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STATE OF THE ART

Race Differentials in the Credit Market Experiences of Small Business Owners

Improved Estimates

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Abstract

Small businesses employ more than half of the entire workforce, account for more than sixty percent of new jobs created in the United States, and are responsible for about fifty percent of private domestic gross product. It is noteworthy, however, that small business owners in credit markets, in particular minority owners, have difficulty in securing sources of capital for their business operation. The literature on credit market discrimination shows consistent results that can be interpreted as evidence that minority owners are discriminated against compared to their counterparts (i.e., White owners) in obtaining loans, which may be caused by lenders' discrimination, although such behavior is prohibited under current fair-lending laws. This paper uses pooled cross-sectional data from the Survey of Small Business Finances (1993, 1998, and 2003) and a bivariate probit model based on James J. Heckman's approach to deal with sample selection bias for those choosing to apply for loans. Those who didn't apply for loans have been ignored in analyses of credit markets for small business owners. This paper adds to the small business lending market literature by 1) combining cross sectional data from the Survey of Small Business Finances (SSBF) for 1993, 1998, and 2003 to get more precise estimates and test statistics with more power; 2) conducting regression analyses with different model specifications to show the robustness of the empirical results; and 3) dealing directly with problems of sample selection based on Heckman's approach with particular attention to the assumptions required to justify the identification of the effect (i.e., exclusion restrictions).

The analysis confirms previous results, suggesting that minority owners are discriminated against in credit markets. These conclusions are supported in a variety of model specifications.

Keywords: Lending Market Discrimination; Small Business; Selection Bias; Heckman Correction; Exclusion Restriction

Introduction

According to the Small Business Administration (SBA), small businesses, defined as businesses with fewer than 500 employees, employ more than half of the entire workforce and account for more than sixty percent of new jobs created in the United States economy, in addition to being responsible for about fifty percent of private domestic gross product (as of 2016).[1] In this context, it is noteworthy, however, that small business owners in credit markets, in particular minority owners, have difficulties in securing sources of capital for business operations in spite of their economic importance (Ang 1991; Ennew and Binks, 1995; Pettit and Singer, 1985).

The fact that minority-owned small businesses have difficulty in obtaining loans in credit markets may be attributed to 1) economic and financial differences between minority-owned and non-minority-owned small businesses, 2) lender discrimination against minority owners (based on statistical or preference-based discrimination),[2] or 3) cultural differences between lenders and borrowers, which may cause lenders to make less effort to collect information on the creditworthiness of minorities than that of White applicants (Calomiris, et al., 1994; Cavalluzzo et al., 2002; Longhofer and Peters, 2005).[3]

Discriminating against minority owners who apply for loans in credit markets is prohibited under current fair-lending laws, in particular the Equal Credit Opportunity Act (ECOA) of 1974. According to the United States Department of Justice, ECOA "prohibits creditors from discriminating against credit applications on the basis of race, color, religion, national origin, sex, marital status, [or] age."[4] Several studies however, provide evidence that minority-owned businesses face discrimination in loan approval (Blanchard et al., 2008; Blanchflower et al., 2003; Fairlie et al., 2022).

It follows that studies of lending discrimination for small businesses must be implemented based on statistical approaches (e.g., multivariate regression equations) to detect whether there exists lender discrimination in credit markets. As pointed out by Stephen Ross and John Yinger (2002) (also see Blanchard et al., 2008, p. 468), studies of lending discrimination based mainly on statistical approaches should address the potential sources of biases: omission of relevant explanatory variables; sample selection issues; endogeneity; and functional misspecification.

However, little research on lending market discrimination has been conducted that deals properly with selection bias problems that may arise in credit markets (Blanchard et al., 2008; Cavalluzzo et al., 2002). Phillips Robert and Yezer Anthony (1996), in this context, criticize the lending market literature that uses simple single-equation models of credit application rejection and loan default and argue for corrections for sample selection bias. James J. Heckman (1976, 1979) shows in his seminal work how a nonrandomly selected sample can cause bias in estimating coefficients of interest and how to remedy selection bias problems to get consistent estimates.

This paper adds to the small business lending market literature by 1) combining cross sectional data from the Survey of Small Business Finances (SSBF) for 1993, 1998, and 2003 to get more precise estimates and test statistics with more power; 2) conducting regression analyses with different model specifications to show the robustness of the empirical results; and 3) dealing directly with problems of sample selection based on the Heckman's approach with particular attention to the assumptions required to justify the identification of the effect (i.e., exclusion restrictions).

Literature Review

The literature on lending market discrimination, which bases its theoretical framework on Gary S. Becker's model of discriminatory employer preference, has been focused on small business owners' access to credit markets (Ando 1988; Cohn and Coleman, 2001; Cole 2013; Grown and Bates, 1992). Most studies have analyzed data from either the Characteristics of Business Owners (CBO) or the Survey of Small Business Finances (SSBF).

Early work on lending market discrimination against small business owners used the CBO data to analyze the relationship between small business owners, in particular minority-owned small businesses, and credit accessibility (e.g., loan approval and loan amount). Faith H. Ando (1988), for example, shows that Black-owned small businesses are less likely than White-owned small businesses to obtain commercial bank loans based on an analysis of CBO data. The study estimates a logit model that controls for the characteristics of firms, applicants' demographic information, and credit risk. Using the same data set as in

Ando (1988), and controlling for a similar set of variables, Timothy Bates (1991) finds that Black-owned small businesses receive smaller loan amounts than those owned by Whites.

Ken S. Cavalluzzo and colleagues (2002) use the 1993 SSBF, which is one of "the most extensive public data sets available on small businesses" (p. 647), to examine differences in loan denial rates and interest rates charged between minority-owned and non-minority-owned small businesses. They find, on the one hand, that there is no evidence that Black-owned small businesses pay more for loans compared to others. Using a logit model, they also find, on the other hand, that Black-owned small businesses are more likely than others to be denied loans even after controlling for a broad set of characteristics.

