The Racial and Gender Interest Rate Gap

in Small Business Lending:

Improved Estimates Using Matching Methods*

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ABSTRACT

This paper studies racial and gender interest rate gaps in small business credit markets using the 1993, 1998 and 2003 waves of the Survey of Small Business Finances (SSBF). These gaps are estimated with a semiparametric (kernel) propensity-score matching method that uses a bandwidth selected by least-squares cross validation. Our findings indicate that, on average, Black and Hispanic owned firms pay an interest rate that is, respectively, 0.791 and 0.486 percentage points higher than the rate paid by comparable White owned firms. We find no evidence of that businesses owned by White women pay different interest rates than comparable businesses owned by White men. We also find that in several cases our estimating method produces significantly different estimates—and even different hypothesis test results—than the traditional Blinder-Oaxaca decomposition method, which is based on more restrictive assumptions.

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

1. Introduction

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 and historically disadvantaged classes (henceforth simply protected classes) are more likely to be denied credit than are businesses owned by those in the majority class, even controlling for characteristics related to credit worthiness.[2] Evidence concerning disparities in interest rates is more mixed. Some studies find no evidence of interest-rate gaps (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 interest-rate gaps in small business lending frequently fail to address problems that arise when behavioral relationships are nonlinear and when the groups being compared have little overlap in their characteristics. They show that these problems can be addressed using semiparametric propensity-score matching and other techniques. Black et al. (2006) use semiparametric matching techniques to study wage differentials, but matching techniques have not yet appeared in the literature on small business credit.[3]

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[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).

[3] There are modeling options other than matching. Hirano, Imbens and Ridder (2003) show that weighting by the inverse of a nonparametric estimate of the propensity score leads to an efficient estimate of the average treatment effect. Busso, DiNardo, and McCrary (2009) provide a comparison of the finite sample properties of propensity-score matching and weighting estimators. Khan and Tamer (2009) and Kahn and Nekipelov (2009) investigate the convergence rate of weighting estimators in the absence of strong support conditions.

Failure to account for nonlinearity in the relationship between the interest rate and its determinants will result in biased estimates. Blanchflower et al. (2003) and Blanchard et al. (2007) provide a partial solution to this problem by splitting their sample and running separate regressions for each part. This strategy, which is equivalent to introducing a set of interaction terms, is less general than the approach used in this paper, which estimates the interest-rate equation using semiparametric methods.

The existing literature on interest-rate gaps also ignores the common support condition, that is, it ignores the problems that arise when observations compared across classes are dissimilar. Previous studies point out that minority owned firms tend to differ from White owned firms in credit relevant characteristics and two studies, Blanchflower et al. (2003) and Blanchard et al. (2007), find that unequal treatment varies with such characteristics. Under these conditions, traditional regression techniques that do not require a common support also yield biased results.

In this study we attempt to address these two empirical problems using semiparametric propensity-score matching with 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, the semiparametric matching method that we employ does not impose assumptions on the functional form of the interest-rate equation.

The study is organized as follows. In section 2 we examine the empirical challenges by reviewing the methodologies adopted in studying the interest rate gap in small business lending. In section 3 we present the theory of the traditional Blinder-Oaxaca decomposition method and the semiparametric propensity-score matching method. The data set used for this study is described in section 4. The estimation results are provided in section 5. We find that minority owned firms pay systematically higher interest rates on approved loans than do White owned firms. Unlike previous studies, however, our results suggest that White female owners of small businesses are not likely to be treated differently than their male counterparts. Concluding remarks can be found in section 6.

2. Previous Literature

The identification of disparate treatment in the setting of interest rates requires the identification of 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 systematic differences in the outcome are attributable to disparate treatment. The implication is that a disparate treatment study should attempt to 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 should aggregate the information in a meaningful way to make a determination about the possible presence of disparate treatment.

The goal of this study is to employ matching to approximate a quasi-experiment to provide a provisional, yet meaningful estimate of the extent of disparate treatment 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.

The existing research on the interest rate gap in small business lending has used a regression approach or a limited dependent variable methods in which interest rates charged on a loan or credit denial are a function of the owner's race and a set of credit-worthiness assessment criteria that might be used by financial institutions. The coefficient on the owner's race, or more generally, an aggregate measure of the systematic differences in coefficients captures disparate treatment. For simplicity, many studies assume a linear functional form in the econometric regression 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 apparent disparate treatment 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. Evidence concerning average 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). The goal of this study is to use semiparametric propensity-score matching to estimate racial and gender interest rate gaps for small business owners and compare these estimates to those obtained by the traditional Blinder-Oaxaca decomposition method.

3. Econometric Methods

3.1. The Blinder-Oaxaca Decomposition Method

The first of our two econometric methods is the traditional Blinder-Oaxaca decomposition method. This method decomposes the difference of two linear regression functions, one for a protected class and one for a majority group, into a "discrimination" effect that estimates the interest rate gap as unequal treatment at the average default-risk component levels of the protected class and a residual "endowment" effect.[4]

[4] Under the assumptions that lenders' weights on each credit characteristic accurately reflects its impact on the probability of default and that no credit characteristics observed by the lender are omitted from the regression, this "discrimination" effect corresponds to the legal concept of disparate-treatment discrimination. See Ross and Yinger (2002). We return to this issue after discussing our results.

