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Abstract Research has found wide disparities in loan denial rates among different racial/ethnic groups. Two competing explanations for these gaps arise. One argument is that these disparities result from underlying racial disparities in credit worthiness. A competing view is that the disparities arise from a pattern of racial discrimination among mortgage lenders. This paper adopts a stratification economics approach to evaluate these competing claims. Using Freddie Mac's Consumer Credit Survey dataset, we test the hypothesis that measures of discrimination disappear when one accounts for racial differences in credit scores. A novel contribution of the paper, built upon the premise that inter-group inequalities sustain themselves through self-fulfilling mechanisms, is to test the hypothesis that loan denials explain misperceptions of credit worthiness. We demonstrate that one cause of the appearance of poor credit risk among black applicants is that blacks with good credit risk underestimate their credit worthiness and apply for loans in lower numbers. Our findings suggest that even nondiscriminatory lending behavior has the unintended effect of screening out low-risk blacks and thereby yields higher denial rates among blacks. This in turn confirms prior beliefs

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about the poor credit of average black applicants. Much, but not all, of the racial disparity in loan outcomes can be explained by racial differences in credit scores and the resulting racial disparity in loan outcomes explains much of the racial difference in false perceptions about bad credit. Thus, a possible self-fulfilling mechanism remains within the credit market that perpetuates views about black bad credit.

Keywords Loan denial rates · Racial discrimination · Mis-perception of credit worthiness · Consumer credit survey

JEL Classification J15 · G21 · H81

Introduction

There are wide racial disparities in loan denial rates. Recent data collected as part of the Home Mortgage Disclosure Act revealed that 28 % of black conventional home purchase loan applicants were denied loans. In the same year, 16 % of white conventional home purchase loan applicants were denied loans (Geonner 2010). In other words, black applicants were nearly two times as likely to be denied home purchase loans as white applicants. One controversial conclusion is that this disparity signals a pattern of racial discrimination among mortgage lenders (Black 1999; Blackburn and Vermilyea 2004; Dietrich 2005; IRP 2009; Ladd 1998; Myers 2002; Turner et al. 2005; Pager and Shepard 2008; Barwick 2009).

In 1992, the Boston Federal Reserve published the pioneering study, “Mortgage Lending in Boston: Interpreting HMDA Data,” that established the existence of racial discrimination in mortgage lending (Munnell et al. 1992, 1996). Initially, the study received widespread media exposure supporting the view that the wide disparity in loan rejection rates was attributable to unequal treatment of equally qualified loan applicants. The Boston study, unlike any before it, controlled meticulously for virtually every conceivable alternative explanation for why blacks (and Hispanics) might be more likely to be denied loans. The study focused explicitly on various measures of credit worthiness and likelihood of default. The conclusion was inescapable: even after controlling for credit risk, blacks and Hispanics were more likely to be denied loans than equally qualified whites.

The Boston Federal Reserve study, however, caused considerable consternation among Boston area lenders and underwriters, national banking regulators, and the Federal Reserve Board’s research staff. Soon after it was published, there was an avalanche of denunciations. These groups had hoped that the Federal Reserve study would “convincingly demonstrate that race was not a determining factor in loan decisions” (Goering and Wienk 1996). The study found, however, that “race was indeed a fairly powerful influence in lending decisions” (Goering and Wienk 1996), and it confirmed earlier data that “revealed that the rejection rates for African Americans were twice as high as those for whites—rates comparable to those found over 20 years earlier (Listokin and Casey 1980) and virtually identical to the disparities found in 1994 HMDA data” (Goering and Wienk 1996).

This finding was opposite of what the lending industry had been preaching. A cottage industry of sorts evolved—much of it financed by the American Bankers

Association and various lender and mortgage lending associations—that was designed to discredit the Boston Federal Reserve's findings.

Criticisms of the Boston Federal Reserve study abound, most of which center on the question of whether the Boston Federal Reserve adequately controlled for all measures of credit risk. A recent illustration of such criticisms comes from work on student loans. Boyd (1997) contends that blacks have a higher rate of default than whites in the Stafford Loan Programs. He finds that blacks are more likely to be studying for degrees that yield lower incomes, they are less likely to graduate, and ultimately, they are less likely to be able to repay their student loans. The dominant cost of the high default rates on these loans is the higher risk that blacks impose on lenders when they apply for future loans. In a nutshell, this view contends, blacks are not discriminated against in the credit market. Instead, race of the loan applicant captures prior defaults. The problem then is risk, not race, in this view.

