Do Minority and Woman Entrepreneurs Face Discrimination in Credit Markets?

Improved Estimates Using Matching Methods*

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March 2010

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* The authors gratefully acknowledge support from the Ewing Marion Kauffman Foundation. They thank Coady Wing for helpful discussion.

ABSTRACT

This paper uses propensity score matching methods to address an unrecognized methodological challenge in estimating discrimination in small business credit markets. The matching methods relax the functional form assumptions implicit in regression-based estimates. We analyze interest rates paid on approved loans pooling 1993, 1998 and 2003 waves of the Survey of Small Businesses Finances. Our findings indicate that, on average, Black and Hispanic-owned firms pay an interest rate that is, respectively, 0.791 and 0.486 percentage point higher than the rate paid by White-owned firms. We find no evidence of discrimination against White women in small businesses loans.

Key Words: Small Business Credit; Lending Discrimination; Blinder-Oaxaca Decomposition; Propensity Score Matching.

Introduction

Given the important role that small business plays in the U.S. economy, lending discrimination against small businesses owned by people in legally protected classes can undermine economic growth as well as violate legislated civil rights. Several recent articles have examined this type of lending discrimination, but these articles have not considered all the biases that may arise when comparing White-owned and minority-owned firms with different characteristics. This paper makes use of propensity score matching to eliminate these biases, thereby providing more accurate estimates of discrimination in the interest rates on small business loans.

About half of private-sector output is attributable to small businesses, defined as nonfarm establishments with fewer than 500 employees,[1] and the share of these businesses owned by people in minority groups and by women has been growing over time (Olson 2005). Researchers find consistent evidence that businesses owned by people in legally protected classes are more likely to be denied credit than are businesses owned by Whites, even controlling for characteristics related to credit worthiness.[2] Evidence concerning discrimination in the interest rates charged to small businesses is more mixed. Some studies find no evidence of discrimination in setting interest rates (Cavalluzzo and Cavalluzzo 1998; Cavalluzzo et al. 2002; Blanchard et al. 2007), while other studies find that minority and women business owners pay higher interest rates than do comparable firms owned by White men (Blanchflower et al. 2003).

Barsky et al. (2002) point out that studies of discrimination fail to address problems that arise because behavioral relationships may be nonlinear and because groups being compared may have little overlap in their characteristics. They show that these problems can be addressed

[1] According to "Frequently Asked Questions" at the website of the U.S. Small Business Administration (SBA), Office of Advocacy, http://appl.sba.gov/faqs/faqIndexAll.cfm?areaid=24.
[2] This evidence is reviewed in Blanchard et al. (2007).

using propensity-score matching and other matching techniques. Black et al. (2006) use nonparametric matching techniques to study wage discrimination, but matching techniques have not yet appeared in the literature on small business credit.

When the relationship between the interest rate and its determinants are nonlinear, then failure to account for this nonlinearity can result in biased estimates. Blanchflower et al. (2003) and Blanchard et al. (2007) provide a partial solution to this problem by splitting their sample in various ways and running separate regressions for each part of the sample. This strategy, which is equivalent to introducing a set of interaction terms, is less general than the approach we use in this paper, which is to estimate the interest-rate equation using nonparametric methods.

Second, the existing literature ignores the support condition, that is, it ignores the problems that arise when dissimilar observations are compared. Previous studies point out that minority-owned firms tend to differ from White-owned firms in credit worthiness, firm size, firm age, and many other characteristics. Moreover, Blanchflower et al. (2003) and Blanchard et al. (2007) find that discriminatory treatment varies with the characteristics of the business. Under these conditions, standard regression techniques may yield biased results.

In this study we attempt to address these two empirical problems using propensity-score matching and nonparametric estimation using data from the 1993, 1998, and 2003 waves of the Survey of Small Business Finances (SSBF). Matching allows us to examine the support condition in a straightforward way. In addition, unlike previous studies, our semi-parametric matching method does not impose assumptions on the functional form of the interest rate equation.

We also take advantage of the large sample obtained from pooling all three waves of the SSBF data. The increased sample size allows us to produce more precise estimates of the extent of discrimination in the small business. We can also check the robustness of our model under

alternative assumptions with this relatively large sample, in which the minority firms are well represented. The number of minority-owned firms is 185, 130, and 146 respectively in the 1993, 1998, and 2003 waves of the data. By pooling these data, we obtain a sample size of 461 minority-owned firms.

The study is organized as follows. In section 2 we examine the empirical challenges by reviewing the methodologies adopted in studying discrimination. In section 3, we provide a conceptual framework used to investigate discrimination in small business. The data set used for this study is described in section 4. In the next section we introduce the propensity-score matching method and its assumptions. Estimation results are provided in section 6. Concluding remarks can be found in section 7.

We find that minority-owned firms have to pay systematically higher interest rates on approved loans than do White-owned firms. Unlike previous studies, however, our study shows that White female owners of small businesses are not likely to be treated differently than their male counterparts.

2. Previous Literature

Discrimination is defined to be the unfavorable treatment of an individual solely on the basis of race or gender. As pointed out by Ross and Yinger (2002, 2006), the best models for detecting the presence of lending discrimination incorporate information on loan performance. They also show, however, that credible estimates can also be obtained using only loan pricing information, as long as one takes into account the possibility that different lenders draw on different applicant pools. The Equal Credit Opportunity Act of 1974 (ECOA) establishes two broad types of discrimination, disparate treatment (different rules for different groups) and disparate impact (rules that lead to different outcomes across groups and that are not justified by

business necessity). Although several methods exist for detecting discrimination generally, these two types are difficult to distinguish.

To identify discrimination in the setting of interest rates, this study, like previous studies, identifies the interest rate that would have been offered to a minority-owned (female-owned) small business if it had been owned instead by a White (male). The task then is to create this *ceteris paribus* condition so that the unexplainable differences in the outcome are attributable to discrimination. The implication for a study on discrimination is that it should first find pairs of individuals, one from the majority class and one from the protected class, with otherwise identical characteristics. Second, the study should construct pairwise differences in loan outcomes, such as denial of the loan or the interest rate obtained. Third, the study must aggregate the information in a meaningful way to make a determination about the presence of discrimination.

Our approach to this issue can be illuminated by first considering an alternative, namely an audit study, which is a quasi-experimental design that controls for observed differences across pairs. In this type of study, audit teams typically consist of two teammates, one from the White majority and one from a protected class. To achieve the ceteris paribus condition within each audit, the teammates are chosen to have the same observable demographic characteristics, such as gender and age, and, for the purposes of the audit, are assigned similar demographic and economic characteristics, such as income, occupation, and marital status. Each audit teammate is sent to visit an employer to apply for a job or to a real estate agent to inquire about an available housing. Discrimination is measured by comparing the incidence of less favorable treatment for the teammate from the protected class and for their majority teammate.

In addition to being a research methodology to examine the existence of discrimination prevailing in the society, audits also serve as a legal tool to collect evidence against firms or

institutions, against which cases have been filed alleging discrimination. This latter function is more consistent with our civil rights laws, which target individual firms rather than averages. But its value as a methodology is also crucial for policy purposes, because it helps to identify the existence of discrimination, which policymakers can then try to eliminate.

Although audits have been widely used in investigating discrimination in labor and housing markets,[3] they have not been used to investigate the existence and the degree of discrimination in the context of small business loans.

Using the audit methodology for the study of small business loans in the United States is problematic for two reasons. First, the number of credit-relevant variables involved is extremely large, making it difficult to create fully comparable teammates. Second, it is against the law to lie on a credit application for purposes of fraud. Whether testing for discrimination constitutes fraud is debatable, but it is a point on which no court has yet ruled. Because of this, nonprofit anti-discrimination organizations and government agencies are understandably reluctant to force the issue. If it is not possible to assign teammates fictional financial characteristics, an agency faces a virtually insurmountable problem in assembling teams with "similar" teammates.

Instead, existing research has used a standard regression approach. The goal of this study is to employ matching to approximate a quasi experiment, such as an audit, to estimate the existence and extent of discrimination in interest rates on loans to small business owners. This study also contributes to the literature by pooling three different Surveys of Small Business Finances to produce more precise estimates.

Existing studies of discrimination in small-business are based on regression methods in which credit denial or interest rates charged on a loan are a function of the credit worthiness assessment criteria used by financial institutions and the owner's race. The coefficient on the

[3] For discussions of the audit methodology, see Ondrich et al. (2000, 2003), Ross and Turner (2005), and Yinger (1995) on housing markets; Heckman (1998), and Bertrand and Mullainathan (2004) on labor markets; Galster et al. (2001) in insurance markets; and Ross et al. (2005) on mortgage markets.

owner's race captures discrimination. For simplicity, many studies assume a linear functional form in the econometric model, although no theorem suggests this is the case. Some studies, for example, Blanchflower et al. (2003) and Blanchard et al. (2007), challenge this linearity assumption by running separate regressions for subsamples defined by organization type, firm size, firm age, the scope of the market in which the firms operate, etc. The findings in Blanchflower et al. (2003) indicate that discrimination is not the same under all circumstances. For instance, Black owners of firms that were recently established are 36 percentage points more likely to be charged higher interest rate than Black owners of firms that have existed for more than 12 years.

Split-sample regressions only address one specific form of nonlinearity, namely, interactions between one explanatory variable and all the others. The researcher must decide which variables to interact with each other, i.e., along which dimension the sample should be split. Because of the difficulty of attempting all possible combinations, some potentially important heterogeneous effects might not be included in the study. In this case, the split-sample regressions may still suffer from bias because of the unmodeled non-linearity.

Another source of nonlinearity comes from higher order terms. For instance, in labor economics, in order to test the hypothesis that experience affects earnings in a nonlinear way, squares and even higher-order terms in experience are usually included in the earnings equation. Split-sample regressions cannot capture this type of nonlinearity. A model with a sufficient number of higher-order and interactive terms might be able to approximate an underlying nonlinear relationship fairly well, but it becomes difficult to construct when there are many explanatory variables, and no-one has attempted to construct such a model for the analysis of interest rates.