The Blinder-Oaxaca decomposition method is a regression-based method that assumes a linear functional form. Write the regression model for the interest rate charged to the majority class as:

$$\begin{aligned} \mathrm{Y}_0 &= \iota\alpha_0 + \mathbf{X}_0\boldsymbol{\beta}_0 + \boldsymbol{\varepsilon}_0, \\ \mathbf{E}(\boldsymbol{\varepsilon}_0) &= \mathbf{0}; \quad \mathbf{V}(\boldsymbol{\varepsilon}_0) = \sigma_0^2\mathbf{I}, \end{aligned} \tag{1}$$

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

$$\overline{Y}_0 = \hat{a}_0 + \overline{\mathbf{X}}_0\hat{\boldsymbol{\beta}}_0 \ , \tag{2}$$

where $\overline{Y}_0$ is the sample mean of the dependent variable, $\overline{\mathbf{X}}_0$ is the row vector of regressor means, and the "hat" signifies OLS estimator .

Write the regression model for the interest rate charged to the protected class as:

$$\begin{aligned} \mathbf{Y}_1 &= \boldsymbol{\iota}\alpha_1 + \mathbf{X}_1\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1, \\ \mathbf{E}(\boldsymbol{\varepsilon}_1) &= \mathbf{0}\,; \ \mathbf{V}(\boldsymbol{\varepsilon}_1) = \sigma_1^2\mathbf{I}\ , \end{aligned} \tag{3}$$

where $\mathbf{Y}_1$ is the $N_1\ x\,1$ dependent variable vector of protected class interest rates, $\boldsymbol{\iota}$ 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 of protected class characteristics of default risk, and $\boldsymbol{\beta}_1$ is $k\,x\,1$. Again, OLS is best linear unbiased and satisfies the following equation:

$$\overline{Y}_1 = \hat{\alpha}_1 + \overline{\mathbf{X}}_1\hat{\boldsymbol{\beta}}_1 \tag{4}$$

where $\overline{Y}_1$ is the sample mean of the dependent variable, and $\overline{\mathbf{X}}_1$ is the row vector of regressor means.

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:

$$\Delta\overline{Y} = \hat{\alpha}_1 - \hat{\alpha}_0 + \overline{\mathbf{X}}_1\Delta\hat{\boldsymbol{\beta}} + \Delta\overline{\mathbf{X}}\hat{\boldsymbol{\beta}}_0 \quad , \tag{5}$$

where the sum of the first three terms on the right-hand side of equation (5) is the total effect of disparate treatment.

A simple method for obtaining the Blinder-Oaxaca discrimination effect uses the following pseudo-model. The interest-rate equation for the majority class is written as:

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

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 $(k+1)\ x\,1$, while the interest-rate equation for the protected class is written as:

$$\begin{aligned} &\mathbf{Y}_1 = \boldsymbol{\iota}\alpha + \mathbf{Z}_1\boldsymbol{\beta} + \boldsymbol{\varepsilon}_1, \\ &\mathbf{E}(\boldsymbol{\varepsilon}_1) = \mathbf{0}\,;\ \mathbf{V}(\boldsymbol{\varepsilon}_1) = \sigma_1^2\mathbf{I}\,, \end{aligned} \tag{7}$$

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

$$\frac{1}{N_1}\sum_{i\in I_1}\left(Y_{1i} - \mathbf{Z}_{1i}{}'\hat{\boldsymbol{\beta}}\right) \quad , \tag{8}$$

where I_1 denotes the set of sample members of the protected class. It is obtained by the following two-step method. First, run an OLS estimation of the model for the majority 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 (4) 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.

3.2. The Semiparametric Propensity-Score Matching Method

The more modern semiparametric propensity-score matching method relaxes the linearity assumption in the Blinder-Oaxaca interest-rate equations. For a given sample firm *i* the semiparametric propensity score matching model specifies.

$$Y_i = \varphi_{D_i}(X_i) + \varepsilon_i \ , \tag{9}$$

where D_i is 0 (1) when the individual is a member of the protected (majority) class and ε_i is an iid finite-variance mean-zero error term within classes that is independent across classes.

An evaluation problem arises because, at any time, a firm may be either owned by a member of the majority class or the protected class, but not both. The quantity of interest is the interest-rate gap, which is the expected difference in the interest rates paid by otherwise equivalent members of the two classes. This is called the effect of treatment on the treated. Formally, let Y_{1i} be the potential interest rate paid by a protected class firm, and let Y_{0i} be the potential interest rate if the firm had been owned by a member of the majority class. The effect of treatment on the treated is defined as

$$TT = E\left(Y_{1i} - Y_{0i} \mid X_{1i}, D_i = 1\right) = E\left(Y_{1i} \mid X_{1i}, D_i = 1\right) - E\left(Y_{0i} \mid X_{1i}, D_i = 1\right). \tag{10}$$

The average effect of treatment on the treated, *ATT*, is the average value of *TT* across sample members of the protected class. The difficulty in estimating *ATT* is that, while an estimate of the mean protected class outcome, $E\left(Y_{1i} \mid X_{1i}, D_i = 1\right)$, can be obtained using data on protected class firms, a direct estimate of its counterfactual mean, $E\left(Y_{0i} \mid X_{1i}, D_i = 1\right)$, is not available.

