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Anatomy of a Fair-Lending Exam: The Uses and Limitations of Statistics

by Paul S. Calem and
Stanley D. Longhofer

FEDERAL RESERVE BANK OF CLEVELAND

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JEL Subject Codes: G21, G28, J78

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ANATOMY OF A FAIR-LENDING EXAM:
THE USES AND LIMITATIONS OF STATISTICS*

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ABSTRACT

In this paper, we consider the role of statistical analysis in fair-lending compliance examinations. We present a case study of an actual fair-lending examination of a large mortgage lender, demonstrating how statistical techniques can be a valuable tool in focusing examiner efforts to either uncover illegal discrimination or exonerate an institution so accused. Importantly, our case also highlights the limitations of such statistical techniques. The study suggests that statistical analysis when combined with comparative file review offers a reasonably balanced and thorough approach to the enforcement of fair-lending laws.

1. Introduction

In recent years, statistical analysis has played an increasingly important role in the enforcement of the nation's fair-lending laws. Government agencies that regulate depository institutions, especially the Federal Reserve and the Office of the Comptroller of the Currency, have incorporated statistical techniques into regularly scheduled compliance examinations to help identify possible discriminatory patterns in decisions to grant credit and in the pricing of credit. Statistical analysis also has figured prominently in recent fair-lending cases pursued by the Justice Department.

Whereas a purely judgmental examination process tends to focus attention on individual instances in which minority applicants appear to have been treated differently than comparable white applicants (which may reflect purely random outcomes), statistical testing, in principle, can detect a *pattern* of discriminatory treatment. Despite this straightforward rationale, the practice of applying statistical techniques to uncover lending discrimination has been somewhat controversial.

Most pointedly, the logistic regression models such as those used by compliance examiners have been criticized as being inadequate to represent the complex array of factors underlying lenders' decisions to accept or reject mortgage loan applications. Indeed, these models are similar to those employed in the well-known study by Munell et al. (1992, 1996) that purported to find evidence of discriminatory treatment of minority applicants by mortgage lenders in the Boston metropolitan area ("the Boston Fed study"). Since its initial appearance, this study has generated heated debate regarding its validity and proper interpretation.[1] By implication, the use of these statistical techniques in the examination process is equally suspect.

Missing from this debate, however, has been consideration of the checks and balances on the use of statistics that are inherent in the full examination process. In this paper, we present a case study of an actual fair-lending examination conducted by Federal Reserve staff. Our

[1] Contributions to the debate include Carr and Megbolugbe (1993), Galster (1993), Tootell (1993), Glennon and Stengel (1994), Yezer, et al. (1994), Browne and Tootell (1995), Rachlis (1995), Sandler and Biran (1995), Bostic (1996), Hunter and Walker (1996), Horne (1997), Day and Leibowitz (1998), and Longhofer and Peters (1999).

purpose is to broaden the discussion of the role of statistical analysis by viewing this role from the perspective of the fair-lending examination process as a whole.

Our case demonstrates how the examination process combines the use of examiner judgment and statistical analysis in mutually-enhancing ways. Statistical methods help examiners select markets and loan products on which to concentrate, determine whether a pattern of discrimination appears to exist within the selected category, and identify specific files meriting their close attention. Thus, statistical analysis serves as an important tool bringing additional rigor to the examination process. At various stages, however, examiners apply a critical measure of judgment to overcome the limitations inherent in these statistical techniques. For instance, in the case we study logistic regression analysis suggested the strong possibility of illegal discrimination. Follow-up review of individual loan files, however, revealed legitimate, non-discriminatory, albeit somewhat idiosyncratic factors that explained the statistical results.

Perhaps most importantly, our case demonstrates that arguments against the use of logistic regression models for detecting lending discrimination tend to lose their cogency when the full examination context is considered. For example, a major criticism is that statistical models generally exclude important factors contributing to denials, either inadvertently or because some factors are not amenable to statistical modeling. In the context of a fair-lending examination, however, if indeed there is such reason for denial, it is apt to be identified during the file review stage.

Ours is not the first analysis of the use of statistical techniques to evaluate fair-lending compliance. Stengel and Glennon (1999) use data from three exams performed by the Office of the Comptroller of the Currency to demonstrate the importance of using bank-specific underwriting models in these exams. In contrast to their study, however, our emphasis is on the role of statistics within the larger examination context; in particular, how follow-up file reviews shed light on questions raised by the statistical portion of the exam. Thus, our paper is a natural extension of their initial work in this area. Courchane, et al. (2000) review the statistical examination procedures used at the Office of the Comptroller of the Currency (OCC) and summarize the findings from eight different fair-lending exams undertaken by the OCC since

1994.[2] Once again, however, their focus is on the common factors that arose in the statistical portion of these exams, not on how follow-up file reviews can give a more complete picture of an institution's underwriting practices. Siskin and Cupingood (1996) review the statistical techniques used by the Department of Justice in their investigation of Decatur Federal Savings and Loan, but do not discuss the limitations of such techniques in drawing conclusions about the presence of illegal discrimination. Courchane, et al. (1999) use bank exam data to consider the merits of using generalized maximum entropy rather than logistic regression techniques to uncover discriminatory patterns. Once again, however, they do not investigate how these statistical techniques would fit into the overall examination process.[3]

In the next section, we briefly review the fair-lending examination process currently used by consumer compliance examiners in the Federal Reserve System for the evaluation of mortgage lending decisions. In Section 3, we introduce our case study of one particular fair-lending exam, presenting the statistical results generated for this exam. Section 4 continues the analysis with the matched-pair file review that followed the statistical portion of the exam. In this section, we carefully scrutinize each of the rejected loan files to shed light on the statistical results reported in Section 3. In Section 5, we discuss some of the criticisms of the use of statistical techniques for detecting illegal discrimination, and show how the follow-up file review serves to mute many of these concerns. We conclude and summarize our findings in Section 6.

2. The Federal Reserve's Examination Process

Both the Equal Credit Opportunity Act and the Fair Housing Act prohibit mortgage discrimination on the basis of a number of protected characteristics, including race and ethnic status.[4] The federal bank supervisory agencies are responsible for enforcing these laws with respect to their regulated depository institutions. For the Federal Reserve System, this responsibility covers state member banks and their subsidiaries. If the bank regulatory agency

[2] See also Courchane and Cobas (1995).

[3] Rosenblatt (1997) also looks at data from a single mortgage bank, with particular attention to whether applicants correctly self-select into the proper loan program (conventional vs. FHA/VA). He does not, however, directly focus on the use of statistical techniques as a tool for fair-lending enforcement.