Another conventional explanation for why there is no discrimination against blacks in the loan market, despite the showing of wide racial gaps in lending, is that blacks are more likely to default on FHA loans. This finding, stemming from work of Berkovec et al. (1994), contends that if there were discrimination against blacks, only the very best risks would be allowed access to loans. Thus, only the very best risks among blacks would be observed in default and thereby their default rates should be lower than average. Since their default rates are higher than average, so this reasoning goes, blacks are not being discriminated against. The higher loan denial rate is justified by the higher risk of default. Blacks, bankers contend, are simply worse risks.

Still, strong counter findings support the original results of the Boston Federal Reserve. One careful and detailed replication of the Federal Reserve analysis found "an African American is still more than twice as likely as a white to have his home mortgage loan application rejected" (Carr and Megbolugbe 1993). Another more exhaustive evaluation concluded: "Compared to their white counterparts, African American and Hispanic home seekers are shown far fewer houses and apartments (and indeed sometimes excluded from available housing altogether), given far less assistance in finding the house or apartment that best fits their needs, and in finding a mortgage, and are steered to neighborhoods with minority concentrations or low house values" (Yinger 1995).

In other words, even in the face of skepticism about the Boston Federal Reserve's study, there are those who believe that discrimination plays a significant role in determining loan outcomes for blacks (Myers and Chan 1996). This, however, is neither the dominant belief among social scientists nor the prevailing view among economists. The conventional wisdom continues to be that blacks have worse credit than whites (Agarwal et al. 2003; Holloway and Wyly 2002; Ross and Yinger 2002; Avery et al. 2004; Wu and Birnbaum B. Credit scoring and insurance: costing consumers billions and perpetuating the economic racial divide. National Consumer Law Center/Center for Economic Justice 2007) and that bad credit risk explains the higher loan rejection rates among blacks.

Stratification economics can be useful in helping to model and interpret these competing findings. The cornerstone of the stratification economic approach is the recognition that structural and intentional processes generate hierarchy and, correspondingly, income and wealth inequality, between ascriptively distinguished people (Darity 2005). The stratification economist believes that there are material benefits to being part of a privileged group that motivate the group's fight to maintain dominance. In the absence of prescriptive, conscious policy intervention, discriminatory practices that maintain a dominant group's power will persist indefinitely. The theory frames the world as a perpetual interplay between groups working for the collective self-interest of their corresponding members. The stratification economics approach would not accept a finding of racial differences in credit risk as independent of historically discriminatory policies and practices. Indeed, the continuing legacy of past discrimination in credit markets might manifest itself in current observed disparities in credit worthiness. Thus, even if credit worthiness "explains" racial gaps in lending, there is still the task of understanding why and how credit worthiness disparities arise.

We also point out that credit scores are highly correlated with race although they are proprietary products (Ruetschlin et al. 2013). If credit scores themselves are racially disparate in their predictability of loan default rates, the use of credit scores in and of itself could be a racially discriminatory mechanism in attaining financial capital. This endogeneity issue is akin to the problem that Rodgers and Spriggs (1996) confront regarding the use of Armed Forces Qualification Test (AFQT) scores in predicting wages.

An innovative survey of consumers, the Freddie Mac Consumer Credit Survey (CCS), showed that "having a poor credit record is a relatively common problem in today's society," and "credit problems persist across income groups." (Freddie Mac 1999) Still, the study concludes, "minority borrowers are more likely than white borrowers to experience credit problems" (Freddie Mac 1999). Forty-eight percent of African Americans were deemed to have bad credit, while only 27 % of whites were. Another, less publicized finding from the CCS is that many more blacks than whites with good credit mis-predict their credit worthiness. In short, bad credit explains why many blacks are denied loans; misperceptions of bad credit may explain why the observed pool of black loan applicants contains so many poor credit risks.

This paper uses the CCS data set compiled by Freddie Mac to test the hypothesis that measures of discrimination disappears once one accounts for racial differences in credit scores. We also test the hypothesis that loan denials explain misperceptions of credit worthiness. We demonstrate that one cause of the appearance of poor credit risks among black loan applicants is the lower loan application rates among good risk blacks who underestimate their credit worthiness. This finding suggests that one unintended effect of even nondiscriminatory lending behavior that systematically results in higher denial rates among blacks is to screen out low risk blacks and thereby confirm prior beliefs about the poor credit of average black applicants.

Consumer Credit Survey, Freddie Mac 1999

In 1999, Freddie Mac commissioned a Market Facts telephone survey of 12,000 households, targeted to 20–40 year olds, with incomes under $75,000. The purpose of the survey was: "identify the factors that contribute to people getting into payment difficulties" and to "support the development of educational materials that can more effectively assist people in avoiding these problems."[1] A stratified random sample was selected to assure representation of racial minority group members and of each of several credit "buckets" reflecting the range of borrowing experiences of consumers.[2] The survey instrument was developed in conjunction with five Historically Black Colleges (HBCUs) to help improve consumer credit education.

