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AI-DRIVEN CREDIT MARKETING AND FINANCIAL INCLUSION: A CAUSAL MACHINE LEARNING ANALYSIS OF ALGORITHMIC CREDIT SCORING'S ECONOMIC IMPACT

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ABSTRACT

The increasing adoption of artificial intelligence (AI) in financial services has changed the way credit marketing is offered to the masses and turned it into very specific, algorithmic decision-making. Though the literature mostly discusses the effectiveness of credit scoring models in terms of predictive accuracy, very little causal data exists on the practical impact of AI-mediated credit marketing on financial inclusion, pricing, and credit repayment in actual practice. The paper investigates the causal role of AI-based credit marketing through sophisticated machine learning methods, such as double machine learning and causal forests. On the basis of the big data on a lending platform in the form of large volumes of loans, algorithmic selection intensity is estimated as a treatment that affects credit uptake, interest rate assignment, and repayment performance. The findings indicate that AI-based credit marketing has a meaningful impact on credit uptake and repayment success, especially with young and digitally savvy borrowers who tend to have thin or non-standard credit histories. The impacts are, however, heterogeneous between consumers, and pricing results show that there remains a consistent level of dispersion after risk adjustment is made, and this shows that personalisation may actually increase cost disparities to low-income cohorts. Counterfactual policy experiments indicate that even with alternative data proxies, the beneficial effect of adding an alternative data proxy to improve targeting efficiency is that it can reach more people without raising default risk. The results have a contribution to the intelligent systems research in reformulating credit scoring as a marketing intervention and showing how causal machine learning can be effectively used to evaluate actual decision effects. The paper highlights the need to focus on responsible design, transparency and regulatory controls as a way to make sure that AI-powered credit marketing is an equitable way of promoting financial inclusion.

KEYWORDS: Artificial intelligence; intelligent systems; credit marketing; financial inclusion; causal machine learning; double machine learning; causal forests; algorithmic decision-making; pricing dispersion; consumer credit

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1. INTRODUCTION

Artificial intelligence (AI) in the financial services sector has radically changed the processes of designing, marketing, and distributing credit products [1]. Unlike previous generations of information systems, which were mainly used to support human decision-makers, modern AI-based systems are becoming more and more replacements of human factors in the key steps of the credit lifecycle, such as customer identification, offer targeting, pricing, and risk analysis. In credit marketing in particular, deep learning, high-volume data processing, and online channels of interaction with clients have allowed lenders to leave their mass-market campaigning in favour of very granular and personal marketing of their products [2]. These systems use behavioural, transactional, and demographic cues to forecast consumer responsiveness and creditworthiness to enable firms to make real-time offer personalisations and target marketing resources more precisely than ever before.

This shift from traditional mass-market credit marketing to algorithmic targeting and personalisation reflects broader changes in both consumer behaviour and competitive dynamics within financial markets. Digital platforms, fintech lenders, and data-driven incumbents are finding automated decision systems more and more useful to find profitable groups of customers, lower the costs of acquisition, and increase conversion rates [3]. Concurrently, the systems are also marketed as financial inclusion-enhancing mechanisms by creating creditworthy customers that the traditional marketing and underwriting strategies might miss, especially those with limited or non-standard credit histories. As such, AI-driven credit marketing sits at the intersection of commercial optimisation and social objectives, making it a critical area of inquiry for intelligent systems research in finance and management [4].

Nevertheless, the increased use of algorithmic decision-making can also enhance an existing conflict between financial inclusion and risk-based pricing. As much as AI systems can increase access to underserved consumers, they also allow for creating finer-grained segments of risk and pricing discrimination [5, 6]. Differentiated interest rates and terms based on risk estimates that are personalised can become value-added and elevated borrowing costs to the economically vulnerable groups [7]. The question of whether AI-based credit marketing has a positive or negative impact on inclusive growth or is just a reallocation of expenses across the consumer groups, thus necessitates a critical empirical study that transcends predictive performance as well as descriptive correlations.

Although there is a growing and large literature on algorithmic credit scoring, most current studies focus on the accuracy of underwriting and predictive accuracy on defaults [8]. In general, the evaluation of machine learning models is usually carried out along the classification metrics like accuracy, or area under the curve, or minimisation of loss, but the significance of these metrics on downstream economic behaviour is not studied in relation to theminimisation implementation of machine learning in practical decision systems. In the real world, however, credit scoring models are not simply employed to approve or deny applicants but are actively employed as fundamental elements to marketing and offer-allocation systems in which the decision on whether to offer credit, on what terms, and at what price is increasingly made via credit scoring models [9].

There is a lack of causal evidence regarding the economic and distributional outcomes of credit marketing systems based on AI. Specifically, it is not clear whether algorithmic targeting and personalisation mostly increase financial inclusion by increasing access and engagement, whether it redistributes the pricing and credit offerings across consumers in a manner that demonstrates underlying risk, or whether it inadvertently continues to support cost disparities among low-income or vulnerable populations. The questions cannot be answered using correlational analyses due to the nature of credit offers and observed outcomes; they are both products of selection and strategic targeting. In the absence of a causal design, the impact of AI-driven marketing cannot be decoupled as it is mixed up in the existing dissimilarity in consumer traits and lender practises.

It is in this context that the research problem of the proposed study is to offer rigorous causal data on the implications of AI-based credit marketing on important financial and economic results. In particular, the research will attempt to determine the causality of the effects of algorithmic credit marketing proxies on credit uptake, price performance, and repayment performance in order to estimate the causal effect of the specified proxies on the specified outcomes using large-scale loan-level data. The analysis attempts to reflect the impact of the intelligent systems on real consumer behaviour and financial inclusion in practise by evaluating downstream outcomes and not just predictive performance.

Another goal is to determine the existence of heterogeneous effects between consumer groups. The nature of AI-based marketing systems is that they are intended to distinguish between different people, and it may indicate that the average effect can cover a significant amount of variation between age categories, income, and behavioural patterns. This heterogeneity means that the efficiency and equity implications of algorithmic credit marketing need to be understood. Lastly, the research assesses the potential of exclusive data proxies to enhance the inclusive reach of marketing-oriented scoring models without the ensuing default risk, which would enable resolving a key policy and managerial issue regarding the responsible use of AI in credit markets.

