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# Strategic Responses to Bank Regulation: Evidence From HMDA Data

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**Abstract**

The intent of fair lending regulation is to encourage loans in low income areas and insure that loan decisions are based on economic criteria instead of noneconomic borrower characteristics. We evaluate situations in which banks may find it in their self interest to respond to regulation in a strategic manner intended to improve public relations and appease regulators rather than to adhere to the true spirit of the regulation. We find some evidence consistent with such behavior.

## 1 Introduction

There is a growing body of literature which evaluates the effectiveness, burden, and distributional effects of regulation. One aspect of this literature

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contrasts the intended with the realized effects of regulation. Indeed, perhaps the most difficult aspect of drafting regulation is to effectively address policy objectives without distorting appropriate market behavior. There are numerous examples of constituents in various industries responding to regulatory restrictions in an unplanned and frequently undesired manner.[1] This response frequently results from regulatory avoidance behavior which may require additional regulation to address the unintended responses.[2] One form of strategic response is "window dressing" whereby the regulated firm modifies its behavior to adjust the information used to evaluate adherence to the regulation.[3]

We evaluate the strategic behavior of financial institutions under regulations introduced to encourage loans in low income areas and insure that loan decisions are based on economic criteria instead of noneconomic borrower characteristics. The intent of this regulation was to alter the behavior of institutions under-serving certain markets within local service areas and to decrease disparate treatment of credit applicants. In response to this mandate, however, some banks may find it in their self interest to respond in a manner intended to improve public relations and appease regulators rather than to adhere to the true spirit of the regulation. We undertake the first attempt to identify window dressing and evidence of other forms of strategic behavior in response to mortgage lending regulation.

[1] In the ethical pharmaceutical industry, see Peltzman (1973) and Wiggins (1981). Specific examples in banking include regulatory induced responses to deposit insurance [Brewer and Mondschean (1993, 1994) and McKenzie, Cole, and Brown (1992)], reserve requirements [Evanoff (1990)], and price and geographic restrictions [Pyle (1974), Startz (1979), and Evanoff (1988)].

[2] For a more detailed discussion of this "regulatory dialect," see Kane (1977, 1981).

[3] Examples, which typically evaluate accounting data, include Allen and Saunders (1992), Chevalier and Ellison (1995), Healy (1985), Lakonishok (1991), Oyer (1995), and Stickney (1975).

## 2 Overview of HMDA and CRA Legislation

In response to arguments that banks were failing to adequately serve the credit needs of their service areas, the Community Reinvestment Act (CRA) was enacted in 1978. There were concerns that deposits were being taken out of the local community and redirected to fund assets elsewhere. There were also concerns that low income, frequently minority, neighborhoods were being "red-lined" and credit-worthy customers were being denied funding based on noneconomic criteria. CRA, combined with the 1968 Fair Housing Act, the 1974 Equal Credit Opportunity Act (ECOA) and the 1975 Home Mortgage Disclosure Act (HMDA) constitute what we will term *fair lending* legislation, which regulators were charged with enforcing.[4] For purposes of the CRA, regulators were to determine whether banks were adequately servicing their communities and to use that information when evaluating requests for new branch openings, charter changes, mergers, and acquisitions. For numerous reasons, including data limitations and the lack of precise criteria for evaluating compliance to fair lending regulations, the process for achieving an acceptable CRA rating was quite vague. Bankers, regulators, and community organizations frequently clashed during the 1980s when debating what should constitute adequate servicing of the local community.

To improve the evaluation process and make available more detailed information on lending patterns, in 1989 Congress made two significant changes to the fair lending evaluation process. First, CRA was amended to

[4]The 1974 ECOA addressed discrimination with respect to any form of credit based on the race, ethnic origin, gender, or religion of the applicant. The 1968 act was concerned with this form of discrimination as well as "neighborhood" discrimination in the housing market. Calling these three acts fair lending legislation may be somewhat of a misnomer as the CRA is typically treated separately from the other two. However, the constituents are frequently linked, e.g., minority and low income groups. We group them together since the HMDA data discussed below is used by regulators for evaluating compliance to each of the acts.

require the public release of examiner assessments of compliance. Second, a clause was added to the 1989 Financial Institution Reform, Recovery, and Enforcement Act (FIRREA), requiring banks to provide loan applicant information on race, gender, and income in addition to the data on geographic lending patterns originally collected under HMDA.[5] This information was made available to *both* regulators and the general public for use in assessing whether banks satisfied their fair lending requirements.[6]

The HMDA data are made public annually and are closely scrutinized in the popular banking press. Regulatory agencies have also formally incorporated this information into their supervisory review process in order to evaluate the equity of banks' loan processes and their adherence to fair lending regulations. Although the process differs across regulatory agencies, as part of a bank examination the regulator uses these data as a first screen of whether loan decisions appear to be influenced by noneconomic criteria such as race. The information in HMDA reports may improve regulators' ability to evaluate fair lending compliance, but the data are quite limited. An evaluation process which excludes the applicant's credit and employment history, property value, extent of the applicant's collateral and wealth, availability of mortgage insurance, and various other factors relevant to the applicant's ability to repay the loan, is obviously inadequate. To account for this, when the HMDA data are used and a perceived relationship between applicant race and the loan decision is detected, the bank examination process is extended and information on additional variables thought to influence

[5]FIRREA is best known for reorganizing and recapitalizing the failed savings and loan industry. HMDA was originally enacted in 1975 to give supervisors and the public information on geographic lending patterns. The data requirement added in 1989 allowed for the analysis of discriminatory lending behavior.

[6]The availability of the new HMDA data prompted numerous studies evaluating bank lending patterns, including Munnell et al. (1996), Holmes and Horvitz (1994), Canner and Passmore (1994, 1995a, 1995b), Yezer (1995) and Yezer et al. (1994).

the loan decision are collected from the loan files.[7] After accounting for the additional influential variables, if the analysis continues to indicate that loan decision were influenced by noneconomic characteristics of the applicant, the regulator may consider this in ruling on branch and merger applications, may impose penalties on the institution, and may forward the information to the Justice Department for formal prosecution.[8]

# 3 Model of the Mortgage Loan Decision Process

Fair lending regulations were intended to alter the behavior of institutions underserving certain communities and basing loan decisions on noneconomic criteria. Behavioral change would come as a result of either regulatory mandate or public scrutiny.

The regulations were not intended to alter the behavior of lenders making loan decisions based on the appropriate economic characteristics of the borrower.[9] The "good" lender would see the *fair lending review process*, including the collection and reporting of HMDA data, having the data made public, and having the data utilized in the supervisory process, as a tax which it had to bear to regulate the behavior of other banks. The overtly discriminating, or "bad" institution, would realize that its behavior was now being scrutinized and would respond accordingly. It would alter its lending behavior either because management was previously unaware of the

[7] The process described here is most similar to that used by the Federal Reserve System. See Bauer and Cromwell (1994) for a more complete discussion of the process.

[8] Examples of regulatory action based on poor CRA ratings are discussed in Garwood and Smith (1993).

[9] This was one of the major criticisms of CRA when first enacted. Bankers were concerned that they were being required to make substandard loans to satisfy the fair lending criteria. Legislators and regulators repeatedly emphasized that this was not the case. See Garwood and Smith (1993).

disparate treatment of applicants, or management was aware of it but then realized that regulators would penalize the institution if the behavior continued. The intent of the regulations, therefore, was to have all lenders employ a fair and appropriate loan decision process. If unfair lending practices and inequitable treatment were not altered, the bank would be criticized by community groups and the general public, and regulators could detect it in the data. They could then penalize the firm and monitor it in the future to insure appropriate behavior.

There are a number of potential responses to this regulation. First, the bank could establish its loan approval criteria or scoring model to generate, on average, an "acceptable" minority-majority denial ratio.[10] Given perfect information and a steady, representative flow of credit applicants throughout the year, a bank could choose its loan standards in a uniform manner to generate what it believes to be an acceptable HMDA performance. The bank could then conduct its business based on the predetermined underwriting criteria. This response, many would argue, was the intended effect of fair lending regulations; i.e., basing loan decisions on economic criteria, banks may enter into previously untapped markets and find them more profitable than originally perceived.[11] This seems a relatively inexpensive response,

[10]We will occasionally discuss white or minority denial rates. Typically, however, we will be interested in the relationship between the denial rates, e.g., the ratio of minority to white denial rates. Significant inter-bank differences may exist in the loan evaluation criteria. We, and regulators, however, are interested in disparate criteria being used within the bank, across the two groups. In our empirical analysis we measure this as the minority-majority log-odds ratio.