A more general approach to relaxing the linearity assumption is to conduct semi-parametric estimation; instead of imposing a specific functional form on the relationship between the dependent variable and regressors, this approach allows the data to speak for themselves through a data-generating process. A semi-parametric approach also has the advantage that it automatically accounts for variation in underwriting standards across lenders that takes the form of interactions between lender characteristics and underwriting variables (Ross and Yinger 2002). We pool the Survey of Small Business Finances (SSBF) data from three years to obtain a sample size large enough to implement semi-parametric estimation.

3. Conceptual Framework

An investigation into the existence and extent of discrimination in some market frequently involves two equations characterizing two stages of economic transactions: a denial model that features the screening process that determines whether a customer or employee is eligible for an economic transaction; and a price equation representing the equilibrium prices, such as wage rates or interest rates, which can only be observed for those who pass the screening process.

Following Ross and Yinger (2006), the equations indicating the two behavioral models can be expressed as follows.

$$\text{Screening:} \quad S_i = 1 \text{ if } S_i^* > 0, \text{ where } S_i^* = \beta_s X_i + \gamma_s M_i + \delta_s P_i + \psi_{si} \ , \tag{1}$$

where the dependent variable is binary, such as a job offer or an approval on a loan or mortgage. The vector X_i indicates factors based on which the firm makes its decision on hiring or granting the loan. The variable M_i is a minority group indicator, and P_i is the price associated with the transaction.

Moving to the second equation, we have

Price: $P_i = \beta_p X_i + \gamma_p M_i + \varepsilon_{si}$, if $S_i = 1$. (2)

The transaction price, P_i, such as the wage or interest rate on a loan, is determined by the same factors X_i as in the screening model, as well as minority status, M_i. The variables ψ_{si} and ε_{si} are the error terms. The incidence of discrimination is identified by finding a negative γ_s and a positive γ_p in an application to discrimination in small-business, for instance.

These two equations are really a simplification; in labor markets or credit markets, discrimination might take many forms at many stages, and one can not get a full appreciation of discrimination without analysis covering each and every stage.[4] The presence of discrimination in one stage does not imply the presence of discrimination in another stage. But discrimination in various stages may be connected. If an economic transaction is composed of a sequence of actions, so that discrimination is likely to be present in various stages, the failure to account for potential discrimination in an earlier set of actions may lead to an underestimate of discrimination for a later set of actions. In econometric research this is known as selection bias.[5]

Another problem arises when minority-owned firms that encounter an initial denial of credit eventually end up getting a loan with more stringent terms, such as a substantially higher interest rate. In this case, the denial model underestimates the underlying discrimination in the screening process facing individuals from a protected class. The interest rate model, on the other

[4] The complexity involved in mortgage transactions is discussed in Ross and Yinger (2002).

[5] The importance of accounting for selection bias is based on the observation that agents who are aware of a tradition of discrimination in a market may go out of their way to avoid such discrimination. According to the SSBF, black-owned firms are 40 percentage points more likely than their white counterparts to report that they did not apply for a loan for fearing of denial in 1993, and the statistic is 32 percentage points in 1998 (Blanchflower et al. (2003)). The issue here is the number of firms that would have applied and been granted a loan had there no awareness of discrimination. The group of firms that meet the standards of getting a loan but do not apply constitutes the set of "missing" observations that would otherwise appear in the screening and price equation. Cavalluzzo et al. (2002) and Blanchard et al. (2007) test for selection bias in the approval model and find that accounting for it does not alter estimates of discrimination.

hand, provides a much more reliable framework for estimating discrimination in small-business lending.[6]

There is much less debate about whether discrimination exists in access to credit markets than in interest rates charged on approved loans. This is partly due to data limitations. The sample size on approved loans among minority-owned firms is usually much smaller than that used for the denial model, making it difficult to conduct specification checks on interest rate models (see Blanchflower et al. 2003). One way to deal with this issue is to pool data from multiple years to increase the sample size, which can be done as long as the observations in the survey are independent. Another way to deal with this is to estimate treatment effects using methods that are robust to specification error.

The present study attempts to improve the estimation of discrimination in the interest-rate model by adopting a more sophisticated methodology and using a more complete set of data.

4. The SSBF Data

The principle data set used in the econometric analysis of this study is the Survey of Small Business Finance (SSBF) from 1993, 1998, and 2003.[7] Two related concerns motivate the data pooling strategy. First, the number of minority-owned firms is relatively small in the sample from each single year, making it difficult to obtain precise estimates. Second, it is well known that nonparametric methods require a large sample to perform reasonably well, and the goal of our study is to address nonlinearity by implementing a semi-parametric analysis, in which a nonparametric approach is employed in the second stage. Pooling data is also reasonable because the survey sample was drawn from more than 7.5 million firms each year. This makes it unlikely

[6] In order to take this situation into account, data on firms' credit application history would need to be collected. But even the SSBF, the most comprehensive data set available on the credit utilization of small businesses does not collect such information.

[7] The 1987 survey is not included in our sample mainly because some of the variables in firms' credit histories that are critical in assessing creditworthiness were not available.

that a firm would appear in two surveys and nearly impossible that a firm would be sampled in all four surveys.[8]

The sample is nationally representative, and contains rich information regarding the firm, such as its age, location, employment, industry. In addition, the data set also includes the term and type of the most recent loan each firm obtained.

Since we focus on the interest-rate equation, our sample is limited to the most recent loan that the firm obtained in the past 3 years. Thus the time span for the aggregate repeated cross section data runs from 1991 until 2005.[9] Our complete sample contains 4,193 nonfinancial, nonfarm small businesses.

Table 2 presents the descriptive statistics from the pooled SSBF data for all firms that had an active loan during the survey years, by race/ethnicity, and gender. These statistics are not weighted. On average, firms owned by minority groups pay a higher interest rate than those owned by Whites. In particular, the interest rates charged to Black-owned firms are on average 2.5 percentage points higher than those charged to White-owned firms. The Hispanic-White difference in interest rates is 1.4 percentage points. The interest rates paid by other race/ethnic groups are also higher than those paid by Whites, in this case by 0.8 percentage points. Differences in interest rates by gender are relatively small. The interest rates charged to firms owned by women are in fact 0.07 percentage points lower than those charged to male-owned firms. Firms owned by minority groups also differ from White-owned firms in other characteristics. For example, minority-owned firms are generally younger and smaller. In terms of credit history, minority-owned firms seem less creditworthy than their White counterparts as measured by whether the owner had been delinquent for more than 60 days on personal

[8] http://www.zentralbank.us/pubs/oss/oss3/nssbffaq.html.
[9] All dollar variables are measured in real terms (year 2003=100), and a year indicator is included to account for potential fluctuation of the nominal interest rates across years.

obligations over the past three years, or had legal judgments against him or her over the preceding three years.

5. Empirical Strategy

5.1 The Methodology of Matching and Its Assumptions

This study uses matching methods to examine whether, on average, minority-owned firms have to pay higher interest rates on business loans than do equally qualified White-owned firms. Matching methods have been used widely in the program-evaluation literature as a way to approximate an experiment with non-experimental data (Heckman, Ichimura, and Todd 1997, 1998; Smith and Todd 2001, 2005). This approach has the advantages that it is less expensive and less intrusive than an experiment. Conventional matching estimators match each program participant with an observably similar nonparticipant and derive the average difference in their outcomes to measure the effect of the program.

The evaluation problem arises when we investigate discrimination in small business because, at any time, a firm may be either White-owned or minority-owned, but not both. We are interested in the interest rate minority-owned firms would pay if they were White-owned. This is called the effect of “treatment on the treated".

Formally, let Y_1 be the potential interest rate paid by a minority-owned firm, and let Y_0 be the potential interest rate if the firm had been White-owned. Let the indicator variable $D = 1$ when the firm is minority-owned and let $D = 0$ when the firm is White-owned. Finally, let X be a vector of observed characteristics that affect both the minority status of the firm and the interest rate paid. The mean impact of treatment on the treated is defined as

$$TT = E\left(Y_1 - Y_0 \mid X,\ D = 1\right) = E\left(Y_1 \mid X,\ D = 1\right) - E\left(Y_0 \mid X,\ D = 1\right), \qquad (3)$$

which estimates the average impact of the program among those participating in it. The mean outcome in the minority-owned firm, $E(Y_1 \mid X,\ D=1)$, can be obtained using data on minority-owned firm. However, a direct estimate of its counterfactual mean, $E(Y_0 \mid X,\ D=1)$, is not available. In the next section, we discuss two matching approaches for estimating the missing counterfactual mean.

Matching estimators rely on the assumption that non-treatment outcomes, Y_0, are independent of the treatment *D*, which indicates ownership by a protected class, conditional on a set of observable characteristics, *X*. This selection on observables assumption is also called the Conditional Independence Assumption (CIA), expressed as follows:

$$\text{Assumption 1: } (Y_0 \perp D) \mid X \quad . \tag{4}$$

In particular, it implies that the potential interest rate that a White-owned firm must pay is independent of the firm's race-ownership status conditional on a relevant set of observable characteristics. This assumption produces a comparison group that resembles the control group in an experiment in one key respect: conditional on X the distribution of Y_0 given $D=1$ is the same as the distribution of Y_0 given $D=0$. (Note, of course, that we do not observe Y_0 given $D=1$.) In addition, it is also assumed that for all *X* there is a positive probability of either getting treated ($D=1$) or not ($D=0$), which can be written as follows:

$$\text{Assumption 2: } \Pr(D=1 \mid X) < 1 \text{ for all } X. \tag{5}$$

This is called the "common support" assumption, and it is an important assumption that linear regression fails to address. The support condition implies that a match from the White-owned group can be found for each and every minority-owned firm.