One underlying presumption is that racial differences in *credit knowledge* contribute to racial differences in loan outcomes. The survey asked how much the respondents knew about the followings: (1) interest rates, finance charges, and credit terms, or (2) credit ratings and credit files. It queried respondents about their knowledge of financial and credit terms. We recoded these responses to create a dichotomous variable called "Knowledge about credit." Respondents were asked whether they had any type of credit card before. We recoded these responses to create a variable called "Never had credit card." Respondents were asked whether they had ever experienced eviction, had their utilities turned off for nonpayment, or faced repossession. We recoded these responses to create a variable called "Never had a bad experience." Respondents were asked whether their parents were good at managing finances, and when they were growing up whether they were aware of their parent's financial situation and whether their parents set aside money for savings. We recoded these responses to create a variable called "Positive parental influence."

Other factors that we included in the model measured "good budgeting" (often follows a budget, saves or invests money, postpones a purchase until affordable, controls spending, pays bills on time, or plans for financial future), "risk taker," (plays the lottery or gambles very often or takes risks), "faith," (counts on God in financial matters), "stress," (feels stressful from daily life and has mental or physical symptoms), college graduate, immigrant (parent or respondent not born in US), and personal crisis (experienced major medical expenses, theft, major legal or tax problem, or unemployment). Details of the recoding and the definition of variables are in Table 1.

Table 2 shows that blacks are more likely than whites to report that they have been turned down for a loan or credit card. The data set considers a number of different time periods for which the respondent is asked whether she has been denied credit. We constructed one dichotomous variable that depicts whether the respondent had been turned down within the past 2 years. This time period coincides with what is typically recorded on a credit record and thus can be considered to reflect current and/or recent loan denials. Nearly 60 % of blacks reported recently having been turned down for a loan or credit card, one and one half times the rate at which whites reported recent loan denials.

There are wide variations between blacks and whites in measures of credit knowledge. Blacks are more likely than whites to report never having had credit cards, less likely to report knowledge about common credit terms. Blacks are less likely than whites to report having had no bad credit experiences. And, blacks are less likely to have had strong parental influences regarding credit.

In addition to these basic measures of credit knowledge, blacks are less likely than whites to observe good budgeting practices, they have lower incomes, they are more likely to be female heads of families with young children, and they are less likely than

[1] Bradley, et al., *Freddie Mac Consumer Credit Initiative Research: The Consumer Credit Survey* (*CCS*) *Sampling and Data Development* (2000).

[2] For full details of the sampling methodology see: *CCS Research Design and Methodology Report* (2000).

Table 1 Variable description

Variable	Name in the data set	Definition
Response variable		
Loan denial in the past 2 years	denial2	Turned down for a loan or credit card in the past 2 years
False negative	FalseN1	Individual thinks they have 'bad' credit but their FICO credit score is greater than the overall mean FICO score less one S.D. (includes being greater than missing FICO scores).
False negative buckets	FalseNB	Individual thinks they have 'bad' credit but according to Freddie Mac's 'Bucketing Convention', they do not fall into the 'Bad' bucket. This is relative to the sub-population who thinks they have 'bad' credit.
Explanatory variable		
Age as of 1999	age	Age as of 1999
Bankruptcy ever	bankrupt	Have ever declaired bankruptcy
Black	black	Dummy for Race: Black
Checks returned	checks	Have experienced checks returned for
College graduate	colgrad	Graduated from college and higher
Good budgeting	goodbud	Often follows a budget, saves or invests money, postpones a puchase until affordable, controls spending, pays bills on time, or plans for financial future.
Faith	faith	Count on God on financial matters
Immigrant	immig	Either self or parent(s) not born in U.S.
Income	income	Family's before-tax income in dollars
Knowledge about credit	knowcred	Knows about financial and credit terms
Male	male	Dummy for Gender: Male
Never had bad experience	nobadexp	Never have experienced eviction, utilities turned off for nonpayment, or repossession
Never had credit card	nocard	Never had any type of credit card before
Personal crisis	crisis	Have experienced major medical expenses, theft, major legal or tax problem, or unemployment
Positive parental influence	posprnt	Agreed that parents were good at managing finances, was aware of their financial situation, or set aside money for savings
Risk taker	risktkr	Play the lottery or gamble very often or take risks
Self rated bad credit	badcred	Rated own credit record bad
Self rated good credit	goodcred	Rated own credit record good
Sloppy payer	sloppy	Not good on paying bills on time
Stress	stress	Feels stressful from daily life and has mental or physical symptoms
Other variable		
Race	race	Race/Ethnicity
Bucket	bucket	Bucket
Weights	weights	Weights

