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Differential Access to Capital from Financial Institutions by Minority Entrepreneurs

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This article examines whether minority small business borrowers have the same access to loans from financial institutions as similar white borrowers. Using matching methods, I find that African-American borrowers are rejected at an approximately 30 percent higher probability than similar white borrowers. I also find that the impact of unobservable variables has to be greater than 85 percent the impact of observable variables to show no discrimination. This bound seems to be a high number given that I have controlled for a large number of borrower, firm, and lender characteristics. No such differential effect is found for Asian and other minority borrowers. I also find equal expected default losses between African-American and white borrowers. These results are consistent with the information-based, laissez faire, and group hoarding theories of discrimination, and against the taste-based theory of discrimination.

I. Introduction

The importance of small business to economic growth and employment has long been understood by both policymakers and academics. For example, Federal Reserve Chairwoman Janet Yellen recently stated: "After the onset of the crisis, the Federal Reserve took extraordinary steps to stabilize the financial system and halt the plunge in economic activity. Since then the Fed has continued to use its monetary-policy tools to promote the recovery . . . Crucial to this process . . . is job creation. . . . Small businesses, of course, are responsible for a large share of these new jobs" (National Small Business Week event held at the U.S. Chamber of Commerce, May 15, 2014). But banks are a critical part of financing for small firms. According to the 2003 Survey of Small Business Finance (SSBF), 57 percent of debt funding for U.S. small businesses is from banks.

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But do race-based minority entrepreneurs[1] have similar access to loans? The Equal Credit Opportunity Act of 1974 (ECOA), as amended, prohibits discrimination against any applicant with respect to any credit transaction. The Federal Institutions Examination Council (FIEC) manual issued by the regulators explains that ECOA "applies to any extension of credit, including extensions of credit to small businesses."[2]

The ideal social experiment is to have two identical borrowers who differ only by race (minority vs. white borrower). This is similar to studies undertaken in medicine, wherein one group of patients is given a placebo, and another group of patients the drug that is being tested. The patients do not know whether the pill that they took is the drug or the placebo. The two groups are then followed for differences in the efficacy of the drug and for side-effects in order to examine if the drug *caused* the patients' health to improve. I do not do such an experiment in minority entrepreneurship because Heckman and Seligman (1992) and Heckman (1998) argue that testers are either consciously or unconsciously trained to look for effects that are consistent with their beliefs, experiments are not based on market data, and because it is extremely hard to erase all possible differences in the audit pair due to unobservable effects.

But I can create a pseudo-experiment using causal inference methods.[3] Specifically, I am able to mimic in actual data an experimental audit study wherein similar risk borrowers are randomly assigned to lenders but differ only in one dimension, namely, the race of their principal owner. Accordingly, this article makes the following contributions to the existing literature. First, the prior literature[4] uses standard estimation techniques such as logistic or probit regressions and finds that minority borrowers have a higher probability of their loan application being rejected by their lender than do white borrowers. Consistent with this literature, I find that the regression coefficient for minority borrowers is positive and statistically significantly related to whether the loan was rejected. But the regression coefficient on minority borrowers can be biased if the characteristics of minority borrowers vary statistically significantly from the characteristics of white borrowers (see Section II for details). Using four tests (t test for differences in means with and without normalization, differences in standard deviations, and the Kolmogorov-Smirnov test), I find strong evidence that the characteristics of minority borrowers are statistically significantly different from the characteristics of white borrowers. This suggests that the regression coefficient on minority borrower is biased when one uses logistic or probit regressions.

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[1]In this article I define minorities as borrowers who are either African American, or Asian, or Hispanic, or Native American, or Hawaiian/Pacific Islander small business owners.

[2]See Federal Institutions Examination Council, Intraagency Fair Lending Examination Procedures, Aug. 2009, page i.

[3]See Section II and Dahejia and Wahba (1999).

[4]See Section III for a detailed explanation of the literature on discrimination and access to credit.

I then rectify the above bias by using causal inference estimation methods—derived by the seminal papers of Rubin (1974) and Rosenbaum and Rubin (1983, 1984)—in order to examine whether minority borrowers have their loan application rejected with the same probability as white borrowers. The idea behind the causal inference estimation method is deceptively simple, and can be explained without detailed math. Specifically, the researcher is usually interested in a single intervention or quasi-experiment, often referred to as "treatment" (in my setting, minority borrower), which is then compared to the baseline "control" (white borrower). I can then accurately test if race-based discrimination exists in access to small business loans from financial institutions. With regard to causal inference methods, Imbens and Rubin (2014:7) state: "Another interesting comparison is to the 'but for' concept in legal settings. Suppose someone committed an action that is harmful, and a second person suffered damages. From a legal perspective, the damage that the second person is entitled to collect is the difference between the economic position of the plaintiff had the harmful event not occurred (the economic position 'but for' the harmful action), and the actual economic position of the plaintiff. Clearly, this is a comparison of the potential outcome that was not realized and the realized potential outcome, this difference being the *causal effect* of the harmful action" (emphasis added). In my setting, I am able to mimic in actual data an experimental audit study wherein similar risk firms are randomly assigned to lenders but differ only in one dimension, namely, the race of their owner (the Imbens and Rubin (2014) "but for" argument). When I do so, I find that the regression coefficient on minority borrowers becomes statistically insignificant, suggesting that there is no discrimination.

Second, it is possible that aggregating all minority groups into one category masks the confounding effects of different race-based groups. Accordingly, I divide the full sample of minority borrowers into different races (African American, Asian, and "Others" comprising of Hispanic, Native American, and Hawaiian/Pacific Islander). Of the 127 total minority borrowers, there are 47 African-American borrowers, 61 Asian borrowers, and 19 "Other" borrowers. I could not further categorize the "Other" group because of data availability (my sample has only 6 Hispanics, 12 Native Americans, and 1 Hawaiian/Pacific Islander). I find that African-American-owned firms are generally rejected at a higher probability (approximately 30 percent higher) than similar risk white-owned firms. No such differential effect is found for Asian-owned firms or for the "Others" category. These results show that, wherever possible, based on data availability, researchers should examine for the most granular definition of each minority group.

Third, my results are robust to three different causal inference methods, namely, propensity score matching, inverse probability weighting matching, and nearest neighbor matching. Fourth, I find similar expected default losses between African-American-owned and white-owned firms. Finding higher probabilities of rejection and equal *expected* losses for African-American-owned firms, when compared to white-owned firms, is consistent with the information-based, laissez faire, and group hoarding theories of discrimination. I do not find evidence in support of the taste-based theory of discrimination.

Fifth, I check whether unobservable variables significantly bias my results for African-American borrowers. These unobservable variables could be quantifiable (such as the lender's screening methodology) but are not included due to data unavailability, or could be nonquantifiable (such as the borrower's bargaining power). Although I have included a large set of covariates, one cannot completely control for all unobservable variables. Therefore, I bound my point estimates. In doing so, this is the first article to use the Rosenbaum bounds (2002)[5] to capture the impact of unobservable variables on the probability of a loan application being rejected. I find that the impact of unobservable variables has to be greater than 85 percent the impact of observable variables to show no discrimination. This bound seems to be a high number given that I have controlled for a comprehensive list of borrowers' risk variables that include their actual credit score and wealth. If the effect of the unobservable variables is less than this bound, then I have found a causal impact of race on access to capital for African-American-owned small business firms.

There are a number of limitations of this study. First, I have used Dun and Bradstreet's business credit score, which is the only score provided by SSBF. These credit scores might be different from the credit scores used by the lender (from Equifax, Experian, Trans Union, or a proprietary score). There might not be a high correlation between the credit scores. Second, the number of African-American, Asian, and Other principal owners who borrow from financial institutions in my sample is small. Finding a statistically significant result in a small sample increases the chances that the actual impact might be higher if the sample was larger. But having a small sample suffers from the limitation that these observations may not be representative of the full population. That said, what I need, and have, for good matching is a large sample of white borrowers (over 1,300) from which I can match for each minority borrower. Third, SSBF provides data only for a few lender characteristics. I do not have data on the size of the financial institution or the type of loan (term loan, credit line, etc., which although given, is often missing in SSBF). Fourth, even within races, there are significant differences. It is argued that there are significant differences between the subcategories of Hispanics such as Mexicans, Cubans, Salvadorans, and so forth, and among Asians such as Koreans, Chinese, and so forth. Differences have also been suggested based on skin color (see, e.g., Pulido & Pastor 2013; Hannon 2015; Hannon & DeFina forthcoming). I am unable to make such distinctions due to data limitations. With respect to caveats three and four above, my results on the Rosenbaum bounds suggest that these omitted variables has to have an affect greater than 85 percent of the impact of included independent variables to show no discrimination for African-American borrowers.

II. Causal Inference Methods

Causal inference is inherently a comparison of potential outcomes (see Rubin 1974; Rosenbaum & Rubin 1983, 1984). The causal effect for individual *i* is the comparison of individual *i*'s outcome if the individual receives the treatment ($Y_i(1)$), and the same individual's outcome if she receives the control ($Y_i(0)$). Causality is hence defined as

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[5]See Section V.D. for further details.

equal to $Y_i(1) - Y_i(0)$. In our setting, the outcomes are whether the borrower's loan application is granted or rejected, and treatment is whether the applicant is a minority borrower; the control is whether the applicant is a white borrower. The causal question is whether being a minority borrower increases one's probability of a small business loan application being rejected, ceteris paribus. One observes that minorities have a higher probability of their loan application being rejected when they apply for a loan. The question of causality implies that had the borrower not been a minority, ceteris paribus, his or her loan would have had a lower probability of being rejected.

But estimating causality is challenging. The fundamental problem of causal inference (Holland 1986) is that for each individual borrower I can observe only one of these potential outcomes. In my setting, I can observe if a minority or white borrower was either denied or granted a loan, and not both. The estimation of causal effects can thus be thought of as a missing data problem (Rubin 1974). I would like to compare treated ($R = 1$ for minority) and control ($R = 0$) groups *who are very similar in observable risk variables X.*[6] I use three matching methods, which I describe below.