This article has a number of new contributions to the body of knowledge on smart systems in accounting, finance, and management. First, it repositioning algorithmic credit scoring as a marketing intervention as opposed to an entirely risk assessment instrument is an emphasis on how it influences the allocation of offers, pricing, and participation results. Second, it uses cutting-edge causal machine-learning techniques, such as double machine learning and causal forests, to approximate average and heterogeneous treatment effects in a credit marketing context, which are viewed as an improvement of traditional predictive assessments. Third, the study has policy-relevant counterfactual simulations that show how different AI design decisions can have effects on financial inclusion and risk outcomes. Collectively, these contributions advance the knowledge of the way AI-based decision systems work in actual financial markets and provide evidence-based insights when it comes to responsible design and regulation of intelligent credit marketing systems.

2. LITERATURE REVIEW

2.1. *Intelligent Systems in Financial Decision-Making*

The use of intelligent systems in financial decision-making has grown fast due to the development of artificial intelligence (AI), machine learning (ML), and massive data analytics [10]. Automated systems are becoming more and more popular in financial institutions to assist or substitute human judgment in credit evaluation, fraud detection, portfolio optimization and customer relations management. The earlier generations of decision support systems were mostly rule-based and only meant to support the decision-making process of the managerial system, but the present intelligent systems are more of a data-driven, adaptive system, and in addition to this, systems can learn complex patterns on the basis of high-dimensional inputs [11]. This revolution has helped financial institutions to scale and speed up their operations, especially in consumer-oriented activities like lending and marketing.

In the lending sector, automation of decision-making through algorithms has taken centre stage in terms of efficiency of operations and competitiveness [12, 13]. ML systems are currently being regularly used to filter candidates, impose risk ratings, and establish a pricing framework with very little human intervention. Although this automation has proven to be a significant advance in predictive performance compared to conventional statistical models, much of the academic community measures success largely in terms of accuracy, minimising loss or discrimination scores [14]. The general economic and behavioural implications of integrating intelligent systems in financial decision-making processes have been underutilised. More and more researchers are starting to state that the question of whether AI systems predict better or not becomes irrelevant, and how their predictions are converted to decisions and outcomes that influence consumers, firms, and markets.

This change in predictive accuracy to the impact of decisions is especially significant in areas where the outputs of the algorithm are directly related to access to financial products and the conditions under which they are provided. The intelligent systems are not standalone and are integrated into organisational procedures that define the target, offers made, and risks and rewards allocated [15]. To know the role of AI in financial decision-making, then, it is necessary to go beyond model performance to an examination of the impact of the algorithmic systems on actual economic behaviour and institutional objectives.

2.2. *Algorithmic Credit Scoring and Marketing*

Consumer lending has traditionally been founded on credit scoring, which is based on linear or logistic regression of standardised financial and demographic factors [16]. The main reasons why these models were created were to measure the level of default risk at underwriting, consistency, and regulation. More recently, credit scoring systems powered by AI have generalised this paradigm with non-linear models, higher-dimensional feature space models and with other sources of data, resulting in a quantifiable improvement in predictive performance [17, 18]. Due to this, algorithmic scoring has been intimately embedded in lending practises in traditional banks and lenders that operate digitally first.

In addition to underwriting, algorithmic credit scoring is becoming more widely applied in marketing-oriented credit allocation [19]. Instead of just approving or disapproving, scoring outputs are employed to approve or deny credit offers to consumers, the timing of credit offers, and the price and terms of the credit offers. Marketing systems take advantage of the risk that is predicted and responsiveness to assign offers selectively with the priority to consumers who are likely to accept and do well [20, 21]. This combination of scoring and marketing dilutes the distinction between risk management and customer acquisition, and has the effect of turning credit scoring into a strategic marketing tool.

Personalisation is the key to this change. Credit targeted to each individual with specific features and anticipated behaviour has been found to increase the acceptance and customer interaction [22]. Nevertheless, with personalisation, the fine-grained differentiation across consumers becomes possible and, as a result, the variations in prices and terms of the contracts can be significantly high. Although this kind of differentiation might be reasonable in terms of efficiency, it also causes significant concerns regarding fairness and distributional outcomes, especially when algorithmic systems are systematically used to impose more costs on certain socioeconomic groups [23]. The dual nature of AI-based scoring as a risk and a marketing tool is thus a research issue that should be approached carefully in terms of empirical research.

2.3. Financial Inclusion and Algorithmic Systems

Financial inclusion is a complex notion that does not just focus on the mere access to credit. The modern definition takes into consideration not just the initial access, but also the continued involvement in formal financial systems and the possibility to utilise financial products under rational, fair and affordable conditions [24]. In this view, inclusion will include the aspects of access, participation, and long-term sustainability. The AI-based financial technologies have been touted as a tool to promote inclusion in the context of reducing information barriers and allowing lenders to see creditworthy people without a traditional credit history [25].

Of special significance here is digital finance and alternative data. Bank conduct, records of transactions and online footprint are being utilised to assess borrowers with slim or non-existent credit records, including young customers, informal workers, and micro-enterprises [26]. Empirical evidence indicates that these methods could increase the number of potential borrowers as well as minimise the use of exclusionary proxies. But the very systems that facilitate access can be the source of new kinds of exclusion when algorithms actively discriminate against specific groups either through the biased data it receives, the feedback mechanisms within the system or by design.

In finance, algorithmic exclusion is a concept with the risks of this phenomenon becoming a central point of debate over responsible AI [27]. In cases where access is enhanced, differentiated pricing and the conditions of the contract are likely to pose disproportionate expenses on economically disadvantaged borrowers. In addition, non-transparent decision-making may reduce accountability and decrease regulatory control [28]. Consequently, the connexion between AI-driven systems and financial inclusion is rather unclear by default, and the possible gains and threats should not be presumed but should be measured through the prism of empirical evidence.