Matching estimators rely on the assumption that comparison (non-treatment) outcomes, Y_{0i}, are independent of the treatment, D_i, which indicates ownership by a protected class, conditional on a set of observable characteristics, X_{1i}. This selection on observables assumption is also called the Conditional Independence Assumption (CIA) and is expressed as follows:

$$\text{Assumption 1: } Y_{0i} \perp D_i \mid X_{1i} . \tag{11}$$

In particular, it implies that the potential interest rate that a majority class firm must pay is independent of the class of the firm owner 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_{1i} the distribution of Y_{0i} given $D_i = 1$ is the same as the distribution of Y_{0i} given $D_i = 0$. (It is worth noting that we do not observe Y_{0i} given $D_i = 1$.) In addition, it is also assumed that for all X_{1i} there is a positive probability of being treated ($D_i = 1$) and of not being treated ($D_i = 0$), which can be written as follows:

$$\text{Assumption 2: } \Pr\left(D_i = 1 \mid X_{1i}\right) < 1 \text{ for all } X_{1i} . \tag{12}$$

This is called the "common support" assumption, and it is an important assumption that the Blinder-Oaxaca decomposition method fails to address. The support condition implies that a match from the majority group firms can be found for each and every protected class firm. If Assumptions 1 and 2 are satisfied, then, after conditioning on X_{1i}, the Y_{0i} distribution observed for the matched firms owned by members of the majority group can be substituted for the missing Y_{0i} distribution for protected class 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.

Several consistent matching methods have been developed. 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.

The simplicity of the Blinder-Oaxaca decomposition method rests on a restrictive linearity assumption. In practice, the potential nonlinear functional form problem might be caused by high order terms of explanatory variables and interactions among them. For example, Ross and Yinger (2002) point out that variation in underwriting standards across lenders takes the form of interactions between lender characteristics and underwriting variables. Instead of imposing a specific functional form on the relationship between the dependent variable and the regressors, we relax the linearity assumption by using a kernel regression technique that allows the data to speak for themselves. Unfortunately, if the dimension of X_i is high, one may run into the "curse of dimensionality problem," which arises when some subset of observations in the treatment group have no corresponding firm from the comparison group with exactly the same values of X_i.

Rosenbaum and Rubin (1983) first 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_i 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_i but identical values of

$\Pr(D_i = 1 \mid X_i)$. Matching on the scalar propensity score in this way avoids the curse of dimensionality.

As shown in Smith and Todd (2001), under Assumptions 1 and 2, the mean impact of treatment (being a member of a protected class) can be rewritten as

$$E(Y_{1i} - Y_{0i} \mid D_i = 1) = E(Y_{1i} \mid D_i = 1) - E_P\left[E_Y(Y_{0i} \mid D_i = 1, P_i)\right], \tag{13}$$

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

$$\frac{1}{N_{1s}} \sum_{i \in I_1 \cap S_p} \left[Y_{1i} - \hat{E}(Y_{0i} \mid D_i = 1, P_i)\right], \tag{14}$$

where $\hat{E}(Y_{0i} \mid D_i = 1, P_i) = \sum_{i \in I_0} W(i, j) Y_{0j}$ is the matched outcome. I_0 and I_1 denote the set of sample majority and protected class members respectively, S_p is the common support region, and N_{1s} is the number of individuals both in sets I_1 and S_p (see Smith and Todd 2005). The match for each protected class member i in the summation of (14) 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, Ichimura, and Todd (1997, 1998) and Heckman, Ichimura, Smith and Todd (1998), the weighting function is

$$W(i, j) = K\left(\frac{P_j - P_i}{h}\right) / \sum_{k \in I_0} K\left(\frac{P_k - P_i}{h}\right), \tag{15}$$

where K is a kernel function with bandwidth parameter h.[5] This semiparametric 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

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

estimate the average treatment effect of protected class 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 $h = 0$. Black and Smith (2004), the first to apply the least-squares cross-validation procedure to semiparametric propensity-score matching, claim that 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 Nearest Neighbor, is more arbitrary.

In the SSBF data, we have substantially fewer observations belonging to the protected classes than to the majority classes (Whites in the case of the interest rate gap for Blacks and Hispanics, males in the case of the female interest rate gap, and White males in the case of the interest rate gap for White females.) In fact, there are only 130 Black owned firms and 159 Hispanic owned firms in the pooled SSBF data compared to over 3,266 firms owned by Whites. The semiparametric propensity-score matching estimator that we employ 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.[6]

The semiparametric propensity-score matching estimator is more computationally intensive than the Blinder-Oaxaca decomposition method, because it requires a choice of optimal bandwidth and bootstrapped standard errors. In addition, the speed of convergence is slower for the semiparametric matching estimator than for the Blinder-Oaxaca estimator. However, the payoffs to using the semiparametric matching estimator are also considerable. First, the semiparametric matching estimator relaxes the linearity assumption of the Blinder-Oaxaca decomposition method and is therefore not subject to the biases when this assumption is violated. Second, the semiparametric matching estimator enables a straightforward examination of the support condition that prevents the researcher from erroneously making predictions outside the support of the data.[7] This second advantage of semiparametric matching will be addressed in greater detail in section 5.