[11]This may also be the most common, profit maximizing *strategic* response. However, this is not the strategic behavior we are testing for. As discussed below, it is also not detectable using the techniques we employ. Recent evidence suggests that there is no difference in the performance of banks concentrating in serving low income individuals or markets; see Canner and Passmore (1996). This is consistent with the argument that by not serving these markets, banks are foregoing profitable opportunities. Alternatively, this may be indicative of a comparative advantage for these specializing firms; e.g., see Hunter and Walker (1996).

however, the HMDA data are collected and reported annually and the bank may "miss" the targeted ratio, since it does not have perfect foresight and the flow of applicants over the calendar year may not be representative of the underlying customer base. The miss could result in both public and regulatory criticism.

A second possible response would be for the bank to choose acceptance criteria that it believes will produce an "acceptable" minority-majority denial ratio, continually monitor its lending activity, and aggressively respond to any deviations from the targeted level. While this may better enable the bank to achieve the targeted denial ratio, it is a costly process and the bank may find the cost prohibitive.

The regulatory process could, however, produce other unintended strategic responses that are not in line with the spirit of the regulation. For example, as a third potential response the lender could incorporate a loan review process based on sound economic criteria, with which the bank is very comfortable. It is aware of regulatory and public scrutiny, however, and may review its performance at some time during the calendar year and find that the loan denial rate for minorities is substantially higher than that for non-minorities. This differential may occur for a number of reasons, including, as is typical in the data, the average minority applicant being less qualified for a credit extension. It could also result from the fact that there is uncertainty and unevenness in the flow of applicants throughout the year and costs may prohibit bank management from continually monitoring their denial position. While the lender's behavior may be economically appropriate, management may believe that the denial ratio will be unacceptable to either the public or regulators. Management may fear this will result in poor public relations, mergers being challenged by community groups and regulators, or simply in additional costs being incurred to undergo the analysis required to show that the lending behavior was appropriate. As a result, during the latter part of the data collection period, the cautious banker may find himself in what he believes to be an unacceptable position. In an attempt to improve the annual data he may "window dress" the year-end HMDA reports. That is, the bank may consciously change its underwriting criteria in an attempt to lower the minority-majority denial ratio.[12] If the perceived unacceptable ratio was actually economically appropriate for this bank, the regulation could have distorted the process in a manner neither intended nor desired by regulators.

A fourth potential response to fair lending regulation would be for the bank to set a specific level of minority lending based on both profitability *and* achieving a satisfactory fair lending performance. To obtain this, banks could use *special programs* to improve their minority-majority denial ratio and bring the ratio to an acceptable level. The programs could be planned for any time during the year, i.e., either early or late. If successful, this would result in improved minority approval performance during the period in which the programs were undertaken. Performance would therefore be relatively inferior during the rest of the year. This would allow banks to achieve an acceptable denial ratio without incurring the cost of continually monitoring its performance.

## 3.1 Hypotheses

The intra-year variation in lending to minorities provides an opportunity to measure the extent to which banks engage in strategic behavior, as discussed above, to attain an "acceptable" rating at the end of the year. We would

[12] An alternative unintended response to the regulations would be for banks to attempt to improve their denial ratios by "recruiting" highly creditworthy minorities and discouraging other minorities from applying; see Avery, Beeson, and Sniderman (1994 p. 16).

expect the last two responses, *window dressing* and *special programs*, to result in differences in intra-year denial ratios. Depending on the timing of the special program, for an individual bank the two responses may or may not be distinguishable. The window dressing response suggests an asymmetry in the loss function from missing one's goal. There will typically be no response from regulators to a relatively low minority-majority denial ratio, but banks expect to be chastised for high ratios. This generates an asymmetric response by firms in the latter time period. Firms with a high denial ratio may change their behavior, while those with a low ratio will not. Alternatively, for the special program campaign, organizations choose a period during the year during which they alter their lending behavior. This period, either early or late in the year, will have a lower denial ratio. This generates a symmetric "response" between the periods; one has a high denial ratio, the other a low one. In contrast, for the first two responses, we would expect banks to apply uniform lending criteria throughout the year.

We apply the above reasoning to an empirical model to test if this strategic behavior is supported in the data. There are a number of testable hypotheses resulting from the above discussion.

1. The bank with a relatively high minority-majority loan denial ratio in the first part of the year would have an incentive to respond to this later in the year. This would result in a significant "improvement" (decrease) in the ratio during the latter period. This is consistent with either window dressing or special program behavior.

2. Banks with low first period minority-majority denial ratios may have less incentive to change their behavior later in the year. This is consistent with window dressing behavior. Alternatively, banks with lower first period ratios could decide their performance is satisfactory and

eliminate special minority lending programs in the latter period. Thus, the two strategic responses are distinguishable. Given a low first period denial ratio, symmetric responses across the two periods are consistent with special program responses to fair lending regulation.

3. As bankers recognize the significant costs of having "unacceptable" denial ratios, they may step up their strategic behavior. In recent years the costs have become evident through unfavorable press, regulatory fines, and merger denials.[13] If banks have incorporated this information, the incentives to act strategically should have become more prevalent in recent years.

4. Both the potential costs of having an unacceptable denial ratio and the ability to behave strategically should be greater for larger institutions. Merger active banks could also find the potential cost to be high. Therefore, to the extent window dressing or special programs are used we would expect it to be more prevalent at such institutions.

Information on aggregate loan applications, loans generated, and denial rates are provided in Charts 1 and 2, and Figure 1.[14] Not surprisingly, applications and loan generation show a seasonal trend with the second and third quarters of the year having higher applications and approvals. Fourth-quarter applications and approvals also typically exceed the first quarter. Direct evidence on the denial rates, instead of its components, is presented in Figure 1 and also show a seasonal trend. Denials are relatively high in the first quarter of each year and decline thereafter. While the denial trend appears consistent with strategic behavior, our hypotheses are more directly

[13]For examples, see Wilke (1996) and Garwood and Smith (1993).

[14]These are data for all conventional, owner-occupied home purchases reported in HMDA.

related to *denial ratios* instead of rates; i.e., disparate treatment of applicants within a bank. In addition, the data presented here are aggregated, which may mask the behavior of individual firms.

## 4 Empirical Model

We offer the first test for evidence of year-end window dressing or special program responses in mortgage lending by examining differences in the probability of loan denial on the basis of applicant race *and the time of year* of the decision on the application. Our test is a two-step procedure. First, we compute bank specific minority-majority denial ratios for the two time periods. Then we fit a model relating one to the other. In the theoretical framework we assume that the characteristics of the loan applicants are relatively constant over the calendar year so that the intra-year differences reflect strategic behavior and not simply lenders responding to changes in the quality of the applicant pool.

Assume for bank $b$ that the loan decision process in the early part of the year is chosen to produce a minority-majority denial ratio of:

$$\Gamma_b^* = X_b\Phi + Z_b\phi \tag{1}$$

where $\Gamma_b^*$ is the desired denial ratio. $X$ is a vector of publicly disclosed borrower characteristics and $Z$ is a vector of undisclosed characteristics, both of which influence the loan decision. $X$ can be viewed as information provided in HMDA data (principally loan amount, household income, and race). Other information on applicant creditworthiness (e.g., loan file information), the bank's lending philosophy (stringent vs. lenient), and noneconomic criteria that may enter the decision process are included in $Z$.

The minority-majority denial ratio observed at the end of the first period may differ from the expected value as defined in eq.(1) because the institution does not have complete control over the applicant stream. The variability in the actual outcome implies that:

$$\Gamma_{b,1} = \Gamma_b^* + \epsilon_{b,1} = X_b\Phi + Z_b\phi + \epsilon_{b,1} \tag{2}$$

where $\Gamma_{b,1}$ is the observed denial ratio in the first period. This deviation from the targeted ratio may be either unplanned (window dressing behavior) or planned (special programs behavior). Below we discuss each of these strategic alternatives.