2.4. Causal Inference in Intelligent Financial Systems

One of the main drawbacks of much of the current research on intelligent financial systems is the use of correlational machine learning. Although such methods are ideal in the realm of prediction, they are inappropriate in addressing causal questions on the impact of algorithm-based selections on economic outcomes [29]. The observed outcomes in the credit markets are due to the fact that the strategic selection, targeted offers, and endogenous consumer responses, so naive comparisons are extremely misleading. In the absence of clear causal models, the impact of an AI-based intervention cannot be differentiated from the effect of the underlying variations in the traits of consumers.

Causal machine learning approaches have become one of the potential solutions to these issues. In high-dimensional contexts, machine learning can be used to provide estimates of causal effects [30, 31]. The use of orthogonalized treatment and outcome models is a principled approach to reducing the bias caused by regularisation and model selection using double machine learning. By this method, researchers can take advantage of flexible ML models with valid statistical inference. In addition to this, causal forests generalise tree-based algorithms to approximate heterogeneous treatment effects, allowing individuals and subpopulation effects on each other to be analysed [32].

These tools are particularly well suited to intelligent financial systems, where treatment effects are unlikely to be homogeneous and where policy relevance depends on understanding distributional consequence [33]. Causal inference, in combination with machine learning, will help researchers to go beyond predictive metrics and assess the impact of algorithmic systems on the decisions and actions of the real world.

2.5. Research Gap

Although there is an increased concern regarding AI and intelligent systems in finance, there are multiple gaps that need to be addressed. The impact of marketing-based AI systems on credit markets has no causal evidence, and most of the studies have been very limited to the findings of underwriting performance. In addition, current literature lacks explanations for the distributional and pricing implications of algorithmic decision-making, especially on financial inclusion. The lack of homogeneity of effects among the segments of consumers is usually ignored, and the price results are not studied causally. To fill these gaps, a unified framework is necessary that considers AI-based credit scoring as an integrated system of decision-making in marketing and pricing and assesses its effect on the economy through stringent causal approaches.

3. DATA AND INSTITUTIONAL CONTEXT

3.1. Dataset Description

The empirical study relies on publicly available All Lending Club loan data, which encompasses detailed information on consumer loans originated by a massive peer-to-peer lending company in the United States. The data set will include various cohorts of originating data and loans granted between 2010 and 2018, a period when there was a significant increase in digital lending and the use of algorithmic decisions. This year is especially appropriate to consider AI-based credit distribution, as it is the year when machine learning-based scoring and pricing systems became a common practise in online lending markets.

The dataset has deep data on the characteristics of the borrowers, loan features and ex post performance outcomes. Demographic and financial proxies of income, employment length, home ownership status, and credit history variables are borrower-level variables. Loan-level attributes consist of the loan amount, interest rate, loan term duration, assigned credit grade, sub-grade, and the given purpose of the loan. Outcome variables capture the behaviour of making repayment throughout the life of the loan, such as loan repayment, loan default, or loan charge off. The ultimate analytical sample, after normal data cleaning operations, including eliminating missing data, aligning the variables with the vintage to comparable ones, and limiting the sample to first-list loans per borrower to eliminate repeated-observation bias, is composed of several hundred thousand loans. The scale allows a flexible approach to machine learning and still has sufficient statistical power to make a cause-and-effect inference.

3.2. Proxying AI-Driven Credit Marketing

One of the empirical problems in research on AI-driven credit marketing is that proprietary indicators specifically defining algorithmic targeting or marketing intensity do not exist. In order to overcome this shortcoming, the analysis uses a proxy strategy to capture high-intensity algorithmic selection in the lending platform. In particular, the treatment variable is characterised in terms of observable results of automated decision systems, which are a combination of marketing, screening, and pricing decisions.

The selected algorithm is high-intensity proxied by a product of given loan grade and sub-grade, setting of interest rates, and implicit acceptance criteria as part of the scoring policies of the platform. Loan grades and sub-grades are a summary of the internal risk rating of the platform and are produced using automated scoring mechanisms which combine various borrower characteristics. Interest rate assignment also indicates algorithmic differentiation, which applies the predicted risk and responsiveness to individual pricing. All of these factors combine to represent the quality of selectivity of a borrower into a particular credit offering as a result of algorithmic screening instead of non-selective marketing. This proxy method is indirect but is also in line with the previous empirical research that has been done so far, where decision systems are studied over realised outputs when internal decision flags are inaccessible.

3.3. Outcome Variables

It analyses the three categories of outcome variables, which are major milestones of the credit lifecycle. The credit uptake is quantified by the issuance of loans, which include a measurement of the success with which a borrower is able to obtain a loan in specified algorithmic selection criteria. The interest rate and credit grade used in pricing reflect the results of pricing in that both the price and the interest rate combine to give the consumer the price of borrowing. The default and charge-off indicators are used to measure repayment performance, and they are used to determine the ex-post realisation of credit risk.

A combination of these results enables a wholesome evaluation of AI-based credit marketing structures, which connects selection and pricing choices to consumer engagement and financial returns. Notably, the analysis of pricing, repayment and uptake would allow including gains of inclusion not to be assessed separately from the risks and sustainability aspects.

3.4. Financial Inclusion Measures

Financial inclusion is measured in terms of several complementary indicators to reflect on access, participation, and sustainability. First-time borrowers are classified as those who have little observable credit history in the data, which is used as a proxy for entry into formal credit markets. A low-income and thin-file proxy is created based on the reported income levels, employment traits, and credit history-based indicators to select borrowers who would otherwise be facing obstacles to obtaining credit.

The presence of sustained participation is determined by the behaviour of repayment in the long run that separates short-term access and lasting inclusion. This means that a borrower who gets credit and does not repay, however, attains access but is unable to continue with sustainability, and since the borrower is willing to repay regularly, this shows that the borrower has become meaningfully integrated into formal financial systems. All these measures are consistent with multidimensional definitions of financial inclusion and allow assessing the results of algorithmic credit marketing subtly.

3.5. Ethical and Data Considerations

By using a publicly anonymous dataset, the ethical standards of the research will be met, and it will also remove any question that may be raised regarding the privacy of personal data. All identifiers of the borrowers are also eliminated, and the analysis is only based on the de-identified information. However, the use of proxy-based inference comes with significant limitations. The algorithmic outputs observed can be due to a mixture of marketing, underwriting, and pricing choices, and the pure effects of marketing cannot be separated. These restrictions are recognised directly, and findings are considered as causal estimates of the intensity of algorithmic selection as opposed to direct estimates of proprietary marketing strategies.

