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The Cultural Affinity Hypothesis and Mortgage Lending Decisions

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Abstract

This paper conducts an empirical analysis of the cultural affinity hypothesis put forth by Calomiris, et al. (1994) in the mortgage lending market. This hypothesis implies that white loan officers, because of a lack of familiarity with minority applicants, will rely more heavily on characteristics that can be observed at low cost (e.g., objective loan application measures) in evaluating the creditworthiness of minority applicants relative to white applicants. Using a cleansed sample of 1,991 loan applications drawn from data collected by the Federal Reserve Bank of Boston, the results of the analysis were consistent with the cultural affinity hypothesis. In particular, we found that marginal black and Hispanic applicants appeared to be held to higher quantitative standards on such objective factors as credit history and debt obligation ratios than were similarly situated marginal white applicants.

A well-known result in the economics of information is that when job applicants have different productive potentials, employers will find it worthwhile to subject them to a screening process. Since productivity typically cannot be observed directly, some observable characteristic that is highly correlated with productivity may serve as a substitute. Thus, possession of a college degree or higher level of education may indicate attributes that will prove useful in certain jobs. Similarly, race or sex, whether or not justifiable on legal or ethical grounds, may be taken by employers as predictors of on-the-job performance.

In credit markets, many borrower characteristics serve as signals of borrower quality or creditworthiness. Just as employers may associate the race or sex of job applicants with productivity, so may lenders associate these attributes with creditworthiness. Since the Civil Rights Act of 1964, much legislation has been passed that was aimed at eliminating the use of unalterable personal characteristics such as race in credit approval decisions. Nonetheless, the question remains whether lenders continue to use such information in that way.

A recent hypothesis put forward by Calomiris, Kahn, and Longhofer (1994) suggests that continued discrimination against minorities in credit market situations could result from the lack of cultural affinity between white loan officers and minority applicants. This hypothesis states that white loan officers will rely more heavily on characteristics that can be observed at low cost when appraising the creditworthiness of minorities rather than invest marginal resources in gathering additional information about creditworthiness. Stated differently, if the majority of loan officers and applicants are white, white loan officers may feel they know more about white applicants than about minorities, and thus they are more likely to acquire additional information about the creditworthiness of white applicants. On the other hand, we would expect these lenders to rely more heavily on basic objective loan application information in appraising the creditworthiness of minorities.

This study uses mortgage application data collected under the Home Mortgage Disclosure Act of 1975 (HMDA) augmented by the Federal Reserve Bank of Boston to provide an empirical test of an extended version of the cultural affinity hypothesis. We examine whether loan officers perceive objective information, such as credit history or reputation and financial leverage, differently for minority applicants than for whites. Both characteristics would appear to provide useful information to lenders. If high-quality borrowers find it cheaper to build reputations (superior credit histories) than low-quality borrowers do, then lenders will prefer those borrowers with better reputations—their reputations derive directly from their superior abilities.

The data used in this study, HMDA data for the Boston area in 1990, have been criticized for being unusually "dirty"; that is, they are missing many values and contain many coding errors.[1] We used a rigorously cleaned subset of the original data that maintains the general profile of the full original data set. The criteria used to clean the data are discussed more fully in the following section.

Our empirical results suggest that lenders do treat objective loan application information differently, depending on the race of the applicant. In particular, credit history and the ratio of total monthly obligations to total monthly income both have a substantially greater impact on the probability of loan approval for minorities than for whites. Interestingly, we do not find that gender has a significant impact on the probability of loan approval.

In Section 1, which follows, we present a sketch of recent legislation addressing mortgage credit issues and briefly summarize earlier studies of discrimination in mortgage credit markets. Our data sources and definitions, as well as our statistical model, are described in Section 2. The empirical results are presented and discussed in Section 3. A summary and conclusion follow in Section 4.