If Assumptions 1 and 2 are satisfied, after conditioning on *X*, the Y_0 distribution observed for the matched firms owned by Whites can be substituted for the missing Y_0 distribution for minority-owned firms. The mean effect is then identified by taking differences.

5.2 Propensity Scores and the Common Support Condition

Matching is plausible only when the data contains rich enough information for one to condition on in order to construct a comparable counterfactual group. It is hard to select matched samples when the dimension of X is high. In particular, if matching is employed directly on all the characteristics included in X one would run into the problem commonly known as the "curse of dimensionality," where some observations will have no corresponding untreated firm with exactly the same values of *X*.

In an important paper Rosenbaum and Rubin (1983) introduced the propensity score as a means of reducing the dimension of the conditioning problem by matching on the probability of treatment. They showed that the distributions of X are the same in the treatment and comparison group conditional on the probability of treatment. Thus, propensity-score matching combines groups of firms with potentially different values of X but identical values of $\Pr(D=1|X)$. Matching on the scalar propensity score in this way avoids the curse of dimensionality.

The evaluation of the presence of discrimination proceeds in two steps. In the first step a logit model is used to estimate the propensity score of minority-ownership status based on the SSBF data. Variable selection for the propensity-score estimation is based on two considerations: theory and evidence about the variables related to treatment and the outcome and goodness-of-fit. What we are trying to do is to construct a model that approximates a lender's decision-making process based on the firm's creditworthiness. The existing literature on discrimination in small business (Cavalluzzo et al. 2002, Blanchflower et al. 2003, and Blanchard et al. 2007) suggest

that variables in the following categories should be used to predict a firm's creditworthiness: the firm's credit history, the firm's characteristics, and the features of the specific loan. Within each category, the variables are chosen based on the criterion of goodness-of-fit, that is, whether the coefficient of the included variable is statistically significant at conventional levels and whether it increases the model's prediction power by a substantial amount (Heckman 1998). We do not include the Dunn and Bradstreet credit score in our specification because this credit score is based on the firm's entire credit history, including default or delinquent events on the loan under consideration. Such information postdates the information available to the lender and is likely to introduce bias.

We present the propensity-score estimation results only for the probability of a firm being owned by a member of a protected class in Tables 4A-4C.

The histograms of the estimated propensity scores for each group are shown in Fig.1 through Fig.6, which are used to examine the support condition. In all but the last two groups, the left histogram presents propensity scores for firms owned by Whites (the $D = 0$ group), while the right histogram presents the propensity scores for minority-owned firms (the $D = 1$ group). For the last two groups, treatment refers to the firm being (White) female-owned; the comparison group consists of (White) male-owned firms. The horizontal axis indicates intervals of the propensity score and the height of each bar on the vertical axis defines the fraction of the corresponding sample with scores in the corresponding interval.

The histograms are important because they examine the support condition for the propensity score. Along the dimension of race, the mean propensity score given $D = 1$ is about 0.15, while the mean propensity score for $D = 0$ is about 0.06. In the case of gender, the mean propensity score given $D = 1$ is about 0.27 while the mean propensity score for $D = 0$ is about 0.20. This disproportional concentration of the propensity score at the lower tail (especially

among the racial/ethnic groups) is not surprising. The sample consists of 461 minority-owned firms and 3,266 firms owned by Whites. As discussed in greater detail below, the kernel estimation techniques that we use can handle oversampling.

In addition to the histograms regression-based balancing tests are conducted to check whether the distributions of the covariates are balanced, conditional on the value of the propensity score. The logic of the regression-based balancing test is simple: it regresses each conditioning variable on a polynomial in the propensity score and an interaction between the treatment dummy and the same polynomial. If balance has been achieved, then the coefficients on all the interactions should equal zero.[10] Almost all of the covariates pass the balancing test. For reasons of parsimony, the results of the balancing tests are not presented, but are available from the authors upon request.

5.3 Comparison of Two Matching Methods

We can choose from a variety of consistent matching methods. As the sample gets arbitrarily large, all matching estimators are conducting exact cell matching. In a finite sample, the choice of a matching estimator is more of a practical issue, in the sense that it not only depends on the data but also on the capability of the particular matching estimator to deal with specific data issues.

We present two estimates: one from the Blinder-Oaxaca Decomposition and one using semi-parametric propensity-score matching. The two techniques are similar in the sense that they both conduct out-of-sample prediction. The mechanism is as follows: an interest-rate equation is estimated using a subsample containing only Whites, the coefficients of the determinants of interest rates obtained from the Whites are then used to generate the counterfactual effect, which is the predicted interest rates that minority would have to pay had they been White. The mean

[10] See Smith and Todd (2005) for a discussion of other standard balancing tests.

difference between the actual and the predicted interest rates thus constitutes the estimates of the disparate treatment.

The Blinder-Oaxaca Decomposition method is a regression-based matching method that assumes a linear functional form. Write the model for the unprotected class as:

$$\begin{aligned} &\mathbf{Y}_0 = \boldsymbol{\iota}\alpha_0 + \mathbf{X}_0\boldsymbol{\beta}_0 + \boldsymbol{\varepsilon}_0, \\ &\mathbf{E}(\boldsymbol{\varepsilon}_0) = \mathbf{0}\,;\ \ \mathbf{V}(\boldsymbol{\varepsilon}_0) = \sigma_0^2\mathbf{I}\,, \end{aligned} \tag{6}$$

where $\mathbf{Y}_0$ is the $N_0\ x\,1$ dependent variable vector, $\boldsymbol{\iota}$ is an $N_0\ x\,1$ vector of ones, α_0 is the intercept for the unprotected class, $\mathbf{X}_0$ is the $N_0\ x\ k$ regressor matrix, and $\boldsymbol{\beta}_0$ is the $k\,x\,1$ coefficient vector. OLS is best linear unbiased and satisfies the following equation:

$$\overline{Y}_0 = \hat{\alpha}_0 + \overline{\mathbf{X}}_0\hat{\boldsymbol{\beta}}_0\,, \tag{7}$$

where $\overline{Y}_0$ is the sample mean of the dependent variable and $\overline{\mathbf{X}}_0$ is the row vector of regressor means.

Write the model for the protected class as:

$$\begin{aligned} &\mathbf{Y}_1 = \boldsymbol{\iota}\alpha_1 + \mathbf{X}_1\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1, \\ &\mathbf{E}(\boldsymbol{\varepsilon}_1) = \mathbf{0}\,;\ \ \mathbf{V}(\boldsymbol{\varepsilon}_1) = \sigma_1^2\mathbf{I}\,, \end{aligned} \tag{8}$$

where $\mathbf{Y}_1$ is the $N_1\ x\,1$ dependent variable vector, $\boldsymbol{\iota}$ is an $N_1\ x\,1$ vector of ones, α_1 is the intercept for the protected class, $\mathbf{X}_1$ is the $N_1\ x\ k$ regressor matrix, and $\boldsymbol{\beta}_1$ is $k\,x\,1$. Again, ordinary least squares (OLS) is the best linear unbiased estimator and satisfies the following equation:

$$\overline{Y}_1 = \hat{\alpha}_1 + \overline{\mathbf{X}}_1\hat{\boldsymbol{\beta}}_1 \tag{9}$$

where $\overline{Y}_1$ is the sample mean of the dependent variable, $\overline{\mathbf{X}}_1$ is the row vector of regressor means, and the “hat” again signifies OLS estimator.

Let $\Delta\overline{Y} = \overline{Y}_1 - \overline{Y}_0$ denote the difference in mean outcomes across classes, let $\Delta\overline{\mathbf{X}} = \overline{\mathbf{X}}_1 - \overline{\mathbf{X}}_0$ denote the difference in mean endowments, and let $\Delta\hat{\boldsymbol{\beta}} = \hat{\boldsymbol{\beta}}_1 - \hat{\boldsymbol{\beta}}_0$ denote the differences in coefficients. Then the difference in mean outcomes can be decomposed as follows:

$$\Delta\overline{Y} = \hat{\alpha}_1 - \hat{\alpha}_0 + \overline{\mathbf{X}}_0\Delta\hat{\boldsymbol{\beta}} + \Delta\overline{\mathbf{X}}\hat{\boldsymbol{\beta}}_1 \quad , \tag{10}$$

where the sum of the first three terms on the right-hand side of equation (10) is the total effect of discrimination on the difference in mean outcomes and the final term is the total effect of the difference in endowments.

An alternative method, perhaps simpler, for obtaining the Blinder-Oaxaca discrimination effect starts by including the constant term in the regressor matrix with the other slope variables. The model for the unprotected class can then be written as:

$$\begin{aligned} &\mathbf{Y}_0 = \mathbf{Z}_0\boldsymbol{\beta} + \boldsymbol{\varepsilon}_0, \\ &\mathbf{E}(\boldsymbol{\varepsilon}_0) = \mathbf{0}\,;\ \mathbf{V}(\boldsymbol{\varepsilon}_0) = \sigma_0^2\mathbf{I}\,, \end{aligned} \tag{11}$$

where $\mathbf{Y}_0$ is $N_0\,x\,1$, $\mathbf{Z}_0$ is a $N_0\ x\ (k+1)$ matrix that includes a constant term, and $\boldsymbol{\beta}$ is $(k+1)\,x\,1$.