[4] Other protected characteristics include gender, age, marital status, familial status, religion, national origin, receipt of public assistance, and handicap; the specific prohibitions differ slightly between the two acts.

uncovers specific and credible evidence of discrimination, it is required by law to refer the suspect institution to the Department of Justice for further investigation and possible prosecution.

Within the Federal Reserve System, the fair-lending examination process, as it pertains to mortgage credit-granting decisions, combines examiner judgment with statistical methods and involves a number of steps. The full process is discussed in detail in Calem and Canner (1995). Here, we briefly summarize each of the steps in turn.[5] Although other government agencies charged with fair-lending enforcement follow different specific procedures when conducting a statistical analysis of credit granting decisions, critical elements of the process are broadly similar across agencies. For instance, each of the agencies would perform some sort of preliminary analysis to decide whether to proceed with a detailed statistical review, carefully review the institution's written underwriting policies, employ logistic regression analysis, and conduct follow-up review of individual loan files.

2.1. Sample Selection and Data Collection

The data requirements for a full-scale logistic regression analysis of a bank's lending practices are substantial, making such an analysis a costly endeavor for both the bank and the regulatory agency. In order to limit such investigations to those cases where discriminatory treatment appears a more-likely possibility, examiners run an initial statistical analysis of a bank's lending activity using data made available through the Home Mortgage Disclosure Act (HMDA). This process is known internally within the Federal Reserve as "step one."[6] Essentially, the step-one analysis is a screening procedure that helps to allocate examiner resources.

The step-one program first sorts an institution's mortgage loan applications by product type (conventional home purchase, FHA or VA home purchase, conventional refinance, FHA or VA refinance, and home improvement), number of applicants (one or more-than-one), the

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[5] Similar procedures generally are followed for the fair-lending evaluation of pricing decisions. Examiners perform an initial review of pricing and if this yields evidence of disparities, a more-detailed statistical analysis is undertaken.

[6] The following description of the step one procedure is adapted from Avery, Beeson, and Calem (1997), where econometric issues pertaining to this procedure also are discussed.

market or metropolitan statistical area (MSA), quarter of action-date, and applicant race. Each minority application is then matched to all non-minority applications along these dimensions and with respect to having similar income and loan amount.[7] The disposition of the minority application (approved or denied) is then compared with the average disposition of all non-minority applications matched to it. This comparison is averaged over all minority applications within each of the institution's product and product/market cells.

Examiners use the statistics generated by the step-one program to determine whether a full-blown logistic analysis appears warranted and to help select a product category and market area on which to focus if it is. Often, however, these decisions are not based solely on statistics nor arrived at mechanically. Rather, contextual factors are considered and judgment comes into play.

The decision whether to proceed with a more-detailed statistical analysis begins with an evaluation of the matched-pair disparities. First, a product or product/market cell must exhibit a disparity that is statistically significant, preferably at the five percent level or higher, to qualify for further statistical review. Also critical is the economic significance of these disparities—cases involving small disparities typically are not viewed as meriting detailed statistical review.[8] For an institution that operates in many markets, an isolated disparity may not be viewed as worth investigating if there is no statistically significant disparity at the aggregate product level. Examiners must weigh the possibility that such an isolated disparity is an artifact of randomness in the distribution of denials across markets (a "false positive") against the potential for discrimination to be a localized phenomenon reflecting, for example, the activities of a rogue loan officer.[9]

The size and composition of the potential sample of loan applications are also critical considerations. The potential sample must contain an adequate mix of approved and denied

[7] Attention is restricted to loans pertaining to 1-4 family properties. Minority applications that cannot be matched to any non-minority application are not included in the analysis.
[8] This is because small disparities in the HMDA data can often be entirely attributed to underwriting variables such as the loan-to-value ratio and credit history.
[9] One factor that would be taken into account is the degree to which underwriting decisions are centralized.

applications and an adequate mix of applications from minorities and non-minorities.[10] One issue that commonly must be dealt with is the extent to which it is appropriate to pool samples from different markets or years to obtain a sample of adequate size or composition.[11]

In cases where the institution has multiple products or market areas qualifying for further statistical review, judgment frequently is required to determine which to select for further analysis. The size of the disparity in each product or product/market cell is a factor, since one line of reasoning dictates allocating limited resources to where preliminary evidence of discrimination is strongest. In addition, categories that provide a larger sample or more adequate sample composition tend to be favored. Other factors that may be considered include findings from prior examinations, complaints from the public, and whether underwriting is centralized (in which case it may be more appropriate to review an entire product category than isolate a particular product/market cell.)

It is worth reiterating that the purpose of the step-one procedure is to provide an initial screen on the data. In effect, this program is used to conserve examiner resources by screening out cases in which a full regression analysis would be unlikely to uncover any illegal disparities even if it were performed. Importantly, no conclusions are ever drawn based solely on the step-one analysis. Furthermore, even if the step-one analysis does not indicate a full-blown regression is appropriate, examiners may still use the matched applicant pairs generated by the program to conduct a more-traditional comparative file review.

2.2. Sample Selection and Data Collection

If it is determined that a full-scale regression analysis is necessary, the next stage is to identify specific loan files to pull for the sample. A slightly modified version of the matched-pair process used for the initial screening is employed to draw the sample. Each minority

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[10] Alternative statistical procedures for addressing situations in which the denial-rate disparity is large but the denial rate for non-minorities is very low are under development.

[11] Another potential source of difficulty is that any of the broadly delineated product categories in HMDA data may encompass distinct loan products. For example, the home improvement category often includes secured and unsecured term loans as well as home equity lines of credit. Examiners generally will not proceed with further statistical analysis if the category under consideration is expected to be too heterogeneous with respect to the combination of loan types contained therein.

applicant within the targeted product or market/product cell is paired with its closest non-minority applicants, where up to three matches are allowed.[12] A random sample of pairs is taken if the number of minorities is too large for the resources at hand. Otherwise, each of the minority applicants is included in the sample, along with at least one of its matched non-minorities.

It then becomes the examiners' job to determine which data items to collect from these files. Although there are standard variables that are always collected for these examinations, examiners must nevertheless use their knowledge of the bank's underwriting practices to augment this list. Most relevant to determining which variables to collect is the information examiners learn from discussions with the institution's loan officers and underwriting committee and from a review of written lending policies. Variables the institution claims to use in its underwriting process are important to include in a full regression analysis of the institution's underwriting practices.[13]

Once the variables to be collected have been determined, examiners then begin the painstaking task of collecting data from the files selected for the sample. During this process, substitute loan files may be selected if HMDA coding errors and files with missing data are uncovered.

