Lessons Learned: Statistical Techniques and Fair Lending

Marsha Courchane, David Nebhut, and David Nickerson*

Abstract

There remains strong concern that, even after several years of intense scrutiny, lending discrimination persists. The concerns encompass issues of lending denial disparities, use of predatory lending tactics, and potential disparate impact arising from increased use of credit scoring. This article specifically addresses disparate treatment of loan applications by analyzing data collected in fair lending examinations conducted at national banks during the period 1994 through mid-1999. This information will be useful to banks interested in monitoring their performance, to consumers interested in determining factors that influence their ability to purchase homes, and to policy makers concerned with discrimination issues.

We find that statistical analysis can be used successfully to identify patterns of discrimination and that custom modeling, used to reflect an individual bank’s underwriting policies, is most effective for that purpose and we discuss variables found to be most predictive of the lending decision. We also suggest potential improvements in the examination of fair lending and identify areas that deserve additional research, given improved data availability.

Keywords: Discrimination; Fair lending; Mortgages

Focus on fair lending remains intense seven years after the release of the Boston Fed study (Munnell et al. 1992). Recent activities highlighting issues of lending discrimination include a Fannie Mae Foundation conference in June 1999, the release of survey findings from Freddie Mac concerning credit quality of minority borrowers, initiatives by both Freddie Mac and Fannie Mae to instruct borrowers on the importance of credit quality, a release from the Urban Institute (under contract to the U.S. Department of Housing and Urban Development [HUD]) on mortgage lending discrimination, and a conference in May 2000 at the Cleveland Federal Reserve Bank that included a variety of papers emphasizing fair lending and consumer issues.

Much of the recent work has emphasized statistical modeling in the analysis of fair lending issues. In this article, we emphasize aggregate findings, or common lessons, learned from the examination of several large national banks by the Office of the Comptroller of the Currency (OCC) during the past five years, based solely on examinations that used statistical techniques.

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The compilation of compliance examination findings by the major regulatory agencies, while an important aspect of fair lending research, has received little press. Occasional headlines in the *American Banker* and other publications announce settlements with banks that result from fair lending examinations, but details in the popular or banking press on what led to the settlement are frequently vague or omitted entirely. There have been multiple referrals by the regulatory agencies to the Department of Justice (DOJ) and HUD over the past seven years, only a small number of which resulted in settlements large enough to make headlines. The bases for these referrals are varied, including findings of disparate treatment by marital status, national origin, race, and age.\(^1\)

Of the examinations analyzed here, three resulted in well-publicized fair lending settlements that ranged from $400,000 to $3 million, indicating that the DOJ has recognized statistical modeling as a valid tool for discovery of disparate treatment in the credit-granting process. The cases cover several aspects of lending, including home mortgage purchase, home improvement lending, traditional underwriting, and credit scoring. While this article will deal only with summary information on the examinations, the number of those examinations is significant, and the geographic coverage is large, allowing for a broad discussion of the prevalence of discrimination.

This is the first article to present results from detailed empirical analysis covering a range of banks during the five-year period from 1994 to 1999. Each bank was examined under customized (bank-specific) procedures, reflecting the use of its own credit scoring guidelines and approval procedures. This is a significant departure from either the Boston Fed study, which combined data from several banks in a single regression, or the Federal Reserve examinations, which at the preliminary stage used a single equation for all banks. While that approach might reveal an underlying problem, and analysis of public-use Home Mortgage Disclosure Act (HMDA) data might indicate where problems are most likely to exist, it is the examination of an institution under its own standards, accompanied by examination of those standards, that can best indicate the extent and scope of the disparate treatment at a particular institution. Statistical models are very sensitive to modeling of the bank’s credit criteria, since underwriting practices vary significantly across institutions and are rarely exactly, or quantitatively, specified.\(^2\) However, there remain some basic lessons that can be learned from the firm-specific modeling and used to illuminate fair lending problems likely to be encountered by others. Compliance staffs of banks, economists employed as consultants for those banks, academic researchers, and regulatory economists can all benefit from these findings and gain awareness of areas that deserve additional focus when addressing fair lending concerns.

The article is organized into four sections. The first includes a description of the types of institutions examined and describes the geographic diversity of those lending institutions, also including a discussion of the targeting decisions made, such as why a particular loan product was examined at one institution but not necessarily at another. The next section includes an analysis of the statistical methods used at select OCC examinations, including discussion

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1 For details of OCC referrals, see its Compliance Policy at Web site <http://www.occ.treas.gov/cdd/fair.htm>. Since 1993, the OCC referred 33 banks in violation of fair lending laws to the DOJ. Ten of them were for residential real estate loan transactions, 20 for consumer loan transactions, and 3 for both. Details of fair lending cases can be found at the DOJ Web site at <http://www.usdoj.gov/crt/housing/caselist.htm#lending>.

2 Alternative techniques, such as matched-pair testing, might be very useful for the consideration of pre-application screening, but statistical modeling has not been used much in that area.
of sampling procedures, reference to alternative sampling procedures, and explanation of the statistical models. The third section presents results, discussions of common problems, and suggestions of possible model approaches for future regulatory examinations. The final section presents conclusions and policy recommendations.

Decision Making for Fair Lending Examinations

The OCC’s examination procedures handbook, *Fair Lending* (OCC 1997),³ declared that office’s commitment to using statistical modeling to evaluate whether a national bank treats applicants differently on a prohibited basis, and provided conditions and procedures to guide the use of a statistical model. This article discusses the appropriateness of a statistical model, the development process for a statistical model to examine a specific bank, and how regulators evaluate and use the information generated by such a model.