4. The SSBF Data

The principal data used in the econometric analysis of this study are the 1993, 1998, and 2003 waves of the Survey of Small Business Finance (SSBF) from. This aggregate repeated cross-sectional data contains 4,193 nonfinancial, nonfarm small businesses. The sample is nationally representative, and contains rich information regarding the firm, such as its age, location, employment, and industry. In addition, the data set also includes the term and type of the most recent loan each firm obtained. The survey sample was drawn from more than 7.5

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[6] An alternative way of addressing the over-sampling issue is to employ a variant of Nearest Neighbor caliper matching called radius 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 undesirably over a wide range of possible data-generating processes.

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

million firms each year. A firm would be unlikely to appear in two surveys and it would appear in all three surveys with a probability approaching zero.

We take advantage of the large sample obtained from pooling all three waves of the SSBF data allows us to use a larger sample in the estimation and the larger sample in turn allows us to produce more precise estimates of the interest rate gap in small business lending and to check the robustness of the model specification under alternative assumptions. In the analysis of the racial interest rate gap the number of Black-owned firms in the data is 130 and the number of Hispanic-owned firms is 159, while, in the analysis of the gender interest rate gap the number of female-owned firms is a much larger 814 and the number of firms owned by White females is 702.

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 classes 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. 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 classes also differ from White owned firms in their creditworthiness 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 obligations over the past three years, or had legal judgments against him or her over the preceding three years.

5. Results

5.1. Propensity-Score Estimation Results

A logit model can be 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 to the outcome, as well as goodness-of-fit. The goal is to construct a model that estimates the probability that a firm has an owner from the protected class based on all the firms' characteristics that a lender can legitimately consider when it makes a decision about the firm's creditworthiness. The existing literature on discrimination in small business lending (Cavalluzzo et al. 2002; Blanchflower et al. 2003; and Blanchard et al. 2007) suggests 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 delinquent events on the loan under consideration. Such information postdates the information available to the lender and is likely to introduce bias.

The propensity score estimation results for firms owned by Blacks and Hispanics are presented in Table 3A, those for females and White females can be found in Table 3B. More highly educated owners are less likely to be Hispanic generally. When a firm receives a fixed interest-rate loan, it is more likely that its owner is Black, Hispanic or a White female. The histograms of the estimated propensity scores for each group are shown in Figure 1 through Figure 4. In all but the last two groups, the left histogram presents propensity scores for firms owned by Whites (the $D_i = 0$ group), while the right histogram presents the propensity scores for minority owned firms (the $D_i = 1$ 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 can be used to examine the support condition for the propensity score. Along the dimension of race, the mean propensity score given $D_i = 1$ is about 0.15, while the mean propensity score for $D_i = 0$ is about 0.06. In the case of gender, the mean propensity score given $D_i = 1$ is about 0.27 while the mean propensity score for $D_i = 0$ 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 289 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 this oversampling issue.

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 basic intutition behind the balancing test is that after conditioning on the propensity score, additional conditioning on X should not provide new information about D. If it does, this suggests misspecification in the model used to estimate the propensity score. The regression-based balancing test itself 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.[8] 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.

5.2. Blinder-Oaxaca Estimation Results

First-stage Blinder-Oaxaca estimation results for Whites, Blacks and Hispanics are presented in Table 4A, those for males and females are presented in Table 4B, and those for White males and White females are presented in Table 4C. 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.

The results for various racial groups using the SSBF data are shown in Table 5. Panel A presents cross-group differences in interest rates on approved loans using the Blinder-Oaxaca decomposition, and Panel B shows estimates of these differences based on the semiparametric propensity-score matching method. Under the assumption that our extensive list of credit variables adequately controls for cross-group differences in creditworthiness that lenders can legitimately consider, these differences can be interpreted as measures of discrimination.

As shown in Panel A of Table 5, we find businesses owned by Blacks and Hispanics have to pay higher interest rates than businesses owned by Whites, controlling for creditworthiness and other factors shown in Table 1. Black owned firms face the largest degree of discrimination, as defined by this decomposition method; the interest rates these firms pay are 1.109 percentage points higher than the rates paid by their White counterparts. On average, firms owned by Hispanics pay interest rates 0.453 percentage points higher than firms owned by Whites. These estimates are all statistically significant at conventional levels.

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

5.3. Semiparametric Propensity-Score Matching Estimation Results

The estimates in Panel B of Table 5 are based on bandwidths chosen using leave-one-out cross-validation, and the 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 semiparametric propensity-score matching estimates differ from those of the Blinder-Oaxaca decomposition in the following ways. For Hispanic-owned firms the cross-group disparity is slightly larger than that from the Blinder-Oaxaca decomposition. Hispanic owned firms pay on average 0.486 percentage points more interest on approved loans than do comparable White owned firms. The estimate is statistically significant at the 1 percent level. In contrast the estimated treatment effect of Black-ownership decreases from 1.109 to 0.791 using propensity-score matching. This estimate remains economically significant as it represents more than a 10 percent increase in the interest rate over the average charged to White owned firms.

The results for gender-based interest-rate disparities can be found in Table 6. The data suggest that businesses owned by women pay an interest rate that is significantly lower than the rate paid by comparable 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 disparity 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, and we do not 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 suggest, but do not definitively prove, that our matching methods, which are preferable on conceptual grounds, produce significantly different results from results based on more traditional regression 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.[9] Only the last of these three estimates is statistically significant. Thus, matching appears to increase the magnitude of the gap for Black owned firms (and to make this gap significant), to reverse and make insignificant 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.