2.3. Logistic Regression Analysis

Logistic regression techniques are then used to evaluate these data. This detailed statistical analysis is known internally within the Federal Reserve as "step two." As with the Federal Reserve Bank of Boston study, the goal of the step-two analysis is to determine whether applicant race (or some other protected characteristic) appears to be systematically related to the lender's decision to accept or reject an application, after controlling for legitimate underwriting factors.

The initial model specification is based on the examiners' review of the institution's underwriting policies, but additional specifications are tested as well. In particular, different

[12] Matches are selected with replacement, meaning that the same non-minority can be matched to several minorities.

[13] These discussions also give examiners an opportunity to verify that the underwriting "model" used by the institution does not inherently violate fair lending statutes. For example, if a bank claimed to consider an applicant's marital status, this would likely constitute a referable violation.

definitions of acceptable loan-to-value ratios, obligation ratios, and "severe" credit defects are tested to see which best explains the bank's underwriting practices.[14] If the sample is drawn from more than one market, differing market conditions that may affect denial rates are controlled for by means of market-specific dummy variables, regardless of whether market-specific factors are explicitly recognized in the lender's stated underwriting policies. Similarly, variables are included to control for other potential sources of heterogeneity, such as whether the application was for a loan with a fixed or an adjustable interest rate, or whether it was processed by a broker or an in-house loan officer.

2.4. Comparative File Review

Regardless of its outcome, examiners follow the step-two procedure with a detailed review of loan files. The computer program used to implement the step-two statistical analysis uses the final (most-preferred) model specification to pair rejected applications with approved ones that appear to be less qualified than the rejected file in question. Examiners carefully inspect these rejected applications and compare them to those that were approved, noting any special circumstances that were not included in the original regression analysis. They may also examine individual applications not included in such pairs, seeking additional insight into factors that may affect the disposition of a loan application.

If the regression analysis indicates a statistically significant disparity between white and minority applicants, examiners use the follow-up review to confirm or refute this initial indication of illegal discrimination. Information uncovered in this step of the examination will often explain the credit decision and indicate the applicant's race or ethnicity played no role, as demonstrated in the case study below.

At the same time, however, the matched-pair analysis can uncover illegal acts that may have gone undetected by a purely statistical review. For example, hand-written notations by loan officers found in the loan file may cause examiners to ask further questions about the bank's underwriting practices or the actions of a particular employee. Thus, even when the initial

[14] While a bank may have an explicit underwriting policy that it claims to follow, their de facto policies may differ. By testing a variety of specifications, examiners can ensure that the bank's *actual* practices are non-discriminatory.

statistical analysis does not reveal a statistically significant race effect, the matched-file review is an essential element of a comprehensive fair-lending investigation.

3. A Case Study of a Fair-lending Exam

To better understand the role of statistical analysis in fair-lending compliance examinations, we review an examination recently performed by Federal Reserve staff. The subject of the examination was a large institution with a presence in several geographic markets. Although we focus on a single examination, it is important to note that the steps followed in this exam—and the ultimate conclusions that resulted—are quite typical. Thus, this exam provides an excellent illustration of the uses and limitations of statistics in the fair-lending examination process.

3.1. Initial HMDA Analysis

As discussed above, the step-one procedure compares minority and white loan applications to find relatively close matches based on the information available through HMDA. The procedure then evaluates denial-rate disparities between the matched minorities and whites at the aggregate institution level and within product and product/market cells.

Selected output from this analysis is reproduced in Table 1.[15] The columns in this table show the denial rates for paired white and minority applicants and the resulting denial-rate disparity, both for the institution as a whole and within each product classification.[16] Overall, minority applicants at this financial institution during the year under review were roughly 50 percent more likely to be denied loans than were white applicants. Similar disparities existed across all loan product categories.[17]

Table 2 shows the breakdown of denial rates based on the race of the applicant. As is

[15] More information is contained in the step-one reports than is reproduced here. The data presented were chosen to reflect the salient issues in this exam, while protecting the identity of the financial institution in question.
[16] In the initial step-one analysis, an applicant is classified as a minority if either the applicant or the co-applicant is listed as being non-white in the HMDA data (HMDA race codes 1, 2, 3, 4, or 6). HMDA codes 7 and 8 (Not Provided and N/A, respectively) are excluded from the analysis.
[17] The large disparity among FHA/VA refinancings was only significant at the 10% level, due to relatively few loan applications in this product class.

often the case, the relatively small number of American Indian loan applications makes statistical analysis impossible, despite their comparatively high matched denial rate. Although the number of Asian applicants at this bank was sufficient to permit a statistical analysis, the size of the disparity for this group was relatively small and lacking in any statistical significance. This, too, is quite typical. In contrast, Black applicants were 1.8 times more likely to be rejected than matched whites, while Hispanic applicants faced a denial-rate disparity of 1.25 to 1, both of which were statistically significant at the 1 percent level.

The step-one program also allows examiners to separately evaluate the lending activity in each MSA in which the bank does business. Table 3 shows the matched-pair denial-rate disparities within the particular MSA on which examiners ultimately chose to focus their efforts.[18] As can be seen in the table, the overall paired denial-rate disparity in this market was comparable to that for the institution as a whole (1.5 to 1). Within this market, the conventional purchase loan category exhibited a paired denial-rate gap of more than 2 to 1.

Based on the information summarized in these tables and other factors, examiners decided to collect data to perform a full logistic regression on the institution's conventional home purchase lending activity in this MSA. Because the paired denial-rate disparity was relatively modest in magnitude (under 10 percentage points), the decision to proceed was based on a number of additional considerations, including the fact that this institution had not previously been subject to a detailed statistical fair-lending review.

3.2. Data Collection

Using the sample-selection procedure described earlier, 420 conventional home purchase mortgage application files were selected for the full regression analysis. In the end, 10 of these files were removed from the sample because of coding errors in the HMDA data (e.g., they belonged to a different product category) or because the bank was unable to locate the loan files requested. An additional 70 loan files were excluded because they were applications for a

[18] All of the MSAs that this institution served were reviewed in a similar way. This MSA was chosen for the step-two analysis based on a number of factors, including presence of a large number of minorities and the fact that the disparity in this MSA was typical for that of the institution as a whole.

special loan program with different underwriting criteria.[19] This left a final sample of 340 loan files, including 43 denied applications. The number of applications from minorities was 154, of which 30 were denied.[20]

In total, examiners collected 72 data items (including information reported under HMDA), which were then used to create literally dozens of additional variables for the logistic regression analysis. The data collected included personal information about the applicant and co-applicant (e.g., race, gender, income, assets, housing expenses, employment history, credit history, and bankruptcies and foreclosures); characteristics of the requested loan (e.g., principal and interest payments, whether mortgage insurance was obtained, the application and action dates on the loan, and the loan officer processing the application); and information about the subject property (e.g., its appraised value and the census tract in which it was located).