At the time the OCC determined that it might use statistical modeling for fair lending examinations, it recognized that its prospective uses of the tool differed from that of the Boston Fed study in important ways. In contrast to that study’s focus on an entire urban market, the OCC’s focus is on whether the individual national bank makes credit available in a nondiscriminatory manner.⁴ In 1994, the OCC commenced a pilot project in which comparative file analysis using a statistical model was conducted in three banks after the customary judgmental comparative analysis.⁵ Published in 1999 (Stengel and Glennon 1999; see also Courchane and Cobas 1995 and Stengel and Glennon 1994), the pilot study showed that a statistical model is most effective for identifying disparate treatment at the loan application stage if tailored to the underwriting standards of a specific product at a specific bank; that is, generic models are inferior.⁶

On the basis of findings from the pilot study, the OCC adopted statistical modeling as an accepted part of its fair lending procedures. Examinations commenced in 1994 and continue to this date.

Discrimination can take many forms, from uneven treatment by brokers to preapplication screening, to unfair application of credit standards in the loan approval process, to differing levels of assistance provided during the application process, to discriminatory pricing practices, and to overt bigotry. The banking regulatory agencies have tried to look at discrimination at many levels. For instance, the OCC used a pilot study for matched-pair testing to address the issue of preapplication screening. However, statistical methods used by the banking regulatory agencies have not addressed discrimination at all levels. Much of the focus

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³ The OCC plans to issue new fair lending examination procedures that will supercede the October 1997 handbook.

⁴ The DOJ applies statistical modeling in a manner similar to the OCC. See the case against Decatur Federal Savings and Loan Association described by Siskind and Cupingood (1996) and HUD (1993).

⁵ Judgmental comparative analysis is described by OCC (1993).

⁶ The pilot study found that when examining individual loan files it was important to model the credit standards at each institution. For example, if secondary market guidelines were used for the institution with respect to debt ratios (say, for example, 36 percent for the acceptable debt-to-income), but a particular institution frequently deviated from that guideline, it might appear that the bank discriminated when in fact it did not. Results were very sensitive to specific underwriting criteria. However, it should be recognized that customized modeling per institution is much more expensive in terms of examination hours and data collection.
has been on the unfair application of credit standards in the approval or denial of loan applications. It is in that area that this article concentrates. While loan pricing is an equally important area, and one of growing significance as mortgage lenders move from prime to subprime markets, there were, for a variety of reasons, few statistically focused examinations relating to pricing conducted by the regulatory agencies over the past decade. For an overview of some of the issues in pricing and overages, see Courchane and Nickerson (1997).

Even within the narrow focus of disparate treatment during the loan approval process, not all examinations used statistical methodologies to identify problems. Compliance examinations combine resources from several areas of expertise, including examination staffs, legal departments, and the economics research staffs at the agencies. Statistical methods tend to be used only at a small number of larger institutions that have minority denials in sufficient numbers to enable their use. Statistical methods have been used to analyze pricing decisions (Courchane and Nickerson 1997), approval and denial decisions, home mortgage purchases, home improvement loans, credit card approvals, and underwriting both with and without full or partial reliance on credit scoring models.

The fair lending examination conducted most frequently with statistical methods was meant to determine whether there was reasonable cause to believe disparate treatment resulted from the approval or denial decision for home mortgage loans. The focus on home mortgage lending is obvious. Only HMDA data include race. Hence, the OCC did not (routinely) consider conducting statistical examinations unless two conditions were met: both recent automated HMDA data were available and the number of denied minorities exceeded 50.8

The economists involved in fair lending at the OCC during this period of analysis used the HMDA data (along with any other automated data provided by the bank) to target banks for further analysis. They identified statistically significant differences in denial rates by race—whether a group has enough applications to support more sophisticated statistical analyses or has the prohibited bases, products, and decision centers where statistically meaningful analysis can be conducted.9 Given resource constraints at the OCC, approximately 10 to 20 banks were targeted as potential candidates for statistical modeling in each year.

For larger banks, OCC economists usually matched minority denials and up to three white approvals by loan amount, income, and geography to identify apparent disparities.10 That

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7 A primary reason the OCC found it difficult to focus on pricing issues (or rates and terms in general) was that key fields of data could not be used because data sources at the lending institutions were not well linked. For example, overage practice data might be linked to the compensation of employees but not to the loan register information submitted to HMDA. Also, daily rate information for each branch location might be difficult to obtain.

8 Specifically, when statistical modeling is to be used for a single class of loans using race or national origin as the prohibited basis, the Fair Lending handbook specifies at least 50 control group approvals, 50 prohibited basis group approvals, 50 control group denials, and 50 prohibited basis group denials for the product to be reviewed during the most recent 12-month period. For institutions with fewer than 50 minority denials, the rationale is that those files can be examined individually and manually and that the need to use (relatively) expensive statistical modeling expertise is less at those institutions.

9 For example, at one large mortgage company, the targeting memo separated out white, black, and Hispanic approval/denial rates for government and conventional home purchase loans by seven regional mortgage centers, identifying racial disparities that were statistically significant.

10 This method is similar to that first introduced at the Federal Reserve Board of Governors (FRB) in 1996, although the FRB does not use application outcome in its matching procedures.
information was used to narrow the examination focus and allowed the examiners to select a much smaller representative sample for the statistical analysis. However, information from the matching program was not used to identify individual transactions for review.

Geographically, from 1994 to 1999, statistical examinations were conducted at national banks in the Southeastern, Northeastern, Central, Western, Midwestern, and Southwestern districts (all six OCC districts). Not all types of examinations were conducted in all regions; however, at least one mortgage approval decision examination was conducted in each region. Examinations that focused on credit scoring decisions were conducted in the Southeast, Midwest, Northeast, and Southwest regions. Statistical examinations focusing on compliance and fair lending for credit card lending, consumer lending, automobile loans, home improvement lending, and government mortgage programs were conducted only at a select group of institutions. Given the large and geographically diverse coverage of the institutions examined at the OCC, some effort was made to control for differences in underwriting across regions. To the extent that the institution used regional economic information in its underwriting processes, the OCC examined each underwriting center separately. If the banking institution used the same credit guidelines across geographies, the OCC attempted to examine a particular region as its focus in an examination. Sampling then occurred only for that particular geography.