Other research on small-business lending market discrimination also finds that Black-owned small businesses are more likely than others to be denied loans after controlling for a large number of firm and owner characteristics. For example, David G. Blanchflower and colleagues (2003) control for the owner's education, creditworthiness, type of loan, organizational status, age of firm, firm size, industry, and region to analyze loan denial. An extensive set of variables similar to the ones in Blanchflower et al. (2003) are also controlled in existing studies (Blanchard et al., 2008; Bostic and Lampani, 1999; Cavalluzzo and Cavalluzzo, 1998). On the other hand, other studies find empirical results suggesting that Hispanic- and Asian-owned small businesses may also be discriminated against in credit markets (Cavalluzzo and Wolken, 2005; Cole 2008; Coleman 2002).

As pointed out by Robert and Anthony (1996) as well as Gangadharrao Maddala and Robert Trost (1982), however, using only cases where firms submitted loan applications in lending markets to detect discrimination may produce biased estimates due to selection bias problems (i.e., nonrandomly selected subsample driven by self-selection problems). To deal with self-selection problems that arise in lending markets, Cavalluzzo and colleagues (2002) use a bivariate probit model to take self-selection into account and find that the correlation between the application decision equation and the outcome equation (i.e., loan denial) is positive and statistically significant. However, they conclude that adding the selection equation does not seriously influence denial estimates. Replicating the work of Cavalluzzo et al. (2002) using the 1998 SSBF, Lloyd Blanchard and colleagues (2008) also confirm that the selection correction does not alter estimates of the determinants of loan denial.

One of the major limitations in both studies, however, is that regressors used to deal with self-selection are identical in the two equations (i.e., selection and outcome) as mentioned in Cavalluzzo et al. (2002, p. 673). Although the bivariate sample selection model can be theoretically identified without any restriction on the regressors, it is well known that the results are usually less than convincing due to very high standard errors for coefficients caused by multicollinearity and the functional assumptions that are required (Cameron and Trivedi, 2005; Wooldridge 2010).

This paper, in this regard, provides several contributions to the small-business lending market literature. First, unlike the previous literature, this paper uses pooled cross sections—SSBF for 1993, 1998, and 2003—to get more precise estimates and provide statistics with more power. Second, as noted above, although the previous small-business lending market literature addresses self-selection problems, results are generally unconvincing as the same regressors are controlled in the selection and the outcome equation. Here, the paper uses several alternative identifying variables (i.e., exclusion restrictions) and different model specifications for a bivariate probit sample selection model to improve adjustments for sample selection bias.

Theoretical Framework

This paper bases the interpretation of the empirical analysis on theoretical predictions from Becker's (1971) seminal work on the effects of prejudice in the labor market. In the subsection below, therefore, we briefly review the key implications from his model. In what follows, we apply Becker's model to a lender's loan decision process, showing how lender prejudice may influence the likelihood of loan approval for small business owners, in particular, minority-owned small businesses. Last but not least, we will introduce Heckman's approach, one of the sample selection models used in observational studies, to deal with self-selection problems that arise in lending markets.

Becker's Discrimination Model

Throughout his analysis, Becker assumes 1) employers may be racially prejudiced, 2) White and Black workers are perfect substitutes in production, 3) a production function is constant returns to scale, and (4) the market is perfectly competitive.[5] Since employers in Becker's model have prejudice against hiring Black workers, following Kerwin K. Charles and Jonathan Guryan (2008), employer i utility can be written as the function of profit and the disutility (d_i) for each Black worker hired:

$$V_i = \pi_i - d_i L_B, \tag{1}$$

where $\pi_i = f(L_W + L_B) - w_W L_W - w_B L_B$ is the employer's profit; w_W and w_B are White and Black wages, respectively; L_W and L_B are the number of White and Black workers hired by the employer; and $f(\cdot)$ is the production function, assumed constant returns to scale. Since it is assumed that the firm chooses its inputs (here, the number of White and Black workers) to maximize the employer's utility, the first-order conditions for the hiring of White and Black workers, respectively, can be written:

$$\begin{gathered}\text{Marginal product of labor} = w_w \\ \text{Marginal product of labor} = w_B + d_i\end{gathered} \tag{2}$$

Since White and Black workers are assumed to be perfect substitutes in production, for any employer who hires both Black and White workers, it follows that:

$$w_W = w_B + d_i. \tag{3}$$

Equation (2) means that the employer hires either White or Black labor up to the point at which its marginal product is equal to its marginal impact on the employer's utility. Since d_i represents the employer's disutility for hiring a Black worker, Black workers are paid less by d_i. The implications from Becker's model are that 1) an employer with prejudice behaves as if Black workers' wages are higher than they actually are, 2) an employer hires White labor if his/her prejudice is such that $w_W < w_B + d_i$ and vice versa, and 3) in the labor market, the allocation of either White or Black labor to firms is not random. In the next subsection, we will carry the implications from Becker's model over to small-business lending markets. In particular, we will consider the lender's decision process.

Loan Decision Process[6]

As described above, Becker's model assumes an employer with prejudice against hiring, for example, Black workers, and employer utility maximization affects relative earnings of racial groups. Carrying this idea over to small-business lending markets, we can assume a lender has prejudice against approving loan applications from minority-owned small businesses. The lender's objective is to approve loan applications that can "provide a higher return than other potential uses of the capital" (Blanchard et al., 2008, p. 469), taking account of the lender's discriminatory preferences.