## 4.1 Strategic Response: Window Dressing

In the absence of a first period deviation from expectations ($\epsilon_{b,1} = 0$), we would expect the institution to maintain its behavior in the second period ($\Gamma_{b,2}^* = \Gamma_b^*$). However, an institution might adjust its lending criteria in the latter part of the year in response to the first-period outcome, so that the expected second-period behavior is characterized by:

$$\Gamma_{b,2}^* = \Gamma_b^* + g(\epsilon_{b,1}) = \Gamma_b^* + g(\Gamma_{b,1} - \Gamma_b^*) \tag{3}$$

where $g(\cdot)$ is a function describing window dressing behavior. The function is dependent on the unexpected component of the denial pattern in the earlier period. That is, the bank may consider window dressing if it finds itself with an early period minority-majority denial ratio that it believes to be "unacceptable." This may occur because of disparate treatment of applicants, or if the applicant pool appears qualified based on the observed information, $X$, but unacceptable based upon the unobserved information,

$Z$.

As in the early period, outcomes in the second period may also differ from the targeted outcome:

$$\Gamma_{b,2} = \Gamma_b^* + g(\epsilon_{b,1}) + \epsilon_{b,2} = \Gamma_b^* + g(\Gamma_{b,1} - \Gamma_b^*) + \epsilon_{b,2} \tag{4}$$

Estimation of eq.(4) requires a specification for the function $g(\cdot)$ and an identification scheme for the $\Gamma_b^*$ values. The discussion of strategic behavior suggests that $g(\cdot)$ be a monotonically decreasing function allowing for a nonlinearity about the threshold value of $\Gamma_b^*$. The above discussion regarding the lack of a first-period surprise being consistent with no behavioral change suggests that $g(0) = 0$.

Thus, the empirical analysis uses the specification:

$$g(\Gamma_{b,1} - \Gamma_b^*) = \beta(\Gamma_{b,1} - \Gamma_b^*) + \theta \cdot max(0, \Gamma_{b,1} - \Gamma_b^*) \tag{5}$$

and eq.(4) becomes

$$\begin{aligned} \Gamma_{b,2} &= \Gamma_b^* + \beta(\Gamma_{b,1} - \Gamma_b^*) + \theta \cdot max(0, \Gamma_{b,1} - \Gamma_b^*) + \epsilon_{b,2} \\ &= (1 - \beta)\Gamma_b^* + \beta\Gamma_{b,1} + \theta \cdot max(0, \Gamma_{b,1} - \Gamma_b^*) + \epsilon_{b,2} \end{aligned} \tag{6}$$

The parameters $\beta$ and $\theta$ characterize the forms of strategic behavior discussed in Section 3. Values of $\beta = 0$ and $\theta = 0$ correspond to no strategic behavior. Window dressing requires an asymmetric relationship such that firms above the threshold alter their behavior to generate a lower $\Gamma_{b,2}^*$, while firms below the threshold do not alter their planned behavior. This corresponds to values of $\beta = 0$ and $\theta < 0$.

Window dressing behavior will be induced when the relative minority-majority denial ratio exceeds a firm specific critical level, beyond which management believes the cost from public scorn or burden from regulator interaction would exceed the cost of altering the loan approval process for window dressing purposes. Thus, to model window dressing behavior we would ideally have a bank specific threshold value for $\Gamma$, i.e., $\Gamma_b^*$, beyond which strategic behavior is undertaken. This value would be dependent on the merger and acquisition plans of the bank, management sensitivity to public criticism, previous lending patterns, the customer base, etc. However, the data are not rich enough to allow us to generate firm-specific values. Two approaches are used to model $\Gamma_b^*$. Initially, we consider a single threshold for all institutions equal to the mean of the first period measure. We then assume that $\Gamma_b^*$ is determined in the local market (MSA), suggesting that banks are concerned about their minority-majority denial ratios getting "out of line" relative to their local competitors.[15] Banks with $\Gamma$ values above the market mean are assumed to be above the threshold value. Given the two threshold measures, from eq.(6) the regression equation to be estimated is:

$$\Gamma_{b,2} = \alpha + \beta\Gamma_{b,1} + \theta \cdot max(0, \Gamma_{b,1} - \Gamma^*) + \epsilon_{b,2} \tag{7}$$

For the first threshold measure, $\alpha = (1 - \beta)\Gamma^* + \Upsilon$, where $\Upsilon$ allows for any uniform cross-period differences. The MSA-specific threshold measure results in a fixed-effects regression model with market-specific differences.

## 4.2 Strategic Response: Special Programs

Alternatively, the bank could have expected the actual first-period ratio to be above the year-end level because it intends to offset the deviation with a special lending program in the latter period. Equation (7), ignoring

[15] We do this for markets that have a minimum of three banks.

the nonlinearity, has an interpretation in this context of a planned special program strategy. In this case $\Gamma_b^*$ represents the desired end of year outcome, and the difference between $\Gamma_b^*$ and the observed outcome in each period represents a decision of the firm to achieve the target by acting differently in the two periods.[16] For example, the firm might realize that a cost-efficient way to achieve the year-end rating of $\Gamma_b^*$ is to undertake a special program for the last six months of the year. Thus, $\Gamma_{b,1}$ is above $\Gamma_b^*$ in the first period and below it in the latter period. The regression equation, eq.(7), without the nonlinearity, i.e, $\theta = 0$, provides two tests of this form of behavior. First, the test of $\beta = 1$ is a test for inter-period differences of an unspecified form. Second, under the assumption that all firms seek a single year-end target, the coefficient $\beta$ should be negative. The coefficient would be -1.0 if the periods were of equal size.

It should be emphasized that it is strategic behavior in the special program hypothesis which results in a low first-period $\Gamma$ generating a relatively high value in the second period. Special program behavior, therefore, should be distinguished from simple reversion to the mean. In the context of this model, mean reversion implies that a high value of $\Gamma_{b,1}$ relative to $\Gamma_b^*$ (a large positive value of $\epsilon_{b,1}$) will be followed by a value of $\Gamma_{b,2}$ below $\Gamma_{b,1}$. But the expected value of the second-period measure ($\Gamma_{b,2}^*$) is not altered by the size or direction of the first-period deviation. The special program hypothesis suggests that $\Gamma_{b,2}^*$ is revised downward as a result of the positive deviation in period one. A high $\Gamma$ value in one period will be associated with *planned* efforts resulting in a below mean value in the other period.

[16]Discussions with bank examiners suggested that such periodic special programs do exist. The fact that the programs are not kept in place may suggest that the criteria used during the special campaign are not the profit-maximizing terms desired by the bank on a continual basis. The proliferation of special mortgage programs has also been highlighted in the popular press; see Wilke (1996).

Institutions above the threshold ($\Gamma_b^*$) at the end of the first period adjust their second-period behavior to produce a lower expected measure, and vice versa.

## 5 Data and Empirical Results

To test for strategic behavior, we assembled HMDA data for the loan accept/reject decision, applicant income and race, and loan value for conventional loan applications processed by commercial banks for the purchase of one- to four-family owner-occupied homes in 1993 and 1994. An aggregate measure of the monthly mortgage rate was obtained from the Federal Home Loan Mortgage Corporation. HMDA revisions to require information on the race of the applicant were put in place in 1990. Since then, numerous examples of regulators responding to poor lending practices can be documented, e.g., Garwood and Smith (1993). Banks should therefore have expectations of a public and regulatory response to "bad" minority-majority denial ratios. We define minorities as all nonwhite applicants. For inclusion in the data set, we require that banks have a minimum of 120 loan applications per year in the local market and the institution must be an active lender in both time periods, i.e., early and late in the year.[17] To evaluate the year-end effects we divide the year into two periods: the first nine months and the last three months. Separate estimates were made for the full sample of institutions, subsamples based on loan volumes, and the subsample of institutions involved in merger activity.

[17]We also require that the data pass regulator edit checks. Since we utilize an estimate of the probability of denial differential between majority and minority applicants in our analysis of strategic behavior, we also require that we are able to generate these estimates for each included bank, i.e., the logit models must converge. Ignoring banks which either accepted or denied 100% of all majority or minority loans, only one bank failed to satisfy this requirement.

