The Role of FHA Data in the Lending Discrimination Discussion

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Abstract

If minority loan applicants perceive discrimination by conventional lenders, they will crowd into the nondiscriminating Federal Housing Administration (FHA) sector. This movement to FHA will be particularly pronounced among minority borrowers who have difficulty providing easily observable evidence of their creditworthiness. The result will be lower default or loss on minority loans in the FHA portfolio. Thus testing for discrimination based on differential default or loss is a sound procedure, but it can only be done subject to the availability of data on FHA borrowers. The range of data, particularly credit history variables, maintained in FHA data files should be expanded. Ultimately, tests for adverse impact discrimination will require validation of FHA underwriting procedures based on these data.

The interchange between Berkovec, Canner, Gabriel, and Hannan (BCGH) and Ross, Galster, and Yinger (RGY) recalls the old joke about laying all the economists in the world end to end and failing to reach a conclusion. While I do not accept this characterization, it is certainly true that economists generally rely on nonexperimental data and that virtually all empirical studies have many possible flaws. To demonstrate that possible flaws should be taken seriously, it is customary to provide evidence that the possibility has become a reality, to correct estimates for flaws, and/or to demonstrate that the corrected estimates change results.

It is not surprising that RGY have been able to identify possible flaws. Indeed, I will add a few that they have overlooked. To be fully persuasive, however, RGY should provide evidence of the flaws or should at least suggest alternative estimation procedures that BCGH could implement. Unfortunately, RGY provide little empirical evidence to document possible flaws, and they assert the impossibility of detecting discrimination using the BCGH default equation approach. This assertion is at variance with prior literature, and I will demonstrate why it is wrong. Indeed, the RGY position is self-refuting. If they could produce empirical evidence of the importance of the flaws they identify, that very information could be used to correct the BCGH estimates to produce a more accurate test for discrimination. I will also note potential flaws but, because of a lack of hard evidence regarding the importance of these flaws, my criticisms of the BCGH study will take the form of suggestions for future research.

Statement of the Problem and of the BCGH Model

The BCGH problem is to devise a market test for discrimination in mortgage lending. The key word here is *market*, and the test is designed to aggregate data across a variety of lenders rather than to examine a particular firm. The assumption that discrimination against minorities results in better loan performance—as reflected by lower default rates, lower losses, or higher profits—on lending to marginal minority applicants follows directly from the literature on testing for discrimination in labor markets and college admissions.

The five behavioral equations or relations that are potentially important for an understanding of the discussion between BCGH and RGY are:

1. The rejection equation of conventional (non-FHA) lenders.

2. The choice equation of applicants who select either conventional or FHA mortgages.

3. The rejection equation of FHA lenders.

4. The conditional default or default loss equation for FHA lenders, estimated by BCGH using single-equation logit estimation techniques.

5. The unconditional default or default loss equation for FHA lenders, which requires estimation techniques that are capable of addressing the problem of sample selection bias.

Note that the BCGH article discusses only equations 1, 3, and 4. The other two equations are included to illuminate the BCGH and RGY discussion. Equation 2 is necessary because, if FHA lenders are to experience the shift in the distribution of minority applicants needed to produce the selection bias identified by BCGH, minorities would have to alter their application patterns. The interchange between BCGH and RGY appears to concentrate entirely on applicants who first apply for a conventional loan and then, if rejected, turn to FHA. Clearly, many applicants apply to FHA first and others apply only to conventional lenders, even after one or more rejections. The selection mechanism in the BCGH model is based on equation 2, not on equation 1 as RGY implicitly assume. Equation 5 is needed to provide the true determinants of credit risk, adjusting for selection bias that causes applicants to self-select on the basis of risk. Ultimately, estimates of equation 5 are needed to settle public policy debates concerning mortgage discrimination, because intelligent discussion of discrimination in underwriting implies that we know what nondiscriminatory underwriters should be doing. Adverse-impact discrimination requires that both conventional and FHA lenders be able to show that their formulations of equations 1 and 3 are consistent with equation 5. But there is no answer to such questions now because there are no appropriate estimates of equation 5 in the literature, and there do not appear to be any efforts at regulatory agencies or the U.S. Department of Housing and Urban Development (HUD) to produce these estimates.

If conventional lenders treat minorities differentially when applying equation 1, or if this equation cannot pass the adverse-impact test, minority applicants who should have qualified for conventional loans will shift to the FHA sector. This shift will result in lower losses on FHA lending to minorities at the margin, which could be detected as a negative estimated coefficient for minority status in a default or default loss equation. The argument for what has been termed indirect testing for discrimination in conventional lending through “crowding into FHA” was made by Shear and Yezer (1985, 1983) some time ago and follows logically from Becker (1971). BCGH provide a clever adaptation by showing the effect in terms of estimates of equation 4. What is normally a problem of selection bias in estimates of equation 5 is turned to an advantage in detecting discrimination. This indirect test works through equation 2, the choice equation of applicants.