These results indicate that Black owned and Hispanic owned firms pay higher interest rates than White owned firms after controlling for a wide range of factors that are likely to affect a business's credit qualifications. These results are therefore consistent with disparate treatment discrimination in the setting of the interest rates charged to small businesses, but they also could be explained by the omission from our analysis of factors that influence firm creditworthiness and are observed by lenders, but not by us.

6. Conclusions

This study contributes to the literature on cross-group interest-rate disparities in small business lending by using semiparametric propensity-score matching with data from the Survey of Small Business Finances from 1993, 1998, and 2003. Matching methods relax the linear functional form assumption and address data support problems. These issues have been largely

[9] 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.

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 businesses pay significantly higher interest rates on approved loans than do equally creditworthy firms owned by Whites. However, we cannot reject the hypotheses that interest rates in small business lending would be unaffected by a switch in ownership to White men from White women.

APPENDIX ON
CORRECT STANDARD ERRORS
FOR THE BLINDER-OAXACA MODEL

The model in Equation (5) and (6) can be rewritten in matrix notation as following. For the unprotected class:

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

where $\mathbf{Y}_0$ is $N_0\, x 1$, $\mathbf{X}_0$ is $N_0\, x k$, and $\boldsymbol{\beta}$ is $k\, x 1$ and the model for the protected class:

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

where $\mathbf{Y}_0$ is $N_1\, x 1$, $\boldsymbol{\iota}$ is $N_1\, x 1$, α is a scalar, $\mathbf{X}_1$ is $N_1\, x k$, and $\boldsymbol{\beta}$ is $k\, x 1$. 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 (percent)
Credit History	
Personal delinquency	Indicator for whether the owner had delinquent personal obligations in the past three years
Judgments	Indicator for 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 for 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	Indicator for whether the loan was new line of credit/ capital lease / mortgage / vehicle/ loan / equipment loan / other type of loan
Fixed interest-rate loan	Indicator for whether the interest rate was fixed
Collateral required	Indicator for whether collateral were required
Guarantor required	Indicator for 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	Indicator for whether the firm was in a Metropolitan Statistical Area (MSA)
Region indicator	Indicator for 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)

	Whites	Blacks	Hispanics	Men	Women	White Men	White Women
Sample size	3266	130	159	2913	814	2913	702
Dependent Variable							
Interest rate	7.23	9.73	8.62	7.39	7.49	7.39	7.32
	(2.78)	(3.68)	(3.52)	2.90	(2.97)	(2.90)	(2.83)
Credit History							
Personal delinquency indicator	0.16	0.52	0.32	0.18	0.19	0.18	0.16
	(0.63)	(1.03)	(0.89)	(0.66)	(0.67)	(0.66)	(0.61)
Judgments	0.02	0.06	0.06	0.03	0.02	0.03	0.02
	(0.14)	(0.24)	(0.23)	(0.16)	(0.15)	(0.16)	(0.13)
Firm Characteristics							
Sales	7790.90	2025.25	3614.94	8355.59	3946.95	8355.59	4073.46
	(18374.70)	(4647.83)	(8641.30)	(18613.93)	(13877.78)	(18613.93)	(14512.94)
Profit	723.98	348.63	435.61	800.15	281.9498	800.15	283.48
	(4396.14)	(1391.53)	(2795.50)	(4673.18)	(1239.30)	(4673.18)	(1249.10)
Net worth	1367.96	189.12	477.01	1451.45	652.86	1451.45	720.34
	(5260.08)	(760.32)	(1733.07)	(5362.68)	(3464.13)	(5362.68)	(3705.36)
Firm age	17.08	12.16	12.53	17.05	14.30	17.05	14.86
	(13.08)	(8.29)	(9.75)	(13.13)	(11.00)	(13.13)	(11.20)
Employment	51.01	33.82	31.49	53.95	31.52	53.95	31.99
	(74.05)	(72.07)	(54.64)	(77.27)	(53.44)	(77.27)	(53.58)
Owner Characteristics							
High school dropout indicator	0.02	0.03	0.08	0.02	0.02	0.02	0.01
	(0.14)	(0.17)	(0.26)	(0.14)	(0.15)	(0.14)	(0.12)
High school graduate indicator	0.17	0.09	0.19	0.16	0.20	0.17	0.20
	(0.38)	(0.29)	(0.40)	(0.37)	(0.40)	(0.37)	(0.40)
Some college	0.28	0.30	0.31	0.25	0.37	0.25	0.38
	(0.45)	(0.46)	(0.46)	(0.43)	(0.48)	(0.43)	(0.49)
College degree	0.34	0.35	0.25	0.35	0.27	0.35	0.26
	(0.47)	(0.48)	(0.44)	(0.48)	(0.44)	(0.48)	(0.44)
Post-graduate degree	0.19	0.22	0.17	0.21	0.15	0.21	0.14
	(0.39)	(0.42)	(0.38)	(0.41)	(0.35)	(0.41)	(0.35)
Business experience	21.87	15.61	17.42	22.02	18.28	22.02	18.74
	(10.96)	(8.69)	(10.63)	(10.86)	(10.71)	(10.86)	(10.80)

