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When Culture Becomes A Credit Risk: What Lenders Are Getting Wrong

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Problem of practice

Credit decisions at lending institutions are expected to reflect a borrower's creditworthiness and ability to repay. Yet, credit officers routinely and subconsciously allow cultural biases based on caste, religion, ethnicity, or community to contaminate their loan decisions. Biased credit decisions can result in loan approvals to borrowers with poorer credit outcomes, rejection of creditworthy applicants, degraded loan performance, and lost returns. A study by Francesco D'Acunto, Pulak Ghosh, and Alberto G. Rossi shows that data-driven recommendations can reduce such biases and move lenders away from borrowers they may otherwise favour because of shared cultural identity.[1] For credit risk leaders and lending managers, this implies that algorithmic recommendations should be used alongside human judgment to mitigate cultural bias and improve lending decisions

[1] The article 'How costly are cultural biases? Evidence from FinTech' by Francesco D'Acunto, Pulak Ghosh, and Alberto G. Rossi, featured in Volume 175 of the *Journal of Financial Economics*, examines how cultural bias affects peer-to-peer lending in India, finding that lenders favour borrowers from the same caste, religion, or ethnic group, resulting in higher defaults and lower returns, while robo-advice significantly reduces these biased choices

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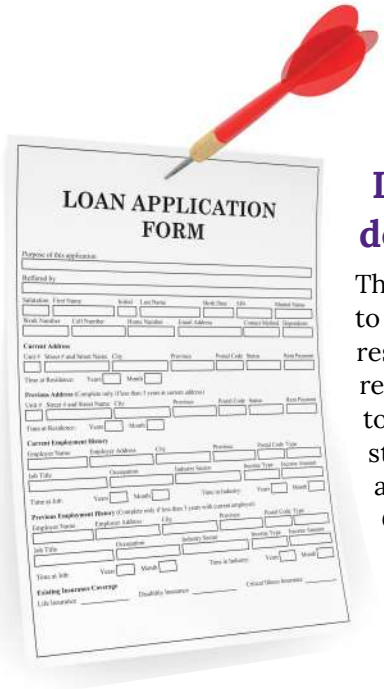
Bias at scale

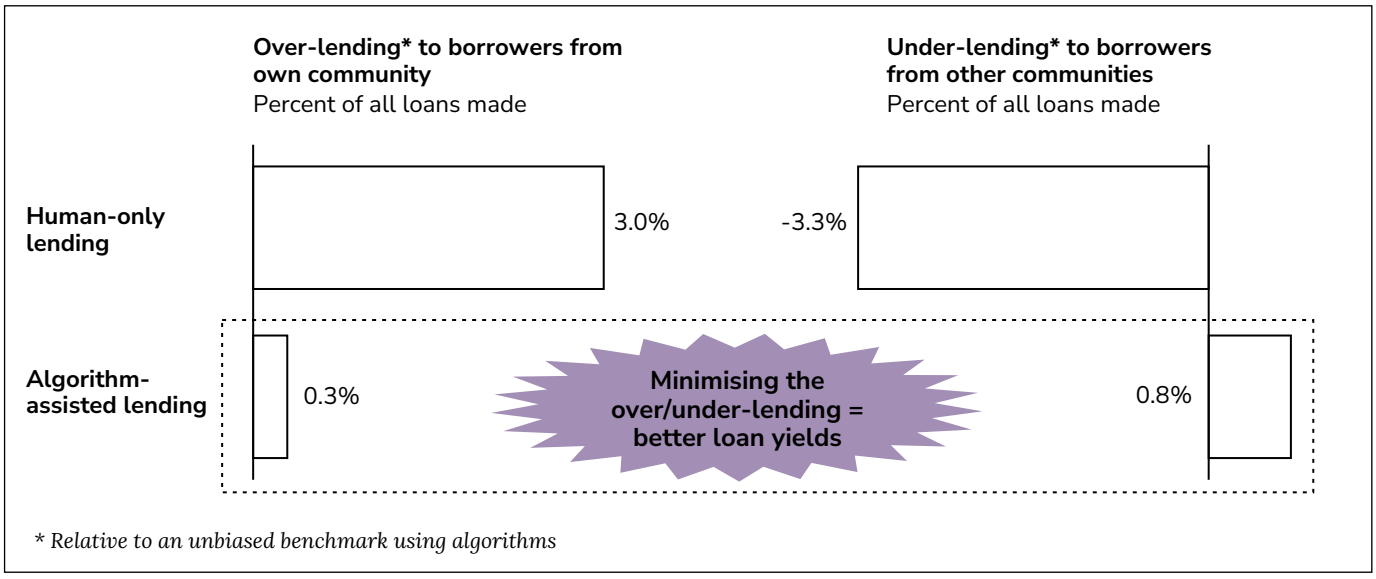
New consumer loans are a huge part of the global economy, totalling US$12 trillion in 2025.[2] The scale of lending makes even small distortions consequential. A US study analysed millions of mortgage loan decisions and found that algorithmic lenders — those using automated underwriting — charged Black and Hispanic borrowers significantly less in excess interest rates than traditional face-to-face lenders did.[3] The human element in lending, it turned out, was where bias entered most powerfully. This story repeats in other markets, for instance, in India and the United Kingdom.[4,5] This is despite the apparent rigour of credit checks across large consumer finance companies. Even though financial institutions build risk models, review credit scores and solvency ratios, the final lending decision often rests with an individual. This loan underwriter may naturally rely on mental shortcuts when making decisions, especially under uncertainty and time constraints, according to behavioural finance research.[6] As a result, lending decisions are influenced not only by formal financial metrics and objective measures but also by a borrower's personal beliefs and socially shaped impressions of their credibility. Repeated bias across a large loan portfolio can translate into missed lending opportunities, poorer borrower selection, and lower returns. The gains can be significant – an Indian study showed a reduction in loan delinquency of more than 21%, while maintaining approval volume and inclusivity.[7]