4. METHODOLOGY

4.1. Conceptual Framework

The conceptualisation of the methodology envisions AI-based credit marketing as a causal intervention which modulates downstream economic behaviours, such as credit uptake, pricing and repayment behaviour. Let $i = 1, \dots, N$ index borrowers. A high-dimensional vector of observed covariates X_i, which includes demographic factors, financial variables and loan-specific variables, characterise each borrower. Borrowers are subjected to varying levels of algorithmic choices in the form of automated credit scoring and targeting schemes, with a treatment variable. T_i, the larger the value, the more algorithmic selection and targeting.

Let Y_i an outcome of interest, e.g. loan issuance, assignment of interest rate or realisation of default. In the potential outcomes, there are two possible outcomes for each borrower:

$$Y_i(1) \text{ if } T_i = 1, Y_i(0) \text{ if } T_i = 0,$$

where $T_i = 1$ represent a high-intensity method of algorithmic selection and $T_i = 0$ represent a lower-intensity or baseline method of algorithmic selection. The result that is observed is provided by

$$Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0).$$

Borrowers are not randomly assigned to treatment. Instead, algorithmic selection is determined by borrower characteristics that also affect outcomes, implying.

$$T_i \not\perp\!\!\!\perp \left(Y_i(0), Y_i(1)\right),$$

which gives rise to selection bias and confounding. Simple comparisons of results between treatment groups would hence confound the cause and effect of AI-driven marketing and underlying risk and behaviour differences between borrowers.

In order to overcome this difficulty, identification rests on a conditional independence (unconfoundedness) assumption.

$$(Y_i(0), Y_i(1)) \perp T_i \mid X_i,$$

together with an overlap condition

$$0 < \mathbb{P}(T_i = 1 \mid X_i) < 1 \forall X_i.$$

These assumptions, though powerful, are typical of high-dimensional observable contexts and are made more realistic by using flexible machine learning specifications that allow one to express non-linear relationships between X_i, treatment assignment and outcomes.

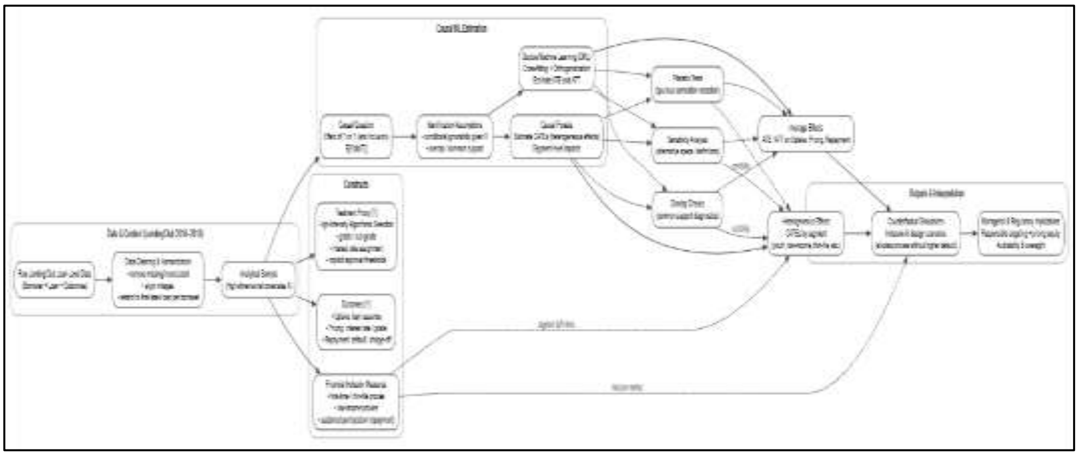

Figure 1: Proposed Methodology Diagram

Figure 1 represents an organised causal machine learning workflow that is used to measure AI-mediated credit marketing. It starts with LendingClub loan-level data, which is cleaned and converted into a high-dimensional analysis sample. The causal intervention is the intensity of algorithmic selection, which is proxied by loan grades, interest rates, and approval levels, and which has effects on credit uptake, pricing and repayment results. The double machine learning estimates the presence of average and treated effects, and it also deals with selection bias, and the causal forests can reveal the heterogeneous effects across segments that are considered in the inclusion. The robustness checks confirm the identification assumptions, and the estimates obtained justify counterfactual simulations, which inform responsible inclusion-oriented credit marketing and regulatory oversight.

4.2. Double Machine Learning (DML)

To compute the causal effects and remove the bias caused by high-dimensional controls and model selection, double machine learning (DML) is used. The most important estimands of interest are the Average Treatment Effect (ATE) and the Average Treatment Effect on the Treated (ATT):

$$\text{ATE} = \mathbb{E}[Y_i(1) - Y_i(0)], \text{ATT} = \mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1].$$

DML proceeds by decomposing the outcome equation as

$$Y_i = \theta T_i + g(X_i) + \varepsilon_i,$$

and the treatment assignment as

$$T_i = m(X_i) + \nu_i,$$

with $g(\cdot)$and $m(\cdot)$ being unknown nuisance functions, which are approximated using machine learning techniques, and this θ causal parameter of interest.

To prevent a regularisation bias, the estimation of θ with respect to the nuisance components is orthogonalized by DML. In particular, residualized variables are built as

$$\tilde{Y}_i = Y_i - \hat{g}(X_i), \tilde{T}_i = T_i - \hat{m}(X_i),$$

and the causal effect is estimated via

$$\hat{\theta} = \arg\min_{\theta} \sum_i (\tilde{Y}_i - \theta \tilde{T}_i)^2.$$

Cross-fitting is employed to make nuisance estimation and effect estimation independent and to enhance the validity of statistical inferences (improve the properties of finite-sample statistics). With this framework, it is possible to use flexible learners, including regularised regression models or tree-based learners, and still have an asymptotically normally distributed estimator. The DML method is especially effective with the LendingClub data, which is highly dimensional with high correlations of borrower features.