There is a possibility of false positives or negatives in the BCGH test. False positives may arise if minorities, believing that lenders discriminate, self-select into FHA loans when conventional lenders actually do not discriminate. False negatives may arise if minorities fail to perceive discrimination or if they avoid discriminatory conventional lenders by going to nondiscriminatory lenders. The BCGH test can detect both differential treatment and adverse-impact discrimination. Lenders may believe that equation 1 is based on business necessity; however, because lenders have little or no statistical support for their underwriting procedures, such good intentions are not sufficient to avoid a finding of discrimination. Because there are no data on the empirical importance of any of these possible flaws, they present opportunities for future research.

The BCGH test has a second component. If there is differential treatment or adverse-impact discrimination in the FHA underwriting process based on equation 3, it will be reflected in a negative effect of minority status on default or default loss in equation 4. The general assumption in the literature has been that FHA is a nondiscriminatory sector, but the BCGH point that discrimination based on equations 1 and 3 should have the same effect on the estimated coefficient of minority status in equation 4 is clever indeed. There is a possibility that discrimination in favor of minorities in FHA lending could mask the test for discrimination in conventional lending, but again there is no evidence other than the positive coefficient of minority status reported by BCGH.

Using the Expanded Model To Resolve RGY Criticisms

The points made by RGY may be understood in terms of the expanded model. Consider, for example, their most extreme criticism of the BCGH approach. In what can only be described as the bell curve hypothesis applied to mortgage lending, RGY contend that minority status is uniquely correlated with credit risk.[1] This amounts to an assertion that minority status would have a positive and significant estimated coefficient in a well-specified and properly estimated version of equation 5. There certainly is a potential flaw in the BCGH approach; how could RGY document its empirical importance? The direct approach would be to estimate equation 5 to determine the sign, significance, and magnitude of the estimated minority coefficient.[2] Should RGY, or anyone else, perform this estimation and determine that minority status has a positive relation to default or default loss in equation 5, this information could be used to adjust the conditional estimates of equation 4 reported by BCGH and thus correct errors in the test induced by the bell curve effect. The claims by RGY that an important bell curve effect on mortgage default would invalidate the BCGH approach are false in the sense that providing proof of the importance of a bell curve effect would give researchers the information needed to correct the BCGH measure. BCGH cannot be faulted for failing to perform an adjustment based on equation 5, because no appropriate estimates of this equation are available. They have noted the potential problem, and that is all that can be done given the current state of research.

RGY argue that lenders may practice statistical discrimination because it is costly to collect all of the variables needed for proper underwriting or because common omitted variables bias by influencing the estimates of equation 4. BCGH respond that an augmented version of equation 3—that is, an equation augmented by variables not included in the lender's files—would reveal statistical discrimination and would correct omitted variables bias in estimates using only data taken from the lender. Indeed, the default equation estimated by BCGH is augmented by several variables added to the FHA data files; certainly some of these variables are not used by conventional lenders. BCGH have made a good-faith effort to include all variables collected by HUD, and their default equations are among the most inclusive that have been estimated. There may be significant omissions in the credit-reporting area, but these limitations arise from problems in HUD data collection.

Ultimately, possible flaws due to statistical discrimination or omitted variables bias that cannot be solved with augmented models are directly analogous to the possible bell curve effects discussed above. Specifically, the issue of the way to specify equation 4 can be settled directly by estimating equation 5. The effects of any ultimate measurement problems will be reflected in the estimated effect of minority status in equation 5. Should the potential flaws identified by RGY prove significant, the estimation results reported for equation 4 can be adjusted accordingly. The RGY contention that the possibility of statistical discrimination or omitted variables bias raises fundamental problems for the BCGH test are mistaken. If the problems can be verified through estimates of equation 5, these estimates can be used to adjust estimates of equation 4.

RGY assert that lenders may foreclose earlier on minorities, a potential flaw that could be tested. However, BCGH are correct in replying that there is no evidence that current levels of forbearance minimize losses and that, if they are not optimal, losses would be decreased if forbearance were increased. Because FHA does not pursue deficiency judgments against foreclosed borrowers, extended forbearance may become quite expensive for the insurance fund.

RGY suggest that events occurring after endorsement are responsible for default, but BCGH reply that such events are properly omitted from estimates of equations 4 and 5. The BCGH view is clearly correct. Testing for discrimination in mortgage underwriting should be based on the observations made by underwriters at the time of the application. Put another way, equations 4 and 5 are the conditional and unconditional before-the-fact default equations used to forecast future default.

Econometric Problems in Estimating Rejection and Default Equations

Underlying the discussion between BCGH and RGY is a decision to use estimates of conditional default or default loss (equation 4) rather than estimates of rejection (equation 1). I would like to point out three potential econometric problems in tests for discrimination at the market level and consider their importance for testing based on either rejection or conditional default. For an elaboration of these points, see Phillips and Trost (1995) and Rachlis, (1995).