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

	Whites	Blacks	Hispanics	Men	Women	White Men	White Women
Loan Characteristics							
Loan amount	979.84	362.54	265.20	1048.44	469.26	1048.44	502.12
	(4545.18)	(1787.31)	(739.06)	(4739.32)	(1977.63)	(4739.32)	(2111.54)
Loan was new line of credit	0.52	0.55	0.52	0.53	0.51	0.53	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Percent Loan was capital lease	0.02	0.05	0.03	0.03	0.02	0.03	0.02
	(0.15)	(0.21)	(0.18)	(0.16)	(0.15)	(0.16)	(0.14)
Loan was mortgage	0.11	0.05	0.08	0.10	0.12	0.10	0.12
					(0.32)		
Loan was vehicle loan	0.12	0.08	0.14	0.11	0.12	0.11	0.13
	(0.32)	(0.28)	(0.35)	(0.32)	(0.33)	(0.32)	(0.34)
Loan was equipment loan	0.13	0.07	0.13	0.12	0.13	0.12	0.12
	(0.33)	(0.25)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Loan was other type	0.10	0.20	0.11	0.11	0.10	0.11	0.10
	(0.30)	(0.40)	(0.31)	(0.31)	(0.30)	(0.31)	(0.30)
Fixed interest-rate loan		0.70	0.62	0.49	0.58	0.49	0.58
	(0.50)	(0.46)	(0.49)	(0.50)	(0.49)	(0.50)	(0.49)
Collateral required	1.60	1.98	1.60	1.62	1.62	1.62	1.60
	(1.83)	(2.27)	(1.85)	(1.83)	(1.93)	(1.83)	(1.91)
Guarantor required	0.58	0.54	0.52	0.57	0.57	0.57	0.58
	(0.49)	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)	(0.49)
Points paid at closing	0.25	0.58	0.40	0.26	0.33	0.26	0.30
	(0.84)	(1.40)	(1.42)	(0.86)	(1.14)	(0.86)	(1.02)

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

	Whites	Blacks	Hispanics	Men	Women	White Men	White Women
Lender Characteristics							
Lender was commercial bank	0.78	0.71	0.74	0.78	0.74	0.78	0.74
	(0.41)	(0.46)	(0.44)	(0.41)	(0.44)	(0.41)	(0.44)
Lender was saving bank, loan association or credit union	0.07	0.02	0.06	0.07	0.09	0.07	0.09
	(0.26)	(0.12)	(0.23)	(0.25)	(0.28)	(0.25)	(0.29)
Lender was finance company	0.08	0.14	0.12	0.08	0.10	0.08	0.10
	(0.27)	(0.35)	(0.33)	(0.27)	(0.30)	(0.27)	(0.30)
Lender was other type of institution	0.06	0.14	0.09	0.07	0.07	0.07	0.07
	(0.24)	(0.35)	(0.28)	(0.25)	(0.26)	(0.25)	(0.25)
Years firm has business relation with lender	8.41	4.70	6.88	8.41	6.98	8.41	7.20
	(9.47)	(5.71)	(7.67)	(9.37)	(8.53)	(9.37)	(8.77)
Metropolitan area	0.75	0.92	0.89	0.77	0.74	0.77	0.72
	(0.43)	(0.28)	(0.32)	(0.42)	(0.44)	(0.42)	(0.45)
Northeast	0.17	0.15	0.11	0.17	0.14	0.17	0.15
	(0.37)	(0.36)	(0.31)	(0.37)	(0.35)	(0.37)	(0.36)
North Central	0.28	0.19	0.13	0.27	0.24	0.27	0.25
	(0.45)	(0.40)	(0.33)	(0.44)	(0.43)	(0.44)	(0.43)
South	0.34	0.54	0.42	0.35	0.36	0.35	0.35
	(0.47)	(0.50)	(0.50)	(0.48)	(0.48)	(0.48)	(0.48)
West	0.21	0.12	0.35	0.22	0.26	0.22	0.25
	(0.41)	(0.32)	(0.48)	(0.41)	(0.44)	(0.41)	(0.44)

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

Table 3A. Propensity Score Estimation Results for Blacks and Hispanics

	Blacks*		Hispanics**	
	Coefficient	Standard Error	Coefficient	Standard Error
Credit History				
Personal delinquency	0.234	0.102	0.160	0.102
Judgments	0.526	0.441	0.576	0.397
Firm Characteristics				
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		
Owner Characteristics				
Firm age	0.085	0.075	-0.026	0.019
Square of firm age	-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 Characteristics				
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 Characteristics				
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		
Geographic Variables				
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
Others				
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:* Authors' 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:* Authors' 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 3B. Propensity Score Estimation Results for Females and White Females

	Females*		White Females**	
	Coefficient	Standard Error	Coefficient	Standard Error
Credit History				
Personal delinquency	-0.063	0.062	-0.107	0.072
Judgments	-0.235	0.278	-0.368	0.337
Firm Characteristics				
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
Owner Characteristics				
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
Loan Characteristics				
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 Characteristics				
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
Geographic Variables				
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
Others				
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:* Authors' calculations using unweighted SSBF data. N = 3,727. A logit model is used to predict the probability of being a female-owned firm.
***Note:* Authors' 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 4A. Blinder-Oaxaca Estimation Results for Whites, Blacks and Hispanics (standard errors in parentheses)

	Whites*		Blacks**		Hispanics***	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Credit History						
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
Firm Characteristics						
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
Owner Characteristics						
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 Characteristics						
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 Characteristics						
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
Geographic Variables						
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
Others						
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*: Authors' calculations using unweighted SSBF data. *N* = 3,266. The dependent variable is the interest rate. The sample is limited to White-owned firms.