1. Previous Studies

Following the passage of the Civil Rights Act of 1964, interest in the issue of discrimination in housing and mortgage credit markets increased significantly. Several additional pieces of legislation were passed in an attempt to outlaw the practice. The Fair Housing Act of 1968 (amended in 1988), the Equal Opportunity Credit Act of 1974, the Home Mortgage Disclosure Act of 1975 (HMDA), and the Community Reinvestment Act of 1977 (CRA) were enacted in part to outlaw discrimination in housing and mortgage credit markets on the basis of factors such as race, age, sex, and geographic location. While the Fair Housing Act and the Equal Opportunity Credit Act addressed the general issue of access to housing and credit, HMDA and CRA (as administered) dealt more directly with mortgage credit. HMDA and CRA were passed to address the perceived problems of housing credit not flowing properly to all neighborhoods within communities at large, and in particular, the failure of some mortgage lenders to adequately serve all segments of their primary trade areas. While HMDA required certain lenders to report, by census tract, the number and dollar value of home loans they made in their communities each year, CRA went one step further by encouraging (through the regulatory process) depository institutions to help meet the credit needs of their communities, including low- and moderate-income neighborhoods, consistent with safe and sound lending practices.

Early studies of discrimination in mortgage markets, such as Bradbury, Case, and Dunham (1989) and Hutchinson, Ostas, and Reed (1977), examined questions related to the issue of redlining—the practice whereby lenders refuse to make mortgage loans in geographic areas characterized by heavy concentration of racial or ethnic minorities regardless of the creditworthiness of the loan applicants. As noted by Benston (1981), most studies of redlining are inadequate since they fail to control sufficiently for borrower characteristics (see also Benston and Horsky, 1992). In addition, as noted by Holmes and Horvitz (1994), these studies do not adequately control for the risk differences across different geographic areas. More recent studies of redlining have produced somewhat mixed results. Holmes and Horvitz (1994), in their study of redlining in Houston, Texas, fail to find clear evidence of the practice, while the paper by Canner, Gabriel, and Woolley (1991) examining nationwide data finds more evidence of it.[2]

Beginning in 1990, lenders were required by HMDA to publicly report the location of residential loans made, along with the loan amount, income, and race of loan applicants plus the action taken on each loan (accepted, denied, or withdrawn by the applicant). The initial HMDA report indicated that mortgage applicants from black and Hispanic households were systematically denied mortgage loans at a higher rate than applicants from white households with similar incomes. HMDA data released since 1991 have shown essentially the same disparate rejection rate. Needless to say, these releases have generated much public concern. However, leading industry groups and individuals in government and academia have maintained that it would be inappropriate to draw the conclusion from these releases that mortgage lenders actively discriminate against minorities. This is because the HMDA data do not take into account information crucial to credit decisions, such as the loan applicant's credit history, other debts, and employment history. Partly in response to this debate, the Federal Reserve Bank of Boston conducted a study of mortgage denial rates in the Boston metropolitan area (Munnell, Browne, McEneaney, and Tootell, 1992) using a much wider range of loan application data. These augmented HMDA data are described briefly in Section 2. As a result of taking account of the personal characteristics of the borrowers, the Boston study reduced the magnitude of discrepancy for black and Hispanic applicants from 2.7 times the white denial norm to 1.6 times. Thus, while allowing for differences in loan applicant wealth and credit history reduces race-related differences in mortgage denial rates, it apparently does not eliminate them.[3,4]

2. The Data and Statistical Model

The data used in this study were taken from the augmented 1990 HMDA data collected by the Federal Reserve Bank of Boston. Augmentation of the HMDA data was necessary because applicant and loan characteristics collected under HMDA are severely limited. The Boston Fed, with the support of other supervisory agencies, obtained additional information on the borrowers and loan applications included in the 1990 HMDA report from the Boston Metropolitan Statistical Area. The Boston Fed data file included a random sample of 3,300 conventional applications made by whites and 722 conventional applications made by blacks and Hispanics. Boston Fed economists used the additional data, combined with census information on neighborhood characteristics, to develop a model of the determinants of mortgage lending decisions in the Boston area. The additional data collected on borrower and loan characteristics included variables measuring the borrower's ability to support the loan (net wealth, the ratio of total debt payments to income, and liquid assets), previous credit history (bankruptcy filings and number of credit reports in the file), default loss potential (loan-to-value ratios), personal characteristics of the applicant (age, marital status, number of dependents), and an estimate of the probability of being unemployed, among others. A detailed description of these data is available in Munnell, Browne, McEneaney, and Tootell (1992).