A. *Propensity Score Matching*

The first method is the propensity score method. Let us define the propensity score $\rho(X)$ as the selection probability conditional on the observable risk variables X, namely, $\rho(X) = \Pr(R = 1 \mid X)$. Under two assumptions, one, the treatment assignment R is independent of potential outcomes $Y_i(1)$ and $Y_i(0)$, namely, $Y_i(1), Y_i(0) \perp R \mid X$; and, two, often called the "common support" assumption, wherein there is a positive probability of receiving treatment for all values (i.e., $0 < \Pr(R=1 \mid X) < 1$). Rosenbaum and Rubin (1983) prove that conditioning on the propensity score is equal to having independence between the treatment indicator R and potential outcomes $Y_i(1)$, $Y_i(0)$. In other words,

$$\Pr\ (R=1 \mid Y_i(1),\ Y_i(0),\ \rho(x)) = (Y_i(1),\ Y_i(0)) \perp R \mid \rho(x).$$

The above equation results in a substantial reduction in the dimensionality of the matching variables as one does not need to match on the covariates (Dahejia & Wahba 1999). In the actual estimation I use a logistic regression to estimate $\rho(X)$. Abadie and Imbens (2006, 2011) derive the standard errors for such an estimate.

B. *Inverse Probability Weighting Estimator*

The inverse probability weighting estimator uses weighted averages of the observed outcome variable to estimate the means of the potential outcomes. Each weight is the inverse of the estimated probability that an individual is a minority. Outcomes of

[6]A number of papers, including Cochran and Rubin (1973), Rubin (1973a, 1974, 2001), Heckman et al. (1998), and Rubin and Thomas (2000), have shown that linear regressions and their adjustments can increase the bias in the estimated treatment effect, especially when there are significant differences between the means and variances between the treated and control groups. I show in Section V.B. that there are significant differences between such observable characteristics in our sample.

individuals who are more likely to be a minority borrower receive a weight close to 1, and outcomes of individuals who are more likely to be a white borrower receive a weight greater than 1. As the propensity score $\rho(X)$ is the probability of being a minority borrower conditional on the observable risk variables X, the weights are therefore $\rho(X)$ and $1 - \rho(X)$.[7]

C. Nearest Neighbor Matching Estimator

Rather than conditioning on the probability of being a minority borrower, the nearest neighbor matching estimator conditions on the covariates X directly. This estimator is nonparametric in that it has no functional form, but it comes with a price. It converges to the true value at a rate of square root of the sample size.[8] I use matching with replacement to reduce the bias.

III. Related Literature

A. Theories of Discrimination

There are many theories of discrimination in sociology and law and economics. While there are overlaps between these theories suggesting they are not always mutually exclusive, for ease of explanation, I categorize them in the following manner. Additionally, I present the predicted testable hypothesis for each theory. As explained below, note that all theories suggest that minority borrowers would be rejected at a higher probability than white borrowers with similar risk characteristics. The distinguishing characteristic between the various theories is the differences in the *expected* default losses between minority and white borrowers. Because lenders can also discriminate when *actual* losses occur, I focus on expected default losses.[9]

1. Taste-Based Discrimination

The study of discrimination in law and economics began with the seminal study by Becker (1957).[10] Under what is now often called the taste-based theory of discrimination, the motive that drives the discriminatory behavior is animus or prejudice toward a particular group. That is, lenders knowingly incur the costs of prejudice when interacting with certain minority groups. Whereas the motive under Becker (1957) is explicit, Bertrand

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[7]See Busso et al. (2014) for conditions wherein this method works well.

[8]See Abadi and Imbens (2006, 2011).

[9]Consistent with Han (2004), I also use expected default losses because they can be empirically estimated. They are defined as the probability of default times the size of the loan, wherein the probability of default is proxied by Ohlson's (1980) O score. This proxy for the probability of default has also been used by Dichev (1998) and Griffin and Lemmon (2002).

[10]Many of the theoretical papers generally focus on the labor market between employers and employees. For ease of explanation, I rephrase their arguments in terms of lenders and borrowers.

et al. (2005) offer a refinement of motive, namely, that discrimination can take place through "implicit" attitudes, which are unconscious mental associations toward agents of a certain group. These implicit associations are often fleeting and impulsive rather than deeply thought and rational. Under this theory, lenders inaccurately perceive minority borrowers to have higher risks than white borrowers and therefore reject them more often. In doing so, the lenders bear a cost that reduces their expected profit on the loan. In a general equilibrium model, Han (2004) shows that expected default losses should be less for minorities than for whites under the taste-based theory of discrimination. Accordingly, if taste-based discrimination is to be confirmed, I would expect to find minorities to have higher loan rejection probabilities and *lower* expected default losses than whites.

2. Information-Based or Statistical Discrimination

Under the information-based or statistical discrimination theory of Phelps (1972), Arrow (1972), and Bordalo et al. (2016), the motive that drives the agent's behavior is expected profit maximization. In an imperfect information world, economic agents discriminate against certain groups because they believe or speculate that these groups have higher risks, which will reduce their profit. In Arrow (1972) and Phelps (1972), stereotypes are accurate as they substitute for missing information. In Bordalo et al. (2016), the decisionmaker only recalls the group's most representative or distinctive group characteristic. Stereotypes are inaccurate because the decisionmaker overreacts to information that confirms the stereotype (exhibiting "confirmation bias") and ignores any information that contradicts the stereotype (exhibiting "base rate neglect"). Interestingly, in these models, the lender's biased beliefs are confirmed in equilibrium, even though the ex ante probability of loss is identical. Calomiris et al. (1994) and Hunter and Walker (1996) suggest that discrimination against minority borrowers could arise because of lack of cultural affinity between white loan officers and minority borrowers. White loan officers will rely more heavily on basic characteristics that can be easily collected and observed for minorities rather than invest resources in gathering additional "soft" borrower information.

According to Han's (2004) model, the expected default losses for minorities should be greater than or equal to those for whites in order to find support for the information-based theory of discrimination. Accordingly, if information-based or statistical discrimination is to be confirmed, I would expect to find minorities to have higher loan rejection probabilities and expected default losses that are *greater than or equal* to those of whites.

3. Laissez Faire Discrimination

Sociologists such as Bobo et al. (1996) and Bobo and Smith (1998) have suggested that racism against African Americans has moved from the rigid and strictly institutionalized Jim Crow form of racism to the free market or laissez faire form of racism. Under the latter, more modern form of discrimination, these sociologists argue that African Americans are wrongly stereotyped and blamed as the architects of their own disadvantaged status. Accordingly, even racially neutral whites would not support compensatory programs such as affirmative action because they wrongly believe that most African Americans deserve the disadvantaged labor market/housing/loan outcome they face because of their culturally inferior behavior that leads to higher crime, welfare dependency, bankruptcy, and the like. Pager (2003) shows that African-American job applicants who were never incarcerated received fewer callbacks from potential employers than similar white job applicants. In my setting, the laissez faire discrimination theory would suggest that loan applications by minority borrowers would be rejected at a higher probability even though their expected default losses are *equal* to those of white borrowers.

4. Group Hoarding Discrimination

The group hoarding theory of discrimination suggests that people who share group traits like belonging to a similar race have monopoly access to valuable resources that they opportunistically hoard at the expense of people with different traits (Blumer 1958; Tilley 1998; Brown et al. 2003). Status identities enable groups to organize and make resource claims against other groups who do not share the same identity (Murphy 1988; DiTomaso 2013, 2015). White borrowers can obtain more loans from the lender at the expense of minority borrowers because white borrowers are known or more accepted to the white lenders who share their racial traits. In other words, minority borrowers with the same expected losses as white borrowers should have the same probability of their loan being rejected, but have a higher probability of loan rejection because minority borrowers do not share the same traits as the white lender. Accordingly, the group hoarding theory of discrimination would suggest that loan applications by minority borrowers would be rejected at a higher probability even though their expected default losses are *equal* to those of white borrowers.

B. Empirical Studies of Discrimination

Empirical studies have examined discrimination in different settings, from home mortgages to the goods and services market to labor market hiring. With respect to home mortgages, studies have found that the likelihood of rejection by a lender is higher if the borrower is from a minority racial group (e.g., Black et al. 1978; Holmes & Horvitz 1994; Berkovec et al. 1998; Munnell et al. 1996; Hunter & Walker 1996; Ross & Yinger 1999; Clarke et al. 2009; Hubbard et al. 2012). The above articles conduct regression analysis using actual market data. In contrast, Ayres and Siegelman (1995) present evidence from a paired audit experiment that shows new car dealerships in Chicago quote significantly lower prices to white males than to African-American or female buyers. List (2004) finds that minorities received lower offers in the baseball sports card market than majorities. Zusman (2013) finds evidence that fictitious advertisements of used cars by Arab sellers received fewer responses than similar fictitious advertisements by Jewish sellers. Ayres et al. (2011) find that baseball cards photographed as being held by an African-American hand sold for less than cards photographed as being held by a white hand in eBay auctions. Goldin and Rouse (2000) find that hiding the identity of a musician via a screen increased the probability of female musicians being hired by symphony orchestras. Fershtman and Gneezy (2001) find evidence of ethnic discrimination by Israeli Jewish males toward men of Eastern origin in a game of trust. In response to help-wanted ads, Bertrand and Mullainathan (2004) find that "black-sounding" names such as Lakisha and Jamal were less likely to be called back for job interviews than "white-sounding" names such as Emily and Greg. In different experiments, Gneezy et al. (2012) find discriminatory behavior against females, sexual orientation, the disabled, nonwhites, and the elderly in different settings. They find support for information-based discrimination when the source of discrimination is uncontrollable (such as race, gender), and for taste-based discrimination when it is perceived to be controllable (such as sexual orientation).

