Credit Scoring and Disparate Impact

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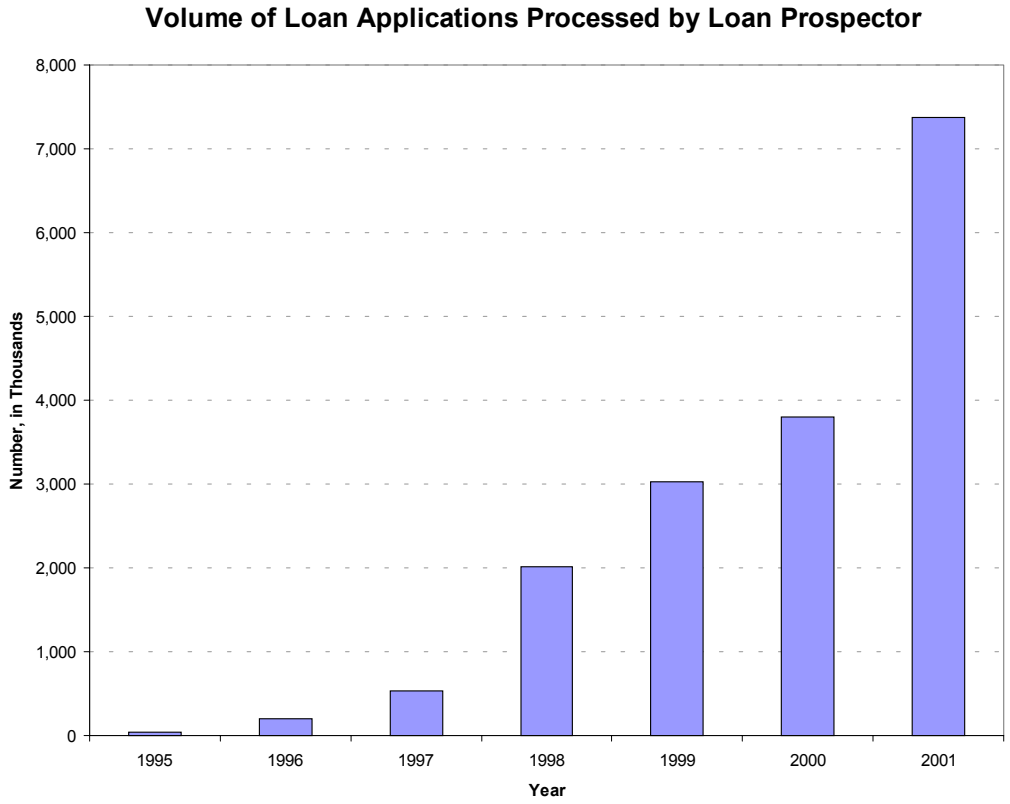
Background

- Credit scoring has been gaining rapid acceptance in the mortgage industry
- HMDA data shows rejection rates for minority mortgage loan applicants is roughly twice that of white applicants
- Regulatory agencies examine scoring systems to ensure they are both statistically sound and produce fair outcomes for all applicants

Rapid Growth in Use of Automated Underwriting



What is Disparate Impact?

- Overt discrimination - a lender openly discriminates based on a prohibited factor.
- Disparate treatment - a lenders treats applicants differently based on a prohibited factor.
- Disparate impact - a business practice is applied uniformly but has a disparate impact on a protected class.

Motivation

- No formal test for disparate impact
- Typical corrective action of dropping variables from the scorecard has never been evaluated
- What should a good disparate impact test do?
- What should a good corrective action do?

Method

- Set up default process using simulated data that generates a disparate impact effect, develop scores based on simulated data
- Default probability is determined by a set of borrower characteristics and an error term.
- Borrower characteristics are distributed differently across protected and and non-protected borrower types

Method (Continued)

- We consider two different default processes
- PROCESS 1: expected error = 0 for non-protected class, > 0 for protected class (generates disparate impact)
- PROCESS 2: expected error = 0 for both classes
- Other than in the error term, both processes are identical

Method (continued)

- TRUE SCORE is derived from simulated default process ignoring the error term
- ESTIMATED SCORE is derived from the estimated parameters of the default process
- Disparate Impact Measure (ψ) is the percentage of rejected protected class members that would not have been rejected were the true score observable