3.3. Statistical Analysis

Given the volume of data collected from each loan file, economists were asked to determine a model specification that most accurately reflected the bank's actual underwriting practices. In doing so, various specifications were considered. The final variables used in the statistical portion of the exam are listed and defined in Table 4. These variables were selected based on several guiding principles. First and foremost was their ability to accurately capture the factors the bank claimed to consider, as well as those theoretically relevant to the underwriting decision. Thus, the final regression model included variables reflecting the applicant's capacity to repay the loan, credit history, and collateral position. Second, variables were included to control for market conditions, which may affect the distribution of credit risk in applicant pools and hence affect the stringency of the lender's underwriting standards (Longhofer and Peters, 2000). Third, more parsimonious specifications were generally preferred, as long as their explanatory power remained high. Ultimately, however, a key factor considered was the robustness of the estimates in the final specification to minor changes in the model. Because our

[19] Examiners performed a detailed analysis of these loans, using both statistical techniques and judgmental file review, and found no evidence of illegal discrimination among these loans.

[20] For this product/market category, the matched-pair denial-rate disparity did not vary much in magnitude with the racial or ethnic classification of the minority applicant. Therefore, all minority groups were included in the analysis.

goal in this article is to contribute to a general understanding of the role of statistical analysis within the overall context of a fair-lending compliance evaluation, we do not present all of the various model specifications that were investigated in the course of this examination.

Several points are worth noting about the variables selected for the regression. First, although examiners collected detailed information about the number and type of delinquencies shown on the credit report, by far the best predictor of loan acceptance was the bankruptcy variable ultimately selected. This was consistent with the bank's stated underwriting policy, under which minor delinquencies were not weighed very heavily. Similarly, several specifications for obligation ratios were considered, including both continuous and discrete versions. In the end, back-end (total debt payment-to-income) ratio bounds of 40% and 45% proved to be the most descriptive of the bank's actual underwriting practices; the front-end (housing debt payment-to-income) ratio did not appear to matter after controlling for the back-end ratio. Third, the size of the loan did not appear to affect its likelihood of being approved once the loan-to-value (LTV) ratio was considered. At the same time, higher LTV cutoffs such as 90% and 95% had no explanatory power above that provided by identifying loans with LTV ratios above 80%.

Other variables were included because of their theoretical importance in how the lender might treat applicants with a given characteristic. For example, seasonal dummies were included to account for changes in market conditions over the course of the year. Similarly, a broker dummy variable reflects the fact that brokers tend to prescreen applicants to verify their compliance with the bank's underwriting guidelines. Co-applicant and retired applicant dummy variables may serve as proxies for applicants whose income is expected to be more stable over time.

Descriptive statistics for the variables used are presented in Table 5. Overall, 87% of all mortgage loan applications in our sample were approved. Some other notable features of the sample are: 48% of the applications were forwarded by a broker rather than by an in-house loan officer; 24% of the applications had a bankruptcy, collection, judgment, or foreclosure on the credit report; and 45% of the sample was comprised of minority applicants.

Logistic regression results are reported in Table 6.[21] All of the variables included in the final specification are statistically significant, with the exception of the co-applicant dummy variable, applicant income, and a dummy variable for applications in the 1st quarter of the year. Most variables are significant at the 1% level or higher. The percentage point impacts are derived by calculating the probability of approval for an applicant with the mean income ($47,956) and for whom all dummy variables are equal zero, and comparing this probability with that of an applicant who is identical in every respect except the characteristic in question. For dummy variables, this means setting the variable in question equal to 1, and for income it involves increasing the applicant's income by $1,000. To clarify the interpretation of this number, note that the probability that this hypothetical "normal" applicant is approved is 97.38%. In contrast, an applicant whose verifiable liquid assets (at the time of application) are below those required for closing (*Deficit* = 1) but is "normal" in every other respect has a 91.58% chance of being approved.[22]

Of primary interest from an examination standpoint is the minority dummy variable. This coefficient is statistically significant at the 2% level. At first glance, the 4.56 percentage point impact for minority approvals may not seem particularly large. But given that the base case denial rate is only 2.62%, this translates into a 2.8 to 1 denial-rate disparity. More strikingly, when other derogatory factors are present, the impact of minority status increases dramatically. For example, a "normal" white applicant with a LTV ratio above 80% is approved 92.81% of the time. In contrast, an otherwise identical minority has only an 81.45% chance of approval. A disparity of this magnitude will generally merit close scrutiny by examiners.

4. Follow-Up File Review

The next step in the examination process is to investigate credit decisions more closely by reviewing matched files. Using the predictions based on the estimated equation along with

[21] The results reported are for a non-weighted regression. The results were essentially unchanged when the equation was re-estimated after assigning weights consistent with the matched-pair procedure used to draw the sample. For that estimation, the weight assigned to a particular white applicant was based on the number of minorities with which the applicant was paired and on the total number of whites matching to these same minorities.

[22] Applications exhibiting such a funding deficit are not necessarily rejected because the applicants may be able to demonstrate alternative sources of funds, such as investments they plan to liquidate or gifts from close relatives.

selected characteristics for matching, the step-two program generates new pairs of rejected and approved loan applications on which examiners can focus their efforts. The rejected application in each pair has an equal or greater predicted likelihood approval than the approved application (after accounting for the predicted effect of race.) Examiners carefully inspect each of these loan files and possibly other files as well, taking detailed notes about information revealed in these files that may have been omitted from or not adequately accounted for in the statistical analysis. Each rejected loan application was included in the follow-up review for the institution that is the subject of our case study.

In this section, we review the findings from this stage of the examination. The primary reasons behind the denial of each of the rejected loan applications are summarized in Table 7. The information gleaned from the follow-up review indicated that most rejections occurred at least in part for legitimate reasons that cannot be effectively controlled for using statistical techniques. Therefore, examiners concluded that there was no evidence of illegal discrimination.