Defining π^* as the lender's required profitability threshold, the lender's decision rule for a loan application is as follows:

$$\begin{aligned} &\text{Loan Approval if } \pi \geq \pi^* \\ &\text{Loan Denial if } \pi < \pi^*, \end{aligned} \tag{4}$$

where π indicates the profit that can be expected from a loan application, which is determined with full information on the loan application. As pointed out by Ross and Yinger (2002), however, it is almost inevitable that lenders have incomplete information on loan applicants and are unable to predict loan performance with certainty. In this context, they must estimate loan profitability based on rules of thumb, their past experience, and so on. Therefore, in practice, the loan decision process can be written as follows:

$$\begin{aligned} &\text{Loan Approval if } \pi^E \geq \pi^* \\ &\text{Loan Denial if } \pi^E < \pi^*, \end{aligned} \tag{5}$$

where π^E is an estimated loan profitability derived from a lender's incomplete information based on a loan performance. If we assume that a lender uses limited information on the characteristics of the applicant (A), the firm (F), and the loan (L) in the loan decision process and has prejudice against approving loan applications from minority-owned small businesses, Equation (5) can be changed to the following loan decision rule if a borrower is a member of a certain ethnic group (e.g., Black):

$$\begin{aligned} &\text{Loan Approval if } \pi^E(A,F,L) \geq \pi^* + Md \\ &\text{Loan Denial if } \pi^E(A,F,L) < \pi^* + Md, \end{aligned} \tag{6}$$

where M is a dummy with value of 1 for members of this ethnic group and d is the disutility the lender experiences if a member of that ethnic group is given a loan. If we assume that the actual loan estimate of profitability has a linear functional form and a normally distributed error term, this estimate can be written as:

$$\pi^E(A,F,L) = \beta_0 + \beta_1 A + \beta_2 F + \beta_3 L + \varepsilon. \tag{7}$$

Since the actual decision rule creates two exclusive outcomes, loan denial (D = 1) or loan approval (D = 0), Equations (6) and (7) imply a probit model, which can be used to analyze the functional relationship between the likelihood that a loan application is denied and the characteristics of interest (i.e., A, F, L, and M).

$$\mathrm{P}(\mathrm{D} = 1 \,|\, \mathrm{A,F,L,M}) = \Phi(\beta_0 + \beta_1 A + \beta_2 F + \beta_3 L + \beta_4 M), \tag{8}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function such that $0 < \Phi(\cdot) < 1$.

Equation (8) shows that if the coefficient of the race dummy variable (M) is positive even after controlling for the explanatory variables in a probit model, this suggests the existence of discrimination in small-business lending markets. One of the limitations, however, of using a probit model to detect discrimination in lending markets is that self-selection on the part of applicants in their decision to apply for a loan is ignored, which in turn can cause estimated coefficients to be biased. In the next subsection, therefore, we will set up a new identification strategy that takes into account applicants' self-selection and corrects for self-selection problems.

Sample Selection Model - Heckman's Approach

As pointed out in Robert and Anthony (1996), much of the lending market literature has used "simple single-equation models of rejection and default" (p. 87) to detect discrimination in lending markets, which ignores problems caused by the sample selection. Although the econometrics literature shows that ignoring the sample selection process can be justified under the assumption that the selection process is solely determined by regressors controlled in a regression equation (i.e., exogeneous sample selection), the assumption may not hold in general, which in turn causes the estimates of coefficients to be biased.

In this context, some of the small-business lending market literature deals with the sample selection process by directly taking into account the loan application process in estimating the loan denial decision (Blanchard et al., 2008; Cavalluzzo et al., 2002), but they do not address the issue, for example, that using the same regressors in both the outcome equation and the selection equation depends on the details of specification for identification. In what follows, therefore, we will set up a bivariate probit sample selection model based on the logic of Heckman's estimator that takes into account the loan denial and the loan application decision jointly, and we will then show how the model deals with sample selection problems.[7]

In the small-business lending market literature, we have no way of getting pure random samples of applications for loans. For example, we may expect that a small business owner is more likely to apply for a loan if the loan approval is more likely. Since small business owners self-select in applying for loans, we can only observe a subset of the population—small business owners who applied for loans—which may not be representative of the underlying population of small businesses. Hence using a selected sample without correcting for the selection can cause parameter estimates to be biased. When we estimate the outcome equation (i.e., loan denial), the loan application decision will be directly taken into account in our estimates of, for example, discrimination in small-business lending markets. The bivariate probit sample selection model, therefore, consists of a selection equation (i.e., whether to apply) and an outcome equation (i.e., loan denial) as follows:

$$\text{Selection Equation: } y_1 = \begin{cases} 1 \text{ } if \text{ } y_1^* > 0. \\ 0 \text{ } if \text{ } y_1^* \leq 0. \end{cases} \tag{9}$$

$$\text{Outcome Equation: } y_2 = \begin{cases} 1 \text{ } if \text{ } y_2^* > 0, \\ 0 \text{ } if \text{ } y_2^* \leq 0, \end{cases} \tag{10}$$

where y_1^* and y_2^* are latent variables for loan application and loan denial, respectively. $y_1 = 1$ means that a small business owner, a potential loan applicant, becomes an actual loan applicant (otherwise $y_1 = 0$) and $y_2 = 1$ means that the loan application is denied (otherwise $y_2 = 0$). Subscripts for individuals are suppressed here. In our estimation strategy, we assume that the two latent variables have specific functional forms as follows:

$$y_1^* = X_S \beta_S + \varepsilon_S. \tag{11}$$

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$$y_2^* = X_O\beta_O + \varepsilon_O. \tag{12}$$

Here, Equation (11) shows that y_1^* —whether a small business owner applies for a loan—depends on a set of observed variables (X_S) and the error term (ε_S), and Equation (12) shows that y_2^*—whether a lender denies the loan application—depends on a set of observed variables (X_O) and the error term (ε_O). Following the standard approach to the bivariate probit sample selection model, we assume that X_S and X_O are exogenous to the error terms and ε_j follows $N\left(0,\sigma_j^2\right), j=S,O$.