Write the model for the protected class as:

$$\begin{aligned} &\mathbf{Y}_1 = \boldsymbol{\iota}\alpha + \mathbf{Z}_1\boldsymbol{\beta} + \boldsymbol{\varepsilon}_1, \\ &\mathbf{E}(\boldsymbol{\varepsilon}_1) = \mathbf{0}\,;\ \mathbf{V}(\boldsymbol{\varepsilon}_1) = \sigma_1^2\mathbf{I}\,, \end{aligned} \tag{12}$$

where $\mathbf{Y}_1$ is $N_1\,x1$, $\boldsymbol{\iota}$ is $N_1\,x1$, α is a scalar, $\mathbf{Z}_1$ is a $N_1\ x\ (k+1)$ matrix that includes a constant term, and $\boldsymbol{\beta}$ is $(k+1)\,x\,1$. By replacing the conditional expectations in equation (3) by their corresponding finite sample analogous, an estimator for the effect of treatment on the treated can be derived as

$$\frac{1}{N_1}\sum_{i\in I_1}\left(Y_{1i} - \mathbf{Z}_{1i}'\hat{\boldsymbol{\beta}}\right) \quad , \tag{13}$$

where I_1 denote the set of program participants. It can be obtained from the following two-step method. First, run an OLS estimation of the model for the unprotected class to get the estimated coefficient vector $\hat{\boldsymbol{\beta}}$. Next, regress $\mathbf{Y}_1 - \mathbf{Z}_1\hat{\boldsymbol{\beta}}$ on constant vector $\boldsymbol{\iota}$ to get an estimate of the

Blinder-Oaxaca discrimination effect. To see that this gives the correct answer, note that the estimate of the intercept is $\overline{Y}_1 - \hat{\alpha}_0 + \overline{\mathbf{X}}_1\hat{\boldsymbol{\beta}}_0$. Substituting for $\overline{Y}_1$ from equation (9) and rearranging gives $\hat{\alpha}_1 - \hat{\alpha}_0 + \overline{\mathbf{X}}_1(\hat{\boldsymbol{\beta}}_1 - \hat{\boldsymbol{\beta}}_0)$, which is exactly the Blinder-Oaxaca discrimination effect.

The most appealing feature of the Blinder-Oaxaca method is its apparent simplicity, although this simplicity is a by-product of a restrictive linearity assumption. Moreover, standard errors have to be adjusted to account for the two steps involved in the model. This is discussed in the Appendix.

The second method that we use is semi-parametric propensity-score matching. As shown in Smith and Todd (2001), under Assumptions 1 and 2, the mean impact of treatment (being a member of a minority class) can be rewritten as

$$E(Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E_P\left[E_Y(Y \mid D = 0, P)\right], \tag{14}$$

where $P = \Pr(D = 1 \mid X)$. The second term can be estimated from the mean outcomes of the matched (on P) comparison group. Matching estimators take the form

$$\frac{1}{N_1} \sum_{i \in I_1 \cap S_P} \left[Y_{1i} - \hat{E}(Y_{0i} \mid D = 0, P_i) \right] \quad , \tag{15}$$

where $\hat{E}(Y_{0i} \mid D = 0, P_i) = \sum_{j \in I_0} W(i, j) Y_{0j}$ is the matched outcome. I_0 and I_1 denote the set of majority and minority respectively, S_p is the common support region, and N_1 is the number of individuals in both the sets I_1 and S_p (see Smith and Todd 2005). The match for each minority individual i in the summation of (15) is a weighted average over the outcomes of members of the majority class, where the weights $W(i, j)$ depend on the distance between P_i and P_j. In the kernel-matching method used by Heckman et al. (1997, 1998) and Heckman et al. (1998), the weighting function is

$$W(i,j) = K\left(\frac{P_j - P_i}{h}\right) / \sum_{k \in I_0} K\left(\frac{P_k - P_i}{h}\right), \tag{16}$$

where K is a kernel function with bandwidth parameter h.[11] This semi-parametric propensity-score matching method that we use involves two steps. The first step is propensity-score estimation using a logit model (as discussed above). The second step uses a kernel function to estimate the average treatment effect of minority ownership on interest rates. The semi-parametric propensity-score matching results provide a robustness check on the Blinder-Oaxaca method. The key advantage of the propensity-score matching method is that it avoids imposing the restrictive linear functional form assumption.

The optimal choice of bandwidth parameter h for the given kernel function K is critical, even in a large sample. As shown by Li and Racine (2007) and Pagan and Ullah (1999), the Least-Squares Cross-Validation procedure selects optimal bandwidth by minimizing mean-squared error $\frac{1}{N_0}\sum_{i \in I_0}\left(Y_{0i} - \hat{Y}_{0i,-i}\right)^2$, where $\hat{Y}_{0i,-i}$ is the "leave-one-out" estimator that omits the *i*th observation in the comparison group and uses the remaining comparison-group observations to generate $\hat{Y}_{0i,-i}$, the estimate of Y_{0i}. Because the *i*th observation is not included in the estimation, this "out-of-sample" forecast avoids the "overfitting" problem at $h = 0$. As explained in Black and Smith (2004), this "leave-one-out" estimator does a good job of replicating the essential features of the estimation problem. In comparison, the choice of bandwidth by other methods, such as the Nearest Neighbor approach, is more arbitrary.

In the SSBF data, we have substantially fewer observations belonging to protected classes than to Whites. In fact, there are only 130 Black-owned firms in the pooled SSBF data

[11] We use the second-order Epanechnikov kernel defined as $K(\psi) = \begin{cases} \frac{3}{4}\left(1-\psi^2\right), & |\psi| \le 1, \\ 0, & otherwise. \end{cases}$

compared to over 3,266 firms owned by Whites. Kernel matching is more efficient in handling this asymmetrically distributed sample because it uses sample information efficiently. Using Monte Carlo analysis, Froelich (2004) shows that kernel matching, or a variant called "ridge" matching, consistently performs well on a mean-squared error criterion.[12]

The propensity-score matching is more computationally intensive than Blinder-Oaxaca, because it requires a choice of optimal bandwidth and bootstrapped standard errors. In addition, the speed of convergence is slower using a semi-parametric approach than regression-based estimates. However, the payoffs of using matching are also considerable. First, matching allows us to examine the support condition in a straightforward way. In other words, it prevents us from making predictions outside of the data support.[13]

6. Results

First-stage Blinder-Oaxaca estimation results for all groups are presented in Tables 3A-3C. The results for Whites, Blacks and Hispanics are in Table 3A, Table 3B contains the results for other races (including comprised of Asians, Native Americans, Alaska natives, and Hawaiian/Pacific Islanders) and minorities generally, while Table 3C has the results for females and White females. While results vary across groups, prior personal delinquency generally increases the interest rate charged and firms with more highly educated owners are generally charged lower interest rates on business loans.

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[12] An alternative way of addressing the over-sampling issue is to use radius matching, a variant of Nearest Neighbor caliper matching, which tends to use all of the comparison members within the caliper to construct the counterfactual. Abadie and Imbens (2006) show that bootstrapping, the most readily available technique of calculating standard errors for matching methods, gives incorrect results for nearest neighbor matching because of lack of smoothness. Therefore, radius matching is problematic. In addition, Froelich (2004) shows that Nearest Neighbor matching performs least desirably over a wide range of possible data-generating processes.

[13] Estimating the wealth gap between black and white households, Barsky et al. (2002) show that support problems can exacerbate misspecification of the parametric model.

The propensity score estimation results for the protected classes are shown in Table 4A-4C. The results for Blacks and Hispanics are in Table 4A, those for other races and minorities are in Table 4B, and Table 4C has the results for females and White females. More highly educated owners are less likely to be Hispanic or from a minority race more generally. The greater the owner's business experience, the less likely the owner is from a racial minority. When a firm receives a fixed interest-rate loan, the more likely its owner is Black, Hispanic, from a racial minority generally, or a White female. Finally, when a firm locates in a metropolitan area, the more likely its owner is from a racial minority.

The race discrimination results using the SSBF data are shown in Table 5. Panel A presents estimates of the Blinder-Oaxaca discrimination effect for interest rates on approved loans, and Panel B shows the estimates of the discrimination effect estimated by the semi-parametric propensity-score matching method.

From Panel A of Table 5 minority-owned firms pay an interest rate that is 0.599 percentage points higher than the rate paid by White-owned firms. After breaking down the analysis by racial category, we find businesses owned by Blacks, Hispanics, and other races all have to pay higher interest rates than businesses owned by Whites, controlling for credit worthiness and other factors appearing in Table 1. Black-owned firms face the largest degree of discrimination; the interest rates they pay are 1.109 percentage points higher than the rates paid by their White counterparts. On average, firms owned by Hispanics and other races pay interest rates 0.453 and 0.349 percentage point more than firms owned by Whites. These estimates are all statistically significant at conventional levels.

The results using semi-parametric propensity-score matching method are shown in Panel B of Table 5. The bandwidths are chosen using leave-one-out cross validation and standard errors are bootstrapped with 2000 replications. Again the key difference between regression-

based estimates, such as Blinder-Oaxaca, and propensity-score matching is that propensity score matching does not depend on a linear functional form assumption.

The semi-parametric propensity-score matching estimates differ from those of Blinder-Oaxaca decomposition in the following ways. For minority firms the discrimination effect is slightly larger than that from Blinder-Oaxaca. Minority-owned firms pay on average 0.671 percentage points more interest on approved loans than do White-owned firms. The estimate is statistically significant at the 1% level. A similar result applies to Hispanic-owned firms; the magnitude of the estimate is slightly larger and significant at conventional levels.

In contrast the estimated treatment effect of Black-ownership decreases from 1.109 to 0.791 using propensity-score matching. The effect of discrimination against other races disappears once we relax the linear functional form assumption.

The results for gender discrimination appear in Table 6. The data suggest that businesses owned by women pay an interest rate that is significantly lower than the rate paid by male-owned firms. The propensity-score matching method produces a larger effect, 0.27, than does Blinder-Oaxaca, which yields 0.17. When the sample is limited to Whites, the discrimination effect declines and becomes insignificant, as shown in the second column of Table 6. Of the 814 female-owned businesses in our sample, only 112 are owned by minorities, so we cannot estimate a separate effect for minority females. Nevertheless, a comparison of the two columns in Table 6 suggests that there is a large and significant male-female disparity in interest rates among minority-owned firms, if not among White-owned firms.