De-biasing the credit decision

The obvious question, then, is how to reduce the lender's bias. The research by D'Acunto and team reveals that a data-driven approach to making lending decisions – with strong safeguards, preparation, and human oversight – can help. Case in point: A study of Faircent, an Indian peer-to-peer lending platform, showed that when investors relied on their own judgment, they favoured borrowers from the same cultural background. Though loans to borrowers from their own community had 8% higher default rates and 7.3% lower returns than comparable loans to borrowers from other communities. **Figure 1** explicitly shows that, before auto-invest, lenders lent less than the unbiased benchmark to borrowers from communities other than their own (out-group). Similarly, the lenders overallocated to borrowers from their own community (in-group). The axis in each bar chart represents the unbiased benchmark, i.e., what the allocation would look like if decisions were purely based on financial merit.

Figure 1: Lending to in-group vs out-group borrowers – Before and after robo-advice (auto-invest)



Source: Adapted by the author from D'acunto, Francesco, Pulak Ghosh, and Alberto G. Rossi. "How costly are cultural biases? Evidence from FinTech." Journal of Financial Economics 175 (2026): 104202

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When the insight works

Recommendation by D'Acunto et al is most useful for institutions where (a) individual human discretion is essential in loan approval, (b) the pool of borrowers is socially diverse, and (c) there is enough historical loan performance data to create or use algorithmic scoring tools. These conditions are widespread among emerging market commercial banks, NBFCs, and fintech lenders. When such conditions apply, financial institutions can improve portfolio returns by using bias-correction tools.

Lenders who have replaced gut-feel decisions with algorithmic checks are already seeing the benefit. In the US, lending platform Upstart's model was tested by the Consumer Financial Protection Bureau and approved 27% more applicants than a traditional model, at an average interest rate 16% lower.[8] These gains held across race, gender, and age groups. In Kenya, the mobile lender Tala has disbursed over US$2 billion in loans, with a repayment rate above 90%, by scoring people on their actual financial behaviour rather than on where they come from.[9] Branch, which operates in Kenya, Nigeria, India, Mexico, and Tanzania, has disbursed 15 million loans worth US$350 million on the same principle.[10]

3 Points to stronger lending

1. **Bias audit:** We recommend reviewing loan approvals, interest rates, and defaults across various borrower classes, accounting for financial factors. Finance leaders and credit risk managers should analyse the data to uncover discrepancies in approval rates, pricing, or loan performance across categories such as age, geographic location, and community membership. Any discrepancy should trigger a deeper investigation into whether non-financial factors are influencing decisions.
2. **Reframe the bias as a performance issue:** Bias correction should not be seen as a compliance or diversity exercise, as this tends to make credit teams





defensive, leading them to believe they are doing their jobs well. So, rewrite the narrative in terms of performance and results. With each biased approval that results in a default, there are lost earnings opportunities. Similarly, each creditworthy applicant rejected for non-financial reasons is an opportunity the lender misses.