To analyze strategic behavior, we use two measures of differences in the probability of denial across the minority and majority groups: 1) a measure of relative denial ratios across the two groups,

$$\Gamma_{b,t}^{(raw)} = ln(M_{b,t}/W_{b,t}) \tag{8}$$

where $M_{b,t}$ is the ratio of minority applicants denied to applicants approved, and $W_{b,t}$ is the same for the non-minority applicants; and 2) a comparable measure of the differential in the denial ratios conditioned on the income and loan value information provided in the HMDA data.

The first measure is a function of simple averages taken from the HMDA data. This "unsophisticated" measure commingles the influence of all factors entering the loan decision process, i.e., both economic and noneconomic characteristics of the borrower. To describe them as minority-majority ratios, without realizing the additional influences on the measure, probably overstates the role of race. Nevertheless, this is the measure typically reported in the popular press and commonly used to challenge merger activity based on disparate minority treatment.

For the second measure we model the probability of a loan application being denied using a logit regression of the form:

$$P(D_{b,i,t}) = (1 + exp(\alpha_b + \beta_b L_{b,i} + \gamma_b L_{b,i}^2 + \delta_b Y_{b,i} + \zeta_b Y_{b,i}^2 + \eta_b L_{b,i} Y_{b,i} + \omega_b R + \Gamma_{b,t}^{(logit)} M_{b,i}))^{-1} \tag{9}$$

where $P(D_{b,i,t})$ is the probability of applicant $i$ being denied a loan by bank $b$ at time $t$, $L$ is the value of the loan, $Y$ is the income of the applicant, $R$ is the average monthly mortgage rate, $M$ is a binary variable indicating whether it is a minority applicant, and $t$ indicates the time period in which the decision is made—early or late in the year.[18] The raw log odds ratio in eq.(8) is an unconditional measure of racial disparity in loan denials. After accounting for the additional information available in the HMDA data, the counterpart from eq.(9) is the coefficient $\Gamma_{b,t}^{(logit)}$.

It should be emphasized that there is no presumption that either $\Gamma$ measure indicates the presence (or absence) of discrimination. While the second measure accounts for some additional economic characteristics of the borrower, numerous relevant variables in $Z$ which influence the loan decision are still excluded from eq.(9). We attempt to further account for differences across markets by estimating eq.(9) for each bank/MSA combination. In all probability, however, we are still not adequately accounting for applicant differences, suggesting that $\Gamma$ is capturing both economic differences and, if present, discriminatory practices. However, *ceteris paribus*, there is no *a priori* reason to expect these influences to vary within the calendar year and, therefore, no reason to expect $\Gamma$ to vary between the early and late time periods unless it is as a result of strategic behavior.

Tables 1 and 2 present summary statistics of the 1994 data used in the analysis.[19] The logit regressions were based on nearly 674,000 applications from 1,118 different institution/MSA combinations in 1994. Approximately one-quarter of the institution/MSA combinations were regulated by the Federal Reserve, one-quarter by the FDIC, and the remainder by the OCC.

The tables include both annual and subperiod figures. Concerning interperiod differences, Table 1 indicates that applications from minorities in-

[18]The logit specification is in the spirit of the model used by regulators as an initial analysis of minority-majority differences in denial rates to determine if more in-depth scrutiny is required. $R$, which is not typically included in these models, is included to capture potential differences in lender stringency across the calendar year.

[19]We exclude the 1993 summary statistics for space consideration. Similar tables for 1993 data are available upon request.

creased from 10,411 to 11,385 per month between the two periods; an increase of more than 9%. As hypothesized earlier, this could result from the recruitment of minorities in the latter period. However, this does not show up as a change in the minority denial rates which remains relatively constant at approximately 26%. Table 2 provides similar data broken down into $\Gamma_{b,1}^{(logit)}$ quartiles. On net, the time pattern of the minority-majority odds-ratio provides little evidence of window dressing. These are aggregate values, however, and they may be masking any strategic behavior by individual institutions. Below, we analyze micro level strategic behavior in the form of window dressing and special programs.

## 5.1 Testing for Window Dressing

Values for $\Gamma_{b,t}^{(logit)}$ were generated by estimating the logit model in eq.(9) for the full sample of banks.[20] Regressions of the form described by eq.(7) were then applied to the $\Gamma_{b,t}^{(logit)}$ and $\Gamma_{b,t}^{(raw)}$ measures to test for strategic behavior. All regressions were run using weighted least squares (WLS) to account for heteroskedasticity introduced by sample size variation in the data used to generate the disparity measures. We assume that the variance of the regression error is inversely related to the total number of applications process by the bank. However, the appropriate weight should consider the composition of minority and majority loans instead of simply the total number of loans. We therefore present OLS estimates as well and compare results.

Results from estimating eq.(7) are presented in Tables 3 and 4.[21] The

[20] "Banks" is somewhat of a misnomer because a bank may appear more than once in the analysis if it has a sufficient number of loans in more than one MSA. Logit estimates for $\Gamma^{(logit)}$ for 1994 were obtained for 1,118 observations but two estimates were significant outliers with exceptionally large standard errors. These observations artificially improved the fit of the model and overstated the amount of window dressing. The observations were excluded from the analysis.

[21] The results were robust to alternative time specifications for the early and late time

columns represent various subsamples of the banks (ranked by loan volume) to test for differences across size groups. In Table 3 we assume $\Gamma_b^*$ is at the sample mean.[22] The fit of the regression model is relatively weak, as illustrated by the adjusted $R^2$ values near 0.2.[23] Table 3 shows no evidence of nonlinearities; the coefficient on the threshold term is not statistically different from zero in any of the specifications and it is positive throughout. The coefficient on $\Gamma_{b,1}$ is positive throughout the table. Recall that the window dressing hypothesis required $\beta = 0$ and $\theta < 0$. These hypotheses, however, assume correct measurement of the threshold $\Gamma_b^*$. We suspect that the results in Table 3 are driven by the firm-level heterogeneity invalidating the assumption of a single threshold value at the mean of the first period measure.

Table 4 repeats the analysis, modeling the threshold as the mean value for the local market–the MSA. The regression's fit improves somewhat but the results still suggest little evidence of window dressing behavior. Although some of the threshold coefficients are negative when the local market threshold is considered, very few are significant. In spite of the fact that the market-specific threshold measure is thought to be preferred to the sample mean used in Table 3, lack of any evidence of window dressing behavior may still be in part the result of measurement error in $\Gamma^*$.[24]

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periods, e.g., using either the first eight or ten months as the early period.

[22]Since the findings are similar, results for the $\Gamma^{(raw)}$ measure are included in the appendix as Tables 3a and 4a. The similar results add credence to our assumption that loan applicant quality is relatively constant and that intra-year differences do not simply reflect changes in the quality of the applicant pool.

[23]The degree of intra-year random variation suggests care in the use of logit models as a regulatory screen for disparate treatment of loan applicants.

[24]Additionally, we attempted to estimate the threshold point as a parameter of the model but were unable to identify any significant nonlinearities. As an additional test for strategic behavior at banks we estimated the basic relationship in Table 3 for mortgage companies which are not affiliated with a bank or bank holding company. These firms are not stringently regulated with respect to fair lending legislation although they do

For reasons discussed earlier, the threshold could differ across banks *and* some banks may have stronger incentives to window dress. In an attempt to capture the latter form of heterogeneity, we reestimated the model using the subsample of firms that were involved in a merger or acquisition during the 1990s. We noted earlier that banks in a merger "mode" may be more interested in keeping the denial ratio down and, therefore, more apt to respond to high ratios in a strategic manner.

Table 5 contains the regression estimates for the subsample of merger active banks. These results are more consistent with window dressing behavior. For each size subsample and threshold specification, the coefficient on the threshold term has the expected negative sign and in most cases is significant. Additionally the size of the nonlinearity increases with loan application activity. This is consistent with the argument that larger firms are more likely to act strategically. As with the larger sample, the coefficient on $\Gamma_{b,1}$ continues to be statistically different from zero.