Overall, these results suggests, but do not definitively prove, that our matching methods, which are preferable on conceptual grounds, produce significantly different results than results based on more traditional regressions methods. The study with the set of controls that are most comparable to ours, namely, Blanchard et al. (2008), finds interest-rate gaps of 0.459 for Black-

owned firms compared to white-owned firms, -0.169 for Hispanic-owned firms compared to white-owned firms, and -0.769 for firms owned by White women compared to firms owned by White men.[14] Only the last of these three estimates is statistically significant. Thus, using matching appears to increase the magnitude of the gap for Black-owned firms (and to make this gap significant), to reverse and make significant the gap for Hispanic-owned firms, and to reduce and make insignificant the gap for firms owned by White women. We cannot rule out the possibility that these results differ from ours because they refer to 1998 instead of 1993-2003; but, because these results refer to the year in the middle of our sample, it is unlikely that they differ from ours because of a trend over this period.

7. Conclusions

This study improves the existing literature on racial and sex discrimination in small-business lending by using semi-parametric propensity score matching with data from the Survey of Small Business Finances from 1993, 1998 and 2003. Matching methods can relax the linear functional form assumption and address data support problems. These issues have been largely ignored in regression-based estimation. Unlike previous studies, we also aggregate the data from the three surveys in order to produce more precise estimates. These methodological innovations lead to new findings. More specifically we find that Black-owned and Hispanic-owned businesses pay significantly higher interest rates on approved loans than do equally creditworthy firms owned by Whites. However, we cannot reject the hypothesis that there is no discrimination in small business lending against other racial/ethnic groups or against White women.

[14] These estimates come from Blanchard et al. (2008, Table 6, row (9)). Blanchard et al. also investigate whether some of the controls for loan terms are endogenous. Corrections for endogeneity have little impact on their estimates. Blanchflower et al. (2003) find significant interest-rate discrimination against blacks and Hispanics in 1998, but they do not use as extensive a set of control variables.

APPENDIX ON
CORRECT STANDARD ERRORS
FOR THE BLINDER-OAXACA MODEL

Write the model for the unprotected class as:

$$\mathbf{Y}_0 = \mathbf{X}_0\boldsymbol{\beta} + \boldsymbol{\varepsilon}_0,$$
$$\mathbf{E}(\boldsymbol{\varepsilon}_0) = \mathbf{0}\,;\ \ \mathbf{V}(\boldsymbol{\varepsilon}_0) = \sigma_0^2\mathbf{I}\,,$$

where $\mathbf{Y}_0$ is $N_0\,x1$, $\mathbf{X}_0$ is $N_0\,x\,k$, and $\boldsymbol{\beta}$ is $k\,x1$.

Write the model for the protected class as:

$$\mathbf{Y}_1 = \boldsymbol{\iota}\alpha + \mathbf{X}_1\boldsymbol{\beta} + \boldsymbol{\varepsilon}_1,$$
$$\mathbf{E}(\boldsymbol{\varepsilon}_1) = \mathbf{0}\,;\ \ \mathbf{V}(\boldsymbol{\varepsilon}_1) = \sigma_1^2\mathbf{I}\,,$$

where $\mathbf{Y}_0$ is $N_1\,x1$, $\boldsymbol{\iota}$ is $N_1\,x1$, α is a scalar, $\mathbf{X}_1$ is $N_1\,x\,k$, and $\boldsymbol{\beta}$ is $k\,x1$.

OLS estimation of the model for the unprotected class gives $\hat{\boldsymbol{\beta}}$, with variance matrix $\sigma_0^2(\mathbf{X}_0'\mathbf{X}_0)^{-1}$, which is estimated by $s_0^2(\mathbf{X}_0'\mathbf{X}_0)^{-1}$. Now regress $\mathbf{Y}_1 - \mathbf{X}_1\hat{\boldsymbol{\beta}}$ on $\boldsymbol{\iota}$ to get an estimator of α. Then

$$\hat{\alpha} = (\boldsymbol{\iota}'\boldsymbol{\iota})^{-1}\boldsymbol{\iota}'(\mathbf{Y}_1 - \mathbf{X}_1\hat{\boldsymbol{\beta}})\,.$$

Therefore,

$$\begin{aligned} var(\hat{\alpha}) &= (\boldsymbol{\iota}'\boldsymbol{\iota})^{-1}\boldsymbol{\iota}'\mathbf{V}(\mathbf{Y}_1 - \mathbf{X}_1\hat{\boldsymbol{\beta}})\boldsymbol{\iota}(\boldsymbol{\iota}'\boldsymbol{\iota})^{-1} \\ &= \frac{1}{N_1^2}\boldsymbol{\iota}'\left(\mathbf{V}(\mathbf{Y}_1) + \mathbf{X}_1\mathbf{V}(\hat{\boldsymbol{\beta}})\mathbf{X}_1'\right)\boldsymbol{\iota} \\ &= \frac{1}{N_1^2}\boldsymbol{\iota}'\left(\sigma_1^2\mathbf{I} + \sigma_0^2\mathbf{X}_1(\mathbf{X}_0'\mathbf{X}_0)^{-1}\mathbf{X}_1'\right)\boldsymbol{\iota}\,. \end{aligned}$$

This matrix is estimated by $\frac{1}{N_1^2}\boldsymbol{\iota}'\left(s_1^2\mathbf{I} + s_0^2\mathbf{X}_1(\mathbf{X}_0'\mathbf{X}_0)^{-1}\mathbf{X}_1'\right)\boldsymbol{\iota}$. Now note that for any $N_1\,x\,N_1$ matrix **A,** $\boldsymbol{\iota}'\mathbf{A}\boldsymbol{\iota}$ gives the sum of the elements of **A.** Hence, to estimate $var(\hat{\alpha})$, add the elements of $s_0^2\mathbf{X}_1(\mathbf{X}_0'\mathbf{X}_0)^{-1}\mathbf{X}_1'$, divide the sum by N_1^2, and add the resulting ratio to s_1^2 / N_1^2.

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Table 1: Variable Definitions from the Pooled SSBF Data

Interest rate	Interest rate on the most recent loan (%)
Credit History	
Personal delinquency	Whether the owner had delinquent personal obligations in the past three years
Judgments	Whether there was judgment against the firm owner
Firm Characteristics	
Sales	Firm's sales of the fiscal year in $1000
Profit	Firm's profit of the fiscal year in $1000
Net worth	Firm's net worth of the fiscal year in $1000
Firm age	The age of the firm in years
Employment	The number of employees and owners
Owner Characteristics	
Education indicator	Whether the owner's education level was high school dropout / high school/ graduate / some college / college / post-graduate degree
Business experience	Owner's years of business experience
Loan Characteristics	
Loan amount	The amount of loan granted in $1000
Purpose of loan	Whether the loan was new line of credit/ capital lease / mortgage / vehicle/ loan / equipment loan / other type of loan
Fixed-interest-rate loan	Whether the interest rate was fixed
Collateral required	Whether collateral were required
Guarantor required	Whether a guarantor is required to co-sign on the loan
Points paid at closing (%)	The points (in interest percentage terms) paid at closing
Lender Characteristics	
Type of lender	Whether the lender was commercial bank, saving bank, loan association or credit union / finance company / other type of institution or source.
Years firm has business relationship with lender	Years the lender had business relationship with the borrower
Geographic Variables	
Metropolitan area	Whether the firm was in a Metropolitan Statistical Area (MSA)
Region indicator	Whether the firm was located in Northeast / North Central / South / West

Source: Survey of Small Business Finances of 1993, 1998, and 2003.

Table 2: Means and Standard Deviations for Pooled SSBF Data
(standard deviations in parentheses)

	All	White	Blacks	Hispanic	Other Races	Men	Women
Sample size	3727	3266	130	159	172	2913	702
Dependent Variable							
Interest rate on the most recent loan (%)	7.41	7.23	9.73	8.62	8.03	7.39	7.32
	2.92	2.78	3.68	3.52	3.16	2.90	2.83
Credit History							
% Personal delinquency	0.18	0.16	0.52	0.32	0.19	0.18	0.16
	(0.67)	(0.63)	(1.03)	(0.89)	(0.70)	(0.66)	(0.61)
% Judgments	0.02	0.02	0.06	0.06	0.05	0.03	0.02
	(0.16)	(0.14)	(0.24)	(0.23)	(0.21)	(0.16)	(0.13)
Firm Characteristics							
Sales	7392.71	7790.90	2025.25	3614.94	7380.88	8355.59	4073.46
	(17779.96)	(18374.70)	(4647.83)	(8641.30)	(17837.89)	(18613.93)	(14512.94)
Profit	686.97	723.98	348.63	435.61	472.22	800.15	283.48
	(4177.16)	(4396.14)	(1391.53)	(2795.50)	(1514.80)	(4673.18)	(1249.10)
Net worth	1277.04	1367.96	189.12	477.01	1112.29	1451.45	720.34
	(5020.25)	(5260.08)	(760.32)	(1733.07)	(3997.19)	(5362.68)	(3705.36)
Firm age	16.45	17.08	12.16	12.53	11.46	17.05	14.86
	(12.75)	(13.08)	(8.29)	(9.75)	(8.52)	(13.13)	(11.20)
Employment	49.05	51.01	33.82	31.49	39.55	53.95	31.99
	(73.32)	(74.05)	(72.07)	(54.64)	(71.63)	(77.27)	(53.58)
Owner Characteristics							
% High school dropout	0.02	0.02	0.03	0.08	0.01	0.02	0.01
	(0.14)	(0.14)	(0.17)	(0.26)	(0.08)	(0.14)	(0.12)
% High school graduate	0.17	0.17	0.09	0.19	0.10	0.16	0.20
	(0.37)	(0.38)	(0.29)	(0.40)	(0.31)	(0.37)	(0.40)
% Some college	0.28	0.28	0.30	0.31	0.20	0.25	0.38
	(0.45)	(0.45)	(0.46)	(0.46)	(0.40)	(0.43)	(0.49)
% College degree	0.34	0.34	0.35	0.25	0.32	0.35	0.26
	(0.47)	(0.47)	(0.48)	(0.44)	(0.47)	(0.48)	(0.44)
% Post-graduate degree	0.20	0.19	0.22	0.17	0.37	0.21	0.14
	(0.40)	(0.39)	(0.42)	(0.38)	(0.48)	(0.41)	(0.35)
Business experience	21.20	21.87	15.61	17.42	16.28	22.02	18.74
	(10.94)	(10.96)	(8.69)	(10.63)	(8.94)	(10.86)	(10.80)