More directly relevant to this study, a number of articles have examined whether minority small business borrowers have the same probability of their loan application being rejected as white small business borrowers. Bates (1997), Bostic and Lampani (1999), Cavalluzzo and Cavalluzzo (1998), Blanchflower et al. (2003), Cavullozo et al. (2002), Coleman (2002), Cavullozzo and Wolken (2005), Blanchard et al. (2008), Roper and Scott (2009), Roomi et al. (2009), Fairlie and Robb (2010), and Bewaji et al. (2015) find evidence in support of discrimination as minority small business borrowers have a higher probability of their loan application being rejected than white small business borrowers.[11]

All the above articles are limited in that they cannot claim a causal effect of discrimination, as the race variable is correlated with the risk covariates (a result I will show later). As they are not experimental audit studies, they are unable to create a random sample of observationally equivalent small business borrowers that differ only in their race. By using the causal inference methodology, I am able to create a pseudo-random experiment using actual market data that successfully addresses the criticism of experimental audit studies by Heckman and Seligman (1992) and Heckman (1998). Additionally, even after including the social capital and liability of newness measures[12] of Bewaji et al. (2015), I still find evidence that African-American borrowers have a higher probability of their loan being rejected than equivalent risk white borrowers. Finally, I examine how much of my results are impacted by unobservable variables.

IV. Data and Variables

I use the latest (2003) version of the Survey of Small Business Finance (SSBF), which is published by the Division of Research and Statistics of the U.S. Federal Reserve Board of Governors. Unfortunately, the Federal Reserve has discontinued the publication of

[11] While not analyzing whether the entrepreneur was denied or granted credit, Marlow and Patton (2005) study female entrepreneurs in the United Kingdom, Kushnirovich and Heilbrunn (2008) study immigrants in Israel, Sepulveda et al. (2011) study the "superdiverse" migrant enterprises within London, Haynes et al. (2008) study the sources of financing for Mexican-American and Korean-American borrowers, and Aldrich and Zimmer (1986) argue for an evolutionary population perspective for successful entrepreneurship.

[12] These measures are the CEO's age, level of education, and prior industry and entrepreneurial experience.

the Survey of Small Business Finance. The SSBF database is the largest and most comprehensive data set of its type. Between June and December 2004, the Federal Reserve surveyed 4,240 small firms with less than 500 employees that were in operation during December 2003. Surveyed firms represent a random sample of small business firms that are stratified by size, geographic location, race, and gender. SSBF has a wealth of financial statement data, as well as data on the types of financial products used by these firms.

My sample consists of 1,512 observations, 1,385 of which are white borrowers and 127 of which are minority borrowers. The latter group consists of 47 African-American borrowers, 61 Asian borrowers, 6 Hispanic borrowers, 1 Hawaiian/Pacific Islander borrower, and 12 Native-American borrowers. I begin by creating the race-based borrower variables. Specifically, I create a dummy variable, *Minority*, which is set to unity if the borrower is either African American or Asian or Hispanic or Hawaiian/Pacific Islander or Native American, and set to 0 if the borrower is white. I also create a dummy variable, *African American*, which is set to unity if the borrower is African American, and set to 0 if the borrower is white. A similar dummy variable for Asian borrowers (*Asian*) is created. Given the small number of observations for each of the Hispanic, Hawaiian/Pacific Islander, and Native-American borrower groups, I create a variable, *Other*, which is set to unity if the borrower is either Hispanic or Hawaiian/Pacific Islander or Native American, and set to 0 if the borrower is white.

For my dependent variable, I create a dummy variable, *Reject*, which is set to unity if the borrower's loan application is rejected, and set to 0 if it is always approved or sometimes approved or rejected. No borrower has applied for more than one loan. If there is race-based discrimination, the dummy variables on race (namely, *Minority, African American, Asian, Other*) should be positively related to the probability of being rejected for a loan (*Reject*) in the presence of other independent variables.

For my control variables (i.e., other independent variables), I create a large set of borrower, firm, and lender characteristics. Table 1 summarizes the different variables and presents, wherever possible, their expected relationship to the probability of the loan application being rejected (namely, *Reject*). No borrower in the sample has more than one loan application. I begin by including variables that capture borrower characteristics that might potentially correlate with the probability of whether the loan application is rejected. First, I include the borrower's Dun & Bradstreet's business credit score variable, which I call *Credit Risk*. SSBF has the following categories: 1 equal to the most risky scores, namely, 0–10; 2 equal to 11–25; 3 equal to 26–50; 4 equal to 51–75; 5 equal to 76–90; and 6 equal to the least risky scores, namely, 91–100. Note that a lower value for *Credit Risk* denotes more risky firms. Accordingly, I expect *Credit Risk* to be negatively correlated with the probability of the loan application being rejected (*Reject*). I then include the borrower's wealth (*Wealth*), defined as the net worth of the borrower excluding the value of her primary home or current business. Given that it is reasonable that lenders look more favorably at wealthy borrowers, I expect *Wealth* and *Reject* to be negatively correlated. I also include a variable that captures the personal financial distress of the business owner. I define a variable *P_bankrupt*, which is set to unity if in the past seven years the business owner has declared bankruptcy, or if in the past three years the

Table 1: Variable Names, Expected Relationship to the Probability of Loan Rejection, and Description

Name	Expected Relationship	Description
Independent variables		
Reject		Dummy variable set to unity if loan application is always denied, and set to 0 if always approved or sometimes approved/denied
Expected default loss		Is equal to loan size times the expected probability of default; the expected probability of default is proxied by Ohlson's (1980) O-score and is −1.32 – 0.407log(assets) + 6.03(liabilities/assets) – 1.43(working capital/assets) + 0.076(current liabilities/current assets) – 1.72(1 if liabilities > assets, 0 otherwise) – 2.37(net income/assets) – 1.83(funds from operations/liabilities) + 0.285(1 if a net loss for last two years, 0 otherwise) – 0.521(change in net income from current year to previous year/absolute value of change in net income from current year to previous year)
Race variables		
Minority	+	Dummy variable set to unity if borrower is African American or Asian or Hispanic or Hawaiian/Pacific Islander or Native American, and set to 0 if borrower is white
African American	+	Dummy variable set to unity if borrower is African American, and set to 0 if borrower is white
Asian	+	Dummy variable set to unity if borrower is Asian, and set to 0 if borrower is white
Other	+	Dummy variable set to unity if borrower is Hispanic or Hawaiian/Pacific Islander or Native American, and set to 0 if borrower is white
Borrower characteristics		
Credit score	–	Dun & Bradstreet's business credit score; SSBF has the following categories: 1 = most risky scores, namely, 0–10; 2 = 11–25; 3 = 26–50; 4 = 51–75; 5 = 76–90; 6 = least risky scores, namely, 91–100
Wealth	–	Natural logarithm of net worth; the net worth of the owner excludes the value of her primary home and current business
P_bankrupt	+	Dummy set to unity if in the past seven years the business owner has declared bankruptcy, or if in the past three years has had any business obligation due for 60 days or more, or has any business judgments rendered against her
CEO age	–	Age of the CEO in years
Education	–	Highest level of education the borrower has received: 1 = less than high school diploma; 2 = high school or GED; 3 = some college but no degree; 4 = associate degree occupational/academic; 5 = trade school/vocational; 6 = bachelors; 7 = graduate and postgraduate degree
Experience	–	Number of years the borrower has worked managing or owning a business, including this business
Female	+	Dummy variable set to unity if borrower is female, and set to 0 if borrower is male
P_loan	+,–	Dummy variable set to unity if the borrower gave the firm a loan, and set to 0 if did not
Ownership	–	Percentage ownership of the borrower
Firm characteristics		
Size	–	Natural logarithm of total assets

Table 1 *Continued*

Name	*Expected Relationship*	*Description*
Family owned	+,−	Dummy variable set to unity if the business is owned by a family, and set to 0 otherwise
Firm age	–	Number of years the business has been established by current owner
Company	–	Dummy variable set to unity if the business is set up as a corporation, and set to 0 otherwise
Profit	–	Ratio of net income to total assets
Debt	+	Ratio of all liabilities excluding equity to total assets
Cash	–	Ratio of cash holdings to total assets
F_bankrupt	+	Dummy set to unity if in the past seven years the firm has declared bankruptcy, or if the firm in the past three years has had any business obligation due for 60 days or more, or has any business judgments rendered against it
Urban	+	Dummy variable set to unity if firm is located in a MSA, and set to 0 if not
Census		SSBF has the following categories:1 = New England; 2 = Middle Atlantic; 3 = East North Central; 4 = West North Central; 5 = South Atlantic; 6 = East South Central; 7 = West South Central; 8 = Mountain; 9 = Pacific
Sic		= 1 if two-digit SIC code is in mining (10–14); = 2 if two-digit SIC code is in construction (15–19); = 3 if two-digit SIC code is in transportation/public utilities (40–49); = 4 if two-digit SIC code is in wholesale trade (50–51); = 5 if two-digit SIC code is in retail trade (52–59); = 6 if two-digit SIC code is in fire, insurance, & real estate (60–69); = 7 if two-digit SIC code is in services (70–89); = 8 if two-digit SIC code is in public administration (91–98); = 10 if unclassified
Lender characteristics		
Commercial	–	Dummy variable set to unity if lender is a commercial bank, and set to 0 if lender is not
Savings	–	Dummy variable set to unity if lender is a savings bank or a savings and loan association, and set to 0 if lender is not
Relation	–	Number of months lender has conducted business with the borrower
Concentration	+	SSBF has the following categories: 1 = if the Herfindahl-Hirschman Index (HHI) is between 0 and 999; 2 = if HHI less than or equal to 1000 and less than 1800; 3 = if HHI greater than or equal to 1800
Distance	+	Distance in miles between borrower and lender offices

business owner has had any business obligation due for 60 days or more, or has any business judgments rendered against her, and 0 otherwise. I expect *P_bankrupt* and *Reject* to be positively correlated.