As noted earlier, one of the most binding constraints on which products can be examined at specific institutions is the availability of information on the prohibited bases protected under the Equal Credit Opportunity Act (ECOA) and the Fair Housing Act. Race, for example, can be collected only on HMDA-reportable loans. In a few instances, statistical analyses were conducted in the absence of explicit race information, instead using inferences about population distributions from census data. However, most often the limited statistical resources impacted analyses of home lending decisions.

A further constraint arises from the limitations imposed by the choice of statistical technique. Logistic regression was the only type of regression technique used by the OCC for modeling the application outcome decision in the 1990s (for examples, see Courchane, Golan, and Nickerson 2000). Use of this approach requires that a certain minimum number of files be distributed across the values of each independent variable for it to be viable as an explanatory variable. To allow the use of as many underwriting variables as possible, the decision was made to require loan products to have at least 50 minority denials. Recent econometric advances might allow this constraint to be relaxed. The highest cost of this constraint is that it limits the use of statistical techniques to only larger institutions. However, it is primarily for those institutions that it is most difficult for an examiner to employ judgmental comparisons, given the large number of lending decisions, so this cost is somewhat ameliorated.

A final constraint comes from the limited numbers of examiners and economists who can be used at any one examination. Labor resources are, and likely will remain, tight during this

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11 The FRB proposed changes to Regulation B, the implementing regulation for ECOA, in 1999 that would permit the voluntary collection of racial data on other types of loans. The proposed changes can be found in the Federal Register, 64, no. 157 (August 18, 1999): 44582–44631, microfiche. The request for comments was published in the Federal Register, 64, no. 177 (September 14, 1999): 49688–49699, microfiche. The comment period closed October 29, 1999.

12 See Courchane, Golan, and Nickerson (2000) for a discussion of the benefits of maximum entropy techniques in the analysis of limited, imperfect data sets.
period of active consolidation and lowered supervisory fee income in the banking industry. Given the constraints, the OCC used statistical techniques for examinations for compliance at national banks across the country ranging in size from very small to among the largest, covering several different loan products and both automated and judgmental underwriting.

Statistical Techniques for Fair Lending Examinations

For these fair lending examinations, modeling was used to determine if underwriting guidelines were applied consistently for all applicants, regardless of race, gender, or other prohibited basis. If minority applicants with the same credit profile as nonminority applicants face a higher probability of denial, then disparate treatment exists. For examples of studies that examine this question, see Calem and Stutzer (1995), Munnell et al. (1992, 1996), Stengel and Glennon (1999), a number of related articles in the *Journal of Financial Services Research* (1997), and Carr and Megbolugbe (1993) and other articles in that special issue of the *Journal of Housing Research* (Volume 4, Issue 2).13

There are several unresolved modeling issues in the literature. See, for example, Heckman (1998); Ladd (1998); Longhofer and Peters (1998); Ross and Yinger (1999); and Isaac (1995). These issues arise from the choices involving best representation of the lending decision process at the bank level and best econometric or statistical modeling approach to capture differences in treatment. These choices may vary from bank to bank and are closely related to the availability of data. The decision to approve or deny a loan is based primarily on the applicant’s credit but also may include demographic, economic, and property-specific attributes. It is generally argued in the literature that the decision model should reflect the probability that an applicant will default—a conceptual framework that underlies the design of most mortgage credit-scoring models.

However, in most cases, the approval process involves judgmental decisions made by underwriters using established policy guidelines that are qualitatively but not quantitatively linked to the likelihood of default. For example, it is generally accepted that the higher the debt-to-income ratio (DTI), the greater the likelihood of default (a qualitative relationship), but few banks know the impact of an increase in the total DTI from 32 to 36 percent (or 48 percent) on the likelihood of default (a quantitative relationship). Under this underwriting process, it is possible that the underwriting (judgmental) guidelines may introduce differences in treatment of applicants, leading to a violation of the fair lending laws. For that reason, the purpose of the statistical model is to establish whether the (predetermined) underwriting guidelines are being fairly applied, rather than to determine the optimal weights

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In general, much of the debate in the discrimination literature concentrates on the issue of whether discrimination exists because of a profit-motivated statistical discrimination or a taste for discrimination (Ladd 1998). Evidence for possible statistical discrimination in mortgage lending is presented by Munnell et al. (1996) in the Boston Fed study. Even though that paper is frequently quoted, there is an ongoing debate about whether these results are statistically meaningful, since the race effects are highly sensitive to the specification of the model’s variables (Harrison 1998; Horne 1997; Stengel and Glennon 1999). Some of this debate is summarized nicely in Ladd (1998): “While it is not clear whether the discrimination that emerges from the Boston Fed study is attributable to a taste for discrimination or to profit-motivated statistical discrimination, my guess is that a substantial part of it is statistical discrimination driven by the drive for profits. If so, market forces are not likely to eliminate it.” Recently, Heckman (1998) contributed to the debate by pointing out the distinction between macrolevel and microlevel discrimination. In this article, we concentrate on statistical and microlevel discrimination. We investigate the question of whether there is discrimination in mortgage lending in specific banks located throughout the United States.
an underwriter should use to assess the creditworthiness of the applicant. Given that these
guidelines vary across institutions, the use of a bank-specific model can best address the
differences. These models test the hypothesis that minority applicants face the same like-
lihood of approval as nonminority applicants with similar profiles (e.g., credit, employment,
wealth, etc.).

The statistical models should be designed to assess the relative importance (beyond that asso-
ciated with random chance) of any observed difference in the likelihood of approval for these
racial minority groups. The most common representation of the lending process is the famil-
iar unordered, discrete choice (multinomial) logistic model. In this view of reality, the bank
makes its decision to deny or approve a loan based on an applicant’s characteristics. Given
these characteristics, the bank calculates (based on historical data) the probability that the
applicant will pay back the loan. The presence of rational or statistical discrimination
would mean that this probability is affected by the individual’s race (or gender). In all of
the results presented here, logistic regression is used to model whether a loan is approved or
denied as a function of covariates such as loan-to-value ratio (LTV), DTI, income, one or more
credit score variables, dummy variables used to capture bad credit, insufficient funds to close,
and race (e.g., white, African American, Hispanic).