Repeated bias across a large loan portfolio can translate into missed lending opportunities, poorer borrower selection, and lower returns

3. **Redesign decision-making process:** It is not about adding objective, data-based assessments after the first impression; rather, the assessments should begin at the start. The point is about sequencing – algorithmic inputs are more effective at influencing decisions when they help shape them, rather than serving as an after-the-fact explanation for decisions made intuitively. Customer Relationship Management systems should be configured to deliver credit data before a human decision is made: An approach that allows for human judgment with objective inputs.

Rethinking the human in credit

Over the last decade, financial decision-making has gradually shifted towards automation. In several developed markets, algorithmic systems are now routinely used in areas such as equity trading, insurance underwriting, and mortgage lending. However, in SME and personal lending in emerging markets such as India, this shift is still underway.

Human judgment continues to play a significant role, even as technological tools gain prominence. Human judgment has a unique capacity to understand context, assess character, and factor in qualitative signals that a risk model cannot capture. This capacity is frequently invoked to resist the shift toward automation. Not all resistance is wrong. In genuinely ambiguous situations, human judgment is valuable.

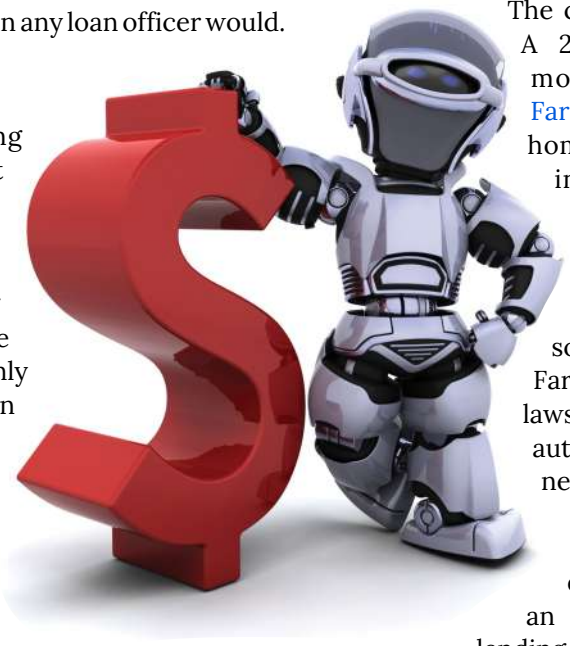
For most lending institutions, advanced risk management tools may not be machine-learning or AI-based credit appraisal models. Instead, they may be methodical, honest reviews of loan approvals, terms, and performance. That look, and the fundamental decision-making adjustments, could be a credit risk function's highest-return investment that year.

However, algorithmic credit lending may not be relevant in two particular situations. First, relationship-based

lending models, such as Grameen Bank's group lending method, intentionally use social proximity and community accountability as substitutes for collateral.[11] In this case, cultural familiarity serves a real economic purpose: it lowers the cost of monitoring and encourages people to repay their debts through peer pressure. Removing this social component would be inconsistent with the model's design.

Second, the algorithm itself can reinforce existing biases. Organisations should not train algorithms on historically biased lending data. Any algorithm trained using such discriminatory information will exacerbate that bias even more quickly than any loan officer would.

Costs and benefits



The costs of implementing the changes above are modest compared to the gains. McKinsey's 2025 banking research shows Artificial Intelligence is already cutting costs for banks that move past the pilot stage — but only for those who first invest in clean data, governance, and explainability, and not just the model.[12] A lending team's true expense is not the software; it is staff retraining and ongoing bias tests. Considering that Upstart has improved its approval rate by 27% and Branch has safely lent US$350 million, this is a fair trade-off.[13,14]

Algorithmic credit lending may not be relevant in two particular situations:

1. Relationship-based lending models intentionally use social proximity and community accountability as substitutes for collateral
2. The algorithm itself can reinforce existing biases

The cost of not fixing this can be steep. A 2022 Bloomberg analysis of US mortgage data found that Wells Fargo approved only 47% of Black homeowners' refinance applications in 2020, compared with 71–72% nationally — the worst gap of any major lender that year, which the US consumer finance regulator called "digital redlining, disguised through so-called neutral algorithms".[15] Wells Fargo is now facing a class-action lawsuit in which plaintiffs allege that its automated underwriting system used neighbourhood-level risk factors that closely tracked race. If that turns out to be true, it is exactly the danger this essay flags elsewhere: an algorithm trained on old, biased lending data can lock in discrimination rather than remove it.

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