4.1. Unverifiable Information or Incomplete Application

Nearly half of all rejected applications (20 out of 43) were denied primarily because of unverifiable information (such as reported income) or incompleteness. Nearly all (12 out of 14) brokered applications and about a quarter of (8 out of 29) direct applications that were rejected had unverifiable information or were incomplete. Table 8 shows the results of a logistic regression in which applications that were rejected for reasons *other* than incompleteness or unverifiable information were excluded from the analysis.[23] As evidenced in this table, when we restricted our attention only to denials for unverifiable information or incompleteness, we found a statistically significant disparity between the minority and white denial rates. The overall disparity was driven by the brokered application denial rates.[24]

Denial-rate disparities arising because of unverified or incomplete information in the loan file can be a particular concern from a fair-lending perspective, because such disparities may

[23] The specification in this regression is more parsimonious than that shown above because the smaller number of rejected loan files reduces the power of the statistical tests.
[24] This was confirmed by re-estimating the equation with interaction terms differentiating among brokered and direct applications from whites and minorities.

reflect disparate treatment by the loan officers and others who collect this information. For example, if underwriters have been less aggressive in verifying the income and assets of minority applicants, then this type of disparity would result. Although statistical analysis can help identify this as an issue for examiners to address, it is an inappropriate tool for determining whether there actually was bias in the bank's efforts to obtain or verify information. Instead, this issue can only be evaluated judgmentally by examiners.

It is noteworthy that the source of this disparity was loans originally solicited by a broker. Brokered loans are substantially less likely to be rejected than loans coming from in-house loan officers. This fact suggests that a broker is unlikely to submit a loan package to this bank if he or she believes this application will not meet the bank's underwriting guidelines. At the same time, brokers know that the bank will diligently verify the information contained on the application, making the broker's verification efforts redundant. Thus, when brokered loans are rejected, it is rarely because the applicant fails to meet the bank's underwriting guidelines, but rather because the information contained in the loan file could not be verified.

In the end, examiners found no cause for concern regarding the collection and verification of information by this institution. In particular, there was no evidence to suggest that time spent by the bank on minority files that were rejected for this reason differed from that spent on white files rejected for the same reason.

4.2. Omitted variables or Idiosyncratic Factors

When applications denied due to unverifiable information or incompleteness were excluded, the statistical model still indicated a statistically significant disparity between white and minority approval rates. The results from this regression are presented in Table 9.[25] The continuing significance of the minority dummy variable suggests that unverified and incomplete loan files alone cannot explain the disparity between white and minority denial rates. A detailed examination however, indicated that there were further factors contributing to denial that were

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[25] Again, the results were robust to performing a multinomial logistic regression incorporating each of the possible outcomes: approvals, denials due to unverifiable information or incompleteness, and other denials.

not included in the statistical model for most of the rejected applications.[26]

The most frequent such factor was the presence of one or more open collection items on an applicant's credit report. The statistical analysis did not distinguish between paid and unpaid collections because this information had not been collected.[27] If the information had been collected, then it may have been feasible to determine whether the presence of an open collection item meant certain rejection or to control for this factor in a statistical model. Instead, examiners relied on a judgmental analysis to determine whether this reason for rejection had been applied in a non-discriminatory manner. In particular, examiners found no cases where comparable minority and white applicants, each with open collections, were treated differently.

Other factors contributing to denial appeared to be more idiosyncratic in nature. These included, for instance, reliance on rental income coupled with a very-high back-end ratio, and issues pertaining to the adequacy of the collateral coupled with a high loan-to-value ratio. Such factors, because they are unusual, cannot feasibly be controlled for in a statistical model. Again, examiners relied on a judgmental analysis to determine whether these reasons for rejection had been applied in a non-discriminatory manner.

5. The Uses and Limitations of Statistics

The recent use of statistical techniques in compliance examinations has not been without its critics.[28] In this section, we highlight some of the more important concerns that have been raised about the use of statistics to detect discrimination in the mortgage underwriting process, and explain how the overall fair-lending examination process may overcome these problems. The intent is not to present a definitive rebuttal to each of the various objections to incorporating statistical techniques into fair lending examinations, but rather to demonstrate the importance of considering the full examination context when assessing the role of statistical analysis.

[26] There were two rejected loan applications that contained no additional information outside that incorporated into the statistical model. In both of these cases, the predicted probability of approval was very low because of a number of derogatory factors. Thus, the model fully explained these rejections.

[27] Collecting data from loan applications, particularly from applicant credit reports, is a time-consuming and painstaking process. As discussed above, to conserve resources examiners limit the collection based on a review of the bank's lending policies, discussions with bank credit officers, and prior experience.

[28] Rachlis (1995) provides a nice summary of these criticisms. See also Phillips and Trost (1995).

5.1. Combining Institutions, Products, and Markets

One of the more fundamental concerns with interpreting the Boston Fed Study's results is their use of multiple institutions with different underwriting guidelines. Similarly, many have expressed concerns about combining applications from different loan programs and different markets, even when only one institution's lending practices are analyzed.

Obviously, the banking regulatory agencies analyze each institution independently for fair-lending compliance. Furthermore, each product type is analyzed in isolation, to ensure that any differences in underwriting practices across product types do not bias the statistical results. Examiners' ability to directly inspect loan files allows them to separate applications belonging to product sub-categories that are characterized by substantially different underwriting. For example, applications for special loan programs generally are analyzed separately from those for the bank's conventional loan products. Finally, examiners at the Federal Reserve analyze markets individually, except when there is a compelling reason to combine observations from different markets.[29]

5.2. Data Problems

The second class of concerns about the use of statistics in detecting discrimination revolves around the reliability of the data used. Unlike the Boston Fed researchers, compliance examiners are able to collect their data directly from each of the loan files in their sample. Furthermore, if there are questions about the interpretation of some information in the loan file (e.g., whether gift funds should be included as liquid assets), they are often able to speak personally with the loan officer or underwriter who processed the loan. As a result, odd or hard-to-interpret data are rarely a problem in bank-specific exams.

A specific concern lies in determining which loans should be counted as accepted and which as rejected. For example, if an applicant fails to provide employment contact information so that the bank cannot verify income or employment, the loan will likely be rejected. At the same time, this failure to provide this information may reflect an applicant who has implicitly

[29] For example, markets will be combined to obtain a sample of sufficient size, but only if the underwriting decisions for these markets are made at a single office and are based on a uniform set of guidelines. We are not familiar with other agencies' policies regarding the combining of markets for a statistical analysis.

decided to withdraw his or her application. Whether such an application should be coded as rejected or withdrawn is a difficult call. Once again, however, examiners' ability to manually inspect the loan files and speak personally with the bank's staff makes it possible for these cases to be interpreted in a consistent way, or for them to be identified and excluded from the statistical analysis.[30]

5.3. Specification Problems

The Boston Fed study and other statistical tests of mortgage discrimination are also criticized for employing an incomplete or inappropriate set of underwriting variables when modeling the bank's decision to accept or reject a loan application. As discussed above, examiners choose the data to collect based on their conversations with the bank's loan officers and loan review committee. Thus, there is every reason to believe that they collect those variables that are most important to the bank's underwriting decisions. Furthermore, because examiners collect very detailed information from the loan files, a variety of model specifications may be tried to ensure that the institution's underwriting practices are adequately represented and to verify the robustness of the statistical results. Finally, examiners are able to follow up the statistical analysis with a review of individual loan files, which often reveals important factors contributing to denial that were not included in the statistical model. Although it often is not feasible to add such factors to the statistical model, examiners are able to use their judgment to determine whether the factors were applied without bias.

