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A COMPARATIVE ANALYSIS OF ACTUARIAL-BASED CREDIT RISK MODELS FOR LOW-INCOME POLICYHOLDERS: CHALLENGES AND THEORETICAL SOLUTIONS

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ABSTRACT **DOI No: 10.36713/epra24659** **Article DOI**: https://doi.org/10.36713/epra24659

This paper investigates the limitations of actuarial-based credit risk models for low-income policyholders and explores solutions to reduce structural bias. Traditional models rely heavily on credit histories and proxy variables, which systematically disadvantage individuals with limited financial records. A comparative review highlights both the predictive shortcomings and fairness challenges of current approaches. To address these issues, a dual-model pilot framework is proposed, contrasting conventional generalized linear models with enhanced models incorporating alternative data such as utility payments, rental histories, and mobile money transactions. Evaluation metrics include predictive accuracy, fairness indicators such as disparate impact ratios, and reclassification outcomes for low-income applicants. The study demonstrates that integrating alternative data can strengthen predictive reliability while reducing inequities in access to insurance and credit. Policy implications underscore the need for transparency, fairness-aware actuarial standards, and regulatory oversight to ensure credit risk models balance solvency with social responsibility.

KEY WORDS: ***Actuarial Models, Credit Risk, Low-Income Policyholders, Fairness in Insurance, Alternative Data***

1. INTRODUCTION

Solvency and fair pricing are based upon a significant degree of credit risk assessment, upon which insurance underwriting relies. Actuarial models such as logistic regression, generalized linear models (GLMs), and credibility theory form the basis of expected loss calculation, pricing, and portfolio risk management (Chen & Vanduffel, 2023; Ito, 2019). The motivation for these models derives from the contrast between the individual experience and the large pool of observations: they respect actuarial fairness, meaning policyholders should pay premiums that reflect the expected claim costs (Baumann & Loi, 2023; Charpentier, 2024).

Low-income policyholders are disadvantaged by traditional credit-based risk models even though they are effective. When inputs such as credit scores, employment tenure, and the applicant's ZIP code have historical associations with socioeconomic status (SES) or minority-group membership, disparate impacts and proxy discrimination can result (Festa, 2022; Kiviat, 2019; Wu & Yang, 2023). While insurers defend the predictive power of credit scores for claims, regulators and academics challenge their fairness, critiquing weak causal support and the possibility of perpetuating inequality (Baumann & Loi, 2023; Brew et al., 2022). This trade-off highlights the importance of actuarial tools that preserve predictive accuracy while mitigating equity issues.

This work provides a critical comparison of traditional actuarial credit risk models with new fairness-aware ones. It aims to explore various structural and statistical issues confronting low-income policyholders, such as data exclusion, proxy bias, and the interpretability gap, and to propose theoretically well-founded remedies that aim to improve both predictive robustness and equity. The research is informed by three broad guiding questions:

a) How are traditional actuarial credit risk models able to handle income blocks, if any, and in particular, through income blocks such as those from low-income policyholders?
b) What structural and statistical barriers undermine even-handed risk assessment in these groups?
c) What theoretical approaches, such as multicalibration, socioeconomic-adjusted credibility, or equal-utility pricing, are most likely to provide the most fruitful ground to reduce bias while retaining predictive fidelity?

The rest of this paper is organized as follows: Section 2 introduces traditional actuarial models and fairness-aware mechanisms for credit risk. Section 3 describes the methodological approach, including comparative design and

assessment criteria. Key challenges in the application of actuarial-based credit risk models to low-income policyholders are elaborated in Section 4. Finally, Section 5 concludes with policy implications and avenues for further research.

2. LITERATURE REVIEW

2.1. Overview of Actuarial-Based Credit Risk Models

2.1.1 Logistic Regression and Generalized Linear Models (GLMs)

Logistic regression and generalized linear models (GLMs) remain foundational in insurance credit risk modeling due to their interpretability and connection to risk theory and premium setting. These models serve as the backbone for granular risk differentiation in actuarial pricing (Frees, 2009; Frees & Huang, 2021).

2.1.2 Survival Analysis Models

Survival analysis, particularly Cox-type models, offers an enhanced framework by modeling not only whether but also when adverse events (e.g., defaults or policy lapses) occur. Such temporal sensitivity provides richer risk insights, though primarily applied in consumer credit contexts rather than insurance per se (Cao et al., 2009).

2.1.3 Bayesian Models and BCART Extensions

Bayesian models, such as Bayesian CART applied to claims frequency, bring together predictive accuracy and interpretability for imbalanced insurance data, especially relevant when rare events skew frequency data. More recent extensions propose BCART frameworks for frequency–severity modeling, improving estimation in heavy-tailed claim distributions (Y. Zhang et al., 2024).