I then control for the signaling, social capital, and lender familiarity variables of Bewaji et al. (2015). I include the CEO's age (*CEO Age*), as younger CEO's might be perceived to be more risky and have less access to social networks (Rai 2008; Mudambi & Treichel 2004; De Carolis & Saparito 2006; Bewaji et al. 2015). Therefore, I expect *CEO Age* and *Reject* to be negatively correlated. Education has often been used as a signal of the economic agent's ability and success in entrepreneurial activity (Spence 1973;

Davidson & Honig 2003; Bewaji et al. 2015). SSBF has the following categories for the highest level of education the borrower has obtained: 1 equal to less than high school; 2 equal to high school graduate or GED; 3 equal to some college but no degree; 4 equal to associate's degree in occupational or academic fields; 5 equal to associate's degree in trade or vocational fields; 6 equal to bachelor's degree; and 7 equal to master's and other postgraduate degrees. I create the education variable, *Education*, which maps exactly to the above SSBF categorization. If education is perceived to be a signal of the borrower's future profitability and success, I expect *Education* and *Reject* to be negatively correlated. The borrower's prior industry experience might signal to the lender the borrower's market knowledge and managerial skill as well as access to valuable social networks (Escriba-Esteve et al. 2009; Finkelstein & Hambrick 1990; Kim et al. 2006; Bewaji et al. 2015). Accordingly, I create a variable, *Experience*, defined as the number of years the borrower has worked managing or owning a business, including this business.[13] I expect *Experience* and *Reject* to be negatively correlated.

A number of papers have examined for differences between male and female entrepreneurs in accessing external financial capital markets (e.g., Carter et al. 1997; Coleman 1999, 2000; Coleman & Robb 2009, 2014; Roper & Scott 2009; Robb et al. 2014). Accordingly, I include a dummy variable, *Female*, that is set to unity if the borrower is female, and 0 if the borrower is a male.[14] I expect *Female* and *Reject* to be positively correlated.

It is possible that other shareholders and the owner of the firm have already given the firm a loan. I create a variable *P_loan* that is set to unity if shareholders or the owner has given the firm a loan, and 0 if they did not. On the one hand, the presence of such a loan might suggest to the lender that the owner or shareholders have confidence in the firm's future profitability. In such a case, I would expect *P_loan* and *Reject* to be negatively correlated. On the other hand, the presence of the loan might suggest to lenders that the firm is financially constrained. In this case, I would expect *P_loan* and *Reject* to be positively correlated. It is possible that managerial agency issues of corporate ownership impact the effort put forward by the borrower in making her firm successful. I hence include the variable, *Ownership*, defined as the percentage ownership of the borrower in the firm. Managerial agency theory suggests that having a higher financial stake in the firm makes the borrower work harder and choose investments that maximize firm value. I would therefore expect *Ownership* and *Reject* to be negatively correlated.

I next include a set of firm-specific variables that might be correlated with the loan application being rejected or accepted. The first firm-specific variable is firm size (*Size*), which I define as the natural logarithm of the firm's total assets. I would expect larger firms to have a higher probability of their loan application being accepted, suggesting a negative relationship between *Size* and *Reject*. I also include a dummy variable, *Family Owned*, which is set to unity if the firm is family owned, and 0 if not. On the one

[13]SSBF does not distinguish between the number of years the entrepreneur managed her current and previous business. Additionally, SSBF does not provide data on whether the borrower is a U.S. citizen or not.

[14]All my results hold when I exclude the gender dummy variable.

hand, family ownership might be perceived as an organizational advantage given that family members are all working toward a common goal. In this case, I expect *Family Owned* and *Reject* to be negatively correlated. On the other hand, family ownership might result in a number of personal and business grudges, resulting in noncooperative behavior between family members, suggesting a positive expected correlation between *Family Owned* and *Reject*.

The next firm-specific variable that I include is the firm's age (*Firm Age*). Younger firms are more likely to be perceived by lenders to have not proven their business success and also have less access to business and social networks. Accordingly, I would expect *Firm Age* and *Reject* to be negatively correlated. Similarly, firms that are incorporated as companies might be perceived by lenders to have lower default risk than firms that are sole proprietorships, partnerships, or S-corporations. I create a dummy variable, *Company*, that is set to unity if the organization form of the borrower is a limited liability company, and 0 otherwise. I expect a negative correlation between *Company* and *Reject*. To further control for the firm's financial health, I include the firm's profitability (*Profit*), defined as the ratio of net income to total assets, *Debt*, defined as the ratio of all liabilities excluding equity to total assets, *Cash*, the ratio of cash holdings to total assets, and *F_bankrupt*, which is set to unity if in the past seven years the firm has declared bankruptcy, or if the firm in the past three years has had any business obligation due for 60 days or more, or has any business judgments rendered against it, and 0 otherwise. I expect *Profit* and *Cash* to be negatively correlated with *Reject*, and *Debt* and *F_bankrupt* to be positively correlated with *Reject*.

The location of the firm might be correlated with the probability of the borrower's loan application being rejected. I include a variable, *Urban*, that is set to unity if the firm's headquarters is located in a Metropolitan Statistical Area (MSA), and 0 otherwise. I expect that urban firms are more likely to have their loan application rejected, suggesting a positive expected correlation between *Urban* and *Reject*. I then create a variable, *Census*, that maps SSBF's geographic categories. Specifically, SSBF has the code 1 for New England; 2 for Middle Atlantic; 3 for East North Central; 4 for West North Central; 5 for South Atlantic; 6 for East South Central; 7 for West South Central; 8 for Mountain; and 9 for Pacific. I do not posit any expected relationship between *Reject* and these geographic regions.

To control for industry effects, I set a dummy variable equal to 1 if the two-digit SIC code is in mining (10–14); equal to 2 if the two-digit SIC code is in construction (15–19); equal to 3 if the two-digit SIC code is in transportation/public utilities (40–49); equal to 4 if the two-digit SIC code is in wholesale trade (50–51); equal to 5 if the two-digit SIC code is in retail trade (52–59); equal to 6 if the two-digit SIC code is in fire, insurance, and real estate (60–69); equal to 7 if the two-digit SIC code is in services (70–89); equal to 8 if the two-digit SIC code is in public administration (91–98); and equal to 10 if unclassified. I do not expect a specific correlation between any industry group and the probability of the loan being rejected.

The final set of independent variables that I include captures the lender's characteristics. The first two variables capture the type of financial institution that is examining the loan application. Specifically, I create a dummy variable, *Commercial*, that is set to unity if the lender is a commercial bank, and 0 otherwise; and another dummy variable, *Savings*, that is set to unity if the lender is a either a saving bank or a savings and loan association, and 0 otherwise. It is possible that commercial banks have higher credit standards than saving banks and S&Ls, which in turn have higher lending standards than credit unions, finance companies, and the like. In such a case, I would expect a larger negative relationship between *Commercial* and *Reject*, and a smaller negative relationship between *Savings* and *Reject*.

A number of papers have shown that lending relationships between the borrower and lender impact access to loans and the terms of the loans. For example, Petersen and Rajan (1994) show that lending rates to small businesses are lower when the borrower and the bank have a longer relationship. Accordingly, I define a variable, *Relation*, which is calculated as the number of months the borrowing firm has had a previous lending relationship with the lender. Given prior experience with the borrower, I would expect lenders to more readily grant loans to entrepreneurs with whom they have previously dealt. I would therefore predict a negative correlation between *Reject* and *Relation*. Petersen and Rajan (1994) also suggest that more concentrated banking markets have financial institutions with stricter lending standards. I create a dummy variable, *Hhi*, equal to 1 if the Herfindahl-Hirschman Index (HHI) is between 0 and 1000, equal to 2 if the HHI is between 1001 and 1799, and equal to 3 if the HHI is greater than or equal to 1800. As a higher HHI denotes a decrease in competition and an increase in market power, I would expect to find a positive relationship between *Hhi* and *Reject*. Finally, Berger et al. (2005) show that banks are better at processing soft information of small business borrowers by being close to them geographically and communicating with them in person. I therefore include the variable *Distance*, defined as the distance in miles between the borrower's and lender's offices, and expect a positive relationship between *Distance* and *Reject*.

V. Tests and Results

A. *Logistic and Probit Regression Results*

Consistent with the prior literature, I begin by estimating logistic and probit regressions. The dependent variable is whether the borrower's loan application is rejected. The independent variables include the dummy variable for a minority borrower and other borrower, firm, and lender characteristics. The results of such regressions are given in Table 2. The first two columns present the regression coefficient and its associated standard error for each independent variable when I estimate a logistic regression. Similarly, the next two columns present the regression coefficient and its associated standard error for each independent variable when I estimate a probit regression. Given that the dependent variable is binary, I present the marginal regression coefficient for each independent variable that is evaluated at the average value of each independent variable.

I find the regression coefficient on *Minority* to be positive and statistically significantly related to the probability of the borrower's loan being rejected. The marginal

Table 2: Estimated Impact of Being a Minority Entrepreneur on the Probability of Being Denied Credit Using Standard Regression Methods

	Logistic Regression		*Probit Regression*	
Variable	*Coefficient*	*(Standard Error)*	*Coefficient*	*(Standard Error)*
Minority	0.036**	(0.011)	0.043**	(0.013)
Credit score	−0.008**	(0.002)	−0.010**	(0.003)
Wealth	−0.001	(0.001)	−0.002	(0.001)
P_bankrupt	0.038**	(0.010)	0.047**	(0.012)
CEO age	−0.001	(0.000)	−0.001	(0.001)
Education	−0.004*	(0.002)	−0.004*	(0.002)
Experience	0.005	(0.007)	0.007	(0.008)
Female	0.002	(0.009)	0.002	(0.010)
P_loan	0.011	(0.008)	0.014	(0.009)
Ownership	0.000	(0.000)	0.000	(0.000)
Size	−0.009**	(0.002)	−0.010**	(0.002)
Family owned	0.003	(0.009)	0.005	(0.010)
Firm age	0.007	(0.005)	−0.007	(0.006)
Company	0.002	(0.008)	0.005	(0.009)
Profit	0.000	(0.000)	0.000	(0.000)
Debt	−0.000	(0.000)	−0.000	(0.000)
Cash	0.003	(0.003)	0.003	(0.004)
F_bankrupt	0.006	(0.008)	0.006	(0.010)
Urban	−0.003	(0.012)	−0.007	(0.013)
Census	0.002	(0.002)	0.002	(0.002)
Sic	−0.002	(0.002)	−0.002	(0.002)
Commercial	−0.022*	(0.011)	−0.027	(0.014)
Savings	−0.007	(0.016)	−0.012	(0.019)
Relation	−0.000	(0.000)	−0.000	(0.000)
Concentration	−0.005	(0.005)	−0.006	(0.006)
Distance	0.000	(0.000)	0.000	(0.000)
Intercept	4.617**	(1.442)	2.267**	(0.722)
Pseudo R^2	0.215		0.215	

*Significant at 5 percent; **significant at 1percent.
NOTES: This table reports the results of logistic and probit regressions where the marginal regression coefficients are calculated at the mean of each independent variable.

coefficients show that minority borrowers have a 0.036 to 0.043 higher probability of their loan application being rejected than does a white borrower. Borrowers with a higher credit score have a lower probability of their loan being rejected, and their wealth does not seem to have a statistically significant effect on the probability of loan rejection. On the other hand, borrowers who went personally bankrupt have a higher probability of loan rejection, as do borrowers with lower levels of education. No statistically significant relationship is found for the borrower's age, gender, experience, ownership level, or whether s/he previously gave the firm a loan.