** *Note:* Authors' calculations using unweighted SSBF data. *N* = 130. The dependent variable is the interest rate. The sample is limited to Black-owned firms.

*** *Note:* Authors' calculations using unweighted SSBF data. *N* = 159. The dependent variable is the interest rate. The sample is limited to Hispanic-owned firms.

Table 4B. Blinder-Oaxaca Estimation Results for Males and Females
(standard errors in parentheses)

	Males*		Females**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Credit History				
Personal delinquency	0.204	0.066	0.289	0.136
Judgments	0.529	0.274	1.528	0.616
Firm Characteristics				
Sales	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000
Net worth	-0.016	0.009	0.000	0.000
Firm age (years)	-0.003	0.004	-0.012	0.011
Employment	-0.003	0.001	-0.002	0.002
Owner Characteristics				
High school graduate	-0.858	0.313	-0.921	0.634
Some college	-0.733	0.307	-0.786	0.621
College degree	-1.141	0.304	-1.206	0.632
Postgraduate degree	-1.185	0.310	-1.143	0.647
Business experience	-0.024	0.005	-0.030	0.011
Loan Characteristics				
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	0.144	0.283	-0.071	0.636
Loan was mortgage	0.105	0.163	-0.270	0.322
Loan was vehicle loan	-0.547	0.159	-1.376	0.311
Loan was equipment loan	-0.230	0.145	-0.017	0.289
Loan was other type	0.474	0.151	0.268	0.318
Fixed interest-rate loan	0.882	0.100	0.576	0.200
Points paid at closing	0.194	0.051	0.048	0.080
Collateral required	-0.053	0.026	-0.036	0.053
Guarantor required	-0.089	0.090	-0.048	0.186
Lender Characteristics				
Lender was saving bank, loan assn. or credit union	-0.071	0.178	-0.273	0.329
Lender was finance company	0.572	0.167	0.612	0.326
Lender was other type of institution	0.520	0.181	0.895	0.362
Years firm has business relation with lender	-0.003	0.005	0.009	0.012
Geographic Variable				
Metropolitan area	0.022	0.105	-0.320	0.208
North Central	-0.111	0.134	-0.161	0.301
South	-0.060	0.129	0.063	0.284
West	0.308	0.140	0.330	0.295
Others				
Survey year 1998	0.230	0.122	0.083	0.260
Survey year 2003	-2.679	0.101	-2.571	0.218
Constant	9.908	0.349	10.379	0.745

* *Note:* Authors' calculations using unweighted SSBF data. N = 2,913. The dependent variable is the interest rate. The sample is limited to female-owned firms.
** *Note:* Authors' 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 4C. Blinder-Oaxaca Estimation Results for White Males and White Females (standard errors in parentheses)

	White Males*		White Females**	
	Coefficient	Standard Error	Coefficient	Standard Error
Credit History				
Personal delinquency	0.204	0.066	0.289	0.136
Judgments	0.529	0.274	1.528	0.616
Firm Characteristics				
Sales	0.000	0.000	0.000	0.000
Profit	0.000	0.000	0.000	0.000
Net worth	-0.016	0.009	0.000	0.000
Firm age (years)	-0.003	0.004	-0.012	0.011
Employment	-0.003	0.001	-0.002	0.002
Owner Characteristics				
High school graduate	-0.858	0.313	-0.921	0.634
Some college	-0.733	0.307	-0.786	0.621
College degree	-1.141	0.304	-1.206	0.632
Postgraduate degree	-1.185	0.310	-1.143	0.647
Business experience	-0.024	0.005	-0.030	0.011
Loan Characteristics				
Loan amount granted	0.000	0.000	0.000	0.000
Loan was capital lease	0.144	0.283	-0.071	0.636
Loan was mortgage	0.105	0.163	-0.270	0.322
Loan was vehicle loan	-0.547	0.159	-1.376	0.311
Loan was equipment loan	-0.230	0.145	-0.017	0.289
Loan was other type	0.474	0.151	0.268	0.318
Fixed interest-rate loan	0.882	0.100	0.576	0.200
Points paid at closing	0.194	0.051	0.048	0.080
Collateral required	-0.053	0.026	-0.036	0.053
Guarantor required	-0.089	0.090	-0.048	0.186
Lender Characteristics				
Lender was saving bank, loan assn. or credit union	-0.071	0.178	-0.273	0.329
Lender was finance company	0.572	0.167	0.612	0.326
Lender was other type of institution	0.520	.181	0.895	0.362
Years firm has business relation with lender	-0.003	0.005	0.009	0.012
Geographic Variable				
in metropolitan area	0.022	0.105	-0.320	0.208
North Central	-0.111	0.134	-0.161	0.301
South	-0.060	0.129	0.063	0.284
West	0.308	0.140	0.330	0.295
Others				
Survey year 1998	0.230	0.122	0.083	0.260
Survey year 2003	-2.679	0.101	-2.571	0.218
Constant	9.908	0.349	10.379	0.745

* *Note:* Authors' calculations using unweighted SSBF data. *N* = 2,564. The dependent variable is the interest rate. The sample is limited to White male-owned firms.
** *Note:* Authors' calculations using unweighted SSBF data. *N* = 702. The dependent variable is the interest rate. The sample is limited to White female-owned firms.