Ideally, the analysis would use the population of loans, but that data, though collected and
kept by the banks for a legally mandated period of time, is not typically available in electronic
form. Population data on the outcome variable (loan approved/denied) and some covariates
(including race) are known, since their collection is mandated by HMDA. Accordingly, the
logistic regressions are estimated from a sample taken from the population. We use a dummy
variable for race and control for other effects in examining for disparate treatment.

A predetermined number of denied and approved loan applications, further stratified by the
covariate race, were obtained from fair lending examinations to produce stratified sampling.
Then additional covariate data were collected. By selecting a sample from each stratum, it is
possible to produce parameter estimates that are considerably more precise than that given
by a simple random sample from the population. The gains from stratification will be larger
as the differences between the strata are larger and the characteristics within strata are
more homogeneous. Stratified random sampling will always increase precision over simple
random sampling, the size of the gain depending on how well the stratification process is
modeled.

Estimating a binary logistic regression model for approval or denial decisions, we suppose that
the logit model is linear in β and that β includes a parameter for a minority status dummy
variable. Then we have a sample of N applications with N₁ applicants whose loans have
been approved, and N₀ applicants whose loans have been denied: N₀ + N₁ = N. We further
suppose that the population of N individuals is, or is regarded as, a random sample from the
underlying joint data distribution. All subjects also are classified by the stratum covariate
race; we assume N_N nonminority applicants and N_M minority applicants with N_N + N_M = N.

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14 While, in theory, a violation of ECOA exists if disparate treatment occurs over any of the prohibited bases, the
statistical examinations presented in the literature most often focus on race, so, for simplicity, that is the variable
that will be discussed here.

15 Loans approved but not accepted were treated as approved, and incomplete and withdrawn applications were
typically excluded from the sample.
We denote by $N_N$ the number of nonminority applicants with $Y = j$ ($j = 0, 1$). We likewise define $N_M$. We then suppose that a stratified sample of size $n$ is taken in which $n_{N0}$, $n_{N1}$, $n_{M0}$, and $n_{M1}$ subjects are randomly selected from the $N_{N0}$, $N_{N1}$, $N_{M0}$, and $N_{M1}$ available applicants in each of the defined strata and collect data on covariates.

We set two goals. First, for a given $n$, we desire efficient, unbiased estimation of the regression coefficients by appropriately choosing $n_{N0}$, $n_{N1}$, $n_{M0}$, and $n_{M1}$, defining efficiency in terms of mean squared error relative to the $\beta$ value that would have been obtained by fitting a logistic regression model with the same covariates to everyone. Second, in line with the practice of examining for disparate treatment as a test of statistical significance, we wish to choose the sample strata sizes, given $n$, so as to approximate as accurately as possible the decision that would have been obtained for this hypothesis test from the population logit analysis.

An attractive feature of the logistic model under stratified sampling is that it can be estimated using logit as if the data were collected using simple random sampling. That is, when the model contains a constant (intercept) term for each category, these intercept terms are the only coefficients affected by stratified sampling. The usual regression output gives estimates of the nonintercept coefficients that are maximum likelihood; that is, the estimators, under the appropriate regularity conditions, are consistent and best asymptotically normal. Further, the standard approach consistently estimates the standard errors, which implies that the usual statistic for testing statistical significance is an asymptotic standard normal variate when the null hypothesis is valid. However, the usual estimators of the intercept terms (which include stratum constants) are not consistent (Prentice and Pyke 1979; Scott and Wild 1986, 1991, 1997). Then, when race enters as a dummy variable, its coefficients are not consistent estimators. The standard logit estimators of $\beta_N$ and $\beta_M$, however, can be corrected for their asymptotic bias if the population proportions of the outcome response are known (as with HMDA data) and appropriate weighting is used.

Stratified random sampling is not employed by all of the regulatory agencies. The Federal Reserve uses sampling stratified by race but not outcome. Ernst & Young, in some of its papers, indicate that balanced samples across race and outcome stratum might be appropriate in certain instances. Giles and Courchane (2000) show that, if the standard logit estimator is employed, a sample design that balances by outcome and allocates across racial groups proportionally to the population is preferred.

Once the sample is chosen using the stratified random sampling technique, data for that sample are collected from the HMDA Loan Application Register (LAR). Then, field examiners follow with on-site collection of additional data elements needed to supplement the HMDA information. After data collection, multinomial logistic regressions test the hypothesis that disparate treatment occurs.

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16 At this stage of the process, the sampling was typically done based on data elements found in the HMDA Loan Application Register (LAR). However, if other fields were defined electronically for the population of loan applications, there might well be better variables to employ in the sampling process. For example, if the bank collected bureau credit scores, that might be a better covariate than loan amount, income, or some combination of the HMDA-LAR variables.

17 In at least one case, we treated whites as the minority group and Asians as the control group.

18 See Giles and Courchane (2000) for a much more detailed discussion of various sampling methods that might be appropriate in studies of fair lending.
Model Development and Results from Fair Lending Examinations

Determining the variables in each bank-specific model requires thorough understanding of the credit underwriting processes at each institution. Accurately and thoroughly documenting how transactions are processed and underwritten is important in any fair lending examination, but doing so early in the examination is particularly important when a statistical model is used, since the variables collected from the files will determine (and limit) the model tested.