Consumer Credit Survey Data

Table 2 Difference in means by race

Variable	White		Black		t-stat
	N	Mean	N	Mean	
Response variable					
Loan denial ever in the past	4,611	0.5927	3,655	0.7812	−12.97 ***
Loan denial in the past 2 years	4,611	0.3954	3,655	0.5958	−13.53 ***
False negative	3,082	0.1139	1,635	0.1919	−5.04 ***
False negative buckets	3,086	0.1376	2,198	0.2320	−6.24 ***
Self rated bad credit	4,584	0.2339	3,662	0.3659	−10.07 ***
Self rated good credit	4,584	0.5423	3,662	0.2970	16.48 ***
Explanatory variable					
Age as of 1999	4,627	32.354	3,667	32.510	−0.96
Automobile owner	4,614	0.9471	3,634	0.7618	22.98 ***
Bankruptcy	4,627	0.1194	3,685	0.1294	−1.01 ***
Calls ever collectors	4,618	0.5371	3,673	0.7486	−14.32 ***
Checks returned	4,617	0.5913	3,666	0.6204	−1.96 **
College graduate	4,633	0.2358	3,687	0.2344	0.11
Contacted by collectors ever	4,614	0.4904	3,666	0.7144	−15.03 ***
Employed	4,631	0.7234	3,702	0.7246	−0.09
Eviction ever	4,623	0.0797	3,669	0.1722	−10.56 ***
Faith	4,617	0.2607	3,690	0.5337	−20.17 ***
Female headed family with kids	4,656	0.0661	3,747	0.2693	−23.58 ***
Good budgeting	4,426	0.6819	3,412	0.6513	6.33 ***
Homeowner	4,577	0.6030	3,602	0.3336	18.15 ***
Immigrant	4,632	0.0597	3,692	0.0708	−1.54
Income	4,579	40,466	3,627	31,562	13.94 ***
Knowledge about credit	4,612	0.6939	3,702	0.6386	3.96 ***
Legal problem ever	4,600	0.0812	3,656	0.1204	−4.59 ***
Major medical problem	4,613	0.2780	3,664	0.2388	2.91 ***
Male	4,656	0.4752	3,747	0.3609	7.71 ***
Never had bad experience	4,635	0.7404	3,699	0.5521	13.96 ***
Never had credit card	4,609	0.0937	3,701	0.1189	−2.82 ***
Numeric FICO scores	3,932	672.94	2,789	599.55	24.95 ***
Overspender	4,564	0.0126	3,624	0.0417	−7.41 ***
Personal crisis	4,636	0.4739	3,711	0.5638	−6.00 ***
Positive parental influence	4,636	0.8696	3,710	0.8312	3.73 ***
Repo ever	4,624	0.0922	3,682	0.1341	−4.66 ***
Risk taker	4,650	0.1935	3,733	0.2415	−4.00 ***
Sloppy payer	4,633	0.2573	3,720	0.4295	−12.84 ***
Stress	4,420	0.4387	3,326	0.4339	1.05
Utility ever shut down	4,610	0.1848	3,666	0.3431	−12.99 ***

Statistically significant *** at 99 %, ** at 95 %, and * at 90 %

Consumer Credit Survey Data

whites to own their own homes or to own automobiles. They are more likely than whites to place their faith in God when facing financial distress, they are more likely to be risk takers, and they are more likely to have confronted personal crises. Despite these differences, there are no statistically significant differences in the composite measure of mental or psychological stresses. Moreover, in this sample there are no differences in age, employment or immigration status.

Blacks are also more likely to mispredict their credit worthiness. We produce two types of false negatives. The first is the probability that the respondent believes she has bad credit when in fact the credit score is within one standard deviation of the mean credit score for all respondents. The second is the probability that the respondent believes he has bad credit but he does not fall into the "bad credit" bucket defined by Freddie Mac. The first false negative is 0.11 for whites and 0.19 for blacks. The second false negative is 0.14 for whites but 0.23 for blacks. Both racial differences in false negatives are statistically significant.[3] The unconditional probabilities of self-rated bad credit are also higher for blacks than they are for whites, although many of the self-rated bad credit respondents indeed have bad credit. The racial gap in self-rated good credit, moreover, is far larger than the racial gap in the self-rated bad credit.

There are also sizeable differences in credit scores. The average black credit score in the data set is 599.55 (s.d. = 52.17). The average white credit score is 672.94 (s.d. = 114.22). White scores are not only higher than black scores, they are also more dispersed. Figure 1 shows that the widely dispersed white scores overlap the black scores that are concentrated around the lower end of the distribution. Thus, there are many whites with low scores, scores as low as the black scores, but the modal white score is at the upper portion of the distribution.