5.4. Selection Effects and Endogenous Variables

Perhaps the most strident criticism of the use of statistics to uncover discrimination has been over the proper way to model the application and underwriting decisions.[31] Most empirical work to date has applied single-equation estimation techniques, focusing on the underwriting decision independent of the application decision. In contrast, it is argued that pre-screening, signaling, or self-selection processes may influence the perceived credit-quality composition of

[30] When they are excluded from the statistical portion of the exam, examiners will typically give such applications a careful independent review.

[31] There has been relatively little theoretical work on this problem; a notable exception is Longhofer and Peters (2000). As a consequence, structural models are rarely used in empirical work in this area.

the applicant pool as well as the eventual underwriting decision, and that such processes may bias the estimated coefficients of a single-equation model or cloud the interpretation of the results.

Such criticism is muted in the fair-lending examination context by consideration of the role of the follow-up file review in the examination process. Consider, for example, the possibility that white individuals who are likely to be rejected are more apt to be pre-screened or to self-select out of the applicant pool than comparable minorities. In this case, a single-equation model indeed may provide a false indication of discrimination. This argument appears to presume, however, that there is an identifiable credit characteristic (possibly a purely idiosyncratic factor) omitted from the statistical model that may have induced some white potential applicants to select out of the sample and that was a cause for rejection of a number of minority applications. Such a characteristic is apt to be identified during the file reviews.

This criticism is further muted because the purpose of a compliance examination is quite distinct from that of a more general econometric study. If signaling, pre-screening, or self-selection processes affect the perceived credit-quality composition of the applicant pool (causing the recorded characteristics of applicants be endogenous, in a sense), then it is certainly reasonable to question whether a single-equation model can provide an effective representation of the credit allocation process. As Stengel and Glennon (1999) effectively articulate, however, the goal in a fair-lending exam is to determine whether the bank's "decision rule … as it was applied against the actual applicant pool" was implemented without bias with respect to an applicant's race or other protected characteristic.[32] In particular, fair-lending exams are *not* intended test the importance of particular loan policies for determining how credit is allocated. Given the goal of a fair-lending exam, signaling or pre-screening processes are irrelevant, except to the extent that they are associated with omission of relevant factors from the statistical model (which, again, are apt to be identified during the file review stage). In other words, the examiner's goal is to determine whether and white applicants with identical credit characteristics *as recorded on their loan applications* are treated differently.

[32] Stengel and Glennon (1999), p. 304.

Potential effects due to signaling, pre-screening, or self-selection effects cannot be entirely ignored, however. It is important that examiners keep in mind during the file review stage that two applications may not be comparable if they differ along a dimension considered important according to the bank's underwriting policies, even if the statistical model does not indicate a significant relationship to the loan decision. For example, the statistical model may indicate the same probability of rejection for applicants with loan-to-value ratios of 95% and those with ratios of 90%, because among the former there are fewer applications having idiosyncratic flaws due to more pre-screening of these applications. Nevertheless, the bank may indeed draw a distinction between these two loan-to-value ratios.

5.5. Sequential Underwriting Processes

A more relevant complication is that underwriting may be a multi-step process, in which new data collected about an individual may depend on the characteristics of data already collected. This raises the concern that a bank may be mistakenly held accountable for rejecting an application when the true cause was the applicant's failure to supply required information or documentation. Indeed, the discussion in the last section showed that unverified information or incomplete loan files played a large part in the decision to reject some applications.

In addition, it raises concern about the quality of the data used in the analysis, particularly among rejected loan files. For example, if an applicant's credit report shows sufficiently severe blemishes to merit rejection, then the applicant's income may never be verified.

It is exactly these kinds of problems that make follow-up file review such an important part of the whole examination process. By looking at individual loan files, examiners can ascertain the degree to which their statistical results may be biased by the underwriting process itself. In the end, informed examiner judgment must be the final arbiter in interpreting the results of any statistical model.

6. Conclusions

The use of statistical procedures for detecting discrimination in mortgage lending has been criticized on the grounds that the potential for data recording errors and problems of model specification raise the possibility that inaccurate conclusions will be drawn from the analysis. Moreover, conducting a logistic regression analysis of an institution's application approval patterns is costly and requires a major commitment of examiner resources, which would seem to be justifiable only if there is clear potential for discrimination to have occurred and only if the results are likely to be reliable.

This case study demonstrates that potential difficulties related to the statistical analysis of mortgage lending decisions can contribute to inappropriate conclusions if the statistical results are taken at face value. A statistically significant relationship was found between minority status and likelihood of denial in a logistic regression equation where each of the major factors in the institution's underwriting policies as interpreted or understood by examiners were controlled for. The empirical model also controlled for conditions not explicitly related to underwriting policies that might affect the disposition of an application; namely, the season when it was filed and whether the loan application was processed and submitted by a mortgage broker. Moreover, a very broad data collection effort was undertaken for the analysis, and the finding was robust to alternative model specifications. Ultimately, however, this finding was attributed to a possible omitted variable (unpaid collections) and to factors that are not amenable to statistical modeling. The latter included incomplete or unverifiable information in the file and idiosyncratic factors specific to individual applications, such as property deficiencies.

Nevertheless, as this study illustrates, statistical tools have a useful role to play within the full compliance examination context. Initial statistical analysis using HMDA data is a cost-effective way to screen institutions before examiner resources are committed to conducting a logistic regression analysis. Institutions that do not exhibit substantial disparities in their HMDA-reported data (and those that would not provide a sample of adequate size and composition) are not subject to further statistical review but undergo more traditional, judgmental review by examiners. When a logistic regression analysis is undertaken, the results provide examiners with important information regarding the extent to which a disparity persists once major underwriting variables are taken into consideration, enhancing their ability to detect a pattern of discriminatory treatment. Further, the logistic regression procedure enables examiners to separate out the effects of major underwriting variables and focus their subsequent, direct investigation of loan files on other factors—including possible discrimination—that might have contributed to an observed disparity. This follow-up review helps ensure that potential limitations of statistical modeling, such as biases due to variables omitted from the logistic regression equation, do not invalidate the examination findings.