## 5.2 Testing for Special Programs

The empirical model suggested two possible tests for special program behavior. The simplest of the two is based on a test of equality of the first and second period minority-majority denial ratios. A likelihood ratio test in the context of the logit model on the 1994 data, rejects the equality of the coefficients at the 99% confidence level and the first-period coefficient exceeds the

report for HMDA purposes through HUD. We therefore would not expect these firms to respond strategically in the same fashion as regulated banks. The estimates were indeed substantially different for these nonregulated firms. The results were not consistent with either special projects or window dressing behavior. The coefficient on the first period denial ratio was not significantly different from zero at the 95% confidence level while the threshold effect was positive and significant. Since these firms are not subject to fair lending guidelines, however, the data do not undergo edits typically made for other reported HMDA data. Any conclusions should therefore be interpreted cautiously.

second in 45% of the cases. These results are similar for the unconditional measure, $\Gamma^{(raw)}$. The equality hypothesis can be assessed more generally using Table 3, ignoring the threshold term. Similar outcomes in the two periods require an intercept equal to zero and a slope coefficient equal to one. We focus only on the slope coefficient to allow for an exogenous time shift in behavior. The slope coefficient estimates in Table 3, across both years and all size classes, are statistically different from 1.0 at the 99% confidence levels. This is evidence of firms behaving differently across the two periods, in a manner consistent with special programs behavior.

The stronger test of special program behavior is based on a specification of the year-end target value in much the same way as the test of window dressing required us to specify a threshold value. In this scenario, we expect the slope coefficient to be negative. The slope coefficient estimates in Table 3 are actually positive and statistically different from zero. The coefficient is negative in only one of the Table 4 specifications. Thus, based on the stronger test we find little support for the special program hypothesis.

## 6 Summary and Conclusions

In this article, we provide the first test for evidence of strategic behavior by banks in response to fair lending regulations. Theory argues that regulated firms may find it in their self interest to respond strategically in a manner intended to improve public relations and appease regulators, instead of adhering to the intent and spirit of the regulation. We analyze intra-year variation in racial disparity in mortgage lending as a test of strategic behavior.

Our findings are somewhat mixed. For the total sample of active lenders, we find little empirical support for what we term window dressing behavior–

a significant year-end adjustment to lending activity in an attempt to lower the annual minority-majority denial ratio reported in HMDA data. We do, however, find some support for what we term the *special programs* approach– a conscience effort by banks to have a lending campaign at a predetermined period during the year in an attempt to lower the annual denial ratio. One potential problem with our test for window dressing is that we proxy what is probably a bank-specific denial ratio threshold, beyond which the strategic response is expected to occur, with an aggregate and market-specific measure. Hence, our results may reflect the commingling of firm heterogeneity and strategic behavior. As a partial response to this problem we conduct the analysis for a subsample of the data for which there could be a significant payoff from window dressing: those involved in merger activity. For this group of banks we find statistically significant differences in outcomes between the two periods and evidence of an asymmetric relationship consistent with year-end window dressing behavior.

The analysis highlights the need for care in drafting regulations to avoid unintended responses by the regulated firms. The findings do not, however, imply that distortions created by strategic behavior significantly offset any benefits of the regulation. The net benefit assessment is left for others to evaluate. Additional areas for future research include the consideration of alternative loan products, alternative means to capture firm-specific threshold levels at which strategic behavior becomes viable, alternative means to categorize institutions into potential users of window dressing and/or special programs, and alternative forms of strategic response.

## References

Allen, Linda and Anthony Saunders. "Bank Window Dressing: Theory and Evidence" *Journal of Banking and Finance* 16 (June 1992), 585–623.

Avery, Robert B., Patricia E. Beeson, and Mark S. Sniderman. "Cross-Lender Variation in Home Mortgage Lending" *Economic Review* Federal Reserve Bank of Cleveland (Quarter 4 1994), 15–29.

Bauer, Paul W. and Brian A. Cromwell. "A Monte Carlo Examination of Bias Tests in Mortgage Lending" *Economic Review* Federal Reserve Bank of Cleveland (Quarter 3 1994), 27–44.

Brewer, Elijah III and Thomas H. Mondschean. "An Empirical Test of the Incentive Effects of Deposit Insurance: The Case of Junk Bonds at Savings and Loan Associations" *Journal of Money, Credit, and Banking* 26 (February 1994), 146–64.

Brewer, Elijah III and Thomas H. Mondschean. "Life Insurance Company Risk Exposure: Market Evidence and Policy Implications" *Contemporary Policy Issues* 11 (October 1993), 56–69.

Canner, Glenn B. and Wayne Passmore. "The Financial Characteristics of Commercial Banks that Specialize in Lending in Low-Income Neighborhoods and to Low-Income Borrowers" *Proceedings of a Conference on Bank Structure and Competition* (May 1996), forthcoming.

Canner, Glenn B. and Wayne Passmore. "Home Purchase Lending in Low-Income Neighborhoods and to Low-Income Borrowers" *Federal Reserve Bulletin* 81 (February 1995a), 71–103.

Canner, Glenn B. and Wayne Passmore. "Credit Risk and the Provision of Mortgages to Lower-Income and Minority Homebuyers" *Federal Reserve Bulletin* 81 (November 1995b), 989–1016.

Canner, Glenn B. and Wayne Passmore. "Residential Lending to Low-Income and Minority Families: Evidence from the 1992 HMDA Data" *Federal Reserve Bulletin* 80 (February 1994), 79–108.

Chevalier, Judith A. and Glenn D. Ellison. "Risk Taking by Mutual Funds as a Response to Incentives" National Bureau of Economic Research, Inc., Working Paper #5234. 1995.

Evanoff, Douglas. "Branch Banking and Service Accessibility" *Journal of Money, Credit, and Banking* 20 (May 1988), 191–202.

Evanoff, Douglas D.. "An Empirical Examination of Bank Reserve Management Behavior" *Journal of Banking and Finance* 14 (March 1990), 131–43.

Garwood, Griffith L. and Dolores S. Smith. "The Community Reinvestment Act: Evolution and Current Issues" *Federal Reserve Bulletin* 79 (April 1993), 251–67.

Healy, R.M.. "The Effect of Bonus Schemes on Accounting Decisions" *Journal of Accounting and Economics* (April 1985), 85–107.

Holmes, Andrew and Paul Horvitz. "Mortgage Redlining: Race, Risk, and Demand" *Journal of Finance* 49 (March 1994), 81–99.

Hunter, William C. and Mary Beth Walker. "The Cultural Affinity Hypothesis and Mortgage Lending Decisions" *Journal of Real Estate Finance and Economics* (1996), forthcoming.

Kane, Edward. "Good Intentions and Unintended Evil: The Case Against Selective Credit Allocation" *Journal of Money, Credit, and Banking* 9 (February 1977), 55–69.

Kane, Edward. "Accelerating Inflation, Technological Innovation, and the Decreasing Effectiveness of Banking Regulation" *Journal of Finance* 36 (May 1981), 355–66.

Lakonishok, Josef et al.. "Window Dressing by Pension Fund Managers" National Bureau of Economic Research, Inc., Working Paper, #3617. 1991.

McKenzie, Joseph A., Rebel A. Cole, and Richard A. Brown. "Moral Hazard, Portfolio Allocation, and Asset Returns for Thrift Institutions" *Journal of Financial Services Research* 5 (April 1992), 315–39.

Munnell, Alicia H. et al.. "Mortgage Lending in Boston: Interpreting HMDA Data" *American Economic Review* 86 (March 1996), 25–54.

Oyer, Paul. "The Effect of Sales Incentives on Business Seasonality" Princeton University Working Paper. 1995.

Peltzman, Sam. "An Evaluation of Consumer Protection Legislation: The 1962 Drug Amendments" *Journal of Political Economy* 81 (September 1973), 1049–91.

Pyle D.H.. "The Losses On Savings Deposits from Interest Rate Regulation" *Bell Journal of Economics and Management* 5 (Autumn 1974), 614–22.

Startz, R.. "Implicit Interest and Demand Deposits" *Journal of Monetary Economics* 5 (October 1979), 515–34.

Stickney, Clyde P.. "Window Dressing the Interim-Earnings Report: An Empirical Assessment for Firms Initially Going Public" *Journal of Business* 48 (January 1975), 87–97.

Wiggins, Steven N.. "Product Quality Regulation and New Drug Introductions: Some New Evidence from the 1970s" *Review of Economics and Statistics* 63 (November 1981), 615–19.

Wilke, John R.. "Mortgage Lending to Minorities Shows a Sharp 1994 Increase" *American Banker* February 13 (1996), 1.

