Evaluation of Credit Decisions for Evidence of Unfair Lending

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Origin of Fair Lending In the USA

- Legal requirements for equal treatment of customers originated in the Civil Rights legislation of the 1960s, notably the Civil Rights Act of 1964 and the Fair Housing Act of 1968
- Further laws followed, including the Equal Credit Opportunity Act (Regulation B) of 1974 and the Americans with Disabilities Act of 1990
- Currently in the USA, it is illegal to discriminate on the basis of race, national origin, religion, sex, familial status, or disability
- Fair Lending Analyses arose to answer the question of, “how can one tell if an entity is discriminating on an illegal basis?”

Potential Consequences

Recent high-profile judgments against lenders in the USA include:

- **$25 MM** against Citibank in 2019, in addition to $24MM in repayments to affected customers

- **$335 MM** against Countrywide in 2013

- **$175 MM** against Wells Fargo in 2012

- **$21 MM** against SunTrust in 2012

Types of Discrimination

Overt Discrimination:
Openly discriminating on a prohibited basis

NO Evidence Needed for a claim!

Banks' focus is training and policies

Disparate Treatment:
Lender treats members of a protected group differently than from others

Banks' Focus is Statistical Analyses

Disparate Impact:
Policy or program with a disproportionately negative impact on a protected group

Evidence Needed for a claim!

Overview of Disparate Impact Analysis

As Disparate Impact is not the result of a specific action, Disparate Impact Analysis (DIA) focuses on identifying statistically significant differences between protected groups and the control group, after controlling for relevant policy factors. This analysis can be done in a variety of ways, depending on the target of the analysis.

However, the underlying idea remains the same: after controlling for relevant credit characteristics, are members of a protected group impacted negatively?

To control for relevant characteristics, a statistical model including these characteristics is created, and the significance of protected groups is then analyzed.

These models fall into two general types:

- Scores analyzed for disparate impacts
- Decisions, that may involve scores, analyzed for disparate impact

Score DIA Methodology

To test that a customer-facing **score** is free from Disparate Impact, the score is tested using generally accepted credit characteristics as controlling factors.

- **Research** - An investigator works with the business unit to agree upon generally accepted credit criteria relevant to the population evaluated by the score.
- **Gather data** - An investigator works with business and IT units to gather the relevant data. This should include:
  - The score in question
  - The protected group indicator(s), or data used to infer this information
  - All relevant credit criteria available at the time the record was scored.
- **Analysis** - The score in question is the target variable, with the accepted credit criteria and the protected group indicators as the independent variables

Decision DIA Methodology

To ensure that a customer-facing **decision** (credit approval, credit line increase/decrease, account closure, etc.) is free from disparate impact, the decision is tested using the stated scores and other criteria that the bank has stated in its policies. Obviously, each of these items must **not** involve protected groups.

- **Research** - An investigator works with the business unit to agree the the policies, scores and other criteria involved in the decision.
- **Gather data** - An investigator works with business and IT units to gather the relevant data. This should include:
  - The stated policies, scores and criteria in question
  - The protected group indicator(s), or data used to infer this information
- **Analysis** - The decision in question is the target variable, with the stated scores, criteria and the protected group indicators as the independent variables

Black Box or White Box?

- The most common models built for fair lending analyses are, by far, linear (for continuous scores) and logistic (for categorical decisions).
- Black box techniques are not currently in wide use in the industry. This is due to the nature of the analyses — the investigator is looking to explain the decisions (or driving factors of a score), rather than predict future behavior
  - These explanations need to be clear factors that can be described as "positive" or "negative" effects (from the customer's point of view).

Inference of Race

- In the USA, data from the US Census is often used for race inference:
  - The most common is: the Consumer Financial Protection Bureau's (CFPB, a US government body), Bayesian Improved Surname Geo Coding (BISG - https://files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf) uses Census data on race correlations of surnames and the racial distribution of the applicant's zip code to infer a race for the customer.
  - Other methods are continually being developed, such as a recent study found improvements by adding the first name to the algorithm (https://doi.org/10.1080/2330443X.2018.1427012)
  - There is no legal/regulatory requirement for a specific method, but using a method other than BISG is normally justified by showing improved results

Inference of Gender

- In the USA, first name data from the US Census is often used for gender inference:
- Depending on location, publicly available datasets from a national census (for the USA, https://www.ssa.gov/oact/babynames/limits.html) may be available
- However, this is an ongoing area of research (https://gender-gap-in-science.org/2018/07/16/telling-the-gender-from-a-name/).
- There is no legal/regulatory requirement for a specific method, but using a method other than Census-based methods is normally justified

Example of an Explanatory Model

- Below is an example of an explanatory model for a mortgage decision — with a negative coefficient correlated to a favorable outcome for the customer

Parameter	Description	Estimate	Wald Chi	Prob ChiSq
Intercept		-4.803	743.569	<.0001
DTI	Debt To Income > 43	5.736	536.590	<.0001
Loan_Amout	Loan amount > $484K	-1.985	93.216	<.0001
FICO_1	FICO <= 700	2.743	57.568	<.0001
FICO_2	700 < FICO <=740	1.985	21.121	<.0001
LTV	Loan to Value ratio	5.157	184.344	<.0001
Term	Term length	1.841	16.670	<.0001
Female	Female Customer Ind	0.341	0.255	0.287

Next Steps After Modeling

If a significant, **unfavorable** (to the customer) result for any protected group indicator is found, the next step is usually a file review — examples with similar credit characteristics for the protected and unprotected group with different results are selected, then compared to see if there are factors not in the models that explain the differences (it is not uncommon that some key factors, such as special offers or daily rate sheets, are not immediately available to investigators — this should be remedied, if possible, in the current or future analyses).

If not, then steps must be taken to remediate these differences — this can include modifying loans, reimbursing customers, retraining staff, among other options. The key goal is for the customers to be treated fairly and for the bank to modify their processes and training to ensure that this happens going forward.

Model Evaluation Metrics

- Fair Lending models are explanatory, backward-looking in nature, with the independent variables known, R2, AUC, etc. can be VERY high — values above 0.95 are not unusual!
- In addition, Multicollinearity isn't an issue (though a bank's internal model governance may not initially agree!) as these models are created and run on a specific timeframe based on the factors leading to the decision — factors that may very well be correlated to each other.
- For each project, the expected model metrics will depend on the underlying score/decision — decisions that are very systematic can have exceptional values, while more judgmental decisions may be close to 0.

Evaluation of Potential Fair Lending Issues

- Once the models have been created, the coefficient(s) of the protected group indicator(s) are evaluated for significance and direction.
- While significant values for any protected groups can be a matter for concern, in the US regulatory environment, only values that are **significant** and **unfavorable** to a customer need to be investigated.
- However, values below a certain level may be considered nonmaterial, e.g., a model explaining interest rate differences in mortgage might have a significant, unfavorable effect for a protected group of 1 BP, but this might not be considered a material difference

Applications Outside the USA

- In the EU, there are a variety of prohibited types of discrimination in the EU Charter of Fundamental Rights, including race, sex, national origin, colour, language, religion, age and sexual orientation. Some specific instances not often covered in the USA:
  - Banks are required to treat citizens of all EU countries fairly -- this could be tested via self-reported or inferred information
  - Since sexual orientation is a prohibited characteristic, testing that a mortgage with two cosigners of the same gender are treated the same as those with two cosigners of different genders
  - In countries with national minorities, such as Scots in the UK or Catalonians in Spain, testing for equal impact could be important

Q & A

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