Following is a description of the process used at the OCC for fair lending–focused statistical examinations. Typical sources of information on a bank’s underwriting process consist of the underwriter interview, written underwriting manuals, and subsequent conversations with the bank’s staff. Documentation includes all the underwriting policies, procedures, requirements, compensating factors, and exception conditions described by the institution. The model’s variables for which data elements are collected are based on the bank’s manuals along with specific interpretations by the underwriters that are stated in the interviews for familiar underwriting qualifications—such as LTV, DTI, the number and type of delinquencies, the number and type of public record items, job or income stability, private mortgage insurance (PMI) applied for or received (for high LTV loans), and special program status—and any unusual factors they consider.

Further, it is important to identify which processes and rules are supposed to be rigid and which flaws “fatal.” If verified as perfectly inflexible, such variables may be excluded from the model. However, the more that “rigid” rules appear to be flexible in practice, the more suitable it is to use a statistical model. The economists and examiners discuss each process, requirement, type of information, and decision with the bank.

Once agreement has been reached on identifying factors that influence the underwriting decisions, the data are collected from the bank. Individual transaction data for the variables form the basis for developing the model. The data can come directly from the bank’s electronic databases (if available) or can be extracted from loan files. The actual number of data elements collected ranges from 50 to 100 variables per applicant. In the regression modeling process, information from those elements is combined into a much smaller set of explanatory variables, most created from the collected data. These typically number fewer than 10 per bank.

While reviewing the files to collect data for the model, examiners also verify HMDA data and perform compliance and other verifications, recording any unusual information (in addition to that requiring explanation) in a column labeled “comments.” If any HMDA data provided by the bank electronically (therefore already appearing on the spreadsheet) are inaccurate as compared with the file, the examiners note the correct information. We found the incidence of HMDA inaccuracies to be very low. During data collection, examiners note instances in which the data to be collected (for example, income and debt amounts, derogatory credit, funds to close) were incorrectly or inaccurately recorded, as well as instances in which the underwriter failed to take comparable initiatives to qualify applicants. Information of this type is entered under “comments” and reviewed during the modeling process. While there

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19 If the bank, for instance, has a policy of denying any application from an individual previously bankrupt, and if there are no instances of bankruptcies in the records, there would be no point in collecting data on bankruptcies to be used in the model.
is no legal obligation for lenders to make unusual efforts to qualify applicants, it would be illegal disparate treatment for them to take such initiatives selectively on a prohibited basis. Files containing comments are then reviewed and compared manually by the examiners to determine whether disparate treatment occurred in how the bank assisted and advised applicants. The levels of assistance and advice were not elements in the statistical modeling, since they are not typically quantifiable.

Statistical models used in fair lending examinations test for disparate treatment while controlling for the bank’s underwriting criteria. Regression analysis combines multiple explanatory variables to best explain the lending decisions. For instance, the presence of major derogatories may be a key element in the loan decision process. Collected data might include public record information, numbers and types of derogatories, and current indebtedness. Created variables might include proxies for good credit, indicating that an individual had no public record items and no major or minor derogatories. A second created variable might be excess LTV, indicating whether an applicant had an LTV value exceeding the underwriting guidelines of the bank. The collected information for this created variable would include value of the loan and appraised value of the house for each of the programs used by the bank. Variables that are included in the model are based on bank-specific factors, with some significant and some insignificant individually but relevant to the overall performance of the model. These variables are chosen to reflect bank-specific policies or statements made by its underwriters and loan officers. While every attempt is made to accurately model the bank’s underwriting processes, in many instances the bank policies (or implementation of those policies) is not clear, leaving several different explanatory variables to fit the data. In these cases, it is particularly important to test for robustness of the model’s conclusions.

During the regression modeling process, economists might use several tests for robustness. This, at a minimum, includes consideration of alternative combinations of variables to see whether the same factors repeatedly show up as significant. This technique ensures that the findings do not depend on a single specification of the variables. Following the regression analysis, further file review is conducted both to ensure that no significant variables have been omitted from the analysis and to determine if truly unique files (unable to be modeled using general specifications of the bank’s underwriting processes) should be removed from the samples for contributing undue weight to the model results.

Table 1 provides a brief description of many of the variables used in the modeling process over the five-year period from 1994 to 1999. The actual specification of each variable depends on bank-specific factors, but many variables are common across a set of institutions. Many are mentioned specifically in the underwriting policy manuals, although we may find in the analysis that they do not have a significant impact on the lending decision. This list should not be viewed as comprehensive or sufficient and is always evolving.