In our analysis of the Boston Fed data set, only conventional loans not associated with any special housing or lending programs were included. Since the original data set had a fairly large number of data errors and missing values, we used the criteria developed by Carr and Megbolugbe (1993) to purge the raw data. This included, for example, deleting applications with a ratio of housing expenses to total monthly income greater than 100 percent and deleting applications with a ratio of the loan amount to the purchase price in excess of 3.0, among others. We deleted approximately 1,000 observations because they contained data errors or were atypical relative to the overall sample. Of the data that remained, there were 1,726 loan applications approved and 265 denied. Among the 1,516 white applicants, the approval ratio was about .9; for the group of 475 black and Hispanic applicants, the approval ratio was .76. The characteristics of our subsample mirror those of the original data set. The explanatory variables are defined in detail in Table 1 and their statistical properties in Table 2.

Our statistical analysis of cultural affinity effects in mortgage credit markets is conducted using the framework of dichotomous choice models. Essentially, cultural affinity effects can be viewed as information that is unobservable to the econometrician, and statistical tests for the effects are conducted using the approach developed in the paper by Albrecht (1981). Intuitively, the approach tests whether white loan officers' decisions on white applicants depend less on formal information, such as credit history, financial obligations, and the like, than they do for minorities.[5] The lender's decision of which loan applicants to approve can be modeled as accepting only those applicants whose perceived creditworthiness (or marginal productivity) exceeds some critical level. We assume that the creditworthiness (or marginal productivity), I_k, of the kth applicant as perceived by the lender can be expressed as a linear combination of borrower characteristics; that is,

$$I_k = x_k' \beta + \epsilon_k, \tag{1}$$

where β is a vector of parameters and x_k is the vector of informational variables for the kth applicant. The error term ϵ_k represents factors known to the lender but unobservable to the modeler; it is assumed to be random noise with mean zero and variance σ^2.

Of course, this continuous index of creditworthiness, I_k, is not observed. We observe only whether a mortgage application is accepted or denied. Let

$y_k = 1$ if I_k is >0, i.e., the application is accepted, and

$= 0$ otherwise.

Table 1. Description of explanatory variables.

Variable Name	Description
HRAT	Ratio of monthly housing expenses to monthly income
OBRAT	Ratio of total monthly obligations to monthly income
MHIST	Mortgage payment history: 1 if two or fewer mortgage payments are recorded as late, 0 otherwise
PUB	Public records credit history: 1 if there are public record default, 0 otherwise
SELF	Self-employed: 1 if applicant is self-employed, 0 otherwise
CHIST	Consumer payments credit history: 1 if there is no history of delinquent credits (defined as one or more accounts 60 days or more past due), 0 otherwise
UEMP	Estimate of probability of unemployment by industry
MULTI	Type of property purchased: 1 if applicant is purchasing a two- to four-family home, 0 otherwise
COSIGN	Co-signer of application: 1 if co-signer, 0 otherwise
MS	Marital status: 1 if married, 0 otherwise
LNPR	Loan-to-price ratio
DEP	Number of dependents
SCH	Years of education: 1 if applicant has more than 12 years in school, 0 otherwise
THK	Thickness of file: 1 if there are more than two credit reports in the file, 0 otherwise
ARAC	Race of applicant: 1 if applicant is white, 0 otherwise
ASEX	Sex of applicant: 1 if applicant is male, 0 otherwise (i.e., female or information not available)
LOC	Characteristic of location: 1 if tract vacancy is less than the MSA median, 0 otherwise
SCHRAC	SCH*ARAC
SCHSEC	SCH*ASEX
SCHTHK	SCH*THK
SCHLOC	SCH*LOC
CHRAC	CHIST*ARAC
CHSEX	CHIST*ASEX
CHTHK	CHIST*THK
CHLOC	CHIST*LOC
OBRAC	OBRAT*ARAC

Then, the probability that the kth applicant will be granted a loan can be written as

$$Pr(y_k = 1) = F(x_k'\beta), \tag{2}$$

where F(·) is the cumulative distribution function of ϵ, assuming that ϵ has a symmetric distribution. Note that because the β parameters are identified only up to a positive scalar, our estimates are actually estimates of β/σ.