I now examine the firm and lender characteristics. Smaller firms are more likely to have their loan application rejected and to some extent commercial banks are more stringent than other financial lenders in approving loans. No other firm or lender characteristic is statistically significantly related to the probability of the loan being rejected.

The regression specifications have a pseudo-R^2 of 0.215, suggesting quite a high goodness of fit.[15]

B. Are There Observable Differences Between Minority and White Borrowers?

Per the instructions of Imbens and Rubin (2014) and the many articles referenced in Section II, I now examine whether there are differences between the observable borrower, firm, and lender characteristics of minority borrowers and white borrowers. The results of such an analysis are given in Panel A of Table 3. I use four types of tests. I explain them in the context of minority borrowers and white borrowers, but they are similar for testing differences in the other samples (Panels B, C, and D).

The first is a simple *t* test in order to check if the means between minority and white borrowers are the same. It is given by $\frac{x_a - x_b}{\left(\frac{\sigma_a^2}{n_a} + \frac{\sigma_b^2}{n_b}\right)^{1/2}}$, where x_a is the mean value for a minority borrower, x_b is the mean value for a white borrower, σ_a is the standard deviation for a minority borrower, σ_b is the standard deviation for a white borrower, and $\mathrm{n_a}$ and $\mathrm{n_b}$ is the sample size of minority and white borrowers, respectively. I find that minority borrowers have a statistically significantly higher loan rejection probability (0.26 percent) than white borrowers (0.06 percent). Minority borrowers also have lower credit risks (remember that in SSBF's classification, a higher number suggests lower credit risk), lower wealth levels, higher personal bankruptcy problems, younger CEOs, entrepreneurs with lower education and experience levels, higher numbers of female entrepreneurs, are younger firms, more likely to be located in urban areas, have less of a relation with their lender, the latter of which tends to be in a more concentrated banking market. The above *t*-test might potentially suffer from finding statistical significance because the sample sizes $\mathrm{n_a}$ and $\mathrm{n_b}$ might be large. Therefore, Imbens and Wooldridge (2008) suggest using the normalized difference in means test, defined as $\frac{x_a - x_b}{\left(\frac{\sigma_a^2 + \sigma_b^2}{2}\right)^{1/2}}$. They suggest that if the absolute value of the normalized difference is greater than 0.25, it shows that the means are statistically significant. I find similar results using the normalized difference test as in the simple *t*-test, suggesting that sample size issues are not overstating our results for differences between minority and white borrowers.

The third test evaluates whether there are differences in the standard deviations between minority and white borrowers. An *F*-test for equality in the dispersion measures finds that there are statistically significant differences in the standard deviations of the various variables. The fourth test, the Kolmogorov-Smirnov test, examines whether the distributions are the same between minority and white borrowers. It is defined as $\sup|F_{a,}(x) - F_{b,\mathrm{n}}{}'(x)|$, where $F_{a,n}$ and $F_{b,n}{}'$ are the empirical distribution functions of minority and white borrowers, respectively. The test shows that the distributions of the various borrower, firm, and lender characteristics significantly differ between minority

[15]Although many studies present a pseudo-R^2 measure, limited dependent regressions are econometrically well known to have low pseudo-R^2 measures (see Greene 2011).

Table 3: Univariate Differences Between Minority and White Borrowers

Variable	*Means for Minority*	*Means for White*	t-*Statistics for Differences in Means*	*Normalized Differences*	p-*Values for Differences in Standard Deviation*	p-*Values for Kolmogorov-Smirnov Test*
Panel A: Minority vs. White Borrowers						
Reject	0.264	0.059	5.059**	0.379	0.000**	0.000**
Credit score	3.517	3.919	2.628**	−0.182	0.169	0.006**
Wealth	11.861	12.650	2.411*	−0.168	0.025*	0.013*
P_bankrupt	0.207	0.091	3.065**	0.225	0.000**	0.099
CEO age	48.884	53.456	4.239**	−0.276	0.476	0.015*
Education	4.983	4.680	1.639	0.109	0.761	0.042*
Experience	2.625	2.991	5.238**	−0.347	0.015*	0.000**
Female	0.248	0.163	2.090*	0.147	0.011*	0.395
P_loan	0.400	0.363	0.691	0.054	0.722	1.000
Ownership	74.876	69.760	1.930	0.128	0.794	0.110
Size	12.954	13.349	1.832	−0.125	0.284	0.377
Family owned	0.826	0.784	1.175	0.075	0.265	0.988
Firm age	2.184	2.598	5.066**	−0.323	0.654	0.000**
Company	0.298	0.302	0.102	−0.007	0.973	1.000
Profit	0.694	0.945	0.849	−0.028	0.000**	0.990
Debt	2.033	1.125	0.910	0.077	0.000**	0.004**
Cash	0.150	0.121	1.131	0.054	0.000**	0.652
F_bankrupt	0.264	0.220	1.060	0.072	0.297	0.981
Urban	0.917	0.766	5.594**	0.287	0.000**	0.011*
Census	5.835	5.095	3.057**	0.202	0.603	0.021*
Sic	6.496	5.443	5.702**	0.334	0.042*	0.000**
Commercial	0.835	0.862	0.769	−0.053	0.226	1.000
Savings	0.091	0.073	0.674	0.047	0.095	1.000
Relation	105.099	138.278	3.882**	−0.206	0.000**	0.071
Concentration	1.868	2.022	2.091*	−0.141	0.333	0.084
Distance	12.281	14.148	0.457	−0.023	0.000**	0.447

Table 3 *Continued*

Variable	*Means for African American*	*Means for White*	t-*Statistics for Differences in Means*	*Normalized Differences*	p-*Values for Differences in Standard Deviation*	p-*Values for Kolmogorov Smirnov Test*
Panel B: African-American vs. White Borrowers						
Reject	0.489	0.059	5.825**	0.609	0.000**	0.000**
Credit score	2.955	3.919	4.232**	−0.418	0.808	0.001**
Wealth	10.858	12.650	3.123**	−0.342	0.012*	0.000**
P_bankrupt	0.383	0.091	4.050**	0.455	0.000**	0.001**
CEO age	49.872	53.456	2.182*	−0.223	0.871	0.522
Education	4.723	4.680	0.156	0.016	0.809	0.864
Experience	2.563	2.991	4.020**	−0.404	0.238	0.001**
Female	0.319	0.163	2.246*	0.251	0.011*	0.217
P_loan	0.379	0.363	0.176	0.024	0.778	1.000
Ownership	80.213	69.760	2.686**	0.263	0.651	0.033*
Size	11.992	13.349	3.843**	−0.391	0.281	0.005**
Family owned	0.872	0.784	1.757	0.163	0.089	0.869
Firm age	2.157	2.598	3.455**	−0.342	0.808	0.006**
Company	0.298	0.302	0.059	−0.006	0.897	1.000
Profit	1.358	0.945	0.758	0.044	0.000**	0.366
Debt	1.585	1.125	0.946	0.080	0.001**	0.003**
Cash	0.231	0.121	2.241*	0.189	0.002**	0.091
F_bankrupt	0.298	0.220	1.135	0.124	0.259	0.947
Urban	0.979	0.766	9.031**	0.429	0.000**	0.031*
Census	4.915	5.095	0.542	−0.054	0.365	0.714
Sic	7.213	5.443	7.267**	0.537	0.007**	0.000**
Commercial	0.745	0.862	1.803	−0.204	0.011*	0.560
Savings	0.128	0.073	1.108	0.128	0.006**	0.999
Relation	92.000	138.278	4.384**	−0.297	0.000**	0.217
Concentration	1.766	2.022	2.131*	−0.227	0.312	0.041*
Distance	20.213	14.148	0.642	0.064	0.444	0.654

Table 3 *Continued*

Variable	*Means for Asians*	*Means for White*	t-*Statistics for Differences in Means*	*Normalized Differences*	p-*Values for Differences in Standard Deviation*	p-*Values for Kolmogorov-Smirnov Test*
Panel C: Asian vs. White Borrowers						
Reject	0.098	0.059	1.019	0.103	0.004**	1.000
Credit score	4.000	3.919	0.389	0.038	0.399	0.848
Wealth	12.392	12.650	0.601	−0.057	0.322	0.855
P_bankrupt	0.098	0.091	0.180	0.017	0.613	1.000
CEO age	47.049	53.456	4.494**	−0.381	0.999	0.002**
Education	5.475	4.680	3.178**	0.280	0.975	0.005**
Experience	2.598	2.991	3.945**	0.365	0.039*	0.004**
Female	0.180	0.163	0.334	0.031	0.569	1.000
P_loan	0.412	0.363	0.688	0.070	0.698	1.000
Ownership	70.016	69.760	0.067	0.006	0.456	0.998
Size	13.670	13.349	1.244	0.110	0.388	0.391
Family owned	0.820	0.784	0.701	0.063	0.567	1.000
Firm age	2.112	2.598	4.327**	−0.372	0.805	0.000**
Company	0.311	0.302	0.157	0.015	0.812	1.000
Profit	0.294	0.945	2.689**	−0.074	0.000**	0.615
Debt	2.715	1.125	0.820	0.101	0.000**	0.624
Cash	0.105	0.121	0.595	−0.032	0.000**	0.975
F_bankrupt	0.197	0.220	0.454	−0.041	0.761	1.000
Urban	0.918	0.766	4.137**	0.288	0.000**	0.129
Census	6.295	5.095	3.377**	0.308	0.285	0.001**
Sic	6.016	5.443	2.258*	0.190	0.147	0.094
Commercial	0.885	0.862	0.565	0.050	0.482	1.000
Savings	0.066	0.073	0.219	0.020	0.714	1.000
Relation	107.000	138.278	2.415*	−0.187	0.005**	0.095
Concentration	1.852	2.022	1.733	−0.159	0.829	0.612
Distance	7.000	14.148	3.271**	−0.101	0.000**	0.552