Yezer, Anthony M.J., Robert F. Phillips, and Robert P. Trost. "Bias in Estimates of Discrimination and Default in Mortgage Lending: The Effects of Simultaneity and Self-Selection" *Journal of Real Estate Finance and Economics* 9 (November 1994), 197–215.

Yezer, Anthony M.J.. *Fair Lending Analysis: A Compendium of Essays on the Use of Statistics.* Washington: American Bankers Association. 1995.

Chart 2. Mortgage Approvals: HMDA Data, Conventional, 1-4 Family, Owner Occupied.

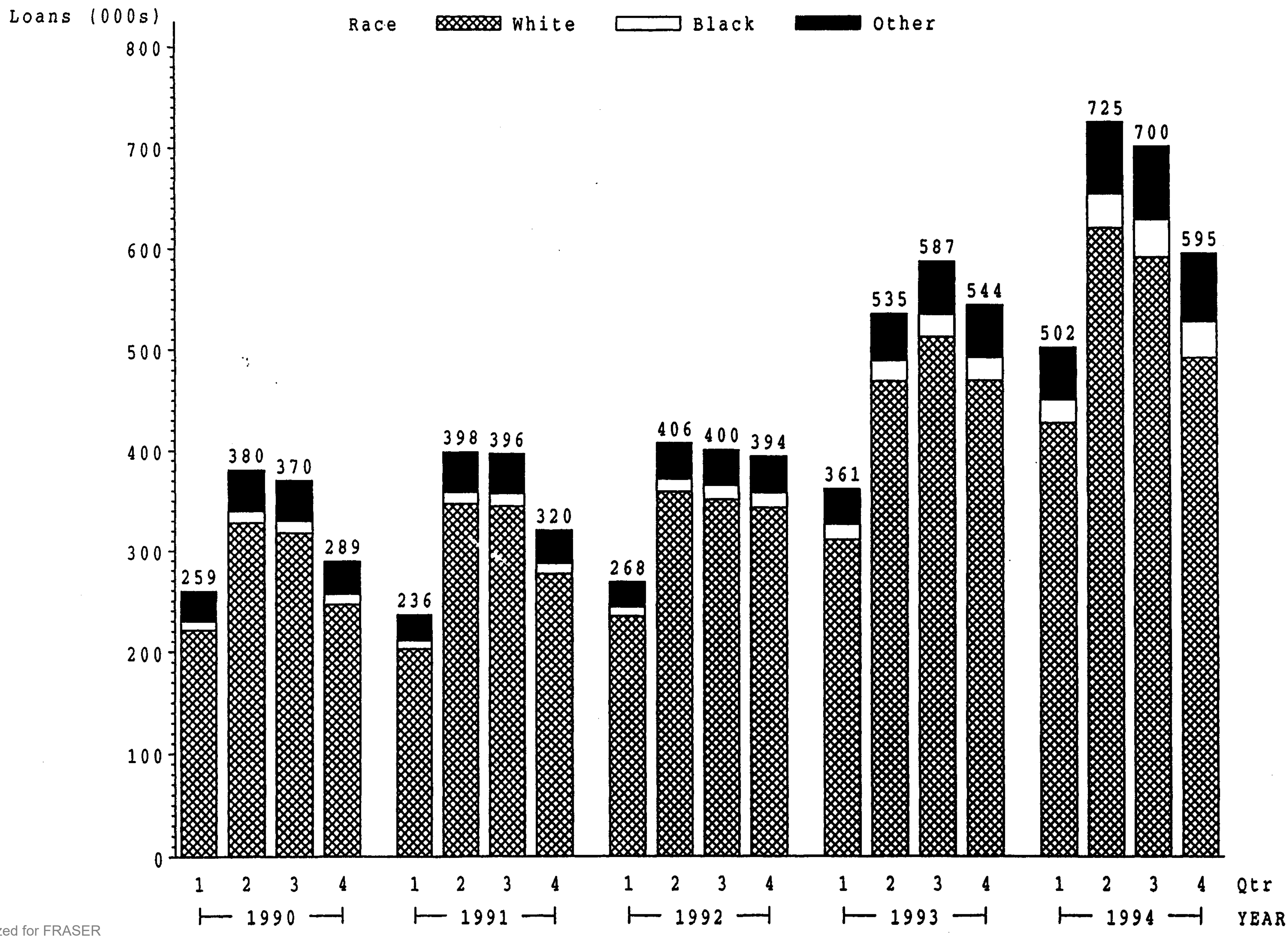

Chart 1. Mortgage Applications: HMDA Data, Conventional, 1-4 Family, Owner Occupied.

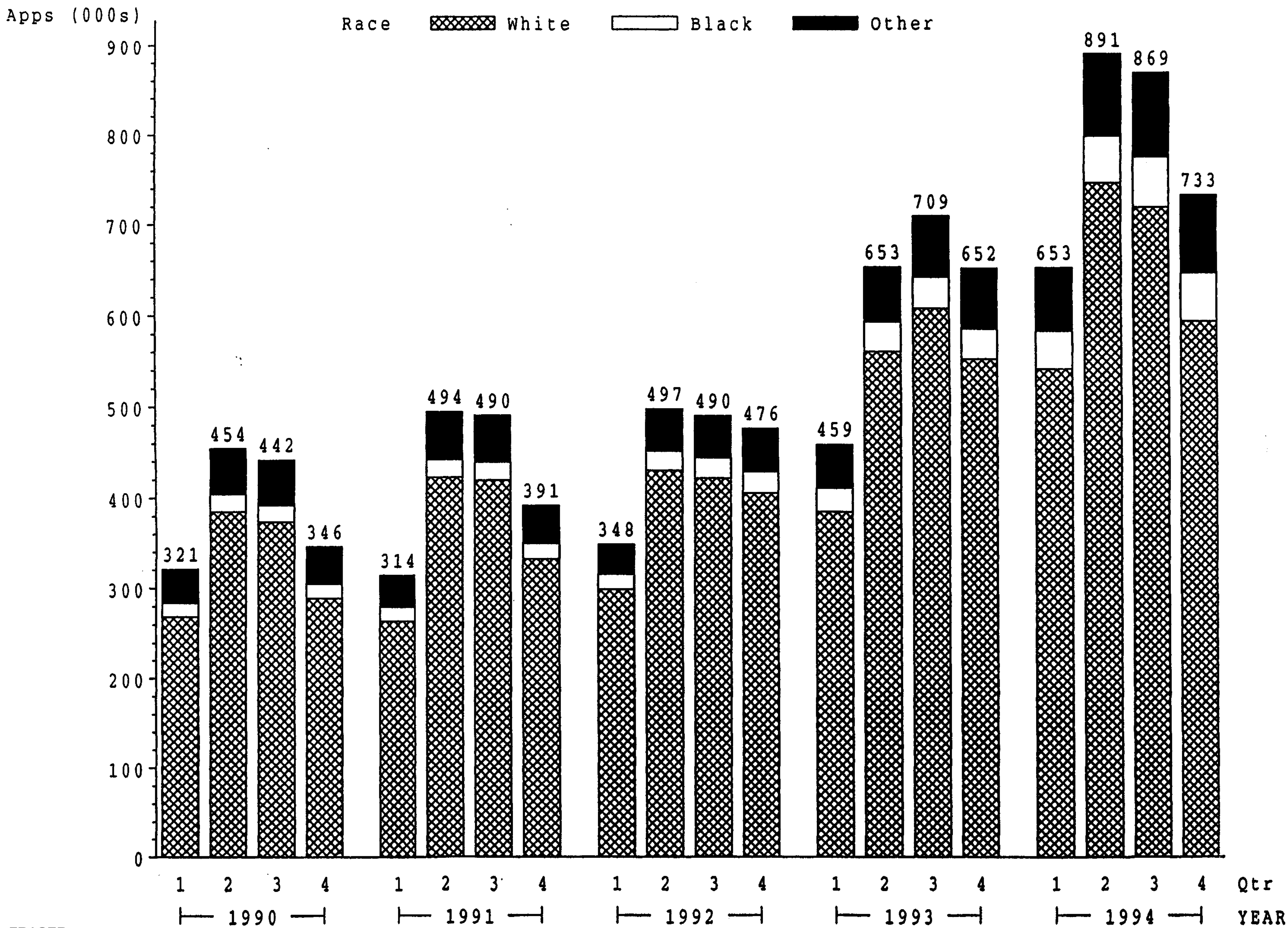

Figure 1. Mortgage Denial Rates: HMDA Data, Conventional, 1-4 Family, Owner Occupied.