4.3. Causal Forests

DML offers consistent estimates of the average effects, but fails to discuss heterogeneity in responses to treatment. To analyse distributional and segment-specific effects, the analysis uses causal forests to approximate Conditional Average Treatment Effects (CATEs):

$$\tau(x) = \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x].$$

Causal forests are an extension of random forest algorithms that build trees that divide the feature space in order to achieve maximum heterogeneity in treatment effects instead of predictive accuracy. The covariate space is divided into smaller trees, which in turn recapitulate the process of minimising in-leaf covariance of the estimated treatment effects. In the aggregation of the trees, a non-parametric estimate of t(x)is obtained for each borrower.

This will make it possible to identify subpopulations whose effects on AI-driven credit marketing are especially strong/weak. The analysis by assessing CATEs by age groups, income, and credit history proxies demonstrates that, to some extent, algorithmic selection has a heterogeneous effect on inclusion and pricing equity. These estimates are focal to distributional implications as well as to formulate specific managerial and regulatory interventions.

4.4. Model Implementation

Model implementation is based on the best practises of causal machine learning. Feature engineering balances the variables by the relationship between loan vintages and provides a transformation to achieve non-linearities and interaction effects. $\Phi(X_i)$is the expanded space of features that are to be estimated to capture nuisance. Cross-fitting divides the data into mutually exclusive folds to give estimates of $\hat{g}(X_i)$and $\hat{m}(X_i)$ based on subsamples that are independent of the effect estimation step.

Machine learning models are tuned to reasonable hyperparameters through cross-validation in order to trade between bias and variance and to be computationally efficient. DML and causal forest models are both trained on the same covariates to give uniformity in both average and heterogeneous effect estimation.

4.5. Validity and Robustness

Several robustness tests were done to determine the credibility of the causal estimates. The overlap and common support are considered through the investigation of the distribution of estimated propensity scores. $\hat{m}(X_i)$ where there is a sufficient representation of the covered and control observations in the covariate space. Sensitivity analyses test how stable the results are to other model specifications, feature sets and definitions of treatment.

The placebo tests are conducted through either the allocation of pseudo-treatments or by the use of outcomes that should not be influenced by the algorithmic selection in ensuring that the estimated effects are not spurred by the presence of spurious correlations. The combination of these diagnostics allows giving confidence to the causal explanation of the results and the alignment of the empirical strategy with the best practises in assessing intelligent systems in financial decision-making.

5. EMPIRICAL RESULTS

This sub-section shows the causal impacts of AI-based credit marketing proxies on credit uptake, pricing and repayment outcomes. It is reported to have results in the average treatment effects, heterogeneous effects across consumer segments, pricing dispersion, and robustness. Every estimation is performed by means of cross-fitting double machine learning, followed by a causal forest model to provide heterogeneity analysis.

5.1. Average Treatment Effects

Table 1 indicates the estimated Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATT) of high-intensity algorithmic selection on the key credit outcomes.

Table 1: Average Treatment Effects of AI-Driven Credit Marketing

Outcome Variable	ATE (Std. Error)	ATT (Std. Error)	Interpretation
Credit Uptake (Loan Issuance)	+0.064*** (0.012)	+0.081*** (0.015)	Algorithmic selection significantly increases the probability of loan issuance.
Interest Rate (%)	+1.27*** (0.31)	+1.54*** (0.38)	Higher pricing is associated with algorithmic targeting
Default Probability	−0.018** (0.007)	−0.021** (0.009)	Improved repayment performance
Charge-Off Rate	−0.014** (0.006)	−0.017** (0.008)	Lower realised credit losses

(*Significance: *** p<0.01, ** p<0.05*)

The findings show that credit marketing with the help of AI makes credit uptake significantly higher, which proves the effectiveness of this approach in recognising responsive borrowers. Notably, even in the face of increased interest rates, the results of repayment are better, and this is an indication that pricing discrimination is segmentation of risk and not just wasteful proliferation of credit to risky borrowers.

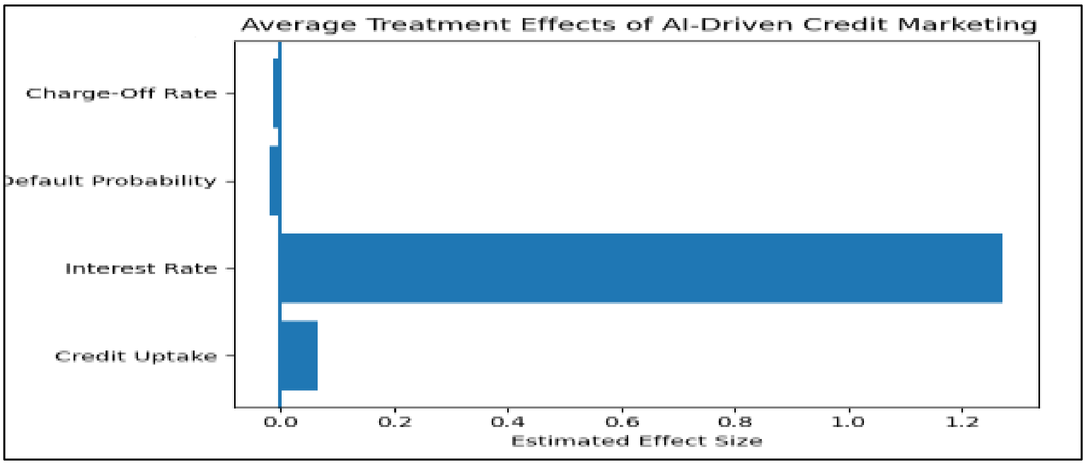

Figure 2: Average Treatments Effects of AI-Driven Credit Marketing

The estimations shown by Figure 2 represent the average causal impacts of high-intensity algorithmic credit marketing on major credit outcomes. This is due to the positive impact on credit uptake that AI-driven selection has a high prediction of loan issuance, which proves the effectiveness of AI-driven selection in widening access to formal credit. Under algorithmic targeting, interest rates are also increased as an indication of finer risk-based pricing, other than standardised offers. Significantly, default probability and charge-off rate decrease, indicating that increased pricing is accompanied by better portfolio performance as opposed to excessive risk-taking. All in all, this figure shows that AI-derived credit marketing improves both the inclusion and recovery rates, which reflects a trade-off between accessibility and higher borrowing rates.