Finally, we reiterate that our purpose in this article has not been to present a definitive rebuttal to each of the various objections to incorporation of statistical analysis into fair lending examinations. Rather, we have attempted to convey the importance of considering the full examination context when evaluating the uses and limitations of statistical analysis. Our case study suggests that statistical analysis, in combination with comparative file review and other opportunities for the exercise of judgment by examiners, can provide a balanced and thorough approach to enforcement of fair-lending laws.

7. Tables

Table 1
Step-one Analysis
Nationwide HMDA Data

Loan Class	***Paired Minority Denial Rate***	***Paired White Denial Rate***	***Paired Denial-rate Disparity***
Overall	16.9%	11.3%	5.6%***
Conventional Purchase	15.7%	10.7%	5.0%***
Conventional Refinance	19.1%	12.6%	6.5%***
FHA/VA Purchase	19.9%	13.0%	6.9%***
FHA/VA Refinance	40.0%	8.1%	31.9%*

*** Denial-rate disparity significant at the 1% level.
** Denial-rate disparity significant at the 5% level.
* Denial-rate disparity significant at the 10% level.

Note: The disparities among FHA/VA refinancings are less significant due to the small number of such loans processed by this institution.

Table 2
Step-one Analysis
Nationwide HMDA Data by Race

Minority Group	***Paired Minority Denial Rate***	***Paired White Denial Rate***	***Paired Denial-rate Disparity***
All minority	16.9%	11.3%	5.6%***
American Indian	16.9%	9.7%	7.2%
Asian	12.0%	8.8%	3.2%
Black	19.8%	10.9%	8.9%***
Hispanic	16.1%	12.9%	3.2%***

*** Denial-rate disparity significant at the 1% level.
** Denial-rate disparity significant at the 5% level.
* Denial-rate disparity significant at the 10% level.

Table 3
Step-one Analysis
HMDA Denial Rates by Product Type
Target MSA

Loan Class	***Paired Minority Denial Rate***	***Paired White Denial Rate***	***Paired Denial-rate Disparity***
Overall	21.0%	13.6%	7.4%***
Conventional Purchase	17.3%	8.4%	8.9%***
Government Purchase	26.3%	20.8%	5.5%
Conventional Refinance	24.5%	19.1%	5.4%
Government Refinance	14.3%	11.7%	2.6%

*** Denial-rate disparity significant at the 1% level.
** Denial-rate disparity significant at the 5% level.
* Denial-rate disparity significant at the 10% level.

Table 4
Step Two Variable Definitions

Variable	*Definition*
Accept	1 if the loan was accepted 0 if the loan was rejected
Back1	1 if 40% ≤ back-end ratio < 45% 0 otherwise
Back2	1 if back-end ratio ≥ 45% 0 otherwise
Bankruptcy	1 if the applicant or co-applicant had a bankruptcy, judgement, collection,or foreclosure recorded on the credit report 0 otherwise
Broker	1 if application was processed by a broker 0 if application was processed by an internal loan officer
Co-applicant	1 if a co-applicant was present 0 if there was only one applicant
Deficit	1 if the applicant had insufficient documented liquid assets to close the loan 0 if the applicant's documented liquid assets were greater than the cash required to close
Income	Combined applicant and co-applicant annual income
Liquid	1 if documented liquid assets were more than twice that required to close the loan 0 otherwise
LTVGT80	1 if loan-to-value ratio > 80% 0 if loan-to-value ratio ≤ 80%
Minority	1 if either the applicant or the co-applicant was a minority 0 if both the applicant and co-applicant were white
Retired	1 if the applicant was retired 0 otherwise
Spring	1 If the application was received during the second quarter of the year 0 otherwise
Summer	1 If the application was received during the third quarter of the year 0 otherwise
Stable Income	1 If both applicants had been working in their current jobs for at least 3 years 0 otherwise
Winter	1 If the application was received during the first quarter of the year 0 otherwise

Table 5
Descriptive Statistics of
Variables Used in the Analysis

Variable	***Mean***	***Standard Deviation***	***Minimum***	***Maximum***
Accept	0.8735	0.3329	0	1
Back1	0.0941	0.2924	0	1
Back2	0.0529	0.2243	0	1
Bankruptcy	0.2441	0.4302	0	1
Broker	0.4794	0.5003	0	1
Co-applicant	0.7000	0.4589	0	1
Deficit	0.0500	0.2183	0	1
Income	47.9559	27.9901	13	197
Liquid	0.5294	0.4999	0	1
LTVGT80	0.5441	0.4988	0	1
Minority	0.4529	0.4985	0	1
Retired	0.2029	0.4028	0	1
Spring	0.2559	0.4370	0	1
Summer	0.2647	0.4418	0	1
Stable Income	0.3677	0.4829	0	1
Winter	0.1382	0.3457	0	1

Table 6
Final Logistic Regression Results
Dependent Variable: Accept

Variable	*Parameter Estimate*	*Standard Error*	*P-Value*	*Percentage Impact*
Intercept	3.2496	0.8524	0.0001	
Back1	–1.5129	0.6149	0.0139	-8.27%
Back2	–2.6880	0.7546	0.0004	-25.75%
Bankruptcy	–1.0574	0.4548	0.0201	-4.57%
Broker	1.4339	0.4774	0.0027	1.99%
Co-applicant	0.3973	0.5495	0.4697	0.84%
Deficit	–1.2276	0.7215	0.0889	-5.80%
Income	0.0076	0.0091	0.4032	0.02%
Liquid	1.0793	0.4804	0.0246	1.72%
LTVGT80	–1.0558	0.5058	0.0368	-4.56%
Minority	–1.0787	0.4581	0.0185	-4.72%
Retired	1.1960	0.7006	0.0878	1.82%
Spring	–2.6738	0.6504	0.0001	-25.46%
Summer	–1.8274	0.6711	0.0065	-11.72%
Stable Income	1.8708	0.5873	0.0014	2.21%
Winter	–1.0326	0.8228	0.2094	-4.41%

Note: The base case is an applicant for whom all dummy variables are equal to zero with an income at the sample mean ($47,956). Such an applicant has a 97.38% probability of being approved. The “percentage impact” measures the change in the probability of being approved if the variable is changed from 0 to 1 (or if income is increased by $1,000). Thus, an average income applicant with a bankruptcy, garnishment, or judgement on his credit report (*Bankrupt* = 1) has a 92.80% chance of being approved, assuming all other dummy variables are equal to zero.