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

	Blacks	**Hispanic**
Panel A: Blinder –Oaxaca Estimates		
Coefficient	1.109	0.453
Standard Error	(0.301)	(0.260)
N	3,396	3,425
Panel B: Propensity Score Matching Estimates *		
Coefficient	0.791	0.486
Standard Error	(0.369)	(0.273)
Bandwidth	0.005	0.008
N	3,396	3,425

Source: Survey of Small Business Finances of 1993, 1998, and 2003. The omitted racial/ethnic group in both columns 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: Blinder –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 Blacks

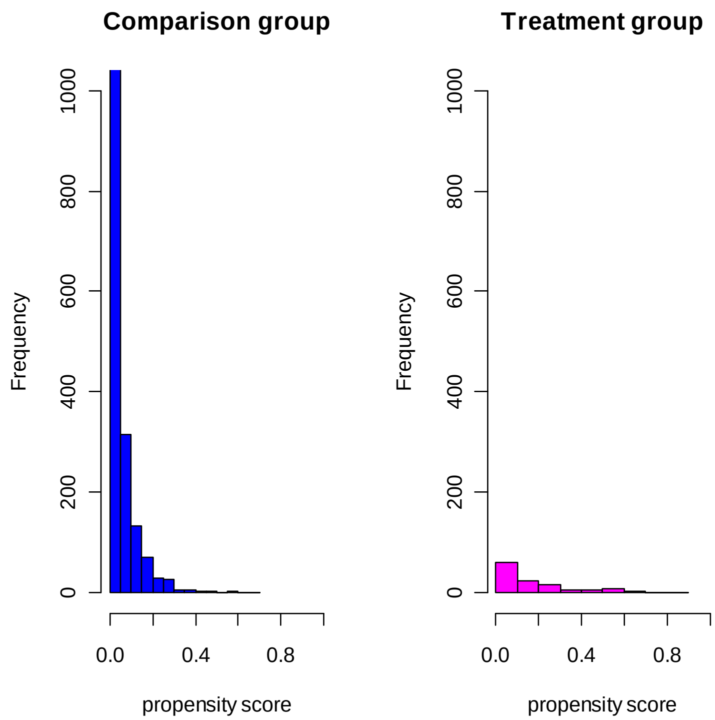

Figure 2: The Distributions of the Propensity Scores for Hispanics

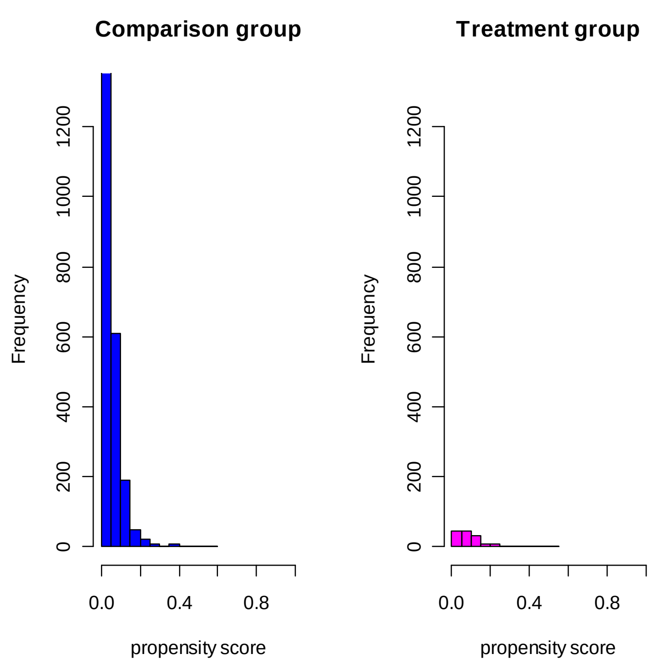

Figure 3: The Distributions of the Propensity Scores for Females

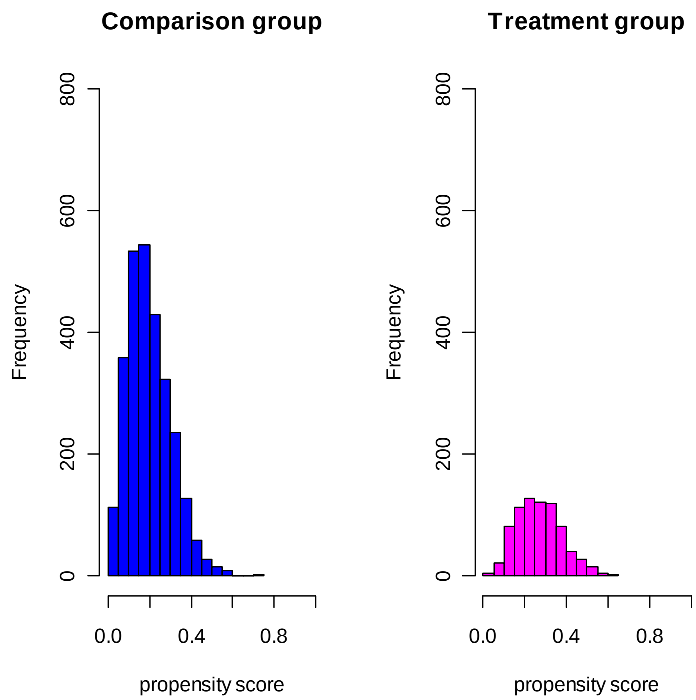

Figure 4: The Distributions of the Propensity Scores