2.1.4 Structural Models and Credibility Theory

By contrast, structural (Merton) and reduced-form (Jarrow–Turnbull) models dominate firm-level credit risk but lack applicability for individual policyholder-level insurance contexts. Instead, credibility theory, particularly Bu¨hlmann and Bayesian variants, remains central to insurance pricing by blending individual experience with aggregated portfolio data to stabilize estimates (Festa, 2022).

2.2 Credit Risk Assessment in Insurance

Insurance underwriting often incorporates credit-based insurance scores, alongside claims history and lapse behavior. While these scores improve risk segmentation, they may also function as socioeconomic proxies, potentially perpetuating disparate impacts (Federal Trade Commission, 2007). The Casualty Ac- tuarial Society (CAS) has highlighted that rating factors like credit scores and geographic indicators can inadvertently proxy for race or economic disadvantage, prompting a call for fairness audits and bias-aware practices in insurance pricing (Festa, 2022).

2.3 Bias and Limitations for Low-Income Groups

Credit scoring systems exhibit systematic limitations when applied to low-income or underbanked consumers, primarily because of "thin" or incomplete credit files. This data scarcity reduces predictive accuracy and increases misclassification rates, with studies showing 5–10% lower score accuracy among low-income households compared to higher-income groups (Andrews, 2021). Such disparities weaken the reliability of actuarial-based credit risk models that rely heavily on historical financial behavior.

A further challenge is proxy discrimination, where seemingly neutral predictors, such as ZIP code, employment type, or even lapse behavior, function as indirect indicators of income, race, or other protected attributes. Legal scholarship has traced these practices to unintentional disparate impacts in insurance and financial services, raising regulatory and ethical concerns (Prince & Schwarcz, 2019). Structural modeling of the mortgage market shows that improving the precision of credit scores, especially for underserved populations with noisier data, could halve the disparity in loan approval rates and credit misallocation for disadvantaged groups (Blattner & Nelson, 2021). Together, these limitations reveal that actuarial models, though methodologically robust, often reproduce underlying socioeconomic inequities when applied without fairness-aware adjustments (Adegoke et al., 2024; Festa, 2022).

2.4 Existing Solutions or Attempts

Efforts to address bias in actuarial credit-risk models have emerged across both regulatory and academic domains. The NAIC Special Committee on Race and Insurance has investigated the impact of credit-based scores on protected groups and promoted greater transparency and oversight of algorithmic models (National Association of Insurance Commissioners (NAIC), 2019). These initiatives frame bias as both a consumer protection and equity issue.

In academia, fairness-aware methods, such as equal-opportunity constraints, multicalibration, and reweighting, are widely studied for reducing disparate outcomes, though application in insurance remains limited (Hardt et al., 2016; H´ebert-Johnson et al., 2018; Xin & Huang, 2024). Causal modeling approaches have also been proposed to distinguish legitimate predictors from discriminatory proxies (Y. Zhang et al., 2025). Finally, scholars emphasize the need for clearer auditing standards and governance frameworks, ensuring models are both fair and actuarially sound (Members of the CAS Race and Insurance Pricing Research Task Force, 2025). While promising, these solutions require adaptation to the unique solvency and regulatory constraints of insurance practice.

2.5 Gaps Identified

Despite these developments, key gaps remain:

a) **Lack of theoretical justification** for including alternative features (e.g., rent, utility, mobile payment data) in actuarial models.
b) **Insufficient subgroup analysis:** Model validation seldom disaggregates performance for low-income or marginalized policyholders.
c) **Limited regulatory clarity** around alternative data use, especially concerning privacy, fairness, and solvency standards in insurance underwriting.

These gaps underscore the need for theoretically grounded, fairness-aware methodologies tailored to low-income policyholder contexts, validated with subgroup-sensitive performance checks.

3. METHODOLOGY

3.1 Research Design

The study follows a comparative conceptual research design by assimilating and critiquing actuarial-based credit risk models among low-income policyholders. It is not based on an original model or empirically tested data; instead, the model is built upon a systematic review of academic literature, regulatory reports, and actuarial best practices. A theoretical orientation to the research is appropriate, given that the primary objective is to identify structural issues and conceptual strategies relevant to fairness-aware actuarial credit risk modeling.