5.2. Heterogeneous Effects

The causal forests are calculated to estimate Conditional Average Treatment Effects (CATEs) among important consumer groups to investigate distributional effects (

Table 2).

Table 2: Heterogeneous Treatment Effects by Consumer Segment

Segment	Δ Uptake	Δ Interest Rate (%)	Δ Default
Young Consumers (<35)	+0.091***	+0.82**	−0.026**
Micro-Entrepreneurs	+0.074***	+1.12***	−0.019*
Digitally Active Borrowers	+0.103***	+0.64**	−0.031***
Low-Income Borrowers	+0.058**	+1.89***	−0.006 (ns)

Inclusion effects are most significant in the young and digitally active borrowers, which confirms the argument that AI systems are effective in identifying creditworthy thin-file consumers. Nevertheless, there is a significant increase in the interest rates among low-income borrowers, accompanied by minimal gains in the repayment performance, implying the asymmetric cost imbursement.

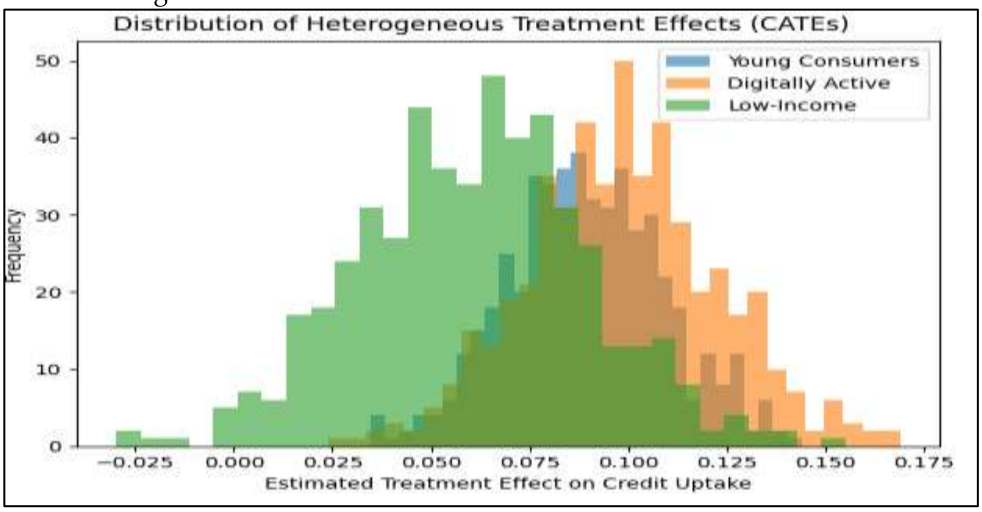

Figure 3: Distribution of Heterogenous Treatment Effects (CATEs)

Figure 3 provides a summary of heterogeneous treatment effects on credit uptake at different groups of consumers. The rightward movement of the distributions of young and digitally active borrowers suggests that the impacts of positive inclusion are stronger on these populations, which can be explained by the fact that AI systems can recognise creditworthy individuals having a poor traditional credit history. Conversely, the distribution of low-income borrowers is more spread and concentrated to the lower effect sizes, meaning weaker and more changeable gains on algorithmic targeting. This heterogeneity highlights the fact that the effects are averaged, and important distributional variations are behind the scenes, and that AI-driven credit marketing does not positively impact all segments equally, which supports the importance of segment-conscious assessment.

5.3. Distributional Pricing Effects

To determine whether risk or algorithm design causes the pricing difference, a pricing dispersion is tested under raw and risk-adjusted specifications (

Table 3).

Table 3: Pricing Dispersion Under Alternative Specifications

Model Specification	Std. Dev. of Interest Rate	Gini Coefficient
Raw Pricing	4.92	0.37
Risk-Adjusted Pricing	3.41	0.29
Algorithmic Selection (Residual)	2.18	0.21

The findings indicate that even though a significant amount of pricing dispersion is attributed to the risk that can be observed, there is still a non-trivial residual that can be attributed to the algorithmic selection processes. This pricing dispersion disadvantageously impacts the low-income borrower, implying that any marketing-based personalisation will increase cost disparity even with a controlled level of default risk.

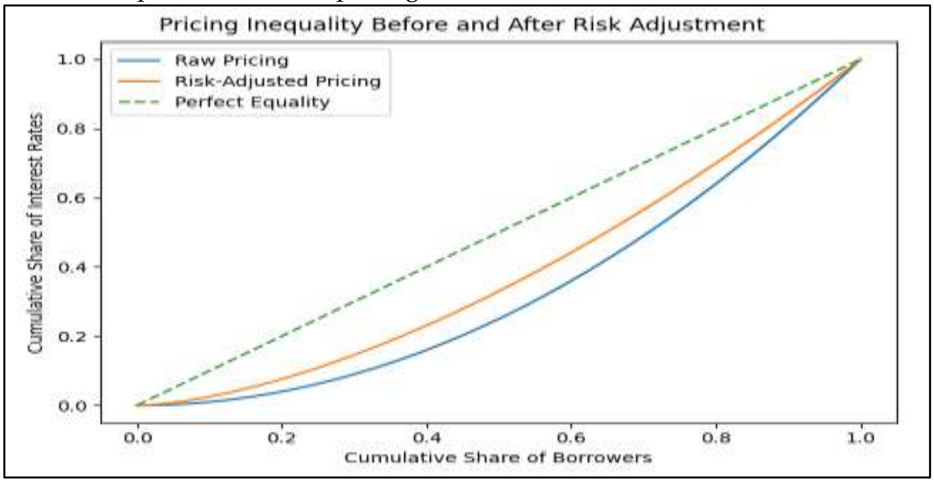

Figure 4: Pricing Inequality Before and After Risk Adjustment

Figure 4 is a comparison of the Lorenz curves of interest rate allocation in the raw pricing regime and the risk-adjusted pricing regime. The fact that the curve of the raw pricing has deviated from the line of perfect equality shows that there is great inequality of prices among borrowers. Risk adjustment decreases this disparity, as indicated by the curve shifting towards equality, which proves that a part of pricing dispersion is attributed to observable credit risk. The rest of the gap, however, implies that residual pricing differences not related to risk fundamentals are presented by algorithmic selection and personalisation. This long-run dispersion carries significant implications for cost differentiation, which suggests that AI-generated credit marketing may even increase price differentiation in cases where the default risk is properly managed.