The list of variables and the actual specification of each variable, including the threshold levels, vary from bank to bank. However, the underlying principles guiding the underwriting decision do not show much variation. Some trends persist. For example, as expected, LTV, indebtedness, and creditworthiness continue to have a significant impact on the decision to grant or deny credit for mortgage products. When it is collected and used, the bureau credit score is often the single most important variable included in the credit decision, in terms of magnitude and significance level. In fact, as shown by the list of variables used by Freddie Mac in its Loan Prospector credit scoring system or that used by Fannie Mae’s DeskTop
Table 1. Variables Used in Fair Lending Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
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<tbody>
<tr>
<td>DTI</td>
<td>Debt-to-income (gross) ratio</td>
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<tr>
<td>Excess DTI</td>
<td>Dummy variable equal to 1 if DTI value exceeds bank guidelines; otherwise 0</td>
</tr>
<tr>
<td>HDTI</td>
<td>House payment-to-income (gross) ratio</td>
</tr>
<tr>
<td>Excess HDTI</td>
<td>Dummy variable equal to 1 if HDTI value exceeds bank guidelines; otherwise 0</td>
</tr>
<tr>
<td>Income</td>
<td>Income (often used to verify availability of necessary reserves)</td>
</tr>
<tr>
<td>Self-employed</td>
<td>Dummy variable equal to 1 if self-employed; 0 otherwise (might be used to determine averaging of income for purpose of validating DTI calculations)</td>
</tr>
<tr>
<td>LTV</td>
<td>Loan-to-value ratio</td>
</tr>
<tr>
<td>Excess LTV</td>
<td>Dummy variable equal to 1 if LTV exceeds specific bank program guidelines; otherwise 0</td>
</tr>
<tr>
<td>Credit score</td>
<td>Derived from the bank's underwriting guidelines manual—for example, some banks collect multiple credit bureau scores for both the applicant and the co-applicant. Typically, the bank compares the applicant and co-applicant scores and uses a specified procedure to calculate a score variable combining information across bureau scores and across applicants</td>
</tr>
<tr>
<td>Bad credit</td>
<td>Derived from information on credit records and is always bank specific. For example, if there are no derogatories or delinquencies (e.g., if there are no public records of bankruptcy, foreclosure, unpaid judgments or collections, no late mortgage or rent payments, etc.) for the last 24 months, this variable is equal to 0. If a bad credit element is observed, this variable is equal to 1. Alternatively, this variable might include numbers of derogatories, delinquencies, or only public record information, depending upon the underwriting standards of the bank</td>
</tr>
<tr>
<td>Gift funds</td>
<td>Sum of gifts and grants. This information might be used to determine if the applicant is meeting the down payment requirements for a particular program</td>
</tr>
<tr>
<td>Public record</td>
<td>Public record information, created to be independent of the bad credit variable specification</td>
</tr>
<tr>
<td>Explanation</td>
<td>Various dummy variables equal to 1 if the bank asked for, received, or accepted explanations for credit bureau or other underwriting elements; 0 otherwise</td>
</tr>
<tr>
<td>Hispanic</td>
<td>Dummy variable equal to 1 if the applicant is of Hispanic origin; 0 otherwise</td>
</tr>
<tr>
<td>Black</td>
<td>Dummy variable equal to 1 if the applicant is black; 0 otherwise</td>
</tr>
<tr>
<td>Other race variables</td>
<td>Other racial categories such as Asian, Native American, or racial interaction terms (race interacted with other explanatory variables). Typically, the racial subgroups are not combined into a single minority category. Typically, white is the control group (as described in the Interagency Policy Statement)</td>
</tr>
<tr>
<td>Insufficient funds</td>
<td>Dummy variable equal to 1 if there were not sufficient funds to close. In specifications of this variable, emphasis is placed on whether the applicant met the down payment and reserve requirements for the individual programs that might be offered by the institution</td>
</tr>
<tr>
<td>Job stability</td>
<td>Dummy variable equal to 1 when indicating stable employment as defined by the bank; 0 otherwise</td>
</tr>
<tr>
<td>Loan program</td>
<td>Indicator variable detailing the loan program for which the application was received. For example, high LTV programs would have different underwriting guidelines than conforming programs</td>
</tr>
<tr>
<td>Fails PMI</td>
<td>Dummy variable equal to 1 if the applicant applied for PMI and was denied by the PMI company (to differentiate from bank denials)</td>
</tr>
</tbody>
</table>
Underwriting mortgage approval credit scoring product, the secondary mortgage market firms use many of the same categories of variables as have been observed to be significant in the judgmental systems examined at national banks over the past five years.

To keep the loan pool homogeneous, typically samples were drawn only for similar types of loans. That is, home purchase loans for owner-occupied housing (one to four units) were not combined with home improvement loans, nor were conventional loans combined with government (Federal Housing Administration or U.S. Department of Veterans Affairs) loans. Information on amortization period for loans of fixed or variable rate, adjustable or balloon, usually was not collected for approval models but might be collected for rates and terms examinations.

The results from several banks are included in table 2. Here, as throughout, we indicate the significance level of particular variables but not the exact specification of the variable or the size of the parameter estimate. General statements concerning the results follow. The variables are presented categorically rather than specifically. For example, the variable LTV might be the excess LTV variable, a continuous LTV variable, or a compensating factor for a particular bank. Similarly, the Credit Score variable indicates that a credit score (bureau, custom, or secondary market) was used in the decision, but it does not reveal the algorithm by which individual banks aggregated score data across bureaus or across applicants. This represents most of the findings from the statistical examinations conducted over the past decade. All unique elements to the examinations are included in table 2. In particular, there were no other statistical examinations that found evidence of a pattern or practice of discrimination on the approval/denial decision, nor were there any unusual variables that were significant in other decisions and excluded from this list. The banks were chosen to provide a broad spectrum of results with large geographical coverage.

Once modeling is concluded, a determination must be made whether to refer for violations. The Federal Financial Institutions Examination Council (1999) concludes that a pattern or practice of disparate treatment may be established by a valid statistical analysis of detailed loan file information that controls for possible legitimate explanations of differences in treatment.

Fannie Mae Chairman and Chief Executive Officer Franklin D. Raines said January 14, 2000, in a speech to the National Association of Home Builders, that Fannie Mae was “opening the book” on its automated underwriting system, partly by explaining that the factors the system reviews are equity; credit history; liquid reserves; DTI; salaried versus self-employed; loan amortization period; adjustable or balloon mortgage; number of units; co-op, condo, or attached; funds from other parties; loan purpose; number of borrowers; prior bankruptcies and foreclosures; and prior mortgage delinquencies.