Table 2: Means and Standard Deviations for Pooled SSBF Data (cont'd)
(standard deviations in parentheses)

Loan Characteristics							
Loan amount	921.94	979.84	362.54	265.20	852.45	1048.44	502.12
	(4297.08)	(4545.18)	(1787.31)	(739.06)	(2066.40)	(4739.32)	(2111.54)
% Loan was new line of credit	0.53	0.52	0.55	0.52	0.62	0.53	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
% Loan was capital lease	0.03	0.02	0.05	0.03	0.05	0.03	0.02
	(0.16)	(0.15)	(0.21)	(0.18)	(0.21)	(0.16)	(0.14)
% Loan was mortgage	0.10	0.11	0.05	0.08	0.11	0.10	0.12
% Loan was vehicle loan	0.11	0.12	0.08	0.14	0.06	0.11	0.13
	(0.32)	(0.32)	(0.28)	(0.35)	(0.23)	(0.32)	(0.34)
% Loan was equipment loan	0.12	0.13	0.07	0.13	0.07	0.12	0.12
	(0.33)	(0.33)	(0.25)	(0.33)	(0.26)	(0.33)	(0.33)
% Loan was other type	0.11	0.10	0.20	0.11	0.09	0.11	0.10
	(0.31)	(0.30)	(0.40)	(0.31)	(0.29)	(0.31)	(0.30)
% Fixed-interest-rate loan	0.51	0.50	0.70	0.62	0.45	0.49	0.58
	(0.50)	(0.50)	(0.46)	(0.49)	(0.50)	(0.50)	(0.49)
% Collateral required	1.62	1.60	1.98	1.60	1.62	1.62	1.60
	(1.85)	(1.83)	(2.27)	(1.85)	(1.88)	(1.83)	(1.91)
% Guarantor required	0.57	0.58	0.54	0.52	0.58	0.57	0.58
	(0.49)	(0.49)	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)
Points paid at closing	0.28	0.25	0.58	0.40	0.47	0.26	0.30
	(0.93)	(0.84)	(1.40)	(1.42)	(1.27)	(0.86)	(1.02)
Lender Characteristics							
% Lender was commercial bank	0.77	0.78	0.71	0.74	0.73	0.78	0.74
	(0.42)	(0.41)	(0.46)	(0.44)	(0.45)	(0.41)	(0.44)
%Lender was saving bank, loan association or credit union	0.07	0.07	0.02	0.06	0.05	0.07	0.09
	(0.25)	(0.26)	(0.12)	(0.23)	(0.22)	(0.25)	(0.29)
% Lender was finance company	0.09	0.08	0.14	0.12	0.09	0.08	0.10
	(0.28)	(0.27)	(0.35)	(0.33)	(0.29)	(0.27)	(0.30)
% Lender was other type of institution	0.07	0.06	0.14	0.09	0.13	0.07	0.07
	(0.26)	(0.24)	(0.35)	(0.28)	(0.33)	(0.25)	(0.25)
Years firm has business relation with lender	8.10	8.41	4.70	6.88	5.91	8.41	7.20
	(9.21)	(9.47)	(5.71)	(7.67)	(6.54)	(9.37)	(8.77)
% in metropolitan area	0.77	0.75	0.92	0.89	0.92	0.77	0.72
	(0.42)	(0.43)	(0.28)	(0.32)	(0.27)	(0.42)	(0.45)
% Northeast	0.16	0.17	0.15	0.11	0.13	0.17	0.15
	(0.37)	(0.37)	(0.36)	(0.31)	(0.33)	(0.37)	(0.36)
% North Central	0.26	0.28	0.19	0.13	0.13	0.27	0.25
	(0.44)	(0.45)	(0.40)	(0.33)	(0.34)	(0.44)	(0.43)
% South	0.35	0.34	0.54	0.42	0.30	0.35	0.35
	(0.48)	(0.47)	(0.50)	(0.50)	(0.46)	(0.48)	(0.48)
% West	0.23	0.21	0.12	0.35	0.44	0.22	0.25
	(0.42)	(0.41)	(0.32)	(0.48)	(0.50)	(0.41)	(0.44)

Source: Survey of Small Business Finances of 1993, 1998, and 2003. These statistics do not reflect sample weights.

Table 3A. Blinder-Oaxaca Estimation Results for Whites, Blacks and Hispanics

	Whites*		Blacks**		Hispanics***	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Personal delinquency	0.134	0.063	0.603	0.295	0.084	0.324
Judgments	0.686	0.276	0.216	1.326	0.785	1.220
Sales	0.000	0.000	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000	0.000	0.000
Net worth	-0.015	0.009	0.491	0.418	-0.221	0.216
Firm age	-0.004	0.004	-0.038	0.057	0.052	0.047
Employment	-0.003	0.001	-0.005	0.005	-0.009	0.008
High school graduate	-0.888	0.297	-2.993	2.055	-0.341	1.167
Some college	-0.855	0.293	-2.158	1.937	0.522	1.100
College degree	-1.240	0.291	-2.961	1.971	-0.898	1.139
Postgraduate degree	-1.240	0.298	-2.170	1.934	-0.796	1.249
Business experience	-0.019	0.004	-0.069	0.050	-0.090	0.038
Loan amount granted	0.000	0.000	0.000	0.000	0.000	0.001
Loan was capital lease	0.466	0.273	-1.140	1.569	0.841	1.701
Loan was mortgage	0.097	0.148	0.764	1.580	-0.664	1.142
Loan was vehicle loan	-0.644	0.142	1.366	1.239	-2.576	1.032
Loan was equipment loan	-0.136	0.130	0.967	1.226	0.073	0.975
Loan was other type	0.356	0.140	1.834	0.856	1.485	0.931
Fixed-interest-rate loan	0.764	0.091	0.577	0.675	0.622	0.653
Points paid at closing	0.129	0.047	0.031	0.224	-0.010	0.195
Collateral required	-0.026	0.024	-0.233	0.145	-0.182	0.161
Guarantor required	-0.045	0.082	0.713	0.639	-0.288	0.594
Lender was saving bank, loan assn. or credit union	-0.070	0.155	-2.619	2.357	1.109	1.347
Lender was finance company	0.247	0.153	3.548	1.041	1.541	0.968
Lender was other type of institution	0.593	0.170	1.153	1.051	-0.745	1.110
Years firm has business relation with lender	-0.003	0.005	0.087	0.061	0.036	0.046
in metropolitan area	-0.105	0.092	0.167	1.122	-0.588	0.859
North Central	-0.034	0.122	-1.439	1.057	-0.586	1.138
South	-0.015	0.118	-1.416	0.847	1.167	0.954
West	0.341	0.129	-1.177	1.175	1.508	0.960
Survey year 1998	0.187	0.114	0.658	0.735	0.803	0.764
Survey year 2003	-2.640	0.093	-2.880	0.877	-1.543	0.690
Constant	9.849	0.329	12.998	2.579	9.990	1.954

*_Note_: Author's calculations using unweighted SSBF data. N = 3,266. The dependent variable is the interest rate. The sample is limited to White-owned firms.
** _Note:_ Author's calculations using unweighted SSBF data. N = 130. The dependent variable is the interest rate. The sample is limited to Black-owned firms.
** _Note:_ Author's calculations using unweighted SSBF data. N = 159. The dependent variable is the interest rate. The sample is limited to Hispanic-owned firms.

Table 3B. Blinder-Oaxaca Estimation Results for Other Races and Minorities

	Other Races*		Minorities**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Personal delinquency	0.613	0.302	0.516	0.164
Judgments	-0.060	1.000	0.545	0.632
Sales	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000
Net worth	-0.073	0.081	-0.122	0.069
Firm age (years)	-0.033	0.040	0.010	0.025
Employment	-0.005	0.004	-0.007	0.003
High school graduate	-0.735	2.868	-0.553	0.833
Some college	-1.119	2.833	-0.200	0.790
College degree	-1.539	2.826	-0.880	0.791
Postgraduate degree	-2.183	2.808	-1.049	0.800
Business experience	-0.031	0.031	-0.074	0.021
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	-1.887	1.053	-0.993	0.768
Loan was mortgage	-0.797	0.752	-0.691	0.551
Loan was vehicle loan	-1.838	0.976	-1.107	0.559
Loan was equipment loan	0.011	0.860	-0.016	0.529
Loan was other type	0.030	0.788	1.312	0.448
Fixed-interest-rate loan	1.156	0.446	0.878	0.312
Points paid at closing	0.330	0.165	0.135	0.106
Collateral required	-0.062	0.122	-0.154	0.076
Guarantor required	-0.385	0.448	-0.145	0.293
Lender was saving bank, loan assn. or credit union	-0.059	1.011	-0.086	0.720
Lender was finance company	1.406	0.800	2.117	0.504
Lender was other type of institution	0.829	0.679	0.644	0.488
Years firm has business relation with lender	0.007	0.043	0.032	0.026
in metropolitan area	0.726	0.797	0.005	0.491
North Central	0.567	0.868	-0.623	0.538
South	-0.159	0.732	-0.279	0.452
West	0.102	0.690	-0.188	0.471
Survey year 1998	0.624	0.568	0.486	0.360
Survey year 2003	-3.111	0.532	-2.448	0.365
Constant	10.492	3.030	10.678	1.115

* *Note:* Author's calculations using unweighted SSBF data. N = 172. The dependent variable is the interest rate. The sample is limited to firms owned by other races.
***Note:* Author's calculations using unweighted SSBF data. N = 461. The dependent variable is the interest rate. The sample is limited to minority-owned firms.