The Model

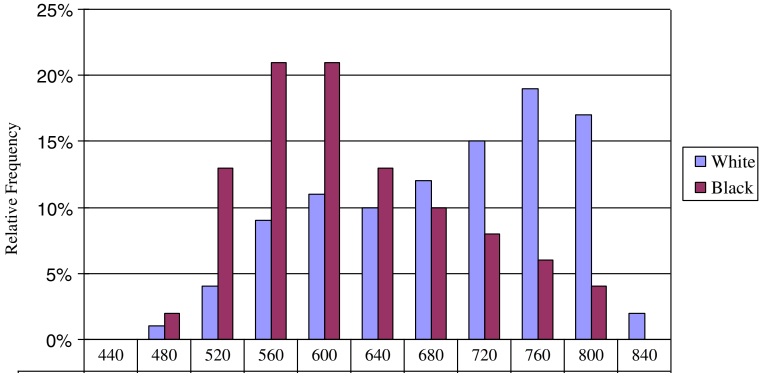
Denote the probability of loan denial by $Pr(d)$. This is assumed to be a function of a vector of credit knowledge variables, K, a number of other background variables, X, and the credit score, s. We can express $Pr(d)$ as a logistic function of the form:

$$\Pr(d) = \frac{1}{1 + e^{-\left(\alpha + \sum \beta_i k_i + \sum \gamma_i x_i + \delta s\right)}} \tag{1}$$

We estimate the loan denial equation separately for blacks and whites and then perform the following decomposition. First, we compute the loan denial rate that whites would have obtained had they the characteristics of blacks:

$$\Pr\left(\widetilde{d}^{\,b}\right) = \frac{1}{1 + e^{-\left(\alpha^w + \sum \beta_i^w k_i^b + \sum \gamma_i^w x_i^b + \delta^w s^b\right)}} \tag{2}$$

[3] We also produce false positive which is the probability that the respondent believes she has had good credit when in fact the credit score is within one standard deviation of the mean credit score for all respondents. The false positive is 0.26 for whites and 0.17 for blacks, which shows that more whites believe they have good credit when in fact they do not have credit.



	440	480	520	560	600	640	680	720	760	800	840
White	0%	1%	4%	9%	11%	10%	12%	15%	19%	17%	2%
Black	0%	2%	13%	21%	21%	13%	10%	8%	6%	4%	0%

FICO

Fig. 1 FICO score distribution by race

This yields an equal treatment measure of loan denial rates for blacks. Or, alternatively, it is the loan denial rate for whites if whites had black characteristics. Subtract from this amount the actual loan denial rate of blacks and one obtains the "unexplained" gap in loan denial rates. This is the difference in loan denial rates between whites and blacks that cannot be attributed to differences in characteristics of blacks and whites. The ratio of this result to the actual gap in loan denial rates is the portion of the unexplained portion (*U*) of the racial gap in loan denials.

$$U = \frac{\Pr\left(\tilde{d}^{w}\right) - \Pr\left(d^{b}\right)}{\Pr\left(d^{w}\right) - \Pr\left(d^{b}\right)} \tag{3}$$

where $\Pr(d^{w})$, $\Pr\left(d^{b}\right)$, *and* $\Pr\left(\tilde{d}^{w}\right)$ denote loan denial rates for whites, blacks, and whites if whites had black characteristics respectively. The explained portion (*E*) of the gap therefore is as follows.

$$E = 1 - \frac{\Pr\left(\tilde{d}^{w}\right) - \Pr\left(d^{b}\right)}{\Pr(d^{w}) - \Pr\left(d^{b}\right)} = \frac{\Pr(d^{w}) - \Pr\left(\tilde{d}^{w}\right)}{\Pr(d^{w}) - \Pr\left(d^{b}\right)} \tag{4}$$

The numerator on the second right is the difference between the actual white loan denial rate and the loan denial rate for whites if whites had black characteristics. The denominator is the actual gap in loan denial rates. We adopt the measure (*E*) to compute the portion of the total gap that is explained by credit knowledge and other factors, *X*.

Next we estimate the false negative probability (measured in two different ways):

$$\Pr\left(\widehat{B}|s > s^{*}\right) = \frac{1}{1 + e^{-\sum \phi_i z_i}} \tag{5}$$

where $\widehat{B}$ denotes "believes bad credit" but the credit score exceeds some threshold. This false negative (and its comparable measure computed using the Freddie Mac buckets) is a function of a vector of variables x. We also estimate the equation:

$$\Pr\left(\widehat{B}\middle|s > s^*\right) = \frac{1}{1 + e^{-\sum \phi_i z_i - \pi \cdot \Pr(d)}} \tag{6}$$

to assess the impacts of loan denials, $Pr(d)$, on perceptions about credit. We then compute the residual difference in false negatives between blacks and whites with and without controls for $Pr(d)$ to determine how much of the racial gap in false negatives can be explained by racial differences in loan denials.