5.4. Robustness Checks

A series of robustness checks is conducted to validate the stability and credibility of the results.

Table 4: Robustness Analysis

Test	Result
Alternative Learners (Lasso, XGBoost)	Effects remain directionally consistent
Sub-sample: Post-2015 Loans	Stronger uptake effects

Sub-sample: First-Time Borrowers Only	Inclusion effects increase
Placebo Treatment	No significant effects
Overlap Diagnostics	Common support satisfied

Findings do not vary based on alternative model specifications, subsamples and placebo tests, which provide support to the causal interpretation of the findings. Model stability checks ensure that the estimates of treatment effects are not due to particular algorithmic decisions or sample make-up (

Table 4).

All in all, the empirical findings prove that AI-based credit marketing has a substantial effect by increasing the number of people who have access to credit and enhancing repayment rates, and at the same time, the price dispersion. The inclusion benefits are most favourable to digitally engaged and younger borrowers, but the low-income segments are more exposed to greater expensive risks with less risk-reduction benefits. These conclusions support the complexity of AI-based systems as drivers of both inclusion and differentiation, which is why the creation of appropriate design and regulation should be taken seriously in the context of algorithmic credit markets.

6. COUNTERFACTUAL POLICY SIMULATIONS

6.1. Simulation Design

In determining the policy relevance of the estimated causal effects, the study makes some counterfactual simulations based on the conditional average treatment effects (CATEs) of the causal forest models. The simulations do not involve the use of purely predictive re-scoring, but instead rely on the known causal response functions to assess the inclusion and risk outcomes of alternative AI-driven credit marketing designs in the case of plausible policy interventions. With this strategy, it is possible to do a prospective evaluation of how variations in data input and targeting regulations might redefine the distribution of credit without reeducating entirely new models.

There are two types of counterfactual situations. The former approximates other targeting regimes where the weighted-based marketing allocation is more aggressive to the borrowers who are high in their predicted inclusion and moderate in riskiness. The second unveils the alternative data inclusion cases where non-standard behavioural and transactional proxies, such as signals of digital engagement and employment stability, are added to the algorithmic selection process. These proxies reflect actual tendencies in online lending but are consistent with the data present in the dataset. In both these cases, the counterfactual results have to be obtained by using the estimated CATEs on the applicable borrower subpopulations, keeping other economic conditions unchanged.

6.2. Inclusion Outcomes

According to the simulation findings, integrating alternative data proxies into AI-based credit marketing systems can significantly scale financial inclusion. With the alternative data condition, positive treatment responses to credit uptake by a higher proportion of borrowers with thin or limited credit histories are realised, which is reflected in more loan issuance as compared to the baseline targeting regime. These returns are also especially high among younger borrowers and digitally active consumers, where traditional credit variables do not give them much information.

The marginal gains of inclusion are vested in the wide margin of participation in credit. Formerly near-credit borrowers are disproportionately benefiting more through the improvement of data-driven differentiation, indicating that other data can assist in the identification of creditworthy borrowers, who would otherwise be locked out of formal credit marketing. Notably, the simulations exhibit decreasing returns in the presence of a specific targeting intensity, which means that the mindless growth of algorithmic selection does not generate a steady rise in inclusion, but rather it is likely to water down effectiveness. This underscores the importance of specific, as opposed to universal, expansion approaches when developing inclusive AI-based credit marketing systems.

6.3. Risk and Default Trade-offs

One of the key issues when it comes to increasing access to credit is the possible inclusion versus portfolio risk trade-off. The counterfactual simulations offer support to the fact that the increase in gains accrued under the alternate data conditions does not come at the expense of increased default or charge-off rates. Mean predicted default probabilities across simulated policies have no statistically significant differences with the baseline, whereas there are minor decreases in charge-off rates due to better borrower selection.

These results imply that using alternative data proxies will make targeting more efficient in that the data will help better isolate responsive and creditworthy borrowers and those with more risky conditions. With the reallocation of marketing exposure to segments where causal response features are favourable, AI-based systems can meet the goals of inclusiveness without affecting financial stability. This finding supports the point of view that inclusion and risk management do not necessarily conflict as long as intelligent systems are constructed based on the causal impact and not the mere predictive accuracy.

6.4. Managerial Interpretation

From a managerial perspective, the counterfactual findings emphasise the role of considering AI-driven credit marketing as a strategic decision system, as opposed to a fixed scoring mechanism. Causal effect estimates can help managers to determine the consumer segments with the highest marginal marketing investment in terms of their inclusion and performance benefits. The introduction of other data in a controlled and transparent form enables the firms to increase their market areas whilst upholding prudent risk standards.

The simulations also indicate the necessity of governance systems that track the distributional results in addition to aggregate performance indicators. Overall inclusion is increased, but since the effects are heterogeneous, one might end with a disproportionate cost burden among segments even with unregulated personalisation. Fairness and pricing dispersion diagnostics should therefore be built into the model evaluation and deployment processes by managers. More broadly, the findings indicate that causal machine learning can be utilised to help evidence-based policy formulation in firms, with the help of smart credit marketing systems, which can help to balance commercial goals with the more inclusive and responsible-oriented goals.

7. DISCUSSION

7.1. Implications for Intelligent Systems Research

The results of the present research support a significant change in the intelligent systems research studies in finance: the evolution of predictive accuracy should be accompanied by the causal implications of the algorithmic decision in the context of the real organisational processes. The credit scoring and targeting systems are built into the pipelines of acquisition, pricing, and servicing, i.e. the results of these processes directly influence the future of the economy for consumers and the institutions alike. The fact that algorithmic processes can enhance credit uptake whilst manipulating pricing and repayment proves that intelligent systems are used as decision systems, rather than prediction systems. This inspires a methodological focus on causal machine-based learning frameworks that would be able to approximate the effects of decisions in the presence of confounding and strategic selection, and would therefore bring intelligent systems research to the practicality of digital financial markets [34, 35].