Table 2. Summary statistics for variables in model.

Variable Name	Mean	Standard Deviation	Minimum	Maximum
HRAT	25.227	7.523	0.52	72.00
OBRAT	32.719	8.259	0.52	79.00
MHIST	0.975	0.155	0.00	1.00
PUB	0.931	0.254	0.00	1.00
SELF	0.119	0.323	0.00	1.00
CHIST	0.802	0.398	0.00	1.00
UEMP	3.776	2.054	1.80	10.70
MULTI	0.136	0.342	0.00	1.00
COSIGN	0.029	0.167	0.00	1.00
MS	0.612	0.488	0.00	1.00
LNPR	.821	.166	.011	2.57
DEP	0.713	1.065	0.00	7.00
SCH	0.727	0.446	0.00	1.00
THK	0.104	0.306	0.00	1.00
ARAC	0.761	0.426	0.00	1.00
ASEX	0.775	0.418	0.00	1.00
LOC	0.533	0.499	0.00	1.00
SCHRAC	0.585	0.493	0.00	1.00
SCHSEX	0.558	0.497	0.00	1.00
SCHTHK	0.076	0.266	0.00	1.00
SCHLOC	0.402	0.490	0.00	1.00
CHRAC	0.639	0.480	0.00	1.00
CHSEX	0.628	0.484	0.00	1.00
CHTHK	0.080	0.271	0.00	1.00
CHLOC	0.438	0.496	0.00	1.00
OBRAC	24.594	15.50	0.00	79.00

3. Empirical Results

We estimate the logit model using 1,991 observations from the 1990 HMDA data file. The basic empirical resutls obtained from the estimation of the logistic regression are given in Table 3. The dependent variable in this regression is the action taken on the mortgage application, i.e., dependent variable = 1 if the application was accepted, and zero if it was denied. A number of control variables other than the reputation and credit experience variables mentioned above were also used in the model. These include standard financial ratios such as housing expenses relative to monthly income, and total debt obligations relative to monthly income, as well as other information on the applicant such as marital status, employment status, and whether the loan applicant had a cosigner. We also use a measure of prior credit market experience (number of credit reports) to examine the so-called "thicker file" phenomenon. Since accepted marginal white mortgage applicants are many times observed to have thicker loan application files than rejected marginal minorities, the common presumption is that the marginal white applicants have received special counseling or extra coaching from sympathetic loan officers while the minorities have not. We proxy file thickness using number of credit reports.

Table 3. Logit results on mortgage acceptances (dependent variable = 1 if mortgage was accepted, 0 if mortgage was denied).

Variable Name	Estimated Coefficient	Estimated Standard Error	Asymptotic T-Ratio
HRAT	0.019223	0.012428	1.5468
OBRAT	−0.12174	0.018657	−6.5251
MHIST	0.75848	0.36495	2.0783
PUB	−1.57350	0.21758	−7.23200
SELF	−0.64513	0.21603	−2.9862
CHIST	1.3570	0.37768	3.5929
UEMP	−0.093505	0.033145	−2.8211
MULTI	−0.60786	0.19700	−3.0855
COSIGN	1.0994	0.56227	1.9552
MS	0.45762	0.17267	2.6502
LNPR	−1.1461	0.48565	−2.3599
DEP	−0.091568	0.073145	−1.2519
SCH	−0.56899	0.42101	−1.3515
THK	−0.24733	0.52209	−0.47372
ARAC	−0.99226	0.79523	−1.2478
ASEX	−0.42984	0.44151	−0.97357
LOC	−0.69419	0.36295	−1.9126
SCHRAC	−0.30177	0.36058	−0.83690
SCHSEX	0.72755	0.42585	1.7085
SCHTHK	0.053618	0.49735	0.10781
SCHLOC	0.72478	0.34161	2.1216
CHRAC	−0.39771	0.34889	−1.1400
CHSEX	−0.23831	0.37715	−0.63186
CHTHK	0.11223	0.47534	0.23610
CHLOC	0.23793	0.33181	0.71707
OBRAC	0.0578	0.0202	2.8702

Log-likelihood = −780.94
Log-likelihood function = −613.33
Likelihood ratio test = 335.228 with 26 d.f.