Results

Tables 3 and 4 present the results of estimating Eqs. 1 and 2 with and without control for credit scores. Older respondents, those will higher incomes, those with good budgeting skills, and those who have never had a credit card reported lower rates of loan denial. Those who have had checks returned for insufficient funds, who have experienced a bankruptcy or who have faced major medical expenses, tax problems or unemployment, reported high rates of loan denial. Table 4 reveals, however, that many factors that are significant determinants of white loan denials are not statistically

Table 3 Coefficient estimates of loan rejection

	Overall		White		Black	
	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error
Constant	3.9577	0.2058 ***	4.2811	0.2278 ***	3.0721	0.4870 ***
Age	−0.0644	0.0046 ***	−0.0683	0.0051 ***	−0.0430	0.0109 ***
Black	0.6925	0.0679 ***	–	–	–	–
Income	−0.0080	0.0013 ***	−0.0096	0.0014 ***	0.0009	0.0032
Never had credit card	−0.2505	0.0848 ***	−0.1474	0.0941	−0.7756	0.1948 ***
Good Budgeting	−3.2278	0.1759 ***	−3.4111	0.1942 ***	−2.3330	0.4234 ***
Bankruptcy ever	1.1893	0.0780 ***	1.2891	0.0850 ***	0.5050	0.1939 ***
Never had bad experience	−0.6611	0.0571 ***	−0.6984	0.0638 ***	−0.4506	0.1292 ***
Crisis	0.3317	0.0495 ***	0.3439	0.0543 ***	0.2742	0.1239 **
Checks	0.6050	0.0517 ***	0.5819	0.0569 ***	0.6546	0.1274 ***
Max Rescaled R-Square	0.3211		0.3985		0.1255	
Number of observations	7,396		4,248		3,148	
Sum of weights	9160.7		7801.3		1359.4	
p-value	< 0.0001		< 0.0001		< 0.0001	
Concordant	74.3 %		76.2 %		69.8 %	

Statistically significant *** at 99 %, ** at 95 %, and * at 90 %

Authors' estimation using the Consumer Credit Survey Data

Table 4 Coefficient estimates of loan rejection model controlling for FICO scores

	Overall		White		Black	
	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error
Constant	9.2783	0.3456 ***	10.0566	0.3872 ***	6.0735	0.7611 ***
Age	−0.0502	0.0057 ***	−0.0565	0.0063 ***	−0.0233	0.0134 *
Black	0.3329	0.0852 ***	–	–	–	–
Income	−0.0044	0.0015 ***	−0.0056	0.0017 ***	0.0020	0.0038
Never had credit card	−0.5317	0.1268 ***	−0.4852	0.1416 ***	−0.8287	0.2862 ***
Good budgeting	−1.9125	0.2178 ***	−1.8140	0.2416 ***	−2.2981	0.5140 ***
Bankcruptcy ever	0.6097	0.0927 ***	0.6556	0.1018 ***	0.1579	0.2238
Never had bad experience	−0.2634	0.0731 ***	−0.2820	0.0823 ***	−0.1837	0.1602
Crisis	0.2187	0.0603 ***	0.2205	0.0664 ***	0.2086	0.1483
Checks	0.3901	0.0637 ***	0.3559	0.0704 ***	0.4788	0.1537 ***
FICO score	−0.0104	0.0004 ***	−0.0112	0.0005 ***	−0.0060	0.0010 ***
Max rescaled R-Square	0.426		0.5038		0.1506	
Number of observations	5,942		3,603		2,339	
Sum of weights	7132.7		6126.9		1005.9	
p-value	< 0.0001		< 0.0001		< 0.0001	
Concordant	78.1 %		80.7 %		72.0 %	

Statistically significant *** at 99 %, ** at 95 %, and * at 90 %

Authors' estimation using the Consumer Credit Survey Data

significant for blacks. For example, controlling for credit scores, higher income blacks are no more or less likely to report loan denials than lower income blacks. Higher income whites experience lower loan denial rates than lower income whites. Whereas bankruptcy, bad credit experiences medical expenses, tax problems or unemployment predict whether whites are turned down for loans, there is no statistically significant impact of these factors in predicting black loan rejection rates, controlling for credit scores.

From Table 7 we conclude that much of the racial gap in loan denial rates can be explained by racial differences in credit scores. The loan denial rates for the subset of cases used in the regression are 60.5 % and 39.69 % for blacks and whites respectively. For equation that controls for credit scores, the loan denial rates are 62.87 % and 37.59 %. In other words, the smaller sample of cases for which credit scores are available produces higher rejection rates for blacks but lower rejection rates for whites.