Reintroducing subscript i to identify business owners, if we do not consider the loan application decision, the conditional probability of being denied a loan (i.e., $y_{2i}=1$) is written as follows:

$$\Pr\left(y_{2i} = 1|X_i\right) = \Pr(X_{Oi}\beta_{Oi} + \varepsilon_{Oi} > 0|X_i) = \Phi\left(\frac{X_{Oi}\beta_{Oi}}{\sigma_{oi}}\right), \tag{13}$$

where Φ is the cumulative standard normal distribution function. Likewise, the conditional probability that small business owner i, given X_i, is approved for a loan is written as follows:

$$\Pr\left(y_{2i} = 0|X_i\right) = 1 - \Phi\left(\frac{X_{Oi}\beta_{Oi}}{\sigma_{oi}}\right). \tag{14}$$

Hence likelihood function (L) that is used to estimate parameters of interest in a standard probit model without considering the loan application decision can be written as follows:

$$\mathrm{L}=\prod_{i=1}^{N_1}\Phi\left(\frac{X_{Oi}\beta_O}{\sigma_o}\right)\prod_{i=N_1+1}^{N}\left[1-\Phi\left(\frac{X_{Oi}\beta_O}{\sigma_o}\right)\right]. \tag{15}$$

The first N_1 observations identify small business owners who are denied loan applications while the latter ($N - N_1$) small business owners are not denied loan applications (i.e., their loans are approved). For clarity, we introduce subscript i to identify cases. However, this specification does not consider the loan application process jointly.

Since we assumed above that a latent variable (y_2^*) has a specific functional form, however, the population regression function for y_2^* can be written as follows:[8]

$$E\left(y_2^*|X\right) = X_O\beta_O. \tag{16}$$

Based on the loan application decision in the population applying for the loan, the regression function can be written:

$$\begin{aligned} E\left[\left(y_2^*|X_O, y_1^* > 0\right)\right] &= X_O\beta_O + E\left(\varepsilon_O|X_O, y_1^* > 0\right) = \\ &X_O\beta_O + E(\varepsilon_O|X_O, X_S\beta_S + \varepsilon_S > 0). \end{aligned} \tag{17}$$

Assuming that ε_{Oi} and ε_{Si} are bivariate normally distributed with ρ correlation coefficient between ε_{Oi} and ε_{Si}, then we have:

$$E\left(\varepsilon_O|X_O, y_1^* > 0\right) = \rho\lambda \text{ and } \lambda = \frac{\phi(X_S\beta_S)}{\Phi(-X_S\beta_S)}, \tag{18}$$

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where ϕ and Φ are the standard normal population density function and cumulative density function, respectively. Hence the regression equation with the loan application decision considered jointly is:

$$y_2^* = X_O\beta_O + \rho\lambda + \eta, \text{ where } \mathrm{E}\left(\eta | y_1^* > 0\right) = 0 \text{ and } E\left(\eta^2 | y_1^* > 0\right) = v^2, \tag{19}$$

where $v^2 = 1 + \rho^2\lambda(X_S\beta_S - \lambda)$.[9]

Equation (19) shows, as proved in Heckman (1979), that using the selected sample of the underlying population can create a functional misspecification if it does not control for the second term ($\rho\lambda$) of Equation (19), and will in turn cause parameter estimates to be biased in the regression equation if $\rho \neq 0$. Since we can obtain consistent estimates $\widehat{\lambda}$ and $\widehat{v^2}$ from Equation (12) by using a probit model explaining whether or not a small business owner applies for a loan, we can set up the following regression equation:

$$y_2 = \begin{cases} 1 \text{ if } \left(\dfrac{X_O\beta_O}{v}\right) + \left(\dfrac{\rho\lambda}{v}\right) + (\xi) > 0, \\ 0 \text{ if } \left(\dfrac{X_O\beta_O}{v}\right) + \left(\dfrac{\rho\lambda}{v}\right) + (\xi) \leq 0, \end{cases} \tag{20}$$

where $\xi = \frac{\eta}{v}$ and $\mathrm{E}\ (\xi | X_s\beta_s > 0) = 0$ and $E\left(\xi^2 | X_S\beta_S > 0\right) = 1$.

Therefore, the likelihood function for estimation of Equation (20) can be written as follows:

$$\mathrm{L} = \prod_{i=1}^{N_1} \Phi(X_{0i}\beta_O, X_{Si}\beta_S; \rho) \prod_{i=N_1+1}^{N} \Phi(-X_{0i}\beta_O, X_{Si}\beta_S; \rho) \prod_{i=N+1}^{M} \Phi(-X_{Si}\beta_S), \tag{21}$$

where the first N_1 observations include small business owners who applied for loans and whose loan applications were approved. The $N - N_1$ observations include small business owners who applied for loans, but whose loan applications were denied. The $M - N$ observations include small business owners who did not apply for loans.

Data

Data used for this study are based on the Federal Reserve Board's 1993, 1998, and 2003 Survey of Small Business Finances (SSBF), which were conducted by the National Opinion Research Center (NORC) for the Board of Governors. In this survey, small businesses are defined as U.S. domestic for-profit, nonsubsidiary, nonfinancial, nonagricultural, nongovernmental businesses that employ fewer than 500 employees. The firms surveyed in each year's cross-sectional data form a nationally representative sample of small businesses operating in the United States as of the survey year (Bitler et al., 2001; Cole and Wolken, 1995; Mach and Wolken, 2006).

The samples were drawn from the Dun & Bradstreet Market Identifier file that is considered as broadly representative of all businesses in the United States (Mach and Wolken, 2006). Small businesses in this survey are selected according to a stratified random sample design. The samples were stratified by urban/rural status, census division (i.e., East North Central, East South Central, Middle Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, and West South Central), and total employment size.