Table 3 *Continued*

Variable	*Means for Other*	*Meansfor White*	t-*Statistics for Differences in Means*	*Normalized Differences*	p-*Values for Differences in Standard Deviation*	p-*Values for Kolmogorov-Smirnov Test*
Panel D: Other (Namely, Hispanic, Hawaiian/Pacific Islander, Native American) vs. White Borrowers						
Reject	0.313	0.059	2.118*	0.427	0.000**	0.259
Credit score	3.125	3.919	2.049*	0.348	0.684	0.393
Wealth	12.494	12.650	0.298	−0.043	0.090	0.503
P_bankrupt	0.188	0.091	0.952	0.190	0.030*	0.999
CEO age	53.500	53.456	0.013	0.003	0.193	0.975
Education	3.375	4.680	2.910*	−0.441	0.755	0.022*
Experience	3.035	2.991	0.259	0.047	0.700	0.962
Female	0.313	0.163	1.242	0.239	0.099	0.873
P_loan	0.455	0.363	0.579	0.128	0.602	1.000
Ownership	79.313	69.760	1.476	0.244	0.775	0.522
Size	12.723	13.349	1.059	−0.193	0.498	0.302
Family owned	0.750	0.784	0.305	−0.056	0.559	1.000
Firm age	2.686	2.598	0.416	0.073	0.944	0.798
Company	0.188	0.302	1.129	−0.184	0.577	0.986
Profit	0.214	0.945	3.289**	−0.084	0.000**	0.712
Debt	1.002	1.125	0.202	−0.023	0.004**	0.112
Cash	0.092	0.121	0.892	−0.060	0.000**	0.751
F_bankrupt	0.438	0.220	1.689	0.312	0.176	0.444
Urban	0.750	0.766	0.139	−0.025	0.676	1.000
Census	6.313	5.095	2.054	0.333	0.856	0.110
Sic	6.500	5.443	1.894	0.316	0.946	0.247
Commercial	0.938	0.862	1.205	0.175	0.142	1.000
Savings	0.063	0.073	0.163	−0.028	0.933	1.000
Relation	149.625	138.278	0.432	0.067	0.295	0.408
Concentration	2.188	2.022	0.881	0.156	0.836	0.999
Distance	7.125	14.148	2.067*	−0.099	0.000**	0.977

*Significant at 5 percent; **significant at 1 percent.

Notes: This table shows that there are significant differences in the means, standard deviations, and sample distributions between minority borrowers (and its constituent categories, African-American, Asian, other minority borrowers), and white borrowers. These results, therefore, show that the regression coefficients estimated in Table 2 are biased.

and white borrowers. In summary, all four tests show significant differences in the borrower, firm, and lender characteristics of minority and white borrowers, suggesting that the results of Table 2 might be statistically biased.

In Panel B of Table 3, I repeat the above analysis, but check for differences between African-American and white borrowers. I find that African-American borrowers have a statistically significantly higher loan rejection probability (0.50) than do white borrowers (0.06). As in Panel A for minority borrowers, I find significant differences in the borrower, firm, and lender characteristics of African-American and white borrowers. In Panel C, I find a statistically insignificant difference in the loan rejection probability between Asian and white borrowers. However, I do find significant differences in the borrower, firm, and lender characteristics of Asian and white borrowers. Finally, I find that the other minority groups (consisting of Hispanic/Hawaiian/Pacific Islander/Native American) have a statistically significantly higher loan rejection probability (0.31) than do white borrowers (0.6%). All four tests show some differences in the borrower, firm, and lender characteristics of other minority and white borrowers.

In summary, the above results suggest that the results of Table 2 might be biased because of significant differences between the borrower, firm, and lender characteristics of minority (and its constituent subcategories of race) and white borrowers. Accordingly, I now examine whether one obtains different results using the causal inference methods.

C. Causal Inference Tests to Examine Whether Minority Borrowers are Rejected More Often than White Borrowers

Before one can estimate three causal inference methods, Imbens and Ruben (2014) suggest that I should check whether the two distributions have common support. Using the min-max condition for minority and white borrowers, I find common support, which is confirmed in the kernel density plot of propensity scores.

I estimate three causal inference regressions to test whether minority borrowers are rejected more often than comparable white borrowers. The results of such an analysis are given in Table 4. The first method, namely, the propensity score method, matches the minority borrower with the closest white borrower by propensity score. I find that the minority borrower loan applications are not rejected at a higher probability than those of comparable white borrowers. Similar statistically insignificant differences are found when I use inverse probability weighting matching or nearest neighbor matching. In summary, in contrast to the logistic and probit regression results, I find no significant differences in the probability of loan rejection between minority and white borrowers. This confirms (along with the results of the four tests for differences between the borrower, firm, and lender characteristics of minority and white borrowers) that the results from probit or logistic regressions can be inaccurate and biased.

I now examine for the more granular subcategories of minority borrowers. I find that the African-American borrower is rejected at a 0.30 higher probability than a similar white borrower. This result is consistent across all three causal inference methods, namely, propensity score matching, inverse probability weighting matching, and nearest neighbor matching. No statistically significant difference is found for loan rejection probabilities between Asian and white borrowers or other minority groups and white borrowers.

Table 4: Estimated Impact of Being a Minority Entrepreneur on the Probability of Being Denied Credit Using Causal Inference Methods

	Minority vs. White	*African American vs. White*	*Asian vs. White*	*Other vs. White*
Propensity score matching	0.047 (0.042)	0.296* (0.121)	0.021 (0.033)	0.091 (0.087)
Inverse probability weighting matching	0.047 (0.042)	0.296* (0.121)	0.021 (0.033)	0.091 (0.087)
Nearest neighbor matching	0.129 (0.07)	0.296** (0.115)	0.021 (0.050)	0.182 (0.116)

*Significant at 5 percent; **significant at 1 percent.
NOTES: The first number is the probability of being rejected credit if the entrepreneur is a minority borrower when compared to a white borrower, and the number in parentheses is its associated standard error. Similar representations are presented for African-American borrowers, Asian borrowers, and other (namely, Hispanic, Hawaiian/Pacific Islander, or Native American) minority borrowers.

D. Tests of the Various Discrimination Theories

The above results have shown that African-American loan applications are rejected with a higher probability than those of similar white borrowers. I now examine the various theories that were described in Section III. Briefly, the taste-based theory of discrimination predicts that African-American borrowers will have lower expected default losses than similar white borrowers, the taste-based theory of discrimination predicts that African-American borrowers will have a greater than or equal to expected loss of default than similar white borrowers, and the laissez faire and group hoarding theories predict equal expected default losses between African-American and white borrowers. Accordingly, I need to calculate the expected default losses for African-American and white borrowers. Given that lenders might also discriminate against African-American borrowers at the default stage, note that I use the expected losses faced by the lender if the borrower defaults rather than the borrower's actual default losses.

The expected loss of default is defined as the probability of default times the size of the loan. As in Dichev (1998) and Griffin and Lemmon (2002), I use Ohlson's (1980) O-score to proxy for the probability of default.[16] The variable O-score is defined as $-1.32 - 0.407\log(\text{assets}) + 6.03(\text{liabilities/assets}) - 1.43(\text{working capital/assets}) + 0.076(\text{current liabilities/current assets}) - 1.72(1 \text{ if liabilities} > \text{assets, } 0 \text{ otherwise}) - 2.37(\text{net income/assets}) - 1.83(\text{funds from operations/liabilities}) + 0.285(1 \text{ if a net loss for last two years, } 0 \text{ otherwise}) - 0.521(\text{change in net income from current year to previous year/absolute value of change in net income from current year to previous year})$. I find the average O-score for African-American borrowers to be 0.44, which is statistically significantly higher (at the 5 percent level) than the 0.287 average O-score for white borrowers. African-American borrowers are found to have higher probabilities of

[16]I am unable to use other measures of default such as Altman's *z*-score because they require the market value of the firm. My borrowers are small businesses who are not traded.

Table 5: Estimated Impact of a Minority Entrepreneur on the Expected Losses Faced by the Lender Using Causal Inference Methods

	African American vs. White
Propensity score matching	0.113
	(0.123)
Inverse probability weighting matching	0.239
	(0.205)
Nearest neighbor matching	−0.319
	(0.197)

*Significant at 5 percent; **significant at 1percent.
NOTES: The first number is the expected losses faced by the lender if the entrepreneur is an African-American borrower when compared to a white borrower, and the number in parentheses is its associated standard error. All numbers are 10^6.

defaults at the 5th, 10th, 25th, 50th, and 75th percentile levels than white borrowers.[17] When I examine loan size, I find that African-American borrowers obtain smaller loans on average (approximately $331K) than do white borrowers (approximately $1.17M).

I now conduct the three causal inference tests while replacing the dependent variable loan rejection probabilities with the expected default losses for the lender. The results of such an analysis are given in Table 5. In all three tests I find that African-American borrowers have statistically insignificantly different expected default losses when compared to white borrowers. Finding a higher loan rejection probability and equal expected loss for African-American-owned firms when compared to white-owned firms is consistent with the information-based, laissez faire, and group hoarding theories of discrimination and against the pure animus taste-based theory of discrimination.