If whites had black characteristics (or if blacks had the same treatment as whites) the white loan denial rate would be higher (or the black loan denial rate would be lower). The explained gap without controlling for credit scores is 36.23 %. The explained gap controlling for credit scores is 80.54 %. That is, much of the racial gap in self-reported loan denials can be explained by racial differences in credit scores. Although there remains a nontrivial "unexplained gap" consistent with a discrimination hypothesis, it is clear that much of the unexplained gap can be explained by the lower credit scores of black respondents in the sample.

Table 5 Coefficient estimates of misperception (false negative) model

	Overall		White		Black	
	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error
Constant	−1.5537	0.3915 ***	−1.6224	0.4257 **	−1.0051	0.9905
Age	−0.0513	0.0093 ***	−0.0510	0.0101 ***	−0.0497	0.0240 **
Black	0.3520	0.1421 **	–	–	–	–
College graduate	−0.4767	0.1262 ***	−0.5661	0.1427 ***	−0.1104	0.2890
Male	−0.2225	0.1026 **	−0.1690	0.1110	−0.4847	0.2805 *
Knowledge about credit	−0.4496	0.1042 ***	−0.4374	0.1132 ***	−0.5105	0.2767 *
Never had credit card	0.9566	0.1916 ***	1.0234	0.2082 ***	0.5795	0.5004
Sloppy payer	1.4506	0.1034 ***	1.4546	0.1130 ***	1.4389	0.2609 ***
Risk taker	0.4338	0.1154 ***	0.4472	0.1259 ***	0.3103	0.2961
Stress	0.1885	0.3612 ***	2.0523	0.3957 ***	1.2210	0.9001
Bankruptcy ever	1.6024	0.1290 ***	1.6680	0.1377 ***	0.9891	0.3852 ***
Never had bad experience	−0.9728	0.1060 ***	−1.0184	0.1160 ***	−0.6982	0.2626 ***
Crisis	0.6021	0.1005 ***	0.5931	0.1092 ***	0.6643	0.2636 **
Checks	0.6434	0.1123 ***	0.6151	0.1225 ***	0.7002	0.2892 **
Max rescaled R-Square	0.3998		0.4411		0.261	
Number of observations	4,295		2,888		1,407	
Sum of weights	5676.0735		5122.6		553.4	
p-value	< 0.0001		< 0.0001		< 0.0001	
Concordant	84.0 %		85.2 %		81.6 %	

Statistically significant *** at 99 %, ** at 95 %, and * at 90 %

Authors' estimation using the Consumer Credit Survey Data

Although the *cause* of loan denials may rest with poor credit, what are the consequences that may reinforce lenders' beliefs that blacks are poor credit risks? We consider the possibility that loan rejections contribute to false perceptions of bad credit among African American customers themselves.

Table 5 shows that although better educated whites are less likely to falsely predict bad credit, there is no statistically significant difference in false negatives between college educated blacks and other blacks. Similarly, although whites who face major stresses are more likely to produce false negative predictions of their credit, there is no effect of these stresses on black misperceptions. Whites who are risk takers[4] (who gamble or play the lottery very often) are more likely to mispredict bad credit; there is no effect of risk taking on black false negative predictions.

Controlling for loan rejection in the false negative equations does not reverse these findings of racially disparate impacts of education, stress, and attitudes toward risk.

[4] When we disaggregate the risk taker variable, the only part of the aggregated measure that remains statistically significant is the component related to self-reported risk taking. Gambler is not statistically significant. There may be a strong social or peer-relations aspect of playing the lottery.

Table 6 does reveal, however, that there is an independent and statistically significant impact of loan rejection on false beliefs that one's credit is bad. The impacts are larger for whites than blacks. The odds of false negative perceptions of bad credit are 5.4 times higher for whites who were recently turned down for loans as compared to whites who were not turned down; the odds of false negative perceptions of bad credit are 2.9 times higher for blacks who were turned down for loans as compared to blacks who were not turned down.

How much of the observed racial gap in misperceptions about bad credit can be explained by racial differences in characteristics? Table 7 shows that without controlling for loan outcomes, more than half of the racial gap in false negatives can be explained by racial differences in credit knowledge, previous bad credit experiences, medical or related crises, bounced checks, and payment histories. Controlling for loan outcomes more than four-fifths of the gap can be explained by racial differences in characteristics.