The SSBF samples provide comprehensive information on individual small businesses, including detailed demographic and financial data. For example, the survey includes each firm's recent borrowing experiences with financial institutions (e.g., loan approval/denial), the firm's location and primary industry (e.g., service, manufacture), and organizational form (e.g., corporation, partnership). The survey also includes the primary owner's characteristics, which include personal demographic variables (e.g., race, education), credit history, business experience, and the like. The survey further provides information on the characteristics of the lenders that approved or denied the firm's loan applications, including type of lender (e.g., commercial bank, savings bank), the lender's location, the length of the relationship between the lender and the firm, and so on.[10]

More interestingly, the SSBF provides information on different reasons for not applying for loans. Small business owners in the survey can be classified into one of four categories of borrower type: non-borrower, discouraged borrower, approved borrower, and denied borrower.[11] Non-borrowers are those who didn't apply for loans because they didn't need credit while discouraged borrowers are those who didn't apply for loans because they feared rejection although they needed credit. Likewise, approved borrowers are defined as those whose loan applications are approved while denied borrowers are defined as those whose loan applications are denied.[12]

To increase the sample size and obtain more precise estimates, this research pools three waves of the SSBF data (1993, 1998, and 2003). Looking at Table A2 in the Appendix, the descriptive statistics from the pooled SSBF data are presented by borrower types (e.g., approved, denied borrower) and across the survey years. Including the descriptive statistics, all the regression results presented in the paper use sampling weights, which are designed to take account of the stratified sampling design.

When different cross sections are pooled as in this paper, however, there is a caveat that should be pointed out. Pooling can be justified only insofar as the relationship between the outcome variable and at least some of the explanatory variables remains constant over time (Wooldridge 2013). To justify pooling different cross sections, we can check whether similar patterns between variables appear across the survey years. For example, the patterns for the proportion of each borrower type is very similar over time. In particular, regardless of the survey year, non-borrowers are the largest proportion, followed by approved borrowers, discouraged borrowers, and denied borrowers. Other patterns are similar as well. Also, each of the three samples was run separately based on Model 8 below (i.e., fully controlled) in Table 1 to check whether the same results can be observed. These show that the coefficients of the African American dummy variable are within sampling error as is that for White females (in each case relative to White males). We do find some statistically significant differences for the coefficients of Hispanic and other races.[13]

Empirical Results

Descriptive Statistics from the pooled SSBF data[14]

As presented by Rebel A. Cole (2008), the weighted descriptive statistics in Appendix Table A2 are classified by borrower type: non-borrowers, discouraged borrowers, approved borrowers, and denied borrowers. The pooled SSBF samples used for Table A2 include 12,412 observations in total—4637 from the 1993 SSBF, 3551 from the 1998 SSBF, and 4224 from the 2003 SSBF.[15] By racial group, the pooled SSBF samples are broken into 2302 minority-owned small businesses (825 African American, 671 Hispanic, and 806 other), 8234 small businesses owned by White males, and 1876 small businesses owned by White females.

Since our approach is to identify the existence of discrimination in small business lending markets, the paper uses extensive information on credit history, firm and owner characteristics, loan and lender characteristics, and geographic characteristics in the pooled SSBF samples. These variables are critical in the sense that lenders' expected profits on the approved loans are based mainly on the probability of loan repayment. Lenders therefore are expected to assess a firm's profitability and likelihood of loan repayment based on these variables (Bostic and Lampani, 1999).

We use the natural log of total sales, profits, and firm net worth to measure firm size, which is shown to be closely related to demand for credit (Jovanovic 1982). A firm's organization status (cooperation, partnership, sole proprietorship) and its industry classification (seven categories) also are used since they are likely to identify differences in borrowing constraints. For example, corporations are anticipated to be more willing to take on debt because of their limited liability protection (Ang 1991). Owners' age, education, and managerial experience are also controlled. Prior research on the relationship between entrepreneurship and small business viability shows that an owner's education and managerial experience are a measure of the owner's human capital, which is positively related to a firm survival (Bates 1990).

There are other variables that may affect a lender's loan decision. We use lender type (commercial bank, savings bank, finance companies, other), and the length of the relationship between a small business and a lender. Caren Grown and Timothy Bates (1992), for example, hypothesize that commercial banks compared to other financial institutions tend to approve larger loans to borrowers, and Cole (2008) argues that specialized lenders such as finance companies and savings associations offer only specialized loans (e.g., equipment loans). Allen N. Berger and Gregory F. Udell (1995) also show that strong relationships (in part measured by the length of time) between small businesses and lenders increase the likelihood of loans. The definitions of all the variables used in the analyses are presented in Appendix Table A1.

One of the main reasons why the weighted descriptive statistics are presented by borrower type in this paper is that the different characteristics among the borrower types provide us with a sense of how sample selection could occur in small-business lending markets. In this context, descriptive statistics in Table A2 suggest that there exist significant differences in characteristics among borrowers. For example, looking at the proportion of business obligations that are delinquent (i.e., Business Delinquency in Table A2), discouraged borrowers are quite similar to denied borrowers across the survey years—their proportions of delinquency are higher than the other two borrower types (i.e., non-borrowers and approved borrowers). Likewise, looking at the proportions of those who had faced bankruptcy (see Table A2), non-borrowers and approved borrowers are similar to one another across the survey years in that their bankruptcy proportions are lower compared with discouraged and denied borrowers.

Although these findings are not observed for all variables, it is confirmed in general that non-borrowers and approved borrowers are similar to one another while discouraged borrowers and denied borrowers are also similar to one another. We can see that discouraged and denied borrowers have poor credit quality (e.g., bankruptcy), small-size businesses (e.g., sales), less education (e.g., college degree), less business experience, and they are younger.

If we calculate descriptive statistics by racial group, similar patterns also arise (results not presented). For example, looking at the proportion of business obligations that are delinquent, Black-owned small businesses have the highest proportions across the survey years. Compared with White-owned small businesses, minority-owned small businesses are generally disadvantaged in terms of credit quality, business size, education, and so on. These differences among racial groups are also observed in the loan denial rate. The rate of loan denial is about 0.51 for African Americans, 0.26 for Hispanics, 0.26 for others, 0.11 for White males, and 0.16 for White females.