Table 3C. Blinder-Oaxaca Estimation Results for Females and White Females

	Females*		White Females**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Personal delinquency	0.204	0.066	0.117	0.069
Judgments	0.529	0.274	0.419	0.299
Sales	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000
Net worth	-0.016	0.009	-0.014	0.009
Firm age (years)	-0.003	0.004	-0.003	0.004
Employment	-0.003	0.001	-0.003	0.001
High school graduate	-0.858	0.313	-0.764	0.320
Some college	-0.733	0.307	-0.725	0.315
College degree	-1.141	0.304	-1.109	0.312
Postgraduate degree	-1.185	0.310	-1.108	0.319
Business experience	-0.024	0.005	-0.018	0.005
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	0.144	0.283	0.521	0.298
Loan was mortgage	0.105	0.163	0.153	0.166
Loan was vehicle loan	-0.547	0.159	-0.504	0.160
Loan was equipment loan	-0.230	0.145	-0.174	0.144
Loan was other type	0.474	0.151	0.370	0.156
Fixed-interest-rate loan	0.882	0.100	0.833	0.102
Points paid at closing	0.194	0.051	0.127	0.056
Collateral required	-0.053	0.026	-0.032	0.027
Guarantor required	-0.089	0.090	-0.062	0.091
Lender was saving bank, loan assn. or credit union	-0.071	0.178	-0.048	0.177
Lender was finance company	0.572	0.167	0.239	0.172
Lender was other type of institution	0.520	0.181	0.451	0.191
Years firm has business relation with lender	-0.003	0.005	-0.005	0.005
in metropolitan area	0.022	0.105	-0.030	0.103
North Central	-0.111	0.134	-0.052	0.133
South	-0.060	0.129	-0.067	0.130
West	0.308	0.140	0.347	0.143
Survey year 1998	0.230	0.122	0.193	0.126
Survey year 2003	-2.679	0.101	-2.696	0.102
Constant	9.908	0.349	9.708	0.355

* *Note:* Author's calculations using unweighted SSBF data. N = 2,913. The dependent variable is the interest rate. The sample is limited to female-owned firms.
** *Note:* Author's calculations using unweighted SSBF data. N = 2,564. The dependent variable is the interest rate. The sample is limited to White female-owned firms.

Table 4A. Propensity Score Estimation Results for Blacks and Hispanics

	Blacks*		Hispanics**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Personal delinquency	0.234	0.102	0.160	0.102
Judgments	0.526	0.441	0.576	0.397
Sales	0.000	0.000	0.000	0.000
Square of sales	0.000	0.000		
Profit	0.000	0.000	0.000	0.000
Net worth	-0.057	0.138	-0.027	0.038
Square of net worth	-0.033	0.033		
Firm age years	0.085	0.075	-0.026	0.019
Square of firm age years	-0.002	0.004	0.000	0.000
Cube of firm age years	0.000	0.000		
Employment	-0.002	0.004	0.000	0.002
Square of employment	0.000	0.000		
High school graduate	-0.717	0.678	-1.276	0.390
Some college	0.187	0.635	-1.185	0.376
College degree	0.025	0.632	-1.607	0.384
Postgraduate degree	0.099	0.642	-1.538	0.402
Business experience	-0.053	0.014	-0.022	0.011
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	-0.657	0.511	-0.375	0.519
Loan was mortgage	-1.642	0.463	-0.363	0.344
Loan was vehicle loan	-1.156	0.374	-0.310	0.287
Loan was equipment loan	-1.138	0.388	-0.325	0.277
Loan was other type	0.038	0.269	-0.222	0.291
Fixed-interest-rate loan	0.832	0.225	0.353	0.195
Points paid at closing	0.706	0.189	0.112	0.069
Square of points paid at closing	-0.065	0.025		
Collateral required	0.080	0.050	-0.001	0.050
Guarantor required	-0.264	0.201	-0.190	0.175
Lender was saving bank, loan assn. or credit union	-1.608	0.733	-0.274	0.368
Lender was finance company	0.479	0.325	0.170	0.291
Lender was other type of institution	0.398	0.326	-0.083	0.324
Years firm has business relation with lender	-0.072	0.065	0.013	0.012
Square of years firm has business relation with lender	0.002	0.005		
Cube of years firm has business relation with lender	0.000	0.000		
Metropolitan area	1.360	0.334	1.137	0.263
North Central	-0.292	0.330	-0.368	0.341
South	0.522	0.280	0.589	0.284
West	-0.701	0.369	0.908	0.292
Survey year 1998	-0.062	0.235	-0.173	0.220
Survey year 2003	-1.261	0.265	-0.609	0.202
Constant	-3.523	0.865	-1.936	0.547

**Note:* Author's calculations using unweighted SSBF data. $N = 3{,}396$. A logit model is used to predict the probability of being a Black-owned firm. The sample is limited to White-owned and Black-owned firms.

***Note:* Author's calculations using unweighted SSBF data. $N = 3{,}425$. A logit model is used to predict the probability of being a Hispanic-owned firm. The sample is limited to White-owned and Hispanic-owned firms.

Table 4B. Propensity Score Estimation Results for Other Races and Minorities

	Other Races*		Minorities**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Personal delinquency	-0.019	0.123	0.165	0.066
Judgments	0.512	0.416	0.563	0.267
Sales	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000
Net worth	0.009	0.020	-0.017	0.019
Firm age years	-0.017	0.037	-0.016	0.007
Square of firm age years	0.000	0.001	—	—
Cube of firm age years	0.000	0.000	—	—
Employment	-0.002	0.002	-0.001	0.001
High school graduate	0.612	1.051	-0.938	0.332
Some college	0.750	1.038	-0.678	0.319
College degree	0.943	1.033	-0.822	0.318
Postgraduate degree	1.554	1.033	-0.495	0.322
Business experience	-0.038	0.011	-0.035	0.007
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	-0.046	0.440	-0.410	0.302
Loan was mortgage	-0.224	0.300	-0.604	0.210
Loan was vehicle loan	-0.759	0.370	-0.690	0.202
Loan was equipment loan	-0.873	0.330	-0.765	0.193
Loan was other type	-0.266	0.294	-0.131	0.172
Fixed-interest-rate loan	-0.078	0.188	0.351	0.120
Points paid at closing	0.160	0.066	0.182	0.045
Collateral required	0.026	0.046	0.044	0.029
Guarantor required	-0.148	0.173	-0.182	0.110
Lender was saving bank, loan assn. or credit union	-0.297	0.367	-0.497	0.254
Lender was finance company	0.253	0.307	0.303	0.188
Lender was other type of institution	0.399	0.277	0.295	0.188
Years firm has business relation with lender	0.005	0.013	0.001	0.008
Metropolitan area	1.139	0.289	1.187	0.173
North Central	-0.341	0.311	-0.313	0.195
South	0.201	0.268	0.445	0.167
West	0.941	0.258	0.648	0.174
Survey year 1998	0.321	0.222	0.071	0.137
Survey year 2003	0.023	0.199	-0.500	0.128
Constant	-4.069	1.121	-1.448	0.400

* *Note:* Author's calculations using unweighted SSBF data. N = 3,438. A logit model is used to predict the probability of being a firm owned by another race. The sample is limited to White-owned firms and firms owned by other races.
** *Note:* Author's calculations using unweighted SSBF data. N = 3,727. A logit model is used to predict the probability of being a minority-owned firm. The sample is limited to White-owned and minority-owned firms.

Table 4C. Propensity Score Estimation Results for Females and White Females

	Females*		White Females**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Personal delinquency	-0.063	0.062	-0.107	0.072
Judgments	-0.235	0.278	-0.368	0.337
Sales	0.000	0.000	0.000	0.000
Square of sales	0.000	0.000	0.000	0.000
Cube of sales	0.000	0.000	0.000	0.000
Fourth power of sales	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000
Square of profit	0.000	0.000	0.000	0.000
Cube of profit	0.000	0.000	0.000	0.000
Net worth	-0.002	0.016	0.004	0.016
Firm age years	0.015	0.010	0.021	0.011
Square of firm age years	0.000	0.000	0.000	0.000
Employment	0.000	0.001	-0.001	0.001
High school graduate	0.180	0.290	0.496	0.365
Some college	0.337	0.285	0.724	0.360
College degree	-0.215	0.287	0.114	0.363
Postgraduate degree	-0.427	0.295	-0.039	0.371
Business experience	-0.070	0.014	-0.079	0.015
Square of business experience	0.001	0.000	0.001	0.000
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	-0.349	0.290	-0.409	0.329
Loan was mortgage	0.041	0.151	0.067	0.163
Loan was vehicle loan	-0.156	0.146	-0.153	0.157
Loan was equipment loan	-0.053	0.136	-0.188	0.149
Loan was other type	-0.149	0.147	-0.102	0.160
Fixed-interest-rate loan	0.155	0.094	0.206	0.103
Points paid at closing %	0.021	0.041	0.032	0.048
Collateral required	0.003	0.025	-0.005	0.027
Guarantor required	0.039	0.086	0.020	0.094
Lender was saving bank, loan assn. or credit union	0.120	0.156	0.129	0.163
Lender was finance company	0.179	0.153	0.260	0.169
Lender was other type of institution	0.077	0.170	0.065	0.191
Years firm has business relation with lender	-0.009	0.006	-0.010	0.006
Metropolitan area	-0.074	0.098	-0.094	0.102
North Central	0.012	0.136	-0.041	0.145
South	0.178	0.129	0.205	0.138
West	0.327	0.136	0.381	0.147
Survey year 1998	0.016	0.120	-0.089	0.133
Survey year 2003	0.272	0.099	0.192	0.106
Constant	-0.462	0.347	-0.660	0.417

**Note:* Author's calculations using unweighted SSBF data. N = 3,727. A logit model is used to predict the probability of being a female-owned firm.

***Note:* Author's calculations using unweighted SSBF data. N = 3,266. A logit model is used to predict the probability of being a White female-owned firm. The sample is limited to White-owned firms.