Put simply, these findings suggest that much but not all of the racial disparity in loan outcomes can be explained by racial differences in credit scores and that the resulting

Table 6 Coefficient estimates of misperception model controlling for loan rejection

	Overall		White		Black	
	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error	Coeff. Est.	Std. Error
Constant	−2.7532	0.4097 ***	−2.9516	0.4465 ***	−1.6612	1.0297
Age	−0.0275	0.0096 ***	−0.0239	0.0105 **	−0.0418	0.0245 *
Black	0.1344	0.1456	–	–	–	–
College graduate	−0.3701	0.1306 ***	−0.4370	0.1477 ***	−0.0690	0.2954
Male	−0.2405	0.1063 **	−0.1764	0.1154	−0.5478	0.2866 *
Knowledge about credit	−0.5040	0.1078 ***	−0.5029	0.1175 ***	−0.5308	0.2823 *
Never had credit card	1.1808	0.1991 ***	1.2607	0.2167 ***	0.7176	0.5166
Sloppy payer	1.2584	0.1070 ***	1.2507	0.1171 ***	1.3152	0.2679 ***
Risk taker	0.4302	0.1190 ***	0.4569	0.1301 ***	0.2645	0.3028
Stress	1.2945	0.3719 ***	1.3725	0.4068 ***	0.9730	0.9313
Bankruptcy ever	1.3501	0.1304 ***	1.4048	0.1388 ***	0.8598	0.3934 **
Never had bad experience	−0.8394	0.1082 ***	−0.8480	0.1186 ***	−0.7150	0.2679 ***
Crisis	0.5358	0.1043 ***	0.5150	0.1136 ***	0.6552	0.2701 **
Checks	0.4689	0.1169 ***	0.4343	0.1279 ***	0.5853	0.2955 **
Loan rejection	1.5948	0.1123 ***	1.6790	0.1217 ***	1.0509	0.2942 ***
Max rescaled R-Square	0.4589		0.5053		0.2916	
Number of observations	4,271		2,880		1,391	
Sum of weights	5659.1		5111.3		547.9	
p-value	< 0.0001		< 0.0001		< 0.0001	
Concordant	86.4 %		88.0 %		83.5 %	

Statistically significant *** at 99 %, ** at 95 %, and * at 90 %

Authors' estimation using the Consumer Credit Survey Data

Table 7 Analysis of residual difference

Estimates/Underlying equation	Loan rejection model		Misperception model	
	Loan rejection without controlling for FICO scores Table 3	Loan rejection controlling for FICO scores Table 4	False negative without controlling for loan rejection Table 5	False negative controlling for loan rejection Table 6
Black (a)	60.50 %	62.87 %	18.92 %	18.95 %
White (b)	39.69 %	37.59 %	11.28 %	11.22 %
Equal treatment value (c)	47.23 %	57.95 %	15.33 %	17.57 %
Gross gap (d=a−b)	20.81 %	25.28 %	7.64 %	7.73 %
Unexplained gap (e=a−c)	13.27 %	4.92 %	3.59 %	1.38 %
% Gross gap explained (f=(d−e)/d)	36.23 %	80.54 %	53.01 %	82.15 %

Regression results are reported in Tables 3, 4, 5, and 6

Author's computation using the logistic regression models, Consumer Credit Survey Data

racial disparity in loan outcomes explains much of the racial difference in false perceptions about bad credit. Thus, there remains a possible self-fulfilling mechanism within the credit market that perpetuates views about black bad credit.

Conclusions

We have pointed out that much of the racial gap in loan denials can be "explained" by racial differences in credit risk. Note that the data we are using in this analysis references consumer lending, such as credit cards, etc., for which credit scores were specifically created. We have also demonstrated that an anomaly of the data is that a small but nontrivial subset of respondents is misinformed about their credit. These good risks who falsely believe they have bad credit are less likely to apply for loans and thus produce a market place that reinforces lender prior beliefs about the poor credit risks of African Americans.

This characterization of the racial disparity in loan rejection rates dictates that interventions or remedies focus at least in part on the information gaps that may have led to the false negatives to begin with. Readily available credit scoring services will help. Easily accessible information on individual credit risk would bring borrower perceptions into line with actual measures of credit worthiness. Desktop underwriting and similar automated risk assessment tools could do exactly this.

Aside for the information asymmetry though is the larger problem of predictive validity of credit scores. Perhaps the scores themselves predict loan rejection rates less well for blacks than for whites. If that is true, there is no reason to believe that improving the information that black potential loan applicants possess will produce substantial changes in how lenders evaluate these applicants. Further research, nevertheless, is warranted in understanding how *good* minority risks are treated in the credit market to determine whether the central problem is one of misinformation by good risks or differential treatment by lenders.

As stated earlier, differences in FICO scores are a major factor in explaining racial differences in loan denial rates. However, if credit scores themselves are racially disparate, then the use of FICO scores in and of itself could be a racially discriminatory mechanism in attaining financial capital. For future research, it would be helpful to examine more factors influencing racial differences in default rates as an outcome with a repetition of the decomposition approached with and without FICO scores used in this analysis. Such an analysis could shed light on whether FICO scores could be used in determining loan default rates across race, and ultimately, whether the use of FICO scores themselves are a racially discriminatory instrument for determining loan eligibility.

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