Table 7
Follow-up File Review
Summary of Reasons for Denial

No.	*Race*	*Broker*	*Likelihood of Approval*	*Verification Issues*	*LTV*	*Back-end Ratio*	*Credit History*[1]	*Collateral or Other Issues*
1	Minority		0.997	Unverified items (details not available)				
2	White	Yes	0.98	Unverified items (details not available)				
3	Minority		0.97				Poor	
4	Minority	Yes	0.96	Liquid assets	> 80			No credit or rental history[2]
5	White		0.95	Incomplete application (details not available)				
6	White		0.95				Poor	Open collections
7	Minority		0.95	Incomplete application (various)[3]	> 80			
8	Minority		0.94		> 80			Collateral[4]
9	Minority		0.94		> 80			Collateral[5]
10	Minority	Yes	0.93	Incomplete application (details not available)	> 80			
11	Minority	Yes	0.93	Incomplete application (coap. credit report)	> 80			
12	Minority		0.92	Incomplete (details not available)				Mobile home transaction[6]
13	Minority	Yes	0.87	Unverified items (details not available)	> 80		Poor	
14	White	Yes	0.84		> 80	40-44		
15	Minority	Yes	0.82	Unverified items (details not available)	> 80		Poor	No employment history[7]
16	White		0.75		> 80			Collateral[8]
17	Minority	Yes	0.74	Liquid assets, work history		40-44		
18	Minority		0.74		> 80	40-44	Poor	Open collections
19	Minority	Yes	0.74	Liquid assets	> 80			
20	White		0.72	Income	> 80	40-44		Collateral[9]

[1] Poor credit history refers to a credit record exhibiting a bankruptcy, foreclosure, collection, judgment, or garnishment.
[2] The applicants were recent immigrants.
[3] Required documentation not in the file included a contract for new construction and a gift letter.
[4] The property was a condo in a building with a high vacancy rate.
[5] The property was appraised "as is." Denial of private mortgage insurance also was listed as a reason for rejection of the application.
[6] The applicant was seeking to finance the purchase of a site and the cost of moving the mobile home.
[7] The applicants were recent graduates.
[8] The property was a condo in a building with a high vacancy rate. Denial of private mortgage insurance also was listed as a reason for rejection of the application.
[9] FNMA guidelines for adjustments against comparable properties were exceeded.

No.	***Race***	***Broker***	***Likelihood of Approval***	***Verification Issues***	***LTV***	***Back-end Ratio***	***Credit History***[10]	***Collateral or Other Issues***
21	Minority	Yes	0.71	Income	> 80		Poor	
22	White	Yes	0.68			> 44		
23	Minority		0.66		> 80		Poor	Current delinquency
24	Minority	Yes	0.64	Income		> 44	Poor	Subordinate financing[11]
25	White	Yes	0.62	Income, liquid assets	> 80		Poor	
26	Minority		0.62		> 80	40-44		
27	Minority		0.59	Incomplete application (details not available)	> 80			
28	Minority	Yes	0.56	Incomplete application (details not available)	> 80		Poor	
29	Minority		0.52				Poor	Open collections
30	Minority		0.50		> 80		Poor	Open collections
31	White		0.44			40-44	Poor	
32	Minority		0.43		> 80	> 44		Rental income
33	White		0.43	Incomplete application (funds-to-close)	> 80		Poor	
34	Minority		0.40			> 44		File remained open[12]
35	Minority		0.36		> 80	> 44	Poor	Open collection, collateral[13]
36	White		0.33		> 80	> 44		Rental income
37	White		0.26		> 80	40-44	Poor	Current delinquency
38	Minority		0.18		> 80	> 44		
39	White		0.11	Liquid assets	>80		Poor	
40	Minority		0.07		> 80	> 44	Poor	
41	Minority		0.07		> 80	40-44	Poor	
42	Minority		0.05		>80	> 44	Poor	
43	Minority		0.02		> 80	> 44	Poor	Open collections

[10] Poor credit history refers to a credit record exhibiting a bankruptcy, foreclosure, collection, judgment, or garnishment.

[11] The application exceeded the bank's minimum loan-to-value ratio guideline for a loan with 10 percent subordinate financing.

[12] The denial was tied to insufficient funds to close and a high back-end ratio resulting from current ownership of a home. The file was to remain open for 90 days pending an agreement for sale of the home.

[13] Severe property deficiencies, including zoning problems, were present.

Table 8

Likelihood of Approval Restricting Attention to
Denials Due to Incomplete/Unverifiable Information
Logistic Regression Results
Dependent Variable: Accept

Variable	***Parameter Estimate***	***Standard Error***	***P-Value***	***Percentage Impact***
Intercept	4.1653	0.7597	0.0001	
Bankruptcy	–1.0686	0.5771	0.0641	–2.80%
Broker	–0.2854	0.5318	0.5915	–0.49%
Deficit	–1.5036	0.7809	0.0542	–5.00%
Liquid	1.5159	0.6232	0.0150	1.19%
Minority	–1.3354	0.5648	0.0181	–4.04%
Spring-or-Summer	–1.5780	0.6178	0.0106	–5.47%
Stable Income	1.4272	0.6914	0.0390	1.16%

Notes: This regression excludes applications that were rejected for reasons *other* than incomplete or unverifiable information, leaving a sample size of 317 applications. *Spring-or-Summer* is a dummy variable that takes the value of 1 if the application was made during the 2^{nd} or 3^{rd} quarters of the year. The percentage impacts are calculated as in Table 6. The "base case" probability of being approved is 98.47%.

Table 9
Analysis of Direct Loans – Incomplete Loan Files Excluded
Logistic Regression Results
Dependent Variable: Accept

Variable	***Parameter Estimate***	***Standard Error***	***P-Value***	***Percentage Impact***
Intercept	6.9267	1.8945	0.0003	
Back-end Ratio	–0.1000	0.0386	0.0096	0.00%
Bankruptcy	–1.9236	0.7155	0.0072	-0.22%
Co-applicant	1.0998	0.8937	0.2184	0.03%
Deficit	–2.6749	1.5099	0.0765	-0.51%
Income	0.0197	0.0156	0.2057	0.00%
Liquid	0.2646	0.7192	0.7129	0.01%
LTVGT80	–1.6225	0.8598	0.0592	-0.15%
Minority	–1.5316	0.7698	0.0466	-0.14%
Retired	2.3625	1.2948	0.0681	0.03%
Spring-or-Summer	–2.3903	0.8215	0.0036	-0.38%
Stable Income	1.9464	1.0348	0.0600	0.03%

Notes: This regression excluded all brokered loans and those files that were rejected because of incomplete or unverified information. This left a final sample size of 169. Because of the reduced number of rejected loan files in the sample, the specification excludes some variables incorporated in the original analysis. *Spring-or-Summer* is a dummy variable that takes the value of 1 if the application was made during the 2^{nd} or 3^{rd} quarters of the year. *Back-end Ratio* is the total debt obligation ratio presented as a continuous variable. The "base case" probability of being approved is 96.96%.

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