Even more than in the usual logistic regression model, the estimated effects of the variables are difficult to interpret because of the multiple interactions terms. To compute the effects of the variables, we must specify the information set we use for conditioning. Suppose we write the equation that specifies the index of creditworthiness for loan applicants as

$$\begin{aligned} I_k = {} & x_k'\beta + \alpha_1 \cdot \text{CHIST} + \alpha_2 \cdot \text{ARAC} + \alpha_3 \cdot \text{ASEX} + \alpha_4 \cdot \text{SCH} + \alpha_5 \cdot \text{THK} + \\ & \alpha_6 \cdot \text{LOC} + \alpha_7(\text{SCH} \cdot \text{ARAC}) + \alpha_8(\text{SCH} \cdot \text{ASEX}) + \alpha_9(\text{SCH} \cdot \text{THK}) + \\ & \alpha_{10}(\text{SCH} \cdot \text{LOC}) + \alpha_{11}(\text{CHIST} \cdot \text{ARAC}) + \alpha_{12}(\text{CHIST} \cdot \text{ASEX}) + \\ & \alpha_{13}(\text{CHIST} \cdot \text{THK}) + \alpha_{14}(\text{CHIST} \cdot \text{LOC}) + \text{error}. \end{aligned} \tag{3}$$

Then, the direct effect of the credit history (CHIST) signaling variable on creditworthiness is given by

$$\partial I/\partial CHIST = \alpha_1, \text{ given ARAC} = \text{ASEX} = \text{THK} = \text{LOC} = 0. \quad (4)$$

This coefficient measures the effect of credit history on creditworthiness given that the applicant is black or Hispanic (ARAC = 0), female (ASEX = 0), does not have a "thick" credit file (THK = 0), and wants to buy property in a location with a high vacancy rate (LOC = 0). An alternative set of conditioning information would give a different effect. For example, the total impact of credit history on creditworthiness with a different conditioning information set is given by

$$\partial I/\partial CHIST = \alpha_1 + \alpha_{11}, \text{ given ARAC} = 1, \text{ ASEX} = \text{THK} = \text{LOC} = 0. \quad (5)$$

Equation 5 gives the impact of credit history on creditworthiness given that the applicant is a white female with a thin credit file and the property to be financed is located in a high vacancy area.

Many of the results in Table 3 are interesting, though not surprising. For example, as the ratio of total debt obligations to monthly income (OBRAT) rose, the probability of loan approval fell. A 10 percentage point increase in this ratio lowered the probability of approval more than 8 percent, and this effect was statistically significant. Applicants with prior public record defaults, i.e., bankruptcies, had a significantly lower probability of being approved. The analysis also revealed that a self-employed applicant had a probability of loan approval more than 3 percentage points lower than an applicant who was not self-employed but otherwise had exactly the same characteristics. It is interesting to note that some variables seemingly had no effect on loan approval; for example, the number of dependents had an insignificant impact. Our model specification provides no evidence to support the thicker file hypothesis; the estimated direct effect of THK was insignificant regardless of the set of conditioning information.

The location variable also produced mostly insignificant results. Our basic finding was that loan approval was somewhat easier to obtain if the property was located in a census tract with a vacancy rate higher than the median for the metro area. This result, however, was not significant at the 5 percent level. Insignificant results were also obtained when other proxies defining good and bad location were used. In particular, when the quality of location was measured using a dummy variable indicating whether the minority population in the census tract of the property exceeded 30 percent, insignificant results were found.

To analyze the impact of race, we must consider the different variables that interact with the race variable. In particular, in our specification, race interacted with OBRAT, the ratio of total monthly obligations to total monthly income. Because OBRAT is a continuous variable, the impact of race on the creditworthiness of a loan applicant will depend on the level of OBRAT. Thus, the coefficient on race alone is not very informative. We computed the effect of race using two levels of the debt obligation ratio, one at the lowest quartile and one at the third quartile. Conditioning on "bad" levels of credit history and education (CH = SCH = 0), we found the effect of race to be small and statistically insignificant for a relatively low level of OBRAT; the coefficient was .626 with a standard error of .396.