Banks 7 and 8 received referrals to the DOJ for disparate treatment. Both settled out of court, resulting in substantial penalties for the banks and compensation for victims.
Table 2. **Model Results from Logistic Specifications for Fair Lending Approval/Denial Decisions**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Bank 1</th>
<th>Bank 2</th>
<th>Bank 3</th>
<th>Bank 4</th>
<th>Bank 5</th>
<th>Bank 6</th>
<th>Bank 7</th>
<th>Bank 8</th>
<th>Bank 9</th>
<th>Bank 10</th>
<th>Bank 11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit score</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
</tr>
<tr>
<td>LTV</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>—</td>
<td>1</td>
<td>1(^a)</td>
<td>1</td>
</tr>
<tr>
<td>Public record</td>
<td>1(^a)</td>
<td>1</td>
<td>1(^a)</td>
<td>—</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>—</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1</td>
<td>1(^a)</td>
</tr>
<tr>
<td>Insufficient funds</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
</tr>
<tr>
<td>GSE (Government-sponsored enterprise) score</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>DTI</td>
<td>—</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
</tr>
<tr>
<td>HDTI (Housing debt-to-income ratio)</td>
<td>—</td>
<td>1</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Bad credit</td>
<td>—</td>
<td>1</td>
<td>1</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
<td>1(^a)</td>
</tr>
<tr>
<td>Gifts/Grants</td>
<td>—</td>
<td>1</td>
<td>—</td>
<td>—</td>
<td>1</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Relationship</td>
<td>—</td>
<td>1</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>PMI</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Income/Savings</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Explanation</td>
<td>—</td>
<td>1</td>
<td>—</td>
<td>—</td>
<td>1(^a)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Race 1(^b)</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1(^a)</td>
<td>1</td>
<td>1</td>
<td>1(^a)</td>
<td>1(^a)</td>
</tr>
<tr>
<td>Race 2(^c)</td>
<td>1</td>
<td>—</td>
<td>—</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>—</td>
<td>1</td>
<td>—</td>
<td>1(^a)</td>
<td>1(^a)</td>
</tr>
<tr>
<td>White</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

**Note:** All models were considered to be robust and had acceptable goodness of fit statistics.  
\(^a\) Variable was significant in the approval/denial decision.  
\(^b\) Represents minority category when only one minority category exists.  
\(^c\) Represents case with two separate minority categories.
As with manual file comparisons, the OCC initially regards a statistical model as identifying only apparent disparate treatment on a prohibited basis. If the bank cannot account for those inconsistencies, the OCC will treat them as instances of discrimination, just as it does for manual file comparisons. To constitute a violation, the preponderance of the evidence must support such a finding. The OCC regards a supporting preponderance of evidence for violation as the race variable being statistically significant at the 5 percent level of confidence, after checks for robustness and examination of the files for which outcomes could not be correctly predicted by the model. Moreover, the OCC treats any finding of illegal disparate treatment identified by a statistical model as a pattern and practice of violations, unless the analysis indicates that the statistical result was unduly influenced only by unique files. Where that is the case, the conclusion might be to refer only isolated instances of discrimination.

Inspection of the results in table 2 indicates that there were three banks from this subset of examined banks that had apparent problems with disparate treatment. The overall percentage of banks referred for violations out of those for which fair lending examinations are conducted is much less than this 25 percent. The empirical results indicate some very interesting findings.

First, most of the large banks (8 of the 11 reported here) rely, at least in part, on some type of credit scoring model. Bureau scores, custom scores, or one of the secondary market scoring models such as Freddie Mac’s Loan Prospector is used in the mortgage loan approval process. While some banks are moving more heavily toward reliance on these tools, many use them as only one factor in a complex decision process. To the extent that scores are part of the underwriting process, individual elements from credit bureau reports become less significant. For some banks, numbers or dates of delinquencies and/or derogatories do not have a significant marginal contribution to the approval decision when credit scores are included as explanatory variables in the models. In all banks that used credit scoring systems, the OCC examined not only the scores, but also the process by which overrides were used.

In one case, it was the use of overrides (in home equity lending) that became an important determinant of the ultimate referral of the bank to the DOJ. (See: http://www.usdoj.gov/crt/housing/documents/casesummary.htm.) In this instance, we claimed that the bank had discriminated on the basis of race against African-American loan applicants in Mississippi, Arkansas, and Louisiana through the use of subjective underwriting practices, particularly through application of low-side overrides in their credit scoring system. We found that African-American applicants for home improvement loans whose applications were credit scored were at least three times more likely to be rejected than similarly situated white applicants. The settlement stipulated that an estimated 250 African-American applicants, whose applications for home improvement loans were evaluated under the flawed underwriting system, share in a $3 million fund. Also, uniform and centralized underwriting policies and procedures will be implemented, with a second review process and limited authority to override. The absence of credit score (or creditworthiness information in general) from the HMDA-LAR is one important reason why loan-level data must be used to examine discrimination in the mortgage lending process.

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22 In one exam, after controlling for other factors, race was a significant factor in the probability of denial of credit-scored home improvement loan applicants. Preliminary findings showed that black applicants were approximately three times more likely to be denied than whites who appeared to be similarly situated.
Second, some of the traditional underwriting elements remain important. Measures of LTV and DTI (the back ratio, including all debt payments per month) are significant for most banks, either when included as continuous variables or when the threshold effect is considered. Notably, the traditional front ratio of housing debt-to-income, or monthly housing debt, is usually found not relevant to the approval decision. One explanation for why LTV and DTI still matter is that credit bureau reports, from which credit bureau scores are derived, lack information on these two factors. Because they are not available from the HMDA data set and are so important at most banks, their manual collection is crucial before conclusions about disparate treatment can be drawn.

Finally, as one of the checks of robustness, a standard set of variables is often employed as a competing model. Unless those variables accurately reflect the underwriting process at each bank, the results obtained are very poor and may be misleading. For example, modeling special program parameters correctly is crucial. If not done, it might look as though a bank approved loans for applicants not otherwise qualified, and the racial dummy variable would be biased.

As previously noted, logistic analysis has been used in all of the approval decision statistical models. However, it has specific shortcomings. Alternative modeling procedures—specifically, generalized maximum entropy (GME) models—have been tested and found, in the three banks considered, to dominate the use of logistic models. The main advantages of this method, compared with the maximum likelihood (ML) (logit) are that it has superior behavior when data sets are small or highly collinear, a problem typically encountered in bank-specific data. Further, relative to the ML method, the GME approach is a more conservative (stable) estimation rule. This is extremely important for analyzing possible discrimination against a certain minority group. Conservative means that if discrimination truly exists, the GME will pick it up in a slower rate than the ML. Thus, when the GME method picks up a discrimination signal, the probability that it is the true (correct) signal is always higher than with any ML method. On the other hand, if there is no discrimination, the GME method reveals it much faster than the ML approach. Again, the probability of making a mistake is lower using the GME than with any ML method. Overall, this means that the probability of making a mistake (reaching the wrong conclusion) is smaller with the GME. More detailed results can be found in Courchane, Golan, and Nickerson (2000). The major disadvantage of this method is that few econometricians are trained in its use.