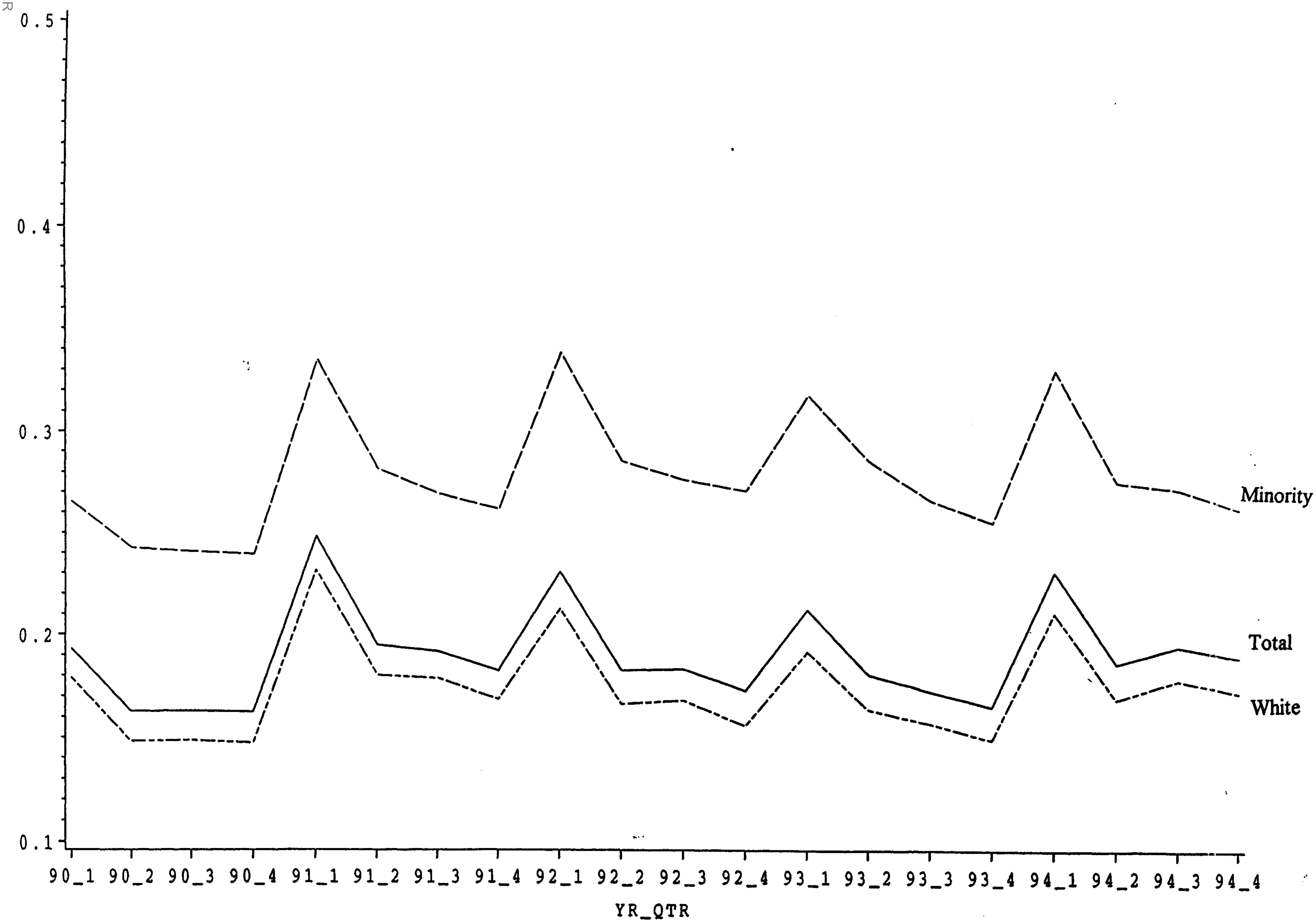

Table1. Sample Summary Statistics: 1994 HMDA Data, Conventional, 1-4 Family, Owner Occupied Loans.[1]

| | Total | Jan - Sep | Oct -Dec |
|---|---|---|---|
| **Applications / Month** | 56133 | 56715 | 54385 |
| FRS | 16736 | 16740 | 16724 |
| OCC | 27711 | 28135 | 26440 |
| FDIC | 11686 | 11841 | 11221 |
| | | | |
| White | 45478 | 46304 | 43000 |
| Minority | 10654 | 10411 | 11385 |
| Black | 4516 | 4398 | 4869 |
| | | | |
| **Institutions[2]** | 1118 | 1118 | 1118 |
| FRS | 282 | 282 | 282 |
| OCC | 555 | 555 | 555 |
| FDIC | 281 | 281 | 281 |
| | | | |
| MSA | 976 | 976 | 976 |
| NonMSA | 142 | 142 | 142 |
| | | | |
| **Denial Rate** | 17.60% | 17.42% | 18.16% |
| White | 15.64% | 15.51% | 16.04% |
| Minority | 25.97% | 25.90% | 26.16% |
| Black | 31.61% | 31.84% | 30.99% |
| | | | |
| **Income ($000s)** | 60.49 | 60.70 | 59.83 |
| White | 63.27 | 63.41 | 62.83 |
| Minority | 48.59 | 48.62 | 48.51 |
| Black | 40.16 | 39.81 | 41.11 |
| | | | |
| **Loan Amount ($000s)** | 103.5 | 104.5 | 100.3 |
| White | 105.9 | 106.9 | 102.8 |
| Minority | 92.9 | 93.7 | 90.7 |
| Black | 71.6 | 71.6 | 71.6 |

[1] The sample is comprised of applications for these loans as reported by institutions with a minimum of 120 loan applications within a local market. The institution must also be an active lender throughout the year -- see footnote 17.

[2] "Institutions" refers to a bank's presence in a market, therefore a bank could be represented by several observations.

Table 2. Sample Summary Statistics Disaggregated by the First Period Odds Ratio of the Institution: 1994 HMDA Data, Conventional, 1-4 Family, Owner Occupied Loans.[1]

| | Highest Quartile | Third Quartile | Second Quartile | Lowest Quartile |
|---|---|---|---|---|
| Full Year | | | | |
| **Applications / Month** | 9895 | 14567 | 19409 | 12262 |
| White | 8431 | 12181 | 15440 | 9427 |
| Minority | 1465 | 2386 | 3969 | 2835 |
| Black | 883 | 1131 | 1618 | 884 |
| | | | | |
| **Denial Rates** | 13.23% | 13.57% | 22.65% | 17.93% |
| White | 10.31% | 11.62% | 20.75% | 17.21% |
| Minority | 29.99% | 23.51% | 30.03% | 20.29% |
| Black | 34.79% | 27.08% | 38.46% | 21.71% |
| Minority / White Odds Ratio | 3.73 | 2.34 | 1.64 | 1.22 |
| October - December | | | | |
| **Applications / Month** | 9631 | 13833 | 18910 | 12011 |
| White | 8037 | 11389 | 14563 | 9011 |
| Minority | 1594 | 2444 | 4347 | 3000 |
| Black | 931 | 1154 | 1851 | 933 |
| | | | | |
| **Denial Rates** | 13.46% | 13.41% | 24.40% | 17.59% |
| White | 10.78% | 11.59% | 22.37% | 16.14% |
| Minority | 26.95% | 21.88% | 31.20% | 21.93% |
| Black | 30.39% | 24.81% | 39.22% | 22.87% |
| Minority / White Odds Ratio | 3.05 | 2.14 | 1.57 | 1.46 |

[1]The first period odds ratio is the coefficient estimate on minority status from an institution / MSA level logit analysis. The sample is comprised of applications for these loans as reported by institutions with a minimum of 120 loan applications within a local market. The institution must also be an active lender throughout the year -- see footnote 17.