Aggregation Bias

In conducting tests for market-level discrimination across lenders, researchers must confront the aggregation problem. Various lenders may have differing underwriting standards and may use different variables, measurement techniques, and functional forms. A given lender may impose different standards for various loan programs. Because the proportion of minority applicants varies across lenders and programs, estimates of equation 1 or 3 may include aggregation bias. Presumably BCGH would contend that FHA underwriting standards should limit the variation in underwriting approaches, even for direct-endorsement lenders. However, there is no proof that minority borrowers do not deal, on average, with lenders who have less stringent standards. The Boston Federal Reserve Bank study (Munnell et al., 1992) makes no attempt to deal with aggregation problems, and it is not clear that a satisfactory solution exists.[3]

Sample Selection Bias

The path that homebuyers follow to a particular mortgage application includes a range of choices. The final sample of loan applicants for a particular type of mortgage is a selected sample, and estimates of equations 1 and 4 only give information conditional on the applicant's choices. The trick of the BCGH test is that it turns this econometric problem into an opportunity by using easily obtained conditional estimates (equation 4) rather than the difficult unconditional estimates (equation 5). Simple estimates of equation 1, such as those in the Boston study, are contaminated by sample selection bias. Recently, Phillips and Yezer (forthcoming) have shown that correcting for selection bias problems created by multiple mortgage programs can, by itself, reverse findings of racial bias in lending.

Simultaneous Equation Bias

Mortgage loan terms ranging from loan amount, term, and cosigner to downpayment are chosen by applicants in anticipation of possible rejection. Indeed, homebuyers base their home purchase price on downpayment constraints. Therefore, loan terms are clearly endogenous to the probability of rejection and should not be assumed to be exogenous, as in the Boston study's estimates of single equation rejection models. Yezer, Phillips, and Trost (1994) demonstrate that the resulting simultaneous equation bias produces false positive indications of discrimination in rejection equations for minorities, who are less able to produce credit enhancements in the face of possible rejection. The production of unbiased estimates of the rejection equation will be difficult, because of identification problems. The BCGH approach also suffers from simultaneous equation bias, to the extent that borrowers select loan terms based on their own internal and unobservable probability of default. Then loan terms are endogenous to the prior probability of default, and estimates of equation 4 will be biased. The connection between this simultaneity and the variables used by BCGH to test for discrimination is less clear than in the case of the rejection equation. Monte Carlo experiments by Yezer, Phillips, and Trost (1994) indicate that simultaneous equation bias presents a major problem in testing for discrimination using rejection equations but not in testing using conditional default equations. Nevertheless, more research is needed on the effects of simultaneity in estimates of equations 4 and 5.

Conclusion

The value of the BCGH contribution does not fully emerge in the discussion with RGY, because BCGH do not criticize the alternative rejection equation approach to testing for lending discrimination at the market level. Compared with the serious problems in tests based on rejection equations, as evidenced by the numerous articles that either confirm or reverse the finding of discrimination in the Boston study, the econometric problems in the BCGH approach are small. Research on the unconditional default equation is certainly needed to determine how serious the potential flaws identified by RGY may be and to correct for them as necessary. Clearly, the measurement of credit history and its role in predicting default should be given more attention, and there are other research questions that should be pursued. One promising public policy application of the BCGH approach is that of testing for fair credit compliance problems across urban housing markets in order to focus concerns on particular geographic areas. BCGH have made a firm start and set us on a path that will provide the research still needed to support concerns about fair lending. In the meantime, we must rely on fair lending examinations of individual institutions as our major source of insight into the prevalence of discrimination.

It appears that many economists and government officials are convinced that discrimination in mortgage lending is an important problem. In response, lenders are scrambling to estimate statistical models of default for use in implementing mortgage credit scoring schemes that will supplement or replace judgmental models. These lenders should be aware that the unconditional equation 5 should be estimated, rather than the conditional equation 4 used by BCGH. If regulators are to follow the RGY suggestion that single-equation estimates of equation 1 be used to prove discrimination—even in the face of a BCGH test showing substantially higher defaults on minority loans—then lenders should consider adopting mechanical credit scoring schemes as their only sure defense against charges of discrimination.

Author

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Notes

1. RGY make this argument for minorities, but it appears to be intended for a subset of all protected groups based on race, sex, ethnicity, and marital status for which BCGH provide estimation results. The bell curve argument is not appealing. Surely it should not be applied equally to all the groups for which BCGH provide estimation results.

2. There may be an indirect approach to this estimation problem, but lack of space and my own uncertainty regarding potential solutions suggest that only the direct approach be discussed here.

3. See Stengle and Glennon (1995) for a discussion of the unique and highly nonlinear nature of individual bank underwriting schemes and for the difficulty of representing these schemes, even in single-bank studies.

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