Regression Results

Since the purpose of the paper is to identify the existence of discrimination that may occur in small-business lending markets based on lenders' loan denial decisions, we will first look at regression results obtained when the choice of whether to apply for a loan is not considered. Next, we will see regression results obtained when this sample selection process is considered jointly with the loan denial decision process.

Table 1. Discrimination estimates[16]

Model Specification	African American	Hispanic	Other	White Women	No. of Observations & R^2
Model 1:	0.3130***	0.1034***	0.1370***	0.0261	N = 4,644
Year fixed effects only	(0.0595)	(0.0328)	(0.0366)	(0.0213)	$R^2 = 0.12$
Model 2:	0.2409***	0.0965***	0.1278***	0.0224	N = 4,644
Model 1 + credit history	(0.0666)	(0.0307)	(0.0346)	(0.0206)	$R^2 = 0.18$
Model 3:	0.1856***	0.0731***	0.1071***	−0.0034	N = 4,644
Model 2 + firm characteristics	(0.0538)	(0.0277)	(0.0334)	(0.0184)	$R^2 = 0.22$
Model 4:	0.1926***	0.0729***	0.1120***	−0.0024	N = 4,644
Model 3 + owner characteristics	(0.0555)	(0.0280)	(0.0332)	(0.0184)	$R^2 = 0.23$
Model 5:	0.1921***	0.0716***	0.1076***	−0.0007	N = 4,644
Model 4 + geographic characteristics	(0.0629)	(0.0274)	(0.0320)	(0.0184)	$R^2 = 0.24$
Model 6:	0.1791***	0.0727***	0.1210***	0.0004	N = 4,644
Model 5 + SIC codes	(0.0549)	(0.0271)	(0.0328)	(0.0186)	$R^2 = 0.25$
Model 7:	0.1572***	0.0490*	0.1024***	−0.0079	N = 4,644
Model 6 + loan characteristics	(0.0468)	(0.0257)	(0.0319)	(0.0178)	$R^2 = 0.27$
Model 8:	0.1552***	0.0495*	0.0977***	−0.0097	N = 4,644
Model 7 + lender characteristics	(0.0451)	(0.0257)	(0.0315)	(0.0177)	$R^2 = 0.28$

[a] This table reports average marginal effects of race dummy variables (e.g., Hispanic) and their robust standard errors. Regarding the full list of variables controlled for here, please see Table A3

No Correction for Sample Selection

Regression results in Table 1 are based on the pooled SSBFs.[17] Model 1 in Table 1 controls race dummy variables and the survey fixed effects (i.e., dummy variables for survey years) only and it shows average marginal effects of minority status in small business lending markets. For example, Model 1 shows that Blacks, Hispanics, and other races face, on average, about 31%, 10%, and 13% greater chance of being denied loans compared to White males (the omitted category), respectively. With more controls, the coefficients associated with minority owned businesses dramatically decline, but they are still statistically significant. Model 2 in Table 1 shows that owners' credit characteristics seem to explain much of the relationship between race and the chance of being denied a loan. However, Model 6 shows that there is little change in the coefficients when firm industry (e.g., manufacture or transportation) is added to Model 5. In Model 8, we see that the relationship declines relatively little when loan and lender characteristics are controlled.

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Following Blanchard et al. (2008), Model 8 controls for all the variables: owners' credit histories, firms' characteristics, owners' characteristics, geographic characteristics, loan characteristics, and lender characteristics. The results in Model 1 – Model 8 confirm the view that minority-owned small businesses face higher chances of being denied loans compared with White male-owned small businesses, even with a large number of factors controlled.[18] Our findings are consistent with others in the credit market literature (Blanchard et al., 2008). We find the coefficients of Hispanic and other races in our model to be statistically significant whereas others do not, which may be mainly due to our greater sample size, which decreases the standard errors of the coefficients of the race dummy variables.

Previous research adds to regression equations a variable that indicates whether the lender was in the same metropolitan area or county as the firm (Blanchard et al., 2008; Petersen and Rajan, 1994), but we do not control for this variable in any model specification presented in the paper since there might exist a possibility that a small business owner may have choice regarding the location of the lender, which causes endogeneity.

In the same context, loan characteristics (e.g., loan type) and lender characteristics (e.g., lender type) can also be viewed as endogenous variables that borrowers can choose (Smith and Cloud, 2018). For estimates not to suffer such bias, it must be the case that, controlling for credit history, owner characteristics, and firm characteristics, unobserved factors in the error term of the loan denial equation must be uncorrelated with loan and lender characteristics that explain the lender's loan denial decision.[19]

Model specifications presented in Table 1, however, do not consider the sample selection process that occurs in small-business lending markets. More specifically, non-borrowers and discouraged borrowers, who didn't submit loan applications, are not considered in the lender's loan decision process. As shown by Jeffrey M. Wooldridge (2010), if the selection process can be solely determined by exogenous variables that are controlled for in the loan denial equations, a standard regression approach such as a probit model can produce consistent estimates regardless of whether the sample selection process is considered jointly. However, since it is a very strong assumption that the factors that determine whether a borrower applies for a loan are the same as those that are controlled in our analyses, we consider corrections for the selection bias problems.

Correction for Sample Selection

As briefly mentioned above, the sample selection process—whether a small business owner applies for a loan—could be related to the lender's loan denial decision. In other words, since the error term in the outcome equation (i.e., the lender's denial decision process) is potentially correlated to the error term in the selection equation (i.e., a borrower's loan application decision), a standard probit approach may not produce consistent estimates. Therefore, we must estimate the outcome equation and the selection equation jointly to obtain consistent estimates of the coefficients of interest.