When OBRAT rose, however, we found that the coefficient became larger (1.1463) and statistically significantly different from zero (standard error was .37). These results suggest that race was relatively unimportant to mortgage lenders when the objective measure of monthly obligations indicated a high-quality applicant. As this objective measure worsened, the results suggest that white applicants were judged more creditworthy than minority applicants. Note that these calculations were performed holding all other applicant characteristics constant.

It is also interesting to compute the effects of the race variable allowing credit history and education to take different values. When we set CH = SCH = 1, we found that race was completely insignificant for a low value of OBRAT, and only marginally significant for a higher OBRAT. Again, the results suggest that for applicants who were high quality in terms of their objective measures, race seemed unimportant to lenders. It appears to be the marginal minority applicant whose creditworthiness was reduced because of race.

With respect to the education level of the borrower, we found no evidence that education played an important role in the accept/reject decision. The only interaction variable involving education level that was statistically significant was that for education and location (the coefficient on SCHLOC was statistically significantly different from zero at a one percent significance level). However, this result may have been a statistical anomaly (Type I error), because we found no empirical evidence that either education (SCH) or location (LOC) had a statistically significant direct effect on creditworthiness. The lack of significance of education may be explained by the binary nature of this variable—we could only distinguish between applicants who had completed high school and those who had not; we did not have sufficient information to distinguish the exact number of years of schooling beyond high school.

The credit history variable (CHIST) produced a more interesting set of results. The estimated direct effect of credit history on the index of creditworthiness was positive and statistically significant for all sets of conditioning information. Not surprisingly, this means that having a good credit rating increased the probability of loan approval for both white and minority applicants and for males and females. An interesting point was that the effect was stronger (the estimated coefficient was larger and the standard error smaller) for minority applicants than for white applicants.

3.1. Predicted Probabilities of Approval

An interesting and somewhat different interpretation of the statistical results appears in Table 4. This table shows the predicted probabilities of approval and changes in approval probabilities for applicants with varying characteristics. We focused on the changes associated with four applicant characteristics: race, credit history, obligation ratio, and location. We held the values of the other variables constant. We measure the continuous variables (e.g., HRAT and UEMP) at their means while assuming that the other categorical variables in the sample had the value held by the majority of applicants (e.g., SELF = 0). The first set of entries in Table 4 show the different effects the variable credit history had on loan approval for white and minority applicants. The probability of loan approval for a white male buying property in a low-vacancy census tract fell about 5 percent as his credit rating

Table 4. Predicted probability of loan approval.

Applicant Characteristics[1]	Predicted Probability of Approval	Change in Probability[2]
ARAC = W, CHIST = good, LOC = good, OBRAT = RW	.9629	−.0542
ARAC = W, CHIST = bad, LOC = good, OBRAT = RW	.9087	
ARAC = M, CHIST = good, LOC = good, OBRAT = RM	.9453	−.1287
ARAC = M, CHIST = bad, LOC = good, OBRAT = RM	.8166	
ARAC = W, CHIST = good, LOC = good, OBRAT = RM	.9587	−.0134
ARAC = M, CHIST = good, LOC = good, OBRAT = RM	.9453	
ARAC = W, CHIST = bad, LOC = bad, OBRAT = RM	.8962	−.0843
ARAC = M, CHIST = bad, LOC = bad, OBRAT = RM	.8119	
ARAC = W, CHIST = bad, LOC = bad, OBRAT = 60	.6929	.245
ARAC = W, CHIST = bad, LOC = bad, OBRAT = 30	.9379	
ARAC = M, CHIST = bad, LOC = bad, OBRAT = 60	.1551	.7211
ARAC = M, CHIST = bad, LOC = bad, OBRAT = 30	.8762	

1. W = White; M = Minority; good and bad credit histories are defined in Table 1; RM—mean of obligation ratio (OBRAT) variable for minorities = 34.06; RW—mean of obligation ratio (OBRAT) variable for whites = 32.3. Note that RM and RW are not statistically significantly different.
2. Change in the approval probability associated with an applicant moving from the set of characteristics given in the top row of each panel to those given in the bottom row.

went from good to bad; even with a bad credit history, his probability of loan approval was still estimated to be slightly over 90 percent. Here, we set the obligation ratio at the mean value for white applicants. In contrast, a minority male, with obligation ratio set to the mean value for minorities, buying a home in a low-vacancy census tract saw his estimated probability of loan approval fall to about 82 percent as his credit rating fell, a change of nearly 13 percent. On the other hand, a white loan applicant with the objective measures set to good values has a predicted probability of loan approval of 96 percent, only slightly higher than the 94 percent probability predicted for a minority applicant with similar characteristics.