The second implication is related to the conceptual positioning of marketing as a first-class AI intervention. To a large extent, the current body of literature focuses solely on AI as the automation of underwriting, when the outcomes presented here demonstrate that algorithmic systems also lead to people receiving an offer and under what conditions [36, 37]. Marketing is no longer an act of peripheral use but a central medium where intelligent systems determine financial inclusion and distributional results. This paper proposes that previous studies on intelligent systems need to view credit scoring as a marketing intervention, i.e. a change in exposure, acceptance, and contract terms, and weigh the implications of targeting and offer design as explicit causal therapies and assess their impact on inclusion and welfare as carefully as they would underwriting and risk forecasting.

7.2. Implications for Financial Institutions

In the case of financial institutions, such outcomes present facts that algorithmic credit marketing can be an effective tool to increase market coverage, especially in markets that typically receive little attention through other methods. The credit uptake boost and the repayment performance improvement show that AI-based selection can be more efficient in outreach and find responsive and creditworthy borrowers that the conventional segmentation may neglect. Nevertheless, the noted pricing gains and the leftover pricing dispersion covering risk adjustment highlight the point that the inclusion through personalisation can incur distributional costs. The institutions thus have a strategic decision to make: personalisation may boost conversion and decrease losses, but it may also become a cost burden that is disproportionately allocated among economically disadvantaged groups.

These two discoveries indicate the significance of responsible personalisation. Instead of maximising either their acceptance or maximum margin, institutions ought to test marketing algorithms based on multi-objective optimisation criteria that collectively measure inclusion, portfolio risk and pricing fairness [38]. Controlling pricing dispersion becomes a governance issue, especially among consumer segments where the marginal increment of repayment performance fails to justify the incremental cost charge. In practice, this implies monitoring interest rate dispersion in relatively similar risk bands, placing guardrails in terms of offers to vulnerable populations, and taking causal effect approximations to inform marketing funding into segments where the gain of inclusion is large, and risk is constant [39]. More generally, the findings indicate that the inclusion-profitability tradeoff is a feasible solution when the institutions do not focus on prediction-based optimisation but on decision-based assessment based on causal effect.

7.3. Regulatory and Ethical Implications

The study also directly relates to the regulation and ethical governance of algorithmic credit markets. Since AI-based credit marketing influences the allocation of offers and prices, transparency is also critical in order to make sure that consumers and regulators can see how the credit opportunities are provided. Clearly stated mechanisms of offer allocation minimise informational asymmetries and enhance accountability, especially in the event that algorithm systems are not intended to discriminate against or be disadvantageous to particular groups. This involves the clear record of the operation of targeting criteria, the data source that drives the selection, or how pricing rules relate to the predicted risk and responsiveness [40].

One of the key ethical issues that arises out of the outcomes is fairness in pricing. Although inclusion can broaden, the continuing rates of pricing dispersion in excess of apparent risk fundamentals are an indication that customisation can create added costs that can support economic inequality [41]. Regulators should consequently be required to examine approval rates and pricing performance not just on a B to C basis, but also where greater cost may not be supplemented by equivalent risk reduction. Lastly, the results depict the necessity of auditing marketing algorithms. Auditability asks institutions to document models, perform an ongoing fairness and stability evaluation and produce repeatable evidence in terms of the way models respond to alterations in policies. The agenda can be facilitated by causal machine learning, which can deliver transparency in the assessment of the effects; however, data access, reporting criteria, and explicit regulations on how algorithms should be governed are essential.

7.4. Limitations

Various restrictions must be recognised when explaining the findings. First, the treatment variable is determined with proxies of high-intensity algorithmic selection instead of the actual proprietary marketing exposure measures. Although this approach is justifiable, considering the limitations of data, it implies that the effects estimated represent a combination of algorithmic selection, underwriting, and pricing processes and not necessarily marketing exposure alone. Second, the access to richer behavioural data that can be used in practise by lenders is limited by the use of publicly available data, which restricts the possibilities to model some forms of inclusion of alternative data directly. Third, the generalizability can be limited by the fact that peer-to-peer lending platforms are different from traditional financial intermediaries in terms of the way of acquiring its customers, underwriting rules, and regulation. These limitations do not disregard the causal framework but give a reason to interpret the results carefully and emphasise the importance of future studies based on even more detailed institutional data.

8. CONCLUSION

This paper offers causal support that AI-based credit marketing proxies raise credit uptake and improve results on inclusion, including among youth and digitally active borrowers. Nonetheless, the impacts are not uniform across the segments, which means that not all consumers can receive the benefits of algorithmic targeting. One issue is the dispersion of prices: despite having a risk-adjusted prediction, the personalised selection is linked to the stable disparity in the cost of borrowing that can disproportionately share the burden on low-income groups. Combined, the results demonstrate that AI-based credit marketing is able to both facilitate inclusion and enhance differentiated pricing, and distributional evaluation is therefore necessary.

The paper has enhanced the Intelligent Systems in Accounting, Finance and Management by developing a decision-impact view on intelligent financial systems. It shows how causal machine learning can be applied to judge AI systems as decision interventions but not as a prediction tool, introduces a new conceptualization of credit scoring as a marketing institution that is inherent to offer allocation and pricing, and presents policy-relevant counterfactual simulations on which responsible system design can be informed. These agreeablenesses reinforce the empirical and methodological basis of assessing the intelligent systems in real-world finance.

Future studies need to build on this framework with proprietary lender data that explicitly measures marketing exposures, provision of presentation, and channels of consumer interaction in order to identify marketing effects more effectively. Further research is necessary to determine the effectiveness of regulatory interventions like pricing guardrails, transparency requirements and auditing requirements, which can be done by employing causal designs. Lastly, the area of human-AI hybrid credit systems research is essential, especially in cases where human control has the potential to reduce pricing differences without decreasing the benefits achieved through inclusion. These extensions would enhance the knowledge on how smart credit marketing systems can be developed to be economically efficient and fair.

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