As pointed out in the empirical literature that uses Heckman's methods, however, the selection equation should normally have exclusion restrictions in the bivariate probit sample selection model (Cameron and Trivedi, 2005; Wooldridge 2010). More specifically, there should be at least one regressor included in the selection equation but not in the outcome equation. Otherwise, the inverse Mills ratio in Equation (18) may be strongly correlated with the other measures in the equation, which may jeopardize the validity of the outcome and the selection equation estimation.

We have implemented an alternative model specification for the bivariate probit sample selection model to see how exclusion restrictions can influence the coefficients of interest. The exclusion restrictions used in this paper assume that the interaction terms of industry and region dummy variables affect the selection equation only but do not affect the outcome equation directly as long as owners' credit histories, firms' characteristics, owners' characteristics, geographic characteristics, industry, loan characteristics, and lender characteristics are controlled.

Our justification for this assumption is that a firm's decision to apply for loans may be based on considerations that matter for a firm's productivity and profit, which means that the location and the characteristics of industry to which a firm belongs jointly affect a firm's behavior. Considering cluster effects promote both competition and cooperation among small businesses in an area, a firm's decision to apply for a loan may be affected by the interaction of region and firm industry (i.e., the interaction terms to which the exclusion restrictions apply), but a bank's decision to evaluate loan applications (e.g., loan denial) may be simpler—a bank takes into account region and industry in a simple way, (i.e., in accord with the additive terms in the outcome equation as long as an extensive set of variables are controlled).

Looking at Table 2, for example, the model with Heckman Correction (i.e., Panel A) shows that Black-owned small businesses have, on average, a 15% higher chance of being denied loans compared to White-owned businesses (the omitted category), where the outcome equation is the same as Model 8 in Table 1 (i.e., loan and lender characteristics included in the outcome equation), but the selection equation is considered jointly. Looking at the selection equation—whether to apply for a loan—that is the same as the outcome equation except it does not include loan and lender characteristics, we see that Black-owned small businesses are not more likely to apply for a loan compared to White-owned small businesses.

What is interesting in Table 2 is that the effects of selection bias seem to underestimate the marginal effects of Model 8 in Table 1, provided that the model specification with Heckman Correction is correct. Regardless of whether exclusion restrictions are implemented (i.e., Panel B), the model specifications in Table 2 show the same consistent pattern, (i.e., that minorities face higher chances of being turned down for loans). These findings also suggest that selection bias can be ignored, and the use of the simple specification can be justified in estimating the effects of race on loan denial if an extensive set of variables controlled as shown in Model 8 in Table 1.

For comparison, regression results in Table 1 based on a standard probit model and those based on the bivariate probit sample selection models in Table 2 show that the coefficients associated with the different minority groups that are statistically significant in a standard probit model remain statistically significant in the bivariate probit sample selection model as well. Also, the sizes of the coefficients for Black and Hispanic ownership in both models are similar to one another, which is consistent with what Blanchard et al. (2008) found. Therefore, it can be argued from the regression results that the effects of selection bias problems are not large in small business lending markets if an extensive set of independent variables are controlled.

Discussion

The first regression results presented in this paper are based on a standard probit regression approach with a variety of control variables (e.g., credit history, firm and owner characteristics) and they show a consistent pattern of differential denial for minorities regardless of model specification. However, in spite of the consistent regression results observed when various measures are controlled in the standard probit regression approach, since

Table 2. Estimates from different bivariate probit sample selection models in loan denial equations with pooled SSBFs data

Model Specification	African American	Hispanic	Other	White Women	No. of Observations
Panel A: Bivariate probit sample selection Model 1[a]	Outcome equation: loan and lender characteristics included Selection equation: loan and lender characteristics excluded with identifying variables				
Denial	0.1490***	0.0585*	0.1489***	0.0187	N = 12,198
	(0.0411)	(0.0322)	(0.0331)	(0.0242)	
Apply[b]	0.0354	−0.0130	−0.0646***	−0.0364***	N = 12,198
	(0.0248)	(0.0224)	(0.0192)	(0.0132)	
Correlation between error terms in estimation equations	−0.8843***				
Panel B: Bivariate probit sample selection Model 3	Outcome equation: loan and lender characteristics included Selection equation: loan and lender characteristics excluded without identifying variables				
Denial	0.1475***	0.0609*	0.1461***	0.0179	N = 12,198
	(0.0360)	(0.0314)	(0.0314)	(0.0243)	
Apply	0.0331	−0.0153	−0.0692***	−0.0369***	N = 12,198
	(0.0250)	(0.0224)	(0.0192)	(0.0133)	
Correlation between error terms in estimation equations	−0.8800***				
Model 8 from Table 1 (No Correction)	0.1552***	0.0495*	0.0977***	−0.0997	N = 4,644
	(0.0451)	(0.0257)	(0.0315)	(0.0177)	

[a] The model specification can be interpreted as follows: The outcome equation includes all the independent variables as in Model (8) in Table 1. However, the selection equation excludes loan and lender characteristics, but includes identifying variables - the interaction terms of industry and region dummy variables.

[b] The coefficients in all selection equations are regression estimates, not marginal effects.

sample selection is not considered, one should be careful not to interpret these results as evidence that minorities are discriminated against in small business lending markets.

The paper implements a bivariate probit sample selection model to consider the outcome and the selection equation jointly. To see how different model specifications—for example, a bivariate probit sample selection model with and without exclusion restrictions—can affect the estimates of interest, this paper implements different bivariate probit sample selection models. As presented in Table 2, the regression results are similar to one another regardless of model specification. More specifically, in the four different bivariate probit sample selection models, the sizes of the coefficients are similar to one another, although the results are not presented here.

Regardless of the methods used to correct for sample selection, the results in Table 2 suggest that selection bias has little effect on estimates of coefficients of interest, although the correction factor is statistically significant in all specifications. We can therefore argue that the simple specification that ignores selection is valid in estimating the effects of race on loan denial.