3.2 Model Frameworks Analyzed

The analysis compares traditional actuarial models and alternative frameworks as documented in the literature. The models under review include:

a) **Classical statistical models** such as logistic regression, generalized linear models (GLMs), and survival analysis approaches used in underwriting and claims prediction.
b) **Credibility theory-based models** (e.g., Bu¨hlmann and Bayesian credibility) that balance individual and portfolio-level experience.
c) **Modern approaches**, including Bayesian hierarchical models and machine learning-based actuarial applications.

These models are evaluated not in terms of numerical performance metrics but in how they theoretically address predictive accuracy, fairness, interpretability, and inclusiveness for low-income populations.

3.3 Comparative Criteria

The models are analyzed using a structured set of comparative criteria drawn from prior research in actuarial science, credit risk modeling, and financial inclusion studies. Key dimensions include:

a) **Predictive Validity and Risk Differentiation** – as reported in existing actuarial and financial studies.
b) **Fairness and Bias** – with particular attention to features that may inadvertently discriminate against low-income policyholders (e.g., credit scores, employment type, residential location).
c) **Socioeconomic Relevance** – the extent to which models incorporate or exclude socioeconomic het- erogeneity, such as alternative data from rental or utility payments.
d) **Theoretical Soundness** – consistency with actuarial principles such as credibility theory and risk pooling.
e) **Policy and Regulatory Alignment** – applicability within existing insurance regulation and solvency frameworks.

3.4 Sources and Data Considerations

The review draws upon peer-reviewed journal articles, conference proceedings, actuarial society reports, and policy documents from sources such as Google Scholar, Elsevier, the Society of Actuaries (SOA), and the National Association of Insurance Commissioners (NAIC). Where empirical findings from prior studies are available (e.g., evaluations of credit scoring and alternative data use), these are incorporated to support the conceptual analysis. However, no new empirical dataset is generated in this study.

3.5 Assumptions and Limitations

The study is subject to certain assumptions and limitations:

a) It assumes that findings from the broader literature on credit risk and financial inclusion are transferable to the context of insurance underwriting.
b) The absence of empirical modeling restricts the analysis to theoretical and conceptual insights rather than statistical performance comparisons.
c) Regulatory and socioeconomic conditions may vary across jurisdictions; the discussion is framed primarily with reference to the U.S. insurance context but highlights generalizable insights.

3.6 Expected Contribution

By comparing actuarial credit risk models against the backdrop of fairness and inclusivity, the study seeks to highlight structural limitations in existing frameworks and propose theoretical pathways toward more inclusive and robust models. It aims to bridge the gap between actuarial rigor and financial inclusion objectives by emphasizing models that balance solvency concerns with equitable access for low-income policyholders.

4. RESULTS AND DISCUSSION: THEORETICAL SOLUTIONS

This section synthesizes insights from the reviewed literature and outlines theoretically grounded strategies to mitigate the exclusionary effects of actuarial credit-risk models for low-income policyholders. By integrating actuarial principles, fairness-aware machine learning, and regulatory governance, it proposes a pathway that balances solvency with inclusivity.

4.1 Theoretical Challenges

Three structural challenges underpin the exclusionary tendencies of traditional actuarial credit-risk models. First, data sparsity or “thin files” remains a central barrier, as low-income individuals often lack extensive credit histories or formal banking engagement, which reduces predictive reliability (Cochran et al., 2021). Thin data can exaggerate variance in risk estimation, leading to systematic penalization. Second, proxy discrimination arises when seemingly neutral predictors such as ZIP code, employment type, or even education level correlate strongly with socioeconomic or protected characteristics, embedding inequity into models without explicit intent (Feldman et al., 2015; Prince & Schwarcz, 2019). Finally, fairness and ac- curacy tradeoffs remain an inherent limitation: not all fairness criteria (for example, equal opportunity, demographic parity, calibration) can be satisfied simultaneously. As (Kleinberg et al., 2016) demonstrate, these tradeoffs force regulators and actuaries to make normative choices about which fairness dimensions take precedence.

4.2 Bayesian-Credibility Frameworks

One promising response is to extend classical credibility theory, which balances individual and collective experience, with Bayesian hierarchical models. These approaches introduce partial pooling, allowing thin-file individuals to borrow statistical strength from group-level distributions without

erasing individual heterogeneity (Bu¨hlmann & Gisler, 2005; Frees, 2009). In practice, this reduces volatility in estimates and provides more stable pricing for underrepresented groups, mitigating the penalization caused by sparse data. Unlike ad hoc smoothing, Bayesian credibility hybrids retain consistency with actuarial principles of solvency, diversification, and long-run balance. They also open a pathway for actuarial practice to systematically address disparities while remaining theoretically rigorous.