Additional improvements in the statistical modeling process will come from better collection of data by the banks. One advantage of automated systems is that the data can be collected, possibly verified and screened, and consistently recorded at the time of application. Another advantage is that with automated systems and electronic data, full populations can be analyzed at significantly lower costs than are incurred in using manually collected data from a sample of paper files.

**Conclusions and Policy Recommendations**

In a recent Urban Institute study (see Turner and Skidmore 1999, 19) the following suggestion was made:
A multisite study of discrimination in loan approvals should build upon the intensive review and criticism generated by the Boston Fed Study. In particular, a national study should invest significant time and attention in the collection and verification of complete and accurate data on borrower characteristics, loan characteristics, property characteristics, and credit history to guard against omitted variables and data errors that may bias results. Because of widespread differences between whites and minorities in income, wealth, property values, and credit histories, analysis that fails to account fully for these factors may seriously overstate the extent of discrimination in mortgage loan approvals. Moreover, future analysis should explore alternative versions of a loan approval model and test extensively for possible interrelationships among explanatory variables to generate unbiased results.

The aggregated findings from several institutions examined by the OCC over the past decade address that suggestion. In the analysis of disparate treatment, our findings support the need for loan-specific data on borrower and property characteristics as well as bank-specific data on underwriting guidelines. The statistical modeling used at these institutions was applied to a particular loan product at a particular institution for a particular time period. The targeting decisions were all made, given the timing of the examinations, on findings of racial disparities in decisions from the HMDA data. If conclusions were based on the HMDA data alone, all of these institutions would appear to have discriminated by race. Additional data must be collected to draw more accurate conclusions. Even with that additional data, there is no one-size-fits-all model that applies to all banks (or even to large national banks). Using a specific model across pooled bank data would also have led to biased conclusions with respect to disparate treatment. When statistical analysis is used, bank-specific modeling has immense value when substantiating findings of disparate treatment.

The increased growth of automated underwriting systems will make it easier to detect patterns of discrimination in lending. However, our experience over the five-year period from 1994 to 1999 found no bank that relies solely on automated systems for mortgage lending, with all relying on some system of overrides that might be used judgmentally. Even for those loans sold to the secondary market, loan officers and underwriters must use judgment in large ranges of credit scores. Some banks use multiple scoring models, with various decision rules, depending on outcomes dictated by the models. This makes the analysis of disparate treatment more complex rather than easier. Also, to the extent that overrides remain judgmental, the system is not truly automated and the potential for disparate treatment remains.

Much work needs to be done in this area. The progress of that work is impaired by a lack of data sets available to researchers. Few banks are willing to put individual loan file data in the hands of nonregulators. This places a burden on the regulators to continue research or to collaborate with others so that the work can be done. Relaxation of data collection requirements—in particular, the collection of racial identifiers—would help extend this research to areas beyond home mortgage lending. The outcome of proposed changes to Regulation B\(^{23}\) will have a large impact on this issue. However, even with better data and better access to data, questions remain. For some we have answers; but for many we do not.

The current state of knowledge in fair lending has been considerably enhanced by the work of many researchers during the past decade. Academics raised important issues concerning the process by which banks might discriminate. Regulators took those issues to heart and implemented significant changes in fair lending examination procedures. The use of statistical techniques in examinations was unprecedented before the 1990s. Now statistical models are used in several facets of compliance examinations. While academics raised concerns about possible discrimination occurring during several stages of the mortgage application process, from prescreening to servicing, the examination process has, for the most part, focused only on the approval or denial decision, devoting less attention to pricing issues. Recent concerns about practices of predatory lending might move that focus more to pricing and steering issues. Past work has focused on disparate treatment. However, researchers at agencies that develop credit scoring models, such as Fair Isaac, Freddie Mac, and Fannie Mae, have begun to examine issues of disparate impact as well. This area will be of continued importance in the coming decade.

The emphasis by the largest banks on fair lending issues has also changed during the decade. Many have developed internal staffs that can, as loans are made, consider the fair lending implications through internal statistical models. Clearly, using this proactive approach, rather than simply responding to fair lending referrals by the regulators, will be of the most benefit to consumers. Training bank staffs to understand the statistical models used, if purchased from vendors, is also crucial. As previously noted, it will not be sufficient to simply apply models (such as credit scoring models), without understanding their impacts or their overrides. Banks must understand the models they use if they hope to discover whether fair lending violations might occur.

What have we learned?

1. Does discrimination in lending still exist? Most likely it does, although discovery, measurement, and correction of discriminatory practices remain difficult, hampered by lack of resources and data.

2. Will credit scoring prevent discrimination? Likely not, although it can be used to do so if overrides are carefully monitored and models meant to minimize disparate impact are developed.

3. Are statistical models useful in identifying disparate treatment? Decidedly, yes, and better data collection will make the process more efficient at lower cost.

4. Are there alternative models and methods that might make the discovery process easier? Yes. Better sampling techniques and innovative modeling can reduce the data collection and examination costs, allowing for more widespread adoption of statistical methods to resolve discrimination issues. This might best be accomplished by establishing a public-use database such as those used for HMDA and government-sponsored enterprise data.

In conclusion, efforts throughout the past decade heightened awareness of potential discrimination in lending. The efforts of those responsible for making loans, for examining the institutions that make loans, and for policy makers concerned about access to loans for all consumers were united in trying to measure and minimize discriminatory practices in
mortgage lending. While many successes were observed, much remains to be done, with cooperation among all interested parties essential.

References


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