Performance Criteria

- A good disparate impact test distinguishes between $\psi > 0$ and $\psi = 0$

- A good corrective procedure achieves $\psi = 0$ (or close to it)

Simulation Data

- Simplified set-up with just three variables: FICO, Debt Ratio, and Income
- We generate a simulated sample based on an empirical joint distribution of these variables for protected and non-protected borrower classes
- Error simulated with logistic distribution.
- Unobserved default process depends on FICO, debt ratio, and error term (not income)

Descriptive Statistics

Variable	Protected Class Mean	Non-Protected Class Mean
FICO	667	712
Debt Ratio	39%	37%
Income	$61,000	$95,000
Sample Size	10,000	80,000

Estimated Equations

	Process1		Process 2	
Variable	Est. Coeff.	P-Value	Est. Coeff.	P-Value
Intercept	1.880	<.0001	-10.487	<.0001
FICO	-0.016	<.0001	-0.026	<.0001
Debt Ratio	0.176	<.0001	0.519	<.0001
Income	-0.336	<.0001	-0.030	.3439

Scorecards for Process 1 & 2

	Scorecard 1 (Process 1)	Scorecard 2 (Process 2)
Base Points	70	50
FICO	-0.058	-0.045
Debt Ratio	0.635	0.899
Income	-1.212	-0.052
	ψ=25.6	ψ=0.1

Univariate Test

		Scorecard 1		Scorecard 2	
Variable	Class Means, Diff.	Point Weight	Point Diff.	Point Weight	Point Diff.
FICO	-45	-0.058	2.61	-0.045	2.03
Debt Ratio	2	0.635	1.27	0.899	1.8
Income	-0.34	-1.212	0.41	-0.052	0.02
Mean Score			51.05		51.17

Univariate Test, Conclusisons

- FICO and Debt Ratio appear problematic (have disparate impact) in both scorecards
- This is a false finding of disparate impact for Scorecard 2
- Income appears to be OK (no disparate impact) for either scorecard when, in fact, income has no effect on default probability

Multivariate Test - Estimated Equations

	Scorecard 1		Scorecard 2	
Variable	Est. Coeff.	P-Value	Est. Coeff.	P-Value
Intercept	-10.33	<.0001	-10.52	<.0001
FICO	-0.025	<.0001	-0.026	<.0001
Debt Ratio	0.51	<.0001	0.519	<.0001
Income	-0.003	0.9116	-0.028	0.3708
Protected	10.27	<.0001	0.04	0.6436

Multivariate Test, Conclusions

- Protected class indicator is significant for Scorecard 1, but not for Scorecard 2
- Conclusion: Scorecard 1 exhibits disparate impact, Scorecard 2 does not
- This is the correct overall conclusion about disparate impact
- Multivariate test also shows that Income is not statistically significant

Next Step: Corrective Action

- First, we investigate the strategy of dropping variables
- Option 1: re-score the observations using the original scorecard weights but leaving out the offending variable
- Option 2: re-estimate the model with the offending variable left out

Effect of Dropping Variables Scorecard 1

Variable	Without Re-estimation	With Re-estimation
FICO	ψ=12.1	ψ=12.4
Debt Ratio	ψ=83.1	ψ=83.3
Income	ψ=22.9	ψ=22.9

Effect of Dropping Variables

- 'ψ ' sometimes indicates greater disparate impact in the "corrected" scorecards than in the uncorrected ones!
- Implication: dropping variables is not an effective corrective action ($\psi \neq 0$)
- Intuition: mere presence of particular variables does not drive disparate impact, overall correlation pattern in data is what drives it

Alternative Corrective Procedure

- Intuition: Disparate impact is caused by the pattern of correlation among all the variables
- Good corrective action must controls for this
- Multivariate test suggests a solution: include protected class status as a control variable during estimation but do not include in in final scorecard

Corrected Scorecard for Process 1

Variable	Point Weight
Base Points	70
FICO	-0.09
Debt Ratio	1.839
Income	-
	ψ=0.0

Discussion & Conclusions

- Using protected class indicator during model development may violate ECOA
- But what about dropping variables based on correlation with protected class? (Also brings class status into model development)
- Multivariate testing has become an accepted methodology. Our suggested corrective action is a logical extension of multivariate testing.