifax (2021) and Brevoort (2017), who both emphasized the reduced risk associated with seasoned borrowers. Agarwal et al. (2018) also noted that new or short-term borrowers face stricter lending terms, further validating the evaluators' perceptions. Maintaining account longevity, limiting closures, and demonstrating consistent borrowing patterns were broadly acknowledged as contributors to higher credit scores, aligning with Dobbie and Song (2021), who highlighted that short credit histories are often linked to more restrictive lending policies.

Evaluators also agreed (mean = 3.05) on the relevance of new credit in the overall credit assessment process. They believed that opening new accounts with reasonable time intervals and low utilization can positively influence credit scores, consistent with Lin et al. (2020), who found that borrowers with high available credit and low usage default less frequently. Respondents also correctly identified that a minimal number of hard inquiries do not severely impact credit scores, a perspective supported by Brevoort (2017), who warned that frequent new applications signal financial distress. Overall, respondents demonstrated sound judgment on how timing, frequency, and utilization of new credit accounts factor into scoring calculations.

Lastly, in terms of credit mix, respondents expressed strong awareness of its role in enhancing credit assessments (overall mean = 3.18). The most strongly agreed-upon item (mean = 3.43) indicated that a well-diversified credit portfolio with a good payment history contributes

significantly to creditworthiness. This reflects FICO (2020) and Chen & Liao (2021), who argued that credit mix is a strong predictor of stability, especially when borrowers responsibly manage both revolving and installment debt. While the standard deviations remained moderate, they still suggested a reasonably uniform understanding across respondents. The findings reinforce that both early and gradual diversification—when paired with repayment discipline—can substantially boost a borrower’s credit profile.

Taken together, the data reveal a well-informed population of credit evaluators who understand the major dimensions of credit scoring. Respondents not only grasp the mechanics of credit evaluation but also reflect a nuanced appreciation for how borrower behavior, credit history, and financial management practices intersect in determining creditworthiness. These insights support the claim that the evaluators are capable of applying a multidimensional risk assessment framework, as suggested by industry standards and empirical research. Yet, some areas—particularly those involving subjective factors like minimum payments and new credit usage—still exhibit interpretative divergence, suggesting a continued need for standardization, training, and financial literacy reinforcement to improve consistency in credit evaluations across institutions.

Level of risk intelligence of financial institutions in the Province of Laguna

The result shows the highest mean of 3.37 and a standard deviation of 0.52, stating that credit scoring helps the institution strike an optimal balance between risk-taking and financial stability. This finding highlights credit scoring as a key tool for minimizing default risk while allowing institutions to extend credit to viable borrowers. It's even more clear how important credit scores are now that Basel III rules say that lending decisions must be based on risk assessment frameworks (Basel Committee on Banking Supervision, 2010). The institution with the lowest mean (2.97) and highest standard deviation (0.71), on the other hand, is more willing to take risks and lose money in order to make more money. This contrast with modern portfolio theory (Markowitz, 1952), which says that you should balance risk and return instead of rushing to make money at the expense of stability.

Findings show that financial institutions are very good at managing risk, especially when it comes to using credit scores to control their risk appetite Altman (2020) as shown by the mean of 3.23 and the standard deviation of 0.42. While Acharya (2007) stated that financial institutions recognize the need for risk-taking to generate returns, they adopt a measured and strategic approach, adjusting their risk tolerance based on credit scoring trends, borrower behavior, and market conditions. The results also support the risk-return tradeoff principle, which says that higher returns come with higher risks. However, financial institutions are not overly risk-seeking, as shown by the fact that they are cautious about taking losses in order to get higher returns. As a result of these new findings, credit assessment is even more important for making sure that financial institutions can keep growing while protecting themselves from credit defaults and changes in the economy.

Significant relationship between credit scoring and risk intelligence

According to the data, Payment History, Amount Owed, Length of Credit, as well as Credit Mix all significantly correlate with multiple resiliency indicators. This affirms their importance in institutional decision-making processes and in determining the risk management and response

behavior of financial institutions. The above mentioned decision-making variables will have a substantial potential for building strong and dynamic risk strategies, which indicates that these institutions should value credit behaviors with consistent patterns and historical performance that calibrate the risk frameworks for the institutions.

On the contrary, New Credit showcases only partial significance across the resiliency indicators. It shows relevance in some areas such as Risk Appetite, Risk Prediction, and Uncertainty. It does not show consistency across indicators of resiliency with respect to risk perception and risk learning, though. This suggests that new credit may indeed be the consideration influencing risk strategy in some cases, but it is unlikely to be essential in all instances regarding how institutions understand or adapt to risk.

Thus, these findings imply that institutions rely on a mix of quantitative credit constituents, particularly concerning payment history, debt levels, credit length, and credit mix, to inform risk decisions and hence develop resilience. This follows an existing discourse focusing on the fact that holistic approaches to credit assessment rather than one-dimensional approaches permit better risk predictions and better decision quality (Altman, 2018; Thomas, 2022). The application of various credit dimensions assists institutions in developing an understanding of borrower behavior and predicting potential risks, thereby allowing the formulation of resilient credit strategies in fast-evolving financial environments.

CONCLUSIONS

There is significant relationship between the credit scoring and risk intelligence on non-bank financial institutions in the Province of Laguna. This reject the initial hypothesis. This suggests that the following factors Payment History, Amount Owed, Length of Credit History, New Credit, and Credit Mix greatly affects the risk assessment of the NBFIs and validates the idea that robust credit scoring and analysis can enhance an institution's ability to anticipate and mitigate risk. Further, even with significant findings, additional studies may examine different populations (e.g., other regions or lending contexts) or explore moderating factors (e.g., economic cycles, regulatory changes) to ensure the generalizability and robustness of these results.

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