Table 3

**Strategic Behavior in Mortgage Lending: Window Dressing Threshold Measured as the Sample Mean**

| | 1994 | | | | | | 1993 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ordinary Least Squares | | | Weighted Least Squares | | | Ordinary Least Squares | | | Weighted Least Squares | | |
| Sample | All (1116) | Top 250 | Top 100 | All (1116) | Top 250 | Top 100 | All (915) | Top 250 | Top 100 | All (915) | Top 250 | Top 100 |
| Intercept | .548** (0.042) | .368** (0.063) | .312** (0.107) | .428** (0.035) | 343** (0.060) | .298** (0.090) | .589** (.057) | .361** (.075) | .338** (.103) | .471** (.046) | .323** (.072) | .283** (.101) |
| First period denial ratio | .405** (0.078) | .353** (0.129) | .559** (0.211) | .404** (0.067) | .427** (0.119) | .562** (0.173) | .186** (.088) | .302** (.131) | .257 (.176) | .201** (.075) | .346* (.126) | .367** (.176) |
| Max $(0, \Gamma_1-\Gamma^*)$ | .002 (0.124) | .232 (0.225) | .087 (0.322) | .126 (0.108) | .221 (0.194) | .174 (0.260) | .529 (.119) | .480 (.241) | .522 (.321) | .605 (.114) | .483 (.222) | .485 (.303) |
| Adjusted $R^2$ | .081 | .136 | .228 | .126 | .202 | .330 | .162 | .162 | .182 | .179 | .212 | .271 |

NOTES: The dependent variable is the fourth quarter minority-majority log-odds ratio from a logit regression controlling for applicant income, loan amount, race, and mortgage rates. The first period denial ratio is measured similarly using loan volume for the first nine months of the year. Standard errors are in parentheses; ** (*) indicates significance at the 95 (90) percent level.

Table 4

**Strategic Behavior in Mortgage Lending: Window Dressing Threshold Measured as the Local Market Mean**

| | 1994 | | | | | | 1993 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ordinary Least Squares | | | Weighted Least Squares | | | Ordinary Least Squares | | | Weighted Least Squares | | |
| Sample | All 843 | Top 250 | Top 100 | All 843 | Top 250 | Top 100 | All 644 | Top 250 | Top 100 | All 644 | Top 250 | Top 100 |
| | | | | | | | | | | | | |
| Intercept | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| | | | | | | | | | | | | |
| First period denial ratio | -.470** (.089) | .516** (.150) | .348 (.338) | .459** (.083) | .441** (.153) | .322 (.349) | .445** (.095) | .301** (.147) | .292 (.280) | .374** (.091) | .321** (.150) | .353 (.277) |
| | | | | | | | | | | | | |
| Max $(0, \Gamma_1 - \Gamma^*)$ | -.317** (.101) | .009 (.300) | .616 (.598) | -.300** (.095) | .198 (.291) | .681 (.588) | -.023 (.146) | .630** (.286) | .439 (.502) | .145 (.150) | .537* (.280) | .367 (.479) |
| | | | | | | | | | | | | |
| Adjusted $R^2$ | .454 | .183 | .094 | .281 | .167 | .101 | .154 | .294 | .245 | .222 | .295 | .312 |

NOTES: The dependent variable is the fourth quarter minority-majority log-odds ratio from a logit regression controlling for applicant income, loan amount, race, and mortgage rates. The first period denial ratio is measured similarly using loan volume for the first nine months of the year. Standard errors are in parentheses; ** (*) indicates significance at the 95 (90) percent level.

Table 5

Strategic Behavior by Merger Active Firms in 1994 Mortgage Lending

| | THRESHOLD MEASURED AS SAMPLE MEANS | | | | | | THRESHOLD MEASURED AS LOCAL MSA MEAN | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ordinary Least Squares | | | Weighted Least Squares | | | Ordinary Least Squares | | | Weighted Least Squares | | |
| Sample | All (425) | Top 250 | Top 100 | All (425) | Top 250 | Top 100 | All (291) | Top 250 | Top 100 | All (291) | Top 250 | Top 100 |
| Intercept | .422** (.060) | .248** (.073) | .117 (.104) | .246 (.051) | .182 (.062) | .110 (.089) | -- | -- | -- | -- | -- | -- |
| First period denial ratio | .535** (.101) | .674** (.123) | .793** (.193) | .680** (.089) | .746** (.110) | .847** (.166) | .531** (.182) | .775** (.200) | .800** (.341) | .666** (.168) | .763** (.185) | .802** (.325) |
| Max $(0, \Gamma_1-\Gamma^*)$ | -.306 (.195) | -.268 (.267) | -.729* (.400) | -.415** (.180) | -.441* (.237) | -.842** (.355) | -.579 (0.355) | -1.002** (0.400) | -1.046 (0.755) | -.778** (0.337) | -.900** (0.379) | -.970 (0.725) |
| Adjusted $R^2$ | .096 | .170 | .159 | .164 | .204 | .215 | .150 | .211 | .216 | .194 | .200 | .162 |

NOTES: The dependent variable is the fourth quarter minority-majority log-odds ratio from a logit regression controlling for applicant income, loan amount, race, and mortgage rates. The first period denial ratio is measured similarly using loan volume for the first nine months of the year. Standard errors are in parentheses; ** (*) indicates significance at the 95 (90) percent level.

## Table 3a

**Strategic Behavior in Mortgage Lending: Using the Unconditional Log-Odds Ratio Threshold Measured as the Sample Mean**

| | 1994 | | | | | | 1993 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ordinary Least Squares | | | Weighted Least Squares | | | Ordinary Least Squares | | | Weighted Least Squares | | |
| Sample | All (1116) | Top 250 | Top 100 | All (1116) | Top 250 | Top 100 | All (915) | Top 250 | Top 100 | All (915) | Top 250 | Top 100 |
| Intercept | .725** (0.044) | .464** (.079) | .553** (.122) | .554** (.039) | .436** (.072) | .463** (.101) | .723** (.054) | .534** (.084) | .429** (.106) | .565** (.048) | .453** (.080) | .361** (.106) |
| First period denial ratio | .346** (.072) | .392** (.132) | .239 (.195) | .365** (.064) | .377** (.120) | .314* (.164) | .350** (.088) | .236* (.143) | .153 (.172) | .321** (.080) | .298** (.133) | .316* (.173) |
| Max $(0, \Gamma_1 - \Gamma^*)$ | -.018 (.114) | .247 (.218) | .539* (.297) | .169* (.102) | .338* (.192) | .514** (.251) | .052 (.132) | .422* (.229) | .636** (.288) | .224* (.123) | .401* (.208) | .462* (.274) |
| Adjusted $R^2$ | .069 | .173 | .227 | .136 | .228 | .325 | .088 | .152 | .217 | .131 | .205 | .285 |

NOTES: The dependent variable is the fourth quarter minority-majority "raw" log-odds ratio. The first period denial ratio is measured similarly for the first nine months of the year. Standard errors are in parentheses; ** (*) indicates significance at the 95 (90) percent level.

Table 4a

Strategic Behavior in Mortgage Lending: Using the Unconditioned Log-Odds Ratio Threshold Measured as Local Market Mean

| | 1994 | | | | | | 1993 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ordinary Least Squares | | | Weighted Least Squares | | | Ordinary Least Squares | | | Weighted Least Squares | | |
| Sample | All (843) | Top 250 | Top 100 | All (843) | Top 250 | Top 100 | All (843) | Top 250 | Top 100 | All (843) | Top 250 | Top 100 |
| | | | | | | | | | | | | |
| Intercept | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| | | | | | | | | | | | | |
| First period denial ratio | .316** (.098) | .535** (.176) | -.140 (.410) | .347** (.096) | .416** (.182) | -.196 (.418) | .275** (.106) | .212 (.159) | .077 (.266) | .270** (.096) | .233 (.153) | .157 (.252) |
| | | | | | | | | | | | | |
| Max (0, $\Gamma_1$-$\Gamma^*$) | -.117 (.152) | -.109 (.294) | .883 (.578) | -.075 (.148) | .071 (.286) | .955* (.578) | .083 (.170) | .343 (.286) | .598 (.499) | .157 (.159) | .332 (.277) | .487 (.462) |
| | | | | | | | | | | | | |
| Adjusted $R^2$ | .101 | .146 | .076 | .121 | .117 | .061 | .143 | .269 | .242 | .229 | .287 | .327 |

NOTES: The dependent variable is the fourth quarter minority-majority "raw" log-odds ratio. The first period denial ratio is measured similarly for the first nine months of the year. Standard errors are in parentheses; ** (*) indicates significance at the 95 (90) percent level.