Table 5: Estimates of Race Discrimination in Interest Rates, SSBF Data

	Minority	Blacks	Hispanic	Other Races
Panel A: Binder –Oaxaca Estimates				
Coefficient	0.599	1.109	0.453	0.349
Standard Error	(0.151)	(0.301)	(0.260)	(0.204)
N	3,727	3,396	3,425	3,438
Panel B: Propensity Score Matching Estimates *				
Coefficient	0.671	0.791	0.486	0.353
Standard Error	(0.176)	(0.369)	(0.273)	(0.253)
Bandwidth	0.013	0.005	0.008	0.029
N	3,727	3,396	3,425	3,438

Source: Survey of Small Business Finances of 1993, 1998, and 2003. The omitted racial/ethnic group in column (1) through column (4) is White. The standard errors are corrected according to the procedure in the Appendix.
*The standard errors are obtained by bootstrapping based on 2,000 replications.

Table 6: Estimates of Gender Discrimination in Interest Rates

	Females	**White Females**
Panel A: Binder –Oaxaca Estimates		
Coefficient	-0.174	-0.132
Standard Error	(0.101)	(0.104)
N	3,727	3,266
Panel B: Propensity Score Matching Estimates		
Coefficient	-0.266	-0.188
Standard Error	(0.129)	(0.135)
Bandwidth	0.034	0.039
N	3,727	3,266

Source: Survey of Small Business Finances of 1993, 1998, and 2003. The reference gender group in column (1) is male, and the omitted group in column (2) is White males. The standard errors are corrected according to the procedure in the Appendix.
*The standard errors in Panel B are obtained by bootstrapping based on 2,000 replications.

Figure 1: The Distributions of the Propensity Scores for Minority

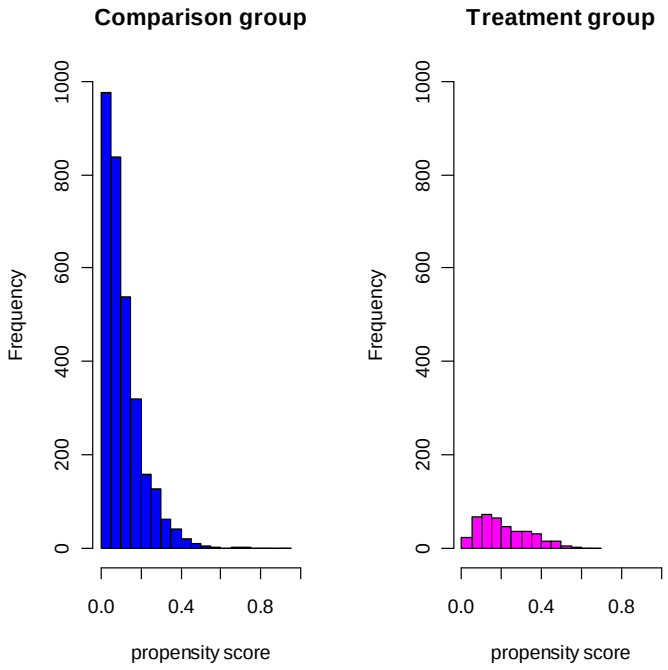

Figure 2: The Distributions of the Propensity Scores for Black

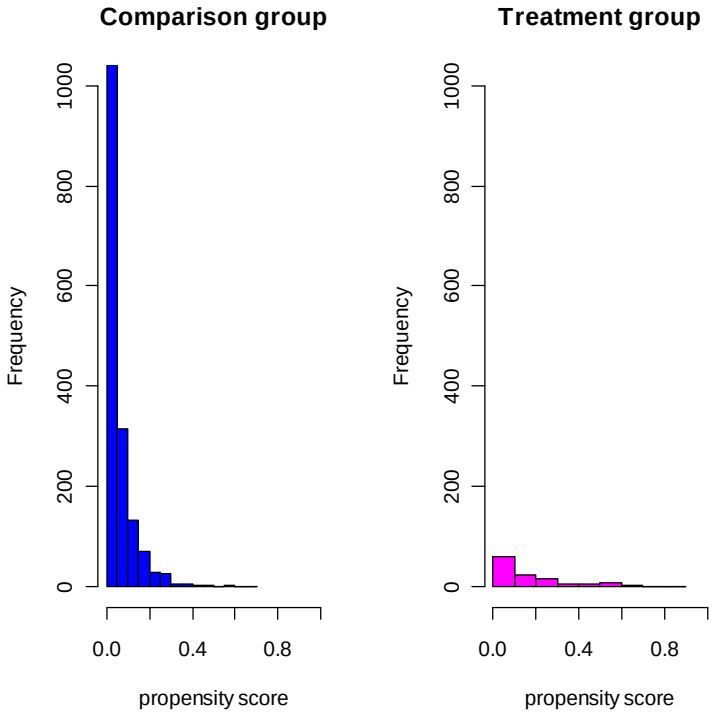

Figure 3: The Distributions of the Propensity Scores for Hispanic

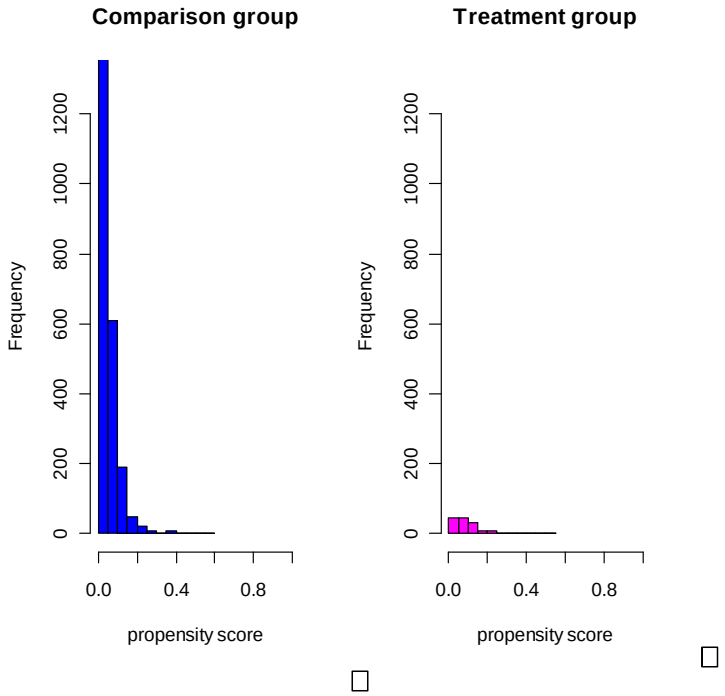

Figure 4: The Distributions of the Propensity Scores for Other Races

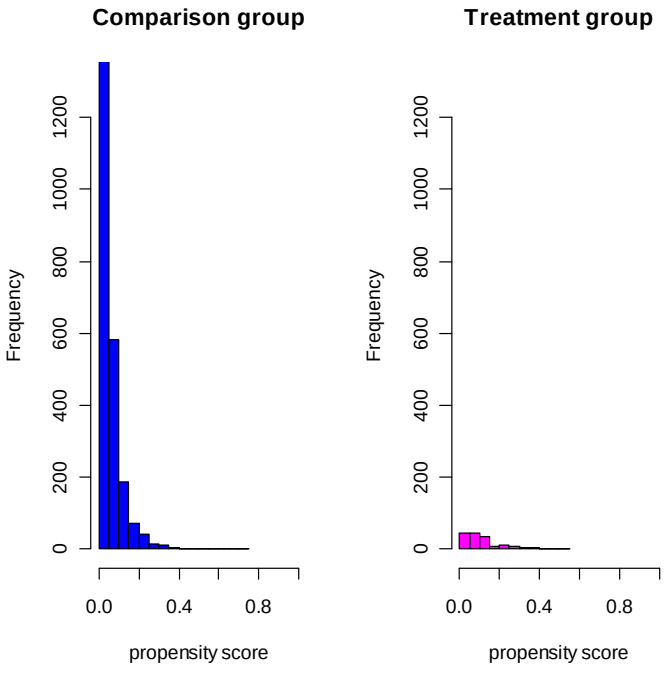

Figure 5: The Distributions of the Propensity Scores for Female

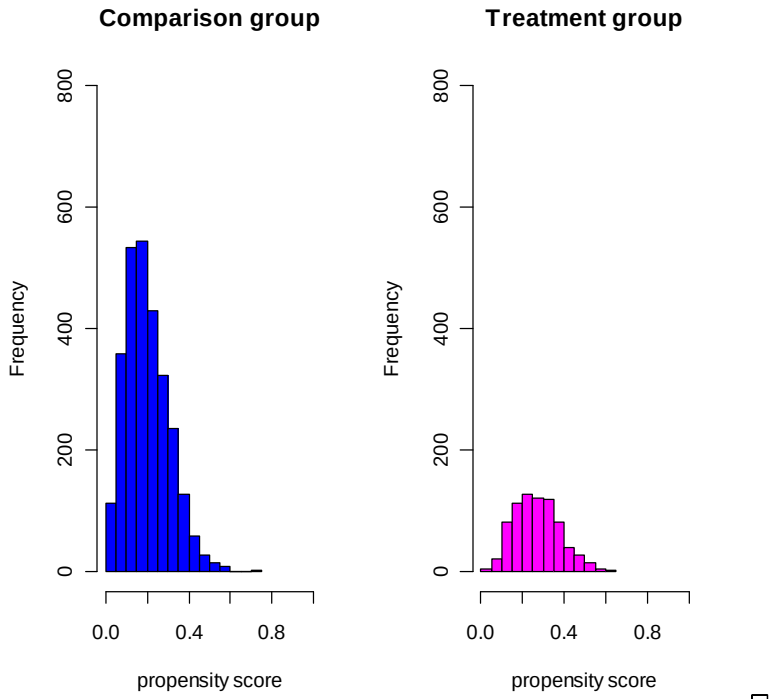

Figure 6: The Distributions of the Propensity Scores, White Females