Summary and Conclusions

The literature on credit market discrimination shows consistent results that can be interpreted as evidence that minority-owned small businesses may be discriminated against compared to their counterparts (i.e., White-owned small businesses) in obtaining loans.

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This paper adds to the literature on small-business credit markets by using pooled cross sections (i.e., the SSBFs) to get more precise estimates and provide statistics with more power. Compared to prior studies, for example, regression estimates in Table 1 have smaller standard errors. In other words, with the large sample used, this paper tries to provide more precise estimates of coefficients using alternative identification strategies. By using a bivariate probit sample selection model, this paper also shows that regression estimates are much the same regardless of whether exclusion restrictions are used.

Regardless of model specification based on either a standard probit or a bivariate probit sample selection model, the paper shows that there exists a positive race differential in loan denial, which indicates that minority-owned small businesses are more likely to be turned down for loans. However, it should be noted that identification strategies used in this paper have some limitations. First, parametric assumptions are used in model specifications. More specifically, it is assumed that we know a specific functional form of a lender's loan denial and of a borrower's loan application decision process. Second, there is a possibility that exclusion restrictions used in our analyses may not be valid. Third, there might be other variables that may not be included in the datasets but affect the likelihood of loan denial and loan application decision, and their omission may bias estimates of the effect of race. For example, if we assume that the owner's bargaining ability is an important factor that can affect a lender's loan decision process, is correlated with race, but cannot be observed by a researcher, then the estimated coefficients for minority-owned small businesses will be biased.

Our findings have policy implications. First, as pointed out in Blanchard et al. (2008), higher denial rates for minority-owned small businesses can be interpreted as evidence that lenders discriminate against minority-owned small businesses and, therefore, regulators can assume that racial discrimination exists in small business lending markets unless lenders prove that any remaining racial differences in loan approval can be justified by legitimate business considerations.

Second, since the constraints in access to financial resources greatly impact small business operations, monetary tightening is expected to have a large effect on small business sales and cause a contraction of lending to small businesses. In this case, minority-owned small businesses may have a harder time to obtain a loan during a period of tight money (Gertler and Gilchrist, 1994). Therefore, federal financial regulatory institutions should be required to help minority-owned small businesses to secure sources of capital for their business operations during economic downturns.

Last but not least, considering difficulty in obtaining sources of capital observed in this research, more financial programs need to be implemented that are designed for minority-owned small businesses to secure financial resources. For example, the U.S. Small Business Association's Minority-Owned Businesses Development Program provides one-on-one counseling sessions, training workshops, and management assistance to help minority-owned firms finance their businesses.[20] Further, financial regulatory institutions such as the Consumer Financial Protection Bureau need to monitor financial institutions (e.g., banks) to keep minority-owned small businesses safe from unfair practices observed in financial industries.

Supplementary Materials

To view supplementary material for this article, please visit http://doi.org/10.1017/S1742058X23000012.

Notes

[1] For more information on statistics about small businesses, see https://www.sba.gov/advocacy/small-business-facts-and-infographics.

[2] For more information on statistical and preference-based discrimination, see Becker (1957), Phelps (1972), and Arrow (1973).

[3] Longhofer and Peters (2005) show an interesting theoretical result that describes how minority owners' self-selection can induce lenders to discriminate against a group even if they do not have discriminatory preferences.

[4] For more information on ECOA and its implications for credit markets, see https://www.justice.gov/crt/equal-credit-opportunity-act-3.

[5] Among different kinds of discrimination analyzed in Becker (1971), we will focus only on employer discrimination since its implications can be applied directly to a lender's loan decision process.

[6] The framework of the loan-denial decision model introduced in this section is based mainly on Ross and Yinger (2002).

[7] Technically, the bivariate probit sample selection model used in this paper is different from Heckman's estimator in that Heckman (1979) derives results in the case where the outcome variable is continuous, whereas it is discrete in this paper. As noted in Van de Ven and Praag (1981, p. 239), however, the bivariate probit sample selection model is virtually identical to Heckman's approach. Hereafter, we will not distinguish between the bivariate probit sample selection model and Heckman's estimator.

[8] The derivation of the likelihood function for the bivariate probit sample selection model provided here is based on Van de Ven and Praag (1981).

[9] See Heckman (1979, pp. 156–157) for a derivation of υ_i^2.

[10] For detailed information on the SSBF, please see Bitler et al. (2001), Cole and Wolken (1995), and Mach and Wolken (2006).

[11] The definition of borrower type follows Cole (2008).

[12] Table A1 in the Appendix shows a list of the variables used in this paper and their definitions.

[13] The coefficients of race dummy variables across the survey years are presented in Table A4 in the Appendix.

[14] The way the descriptive statistics are presented (i.e., by borrower type) is based on Cole (2008).

[15] As pointed out in Blanchard et al. (2008, p. 477), the 1998 SSBF contains ten observations whose most recent loan applications are not identified, so they are dropped from Table A2. For the same reason, thirteen observations in the 2003 SSBF are dropped. Three observations in the 2003 SSBF are also dropped because they belong to two race categories (i.e., Hispanic and the "other" race category).

[16] The format of the regression results is based on Blanchard et al. (2008).

[17] All coefficients for variables in the models can be found in Table A3.

[18] In addition to model specifications presented in Table 1, we also considered racial measures that distinguished by gender (for example, we broke race dummy variables into African American males and females) to see if there exist gender differences for nonWhites in the approval of loan applications, and we found no evidence of such gender differences.

[19] From statistical point of view, conditional on credit history (C), owner characteristics (O), and firm characteristics (F), the relationship between the error term (e) and loan and lender characteristics (L) can be written as E (e | L, C, O, F) = E (e | C, O, F).

[20] For more examples of financial programs, see Palia (2016).

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