E. Impact of Unobservable Variables on the Differential Impact for African-American and White Borrowers

It is possible that the discriminatory effect that I found for African-American borrowers is because I did not include a number of variables that were not provided in SSBF. For example, Hubbard et al. (2002) find that low-capital banks charge higher loan rates to information-captured small borrowers when these banks are hit by a negative shock. Gan and Riddiough (2008) suggest that lenders possess proprietary credit quality information embedded in their screening technologies that is not observable to empirical researchers. Such excluded or unobservable variables could impact my finding for differential access to capital. For the logistic distribution, Rosenbaum (2002) shows that the odds ratio of two matched individuals (i, j) of receiving treatment is bounded as follows: $\frac{1}{e^{\gamma}} \leq \frac{pi(1-pj)}{pj(1-pj)} \leq e^{\gamma}$, where p_j and pi are the probability of being treated, and γ is the sensitivity of being treated to unobservable variables. If e^{γ} is equal to unity there is no bias, and increasing e^{γ} reflects the bias of overtreatment in our results. The overtreatment bias can be calculated using the Mantel and Haenszel test statistic. I provide the *p*-values of this statistic at different

[17] At the 90th percentile, both African-American and white borrowers have a probability of default close to unity.

Table 6: Sensitivity of the Results in Table 4 for African-American Borrowers to Unobservable Variables Using the Rosenbaum Bounds (2002)

Value of Bias (e^{γ})	*Mantel-Haensel Statistic*	p-*Values*
1 (no bias)	2.545**	0.005
1.05	2.494**	0.006
1.10	2.423**	0.008
1.15	2.355**	0.009
1.20	2.290*	0.011
1.25	2.223*	0.013
1.30	2.170*	0.015
1.35	2.114*	0.017
1.40	2.060*	0.020
1.45	2.008*	0.022
1.50	1.959*	0.025
1.55	1.911*	0.028
1.60	1.865*	0.031
1.65	1.820*	0.034
1.70	1.777*	0.038
1.75	1.736*	0.041
1.80	1.696*	0.045
1.85	1.657*	0.049
1.90	1.619	0.053
1.95	1.582	0.057
2.00 (large bias)	1.546	0.061

*Significant at 5 percent; **significant at 1percent.
NOTES: This table shows the Mantel-Haensel test statistic to be statistically significant up to a e^{γ} value of 1.85. This suggests that the impact of unobservable variables has to be greater than 85 percent of the impact of observable variables to show no discrimination for African-American borrowers.

levels of e^{γ} in Table 6. At the 5 percent level of significance, I find that the impact of unobservable variables has to be greater than 85 percent in order to have an impact on my results. This suggests that the impact of unobservable variables has to be greater than 85 percent to show no discrimination. The 85 percent bound seems to be a high number given that I have controlled for a large number of borrower, firm, and lender risk variables. If the effect of the unobservable variables is less than these bounds, I have found a causal impact of race on access to capital for African-American-owned small business firms.

VI. Conclusions

This article examines whether minority small business borrowers have the same access to loans from financial institutions as similar white borrowers. I begin by showing that standard regression techniques (such as logistic or probit regressions) can lead to biased regression coefficients. Accordingly, this is the first article to use matching methods to test if there is a *causal impact* of race on access to entrepreneurial loan capital from financial institutions. These methods allow us to control for observable differences in borrower, firm, and lender characteristics of minority- and white-owned small business firms.

I find that African-American-owned firms have lower access to capital than white-owned firms. They are rejected with an approximately 30 percent higher probability than similar white-owned firms. My results are robust to three different causal inference methods, namely, propensity score matching, inverse probability weighting matching, and nearest neighbor matching. Using the Rosenbaum (2002) bounds, I find that the impact of excluded and unobservable variables has to be greater than 85 percent the impact of included observable variables to show no discrimination. This bound seems to be a high number given that I have controlled for a large list of borrower, firm, and lender characteristics. If the impact of the excluded variables is less than this bound, I have found a causal impact of race for African-American small business borrowers. I also find no causal impact of access to loans from financial institutions for Asian-owned and other minority-owned firms. Based on data availability, these results suggest that researchers should examine minority categories at the most granular level.

Finally, I find similar expected default losses between African-American-owned and white-owned firms. Finding higher probabilities of rejection and equal expected losses for African-American-owned firms when compared to white-owned firms is consistent with the information-based, laissez faire, and group hoarding theories of discrimination. I do not find evidence in support of the taste-based theory of discrimination.

Given that the taste-based theory of discrimination has been refuted, one may not be able to use legal remedies such as class action suits to rectify the lending environment for African-American borrowers. Instead, one might use programs that are more informal in nature in order to decrease the information asymmetry and increase the relationships between African-American borrowers and their potential lenders. For example, the U.S. Small Business Association's Minority-Owned Business Development Program helps minority-owned firms to develop, grow, and finance their businesses through one-on-one counseling sessions, training workshops, and management assistance. Similarly, the organization SCORE provides free advice, mentoring sessions, and live conferences to help small business borrowers become conversant with questions that a lender might ask. Individual bank programs such as Bank of America's Small Business Community enable small business owners to share their experiences and exchange solutions for problems that entrepreneurs might face. Financial institutions might also employ more qualified minority lending officers who are familiar with the behavioral traits of the minority-owned borrower. In a variant of the *Huffington Post*'s "Move Your Money" campaign, Michael Render (aka "Killer Mike") suggests that one should "bank black, bank small, and bank local."[18] The Woodstock Institute recently got Key Bank to sign a $16.5b Community Reinvestment Agreement that would assist in serving underserved communities.[19] Finally, I recommend that the Consumer Financial Protection Bureau empirically examine a much larger sample of loans to check for any differential impact to minority borrowers.

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[18]http://www.huffingtonpost.com/entry/killer-mike-citizens-trust-bank_us_56d48a87e4b0871f60ec2ee5

[19]http://www.woodstockinst.org/blog/2016/small-business-lending-and-cra-issues-trending

References

Abadie, A., & G. Imbens (2006) "Large Sample Properties of Matching Estimators for Treatment Effects," 74 *Econometrica* 235.

——. (2011) "Bias-Corrected Matching Estimators for Average Treatment Effects," 29 *J. of Business & Economic Statistics* 1.

Aldrich, H., & C. Zimmer (1986) "Entrepreneurship Through Social Networks," in D. Sexton & R. Smilor, eds., *The Art and Science of Entrepreneurship*. Cambridge, MA: Ballinger Publishing.

Arrow, K. (1972) "Models of Job Discrimination," in A. Pascal, ed., *Racial Discrimination in Economic Life*. Lexington MA: Lexington Books.

Ayres, I., M. Banaji, & C. Jolls (2011) "Race Effects on eBay," working paper, Yale Univ.

Ayres, I., & P. Siegelman (1995) "Race and Gender Discrimination in Bargaining for a New Car," 85 *American Economic Rev.* 304.

Bates, T. (1997) "Unequal Access: Financial Institution Lending to Black and White-Owned Small Business Start-Ups," 19 *J. of Urban Affairs* 487.

Becker, G. (1957) *The Economics of Discrimination*. Chicago, IL: Univ. of Chicago Press.

Berger, A., N. Miller, M. Petersen, R. Rajan, & J. Stein (2005) "Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks," 76 *J. of Financial Economics* 237.

Berkovec, J., G. Canner, S. Gabriel, & T. Hannan (1998) "Discrimination, Competition, and Loan Performance in FHA Mortgage Lending," 870 *Rev. of Economics & Statistics* 241.

Bertrand, M., D. Chugh, & S. Mullainathan (2005) "Implicit Discrimination," 95 *American Economic Rev.* 94.

Bertrand, M., & S. Mullainathan (2004) "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination," 94 *American Economic Rev.* 991.

Bewaji, T., Q. Yang, & Y. Han (2015) "Funding Accessibility for Minority Entrepreneurs," 22 *J. of Small Business & Enterprise Development* 716.

Black, H., R. Schweitzer, & L. Mundell (1978) "Discrimination in Mortgage Lending," 68 *American Economic Rev.* 186.

Blanchard, L., B. Zhao, & J. Yinger (2008) "Do Lenders Discriminate Against Minority and Women Entrepreneurs?" 63 *J. of Urban Economics* 467.

Blanchflower, D., P. Levine, & D. Zimmerman (2003) "Discrimination in the Small Business Credit Markets," 85 *Rev. of Economics & Statistics* 930.

Blumer, H. (1958) "Race Prejudice as a Sense of Group Position," 1 *Pacific Sociological Rev.* 3.

Bobo, L., J. Kluegel, & R. Smith (1996) "Laissez Faire Racism: The Crystallization of a 'Kinder, Gentler' Anti-Black Methodology," in S. Tisch & J. Martin, eds., *Racial Attitudes in the 1990s: Continuity and Change*. Westport, CT: Praeger.

Bobo, L., & R. Smith (1998) "From Jim Crow to Laissez Faire Racism: The Transformation of Racial Attitudes," in W. Katkin, N. Landsman, & A. Tyree, eds., *Beyond Pluralism: The Conception of Groups and Group Identities in America*. Urbana and Chicago, IL: Univ. of Illinois Press.

Bordalo, P., K. Coffman, N. Gennaioli, & A. Shleifer (2016) "Stereotypes," *Q. J. of Economics*.

Bostic, R., & P. Lampani (1999) "Racial Differences in Patterns of Small Business Finance," in J. Blanton, A. Williams, & S. Rhine, eds., *Business Access to Capital and Credit*. Washington, DC: Federal Reserve System.

Brown, M., M. Carnoy, E. Currie, T. Duster, D. Oppenheimer, M. Shultz, & D. Wellman (2003) *Whitewashing Race: The Myth of a Color-Blind Society*. Berkeley, CA: Univ. of California Press.

Busso, M., J. DiNardo, & J. McCrary (2014) "New Evidence on the Finite Sample Properties of Propensity Score Reweighting and Matching Estimates," 96 *Rev of Economics & Statistics* 885.

Calomiris, C., C. Kahn, & S. Longhofer (1994) "Housing Finance Intervention and Private Incentives: Helping Minorities and the Poor," 26 *J. of Money, Credit, & Banking* 634.

Carter, N., M. Williams, & P. Reynolds (1997) "Discontinuance Among New Firms in Retail: The Influence of Initial Resources, Strategy, and Gender," 12 *J. of Business Venturing* 125.

Cavalluzzo, K., & L. Cavalluzzo (1998) "Market Structure and Discrimination: The Case of Small Businesses," 30 *J. of Money, Credit, & Banking* 771.

Cavalluzzo, K., L. Cavalluzzo, & J. Wolken (2002) "Competition, Small-Business Financing and Discrimination," 75 *J. of Business* 641.