Now compare "high-quality" applicants to "low-quality" applicants. If a white male with a good credit history, average obligation ratio, seeking to purchase property in a good neighborhood, suddenly found his race change to black or Hispanic, his probability of approval would have dropped only 2 percentage points. If this same white male applicant had a bad credit history, average obligation ratio, and were seeking to purchase property located in a bad neighborhood, his probability of approval would have dropped 8 percentage points if his race suddenly changed to black or Hispanic. Stated differently, if a black male with a bad credit history, purchasing property in a bad neighborhood, suddenly found his race changed to white, his probability of approval would have increased 8 percentage points, while if his credit history were good and his neighborhood of choice were good, the change in race would have increased his probability of approval only 2 percentage points.

Finally, we focused on the impact of raising the obligation ratio on the probability of loan approval. That the obligation ratio was an important determinant of loan approval is obvious from the basic logit results in Table 3. The coefficient was a substantial negative number with a small standard error—hardly a surprising result. However, when we analyzed the differential impact of race, the results were surprising. First, consider a white male with poor objective measures of creditworthiness; that is, his credit history was bad, he was buying property in a high vacancy census tract, and his ratio of monthly obligations to monthly income was high, OBRAT = 60.0.[6] This loan applicant had a predicted approval probability of close to 70 percent. The same white male with an obligation ratio of only 30.0 (recall the mean for whites is 32.3) had a 94 percent chance of loan approval. A minority male with this same profile (bad credit history, bad location, OBRAT = 30.0) had a predicted approval probability of 88 percent, not too far from the prediction for whites. But if this minority male had an obligation ratio of 60.0, his predicted loan approval probability was less than 16 percent, far lower than the 70 percent predicted for a similar white male.

3.2. *Implications of the Findings*

Overall, the analysis suggests that the marginal minority applicants in our sample were more likely the victims of statistical discrimination resulting from the lack of a cultural affinity with white lending officers as opposed to invidious racial discrimination. This is suggested by the behavior of the race variable under differing sets of conditioning information. For applicants with good credit profiles, race was not a significant factor in the accept/reject decision. However, race was very significant for those with bad credit histories, and a bad credit history had the effect of lowering the probability of approval for minorities by an amount appreciably larger than that for whites. Similarly, race became an important factor for high levels of the monthly obligation ratio; our results indicate that minority applicants with high debt ratios were very much less likely to receive loan approval than similar white applicants. In addition, we found no evidence that loan officers in the Boston area engaged in redlining on the basis of the economic status of the neighborhood in which the property was located (status measured by vacancy rates, the percent of population at or below the poverty level, and the percentage of the population belonging to a minority group). We also found no evidence supporting the thicker file hypothesis.

While these results are consistent with the cultural affinity hypothesis put forth by Calomiris et al. (1994), it is also possible to interpret these results as the outcome of a simple rational Bayesian updating procedure used by loan officers. Under this interpretation, the precision of estimates of the probability of repayment conditional on all available information, including observable applicant characteristics, improves as loan officers process more and more applications. Clearly, if mortgage loan officers process more white applications than minority applications, the precision of the posterior probability distribution of repayment associated with white applicants will be greater than that for minority applicants. By processing more white applications and observing the outcomes of the lending decisions, the loan officer has more information with which to determine how various applicant characteristics, including less objective (and potentially mitigating) factors, affect the outcome of the loan. Thus, it is quite possible for factors other than credit history to matter for whites, possibly mitigating the impact of a weak credit history, while at the same time credit history may containue to play a dominant role in the accept/reject decision for minorities.