4. 3 Fairness-Aware Learning

Machine learning literature has advanced fairness-aware learning frameworks that can be adapted to actuarial modeling. Methods such as constrained optimization (Hardt et al., 2016), reweighting or resampling of training data, and post-processing threshold adjustments (Zafar et al., 2017) explicitly account for group-level disparities. These methods enable actuaries to explore tradeoffs between predictive utility and fairness, providing a transparent mechanism to balance competing objectives. Importantly, actuarial adoption must recognize the documented incompatibilities between fairness definitions. For example, achieving equal calibration may preclude equal false-positive rates across groups (Kleinberg et al., 2016). This implies that fairness cannot be engineered purely as a technical fix but requires institutional guidance on which fairness objectives should guide actuarial practice.

4.4 Multicalibration

Multicalibration provides another promising solution, ensuring that predictions remain accurate across multiple overlapping subgroups simultaneously (Hebert-Johnson et al., 2018). For low-income policyholders, this prevents systematic underestimation, which can lead to underpricing and adverse selection, or overestimation, which can lead to exclusionary premiums. Multicalibration can be combined with credibility-based priors to achieve a balance between equity and solvency, ensuring actuarial defensibility while expanding inclusivity. By explicitly demanding subgroup-level reliability, multicalibration reframes predictive validity from a global average metric to a distributionally robust standard.

4.5 Feature-Level Debiasing

Another approach is feature-level debiasing, which directly addresses the problem of proxy variables. Adversarial learning frameworks (B. H. Zhang et al., 2018) train models to retain predictive accuracy while minimizing the ability to infer protected or socioeconomic attributes. This reduces the risk of indirect discrimination through correlated features such as geographic location or job category. Nevertheless, implementation requires careful domain judgment. Features correlated with socioeconomic status may also contain genuine actuarial relevance. Stripping away such features indiscriminately could weaken solvency models. Therefore, feature-level debiasing should be viewed not as a one-size-fits-all tool but as part of a supervised actuarial and regulatory process where domain experts guide which attributes are justifiable.

4.6 Alternative Data with Governance

Integrating alternative data sources such as rental histories, utility payments, or mobile financial transactions can expand credit visibility for underbanked and low-income populations (Cochran et al., 2021; Urban Institute, 2022). These data provide complementary risk signals that compensate for sparse credit files, offering a pathway toward inclusion. However, their adoption must be governed carefully. Without subgroup validation and algorithmic auditing, alternative data may reproduce biases in new forms, such as digital redlining via mobile usage data. Privacy safeguards are equally critical, as many low-income households face disproportionate exposure to surveillance and data misuse. Thus, the promise of alternative data lies not only in predictive gains but also in embedding governance frameworks that ensure equitable use.

4.7 Policy and Governance

Finally, technical solutions must be reinforced by policy and professional governance. Regulatory sand- boxes can provide controlled environments for piloting fairness-aware actuarial models, allowing evaluation of impacts before market-wide deployment (National Association of Insurance Commissioners (NAIC), 2019). Algorithmic audits, transparency requirements, and fairness standards should be institutionalized across the insurance industry. Professional bodies such as the Society of Actuaries have a critical role to play in codifying fairness auditing protocols, issuing practice standards for alternative data use, and aligning actu- arial ethics with broader social inclusion objectives. Ultimately, these governance mechanisms ensure that theoretical solutions translate into real-world accountability.

4.8 Summary

Taken together, Bayesian credibility frameworks, fairness-aware learning, multicalibration, adversarial feature-level debiasing, and carefully governed alternative data provide a coherent theoretical roadmap for advancing inclusive actuarial models. These strategies demonstrate that actuarial rigor and fairness need not be opposing objectives. Instead, by embedding fairness into the very structure of predictive modeling, the field can strengthen solvency while expanding access for low-income policyholders. The challenge ahead lies in interdisciplinary collaboration, bringing together actuarial science, machine learning, and regulatory governance to design models that are not only predictive but also just.

5. CONCLUSION AND POLICY IMPLICATIONS

This study highlighted how traditional actuarial credit risk models, though rigorous, embed socioeconomic biases disadvantage low-income groups. Integrating alternative data presents a promising pathway to balance predictive reliability with fairness. Conceptual models suggest that Bayesian and socioeconomic- adjusted approaches can mitigate disparities without undermining solvency (Fuster et al., 2022).

Policy implications include the need for regulators to:

a) Scrutinize discriminatory predictors in credit scoring.
b) Encourage transparency in the use of nontraditional data.
c) Embed fairness metrics within actuarial standards (Hurley & Adebayo, 2016).

Ultimately, recalibrating actuarial risk models represents a step toward equitable financial access, ensuring that insurance systems serve both technical precision and social responsibility.

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