Cavalluzzo, K., & J. Wolken (2005) "Small Business Loan Turn-Downs, Personal Wealth and Discrimination," 78 *J. of Business* 2153.

Clarke, J., N. Roy, & M. Courchane (2009) "On the Robustness of Racial Discrimination Findings in Mortgage Lending Studies," 41 *Applied Economics* 2279.

Cochran, W., & D. Rubin (1973) "Controlling Bias in Observational Studies; A Review," 35 *Sankhya: The Indian J. of Statistics, Series A* 417.

Coleman, S. (1999) "Sources of Small Business Capital: A Comparison of Men- and Woman-Owned Small Businesses," 4 *J. of Applied Management & Entrepreneurship* 138.

——. (2000) "Access to Capital and Terms of Credit: A Comparison of Men- and Woman-Owned Small Businesses," *J. of Small Business Management.*

——. (2002) "Borrowing Patterns for Small Firms: A Comparison by Race and Ethnicity," 7 *J. of Entrepreneurial Finance* 77.

Coleman, S., & A. Robb (2009) "A Comparison of New Firm Financing by Gender: Evidence from the Kaufman Firm Survey," 33 *Small Business Economics* 397.

——. (2014) "Access to Capital by High-Growth Women-Owned Firms," working paper prepared for the National Women's Business Council.

Dahejia, R., & S. Wahba (1999) "Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs," 94 *J. of the American & Statistical Association* 1053.

Davidson, P., & B. Honig (2003) "The Role of Social and Human Capital Among Nascent Entrepreneurs," 18 *J. of Business Venturing* 301.

De Carolis, D., & P. Saparito (2006) "Social Capital, Cognition and Entrepreneurial Opportunities: A Theoretical Framework," 40 *Entrepreneurship Theory & Practice* 41.

Dichev, I. (1998) "Is the Risk of Bankruptcy a Systemic Risk?" 53 *J. of Finance* 1131.

DiTomaso, N. (2013) *The American Non-Dilemma: Racial Inequality Without Racism.* New York: Russell Sage Foundation.

——. (2015) "Racism and Discrimination Versus Advantage and Favoritism: Bias for Versus Bias Against," 35 *Research in Organizational Behavior* 57.

Escriba-Esteve, A., L. Sancho-Peinado, & E. Sancho-Peinado (2009) "The Influence of Top Management Teams in the Strategic Orientation and Performance of Small and Medium-Sized Enterprises," 20 *British J. of Management* 581.

Fairlie, R., & A. Robb (2010) "Disparities in Capital Access Between Minority and Non-Minority Businesses: The Troubling Reality of Capital Limitations Faced by MBEs," working paper, U.S. Department of Commerce, Minority Business Development Agency.

Fershtman, C., & U. Gneezy (2001) "Discrimination in a Segmented Society: An Experimental Approach," 116 *Q. J. of Economics* 351.

Finkelstein, S., & D. Hambrick (1990) "Top-Management Team Tenure and Organizational Outcomes: The Moderating Role of Managerial Discretion," 35 *Administrative Science Q.* 484.

Gan, J., & T. Riddiough (2008) "Monopoly and Informational Advantage in the Residential Mortgage Market," 21 *Rev. of Financial Studies* 2677.

Greene, W. (2011) *Econometric Analysis*, 7th ed. Saddle River, NJ: Prentice Hall.

Griffin, J., & M. Lemmon (2002) "Book-to-Market Equity, Distress Risk, and Stock Returns," 57 *J. of Finance* 2317.

Gneezy, U., J. List, & M. Price (2012) "Towards an Understanding of Why People Discriminate: Evidence from a Series of Natural Field Experiments," NBER working paper 17855.

Goldin, C., & C. Rouse (2000) "Orchestrating Impartiality: The Impact of 'Blind' Auditions on Female Musicians," 90 *American Economic Rev.* 715.

Han, S. (2004) "Discrimination in Lending: Theory and Evidence," 29 *J. of Real Estate Finance & Economics* 5.

Hannon, L. (2015) "White Colorism," 2 *Social Currents* 13.

Hannon, L., & R. DeFina (Forthcoming) "Reliability Concerns in Measuring Respondent Skin Tone by Interviewer Observation," *Public Opinion Q.*

Haynes, G., J. Onochie, & Y. Lee (2008) "Influence of Family's Social Relationships on the Debt Structure of Mexican-American and Korean-American Small Businesses," 13 *J. of Development Entrepreneurship* 343.

Heckman, J. (1998) "Detecting Discrimination," 12 *J. of Economic Perspectives* 101.

Heckman, J., H. Ichimura, & P. Todd (1998) "Matching as an Econometric Evaluation Estimator," 65 *Rev. of Economic Studies* 261.

Heckman, J., & P. Siegelman (1992) 'The Urban Institute Audit Studies: Their Methods and Findings," in M. Fix & R. Struyk, eds., *Clear and Convincing Evidence: Measurement of Discrimination in America*. Lanham, MD: Urban Institute Press.

Holland, P. (1986) "Statistics and Causal Inference," 81 *J. of the American Statistical Association* 945.

Holmes, A., & P. Horvitz (1994) "Mortgage Lending, Race and Model Specification," 49 *J. of Finance* 81.

Hubbard, R., K. Kuttner, & D. Palia (2002) "Are There Bank Effects in Borrowers' Costs of Funds? Evidence from a Matched Sample of Borrowers and Banks," 75 *J. of Business* 559.

Hubbard, R., D. Palia, & W. Yu (2012) "Analysis of Discrimination in Prime and Subprime Mortgage Markets," working paper, Columbia University.

Hunter, W., & M. Walker (1996) "The Cultural Affinity Hypothesis and Mortgage Lending Decisions," 13 *J. of Real Estate Finance & Economics* 57.

Imbens, G., & D. Rubin (2014) *Causal Inference in Statistics, Biomedical and Social Sciences: An Introduction*. New York: Cambridge Univ. Press.

Imbens, G., & J. Wooldridge (2008) "Recent Developments in the Econometrics of Program Evaluation," NBER working paper 14251.

Kim, P., H. Aldrich, & L. Keister (2006) "Access (Not) Denied: The Impact to Financial, Human, and Cultural Capital on Entrepreneurial Entry in the United Sates," 27 *Small Business Economics* 5.

Kushnirovich, N., & S. Heilbrunn (2008) "Financial Funding of Immigrant Businesses," 13 *J. of Developmental Entrepreneurship* 167.

List, J. (2004) "The Nature and Extent of Discrimination in the Marketplace: Evidence from the Field," 119 *Q. J. of Economics* 49.

Marlow, S., & D. Patton (2005) "All Credit to Men? Entrepreneurship, Finance, and Gender," *Entrepreneurship, Theory & Practice* 717.

Mudambi, R., & M. Treichel (2004) "Cash Crisis in Newly Public Internet-Based Firms: An Empirical Analysis," 20 *J. of Business Venturing* 543.

Munnell, A., G. Tootell, L. Browne, & J. McEneaney (1996) "Mortgage Lending in Boston: Interpreting HMDA Data," 86 *American Economic Rev.* 25.

Murphy, R. (1988) *Social Closure: The Theory of Monopolization and Exclusion*. New York: Oxford University Press.

Ohlson, J. (1980) "Financial Ratios and the Probabilistic Prediction of Bankruptcy," 18 *J. of Accounting Research* 109.

Pager, D. (2003) "The Mark of a Criminal Record," 108 *American J. of Sociology* 937.

Petersen, M., & R. Rajan (1994) "The Benefits of Lending Relationships: Evidence from Small Business Data," 49 *J. of Finance* 3.

Phelps, E. (1972) "The Statistical Theory of Racism and Sexism," 62 *American Economic Rev.* 659.

Pulido, L., & M. Pastor (2013) "Where in the World is Juan- and What Color is He?: The Geography of Latina/o Racial Identity in Southern California," 65 *American Q.* 309.

Rai, S. (2008) "Indian Entrepreneurs: An Empirical Investigation of Entrepreneurs Age and Firm Type, Type of Ownership and Risk Behavior," 8 *J. of Services Research* 213.

Robb, A., S. Coleman, & D. Stangler (2014) "Sources of Economic Hope: Women's Entrepreneurship," working paper, Kauffman Foundation.

Roomi, M., P. Harrison, & J. Beaumont-Kerridge (2009) "Women-Owned Small and Medium Enterprises in England," 16 *J. of Small Business & Enterprise Development* 270.

Roper, S., & J. Scott (2009) "Perceived Financial Barriers and the Start-Up Decision," 27 *International Small Business J.* 149.

Rosenbaum, P. (2002) *Observational Studies*, 2nd ed. New York: Springer.

Rosenbaum, P., & D. Rubin (1983) "The Central Role of the Propensity Score in Observational Studies for Causal Effects," 70 *Biometrika* 41.

——. (1984) "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score," 79 *J. of the American Statistical Association* 516.

Ross, S., and J. Yinger, (1999) "Does Discrimination in Mortgage Lending Exist? The Boston Fed Study and its Critics," in M. Turner & F. Skidmore, eds., *Mortgage Lending Discrimination: A Review of Existing Evidence*. Washington, DC: Urban Institute.

Rubin, D. (1973a) "Matching to Remove Bias in Observational Studies," 29 *Biometrics* 159.

——. (1973b) "The Use of Matched Sampling and Regression Adjustment to Remove Bias in Observational Studies," 29 *Biometrics* 185.

——. (1974) "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies," 66 *J. of Education Psychology* 688.

——. (2001) "Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Industry," 2 *Health Services & Outcomes Research Methodology* 169.

Rubin, D., & N. Thomas (2000) "Combining Propensity Scores Matching with Additional Adjustments for Prognostic Covariates," 95 *J. of the American Statistical Association* 573.

Sepulveda, L., S. Syrett, & F. Lyon (2011) "Population Superdiversity and New Migrant Enterprise: The Case of London," 23 *Entrepreneurship & Regional Development* 469.

Spence, M. (1973) "Job Market Signaling," 87 *Q. J. of Economics* 355.

Zussman, A. (2013) "Ethnic Discrimination: Lessons from the Israeli Online Market for Used Cars," 123 *Economic J.* 433.