4. Summary and Conclusion

The search for statistical evidence of racial discrimination in economic life is exceedingly difficult. The results obtained in the literature using approaches that rely exclusively on the sign and significance of a racial dummy variable in a standard regression equation generally appear inconclusive. In this paper, we examined the cultural affinity hypothesis put forth by Calomiris et al. (1994). This hypothesis states that white loan officers, because of a lack of familiarity with minority applicants, will rely more heavily on characteristics that can be observed at low cost (e.g., objective loan application measures) in evaluating the creditworthiness of minority applicants. An interesting feature of this hypothesis is that it allows us to test whether mortgage lenders reward objective measures of borrower quality differently for whites than for minorities. In this way the methodology allows us to conduct a more stringent test of mortgage lender discrimination on the basis of race, sex, and property location.

The empirical model predicts the probability that a mortgage applicant will receive loan approval. We focused on four objective borrower characteristics that are generally believed to be important factors in measuring borrower quality. These are the applicant's education level, credit history, a proxy for previous credit market experience, and the ratio of total monthly obligations to monthly income. To allow for the possibility that these factors were perceived differently by lenders depending on the race of the applicant, each of these four variables was interacted with the applicant's race.

Our results, based on mortgage application data collected and reported by the Federal Reserve Bank of Boston, indicate strong support for the cultural gap hypothesis. We found empirical evidence that certain borrower characteristics were treated differently by lenders. In particular, the loan applicant's credit history and monthly obligation ratio appeared to be assessed differently for minority (black and Hispanic) borrowers than for whites. Interestingly, for high-quality borrowers (applicants with good credit histories and relatively low monthly obligation ratios), race seemed unimportant. The predicted probability of loan approval was very similar for white and minority applicants with good objective measures. For more marginal borrowers, race was much more important. In one case, a minority loan applicant with poor objective measures had only about a 16 percent chance of loan approval. A white applicant with the same poor objective measures had nearly a 70 percent chance of loan approval. Such pronounced differences in the way loan officers view the quantitative loan application information of marginal candidates is indicative of the economic significance of the results and cautions against placing too much weight on the mere statistical significance of regression coefficients in discrimination studies.

These findings, while suggestive, are based on data from the Boston area and cannot be generalized to all U.S. mortgage markets. Nonetheless, this appears to be a fruitful line of research, in that it implies that disparate loan rejection rates for whites and minorities are not the result of all minority applicants' being forced to meet higher standards than white applicants. Instead, it is among the marginal applicants where differences in the credit assessment process seem related to race. Stated differently, those candidates who, by objective measures, appear to be poor credit risks are the ones for whom race matters.

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Notes

1. There were also a number of criticisms leveled at the first study to use the data, Munnell, et al. (1992). We respecified the model used in the Boston Fed study in order to examine whether public information about loan applicants was systematically treated differently by mortgage lenders.
2. The methodology used by Holmes and Horvitz (1994) has received considerable criticism, making their empirical results somewhat suspect.
3. The conclusions of the Boston Fed study have been challenged and criticized by Horne (1994), Liebowitz (1994), and Zandi (1993) for containing numerous data errors, e.g., miscoded and incorrect information, among others. However, Carr and Megbolugbe (1993) conducted a detailed analysis of the Boston Fed study database, systematically eliminating erroneous data and atypical observations, and found that race was still a significant factor in the loan application accept/reject decision. Based on their analysis, Carr and Megbolugbe concluded that their results presented an even stronger case for discrimination than was originally reported in the Boston Fed Study. A recent working paper by Bostic (1994), reexamining the Boston Fed's findings, reports evidence of significant racial effects. Minority applicants were found to face substantial negative biases in terms of debt-to-income requirements but favorable biases regarding loan-to-value requirements relative to identical white applicants. Similar to the results reported in this paper, Bostic finds that the biases hold only for the marginal applicant.
4. It is also suggested that the applications of black and Hispanic applicants failed to meet the underwriting guidelines required for selling these mortgages in the secondary market more often than those of white applicants.
5. In the context of the model presented later, this will result in significantly different coefficients between whites and minorities for these coefficients, rather than different cut-off ratios.
6. The value of 60.0 for OBRAT is higher than approximately 90 percent of the values in the sample.

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