THREE ESSAYS ON RACIAL DISCRIMINATION

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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled

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a candidate for the degree of Doctor of Philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 2.

THREE ESSAYS ON RACIAL DISCRIMINATION

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ABSTRACT

The first chapter shows that small business owners in credit markets, in particular minority owners, have difficulty in securing sources of capital for their business operation in spite of their economic importance. 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. The first chapter uses pooled cross sectional data from the Survey of Small Business Finances (1993, 1998, and 2003) and a bivariate probit model based on Heckman's approach to deal with sample selection bias for those choosing to apply for loans that has been ignored in analyses of credit markets for small businesses owners. Our analyses confirm previous results suggesting that minority owners are discriminated against in credit markets.

The second chapter examines the determinants of discriminatory preferences. The economic literature mainly presumes that racial preferences are exogenous in explaining racial disparities. The research in this area, however, has shown that economic and noneconomic considerations can influence racially prejudiced sentiments. The second chapter adds to the literature by 1) combining repeated cross-sectional survey data - from multiple waves (1976-2018) of the General Social Survey (GSS) - 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; 3) showing how empirical results are affected when careful controls for age, period, and cohort are included in the model; and 4) using a quantile regression approach to examine whether there exist differential effects of the variables of interest across the entire distribution of discriminatory preferences. Our findings show that unemployment rates are closely associated with discriminatory preferences, which is consistent with what classical labor market competition theories predict. Also, education seems to be particularly important in predicting discriminatory preferences, especially at the upper end of the preference distribution.

The third chapter argues that it is important to investigate how age, period, and cohort impact the shift in racial preference, since any temporal change can be attributed to the effects of these three variables. However, it is noteworthy that there are few attempts in this area that examine the effects of these three time-dimensional variables in explaining the shifts in racial preference, reflecting the difficulties of obtaining estimates due to the linear dependence among them. To separate the contributions of age, period, and cohort on racial preference, the third chapter uses the General Social Survey from multiple waves (1972-2018) and estimates the bounds of the effects instead of obtaining point estimates. Our bounding analyses, combined with theoretical assumptions, is consistent with the theory in allowing for positive effects of age on discriminatory preferences, which interact with negative effects of period and cohort in explaining changing discriminatory preferences over time. These findings suggest that discriminatory preferences in the United States will continue to show a general downward trend, although there may be variations over time.

Chapter 1. Race Differentials in the Credit Market Experiences of Small Business Owners: Improved Estimates

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 60 percent of new jobs created in the United States economy, in addition to being responsible for about 50 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 & Binks, 1995; Pettit & 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 (Cavalluzzo, Cavalluzzo, & Wolken, 2002; Calomiris, Kahn, and Longhofer; 1994; Longhofer & Peters, 2004[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

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[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 (2004) 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.

(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 provide, however, evidence that minority-owned businesses face discrimination in loan approval (Blanchard, Zhao, & Yinger, 2008; Blanchflower, Levine, & Zimmerman, 2003; Fairlie, Robb, & Robinson, 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 in Ross and Yinger (2002) (also see Blanchard et al., 2008, p. 468), studies of lending discrimination based mainly on statistical approaches should address potential sources of biases: 1) omission of relevant explanatory variables, 2) sample selection issues, 3) endogeneity, and 4) 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). Robert and 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 (p. 87). 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.

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

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 Becker's model of discriminatory employer preference, has been focused on small business owners' access to credit markets (Ando, 1988; Cole, 2013; Cohn & Coleman, 2001; Grown & 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). 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, Bates

(1991) finds that black-owned small businesses receive smaller loan amounts than white-owned.

Cavalluzzo et al. (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, Blanchflower et al. (2003) controls 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. are also controlled in existing studies (Blanchard et al., 2008; Bostic & Lampani, 1999; Cavalluzzo & 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 & Wolken, 2005; Coleman, 2002; Cole, 2008).

As pointed out in Robert and Anthony (1996) and Maddala and 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 et al. (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 (p. 675). Replicating the work of Cavalluzzo et al. (2002) using the 1998 SSBF, Blanchard et al. (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 & 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 his 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[5]

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. Since employers in Becker's model have prejudice against hiring black workers, following Charles and Guryan (2008), employer *i* utility can be written as the function of profit and the disutility (d_i) for each black worker hired:

$$(1)\ V_i = \pi_i - d_i L_B,$$

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

[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.

white and black workers) to maximize the employer's utility, the first-order conditions for the hiring of white and black worker, respectively, can be written

$$(2)\ \text{Marginal product of labor} = w_W$$

$$\text{Marginal product of labor} = w_B + d_i.$$

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

$$(3)\ w_W = w_B + d_i.$$

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

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

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:

$$\text{(4) Loan Approval if } \pi \geq \pi^*$$
$$\text{Loan Denial if } \pi < \pi^*,$$

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 in 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 (p. 38). Therefore, in practice, the loan decision process can be written as follows:

$$\text{(5) Loan Approval if } \pi^E \geq \pi^*$$
$$\text{Loan Denial if } \pi^E < \pi^*,$$

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):

$$(6) \text{ Loan Approval if } \pi^{E}(A, F, L) \geq \pi^{*} + Md$$

$$\text{Loan Denial if } \pi^{E}(A, F, L) < \pi^{*} + Md,$$

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:

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

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).

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

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 correcting 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 of 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

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[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.

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.

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

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

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.

$$\text{(11) } y_1^* = X_S\beta_S + \varepsilon_S.$$

$$\text{(12) } y_2^* = X_O\beta_O + \varepsilon_O.$$

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.

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

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.

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

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.

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

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]

$$(16)\ E(y_2^*|X) = X_O\beta_O.$$

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

$$(17)\ E[(y_2^*|X_O, y_1^* > 0)] = X_O\beta_O + E(\varepsilon_O|X_O, y_1^* > 0) =$$
$$X_O\beta_O + E(\varepsilon_O|X_O, X_S\beta_S + \varepsilon_S > 0).$$

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

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

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

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

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 $\hat{\lambda}$ and $\widehat{v^2}$ from Equation (12) by using a probit model explaining whether or not

[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, p. 156-157) for a derivation of v_i^2.

a small business owner applies for a loan, we can set up the following regression equation.

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

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

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

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

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 US 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 U.S. as of the survey year (Bitler, Robb, & Wolken, 2001; Cole & Wolken, 1995; Mach, Wolken, Carter, Holmes, &Hazelwood, 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 et al., 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

[10] For detailed information on the SSBF, please see Bitler et al. (2001), Cole and Wolken (1995), and Mach et al. (2006).
[11] The definition of borrower type follows Cole (2008).

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 A.2 in 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, p. 433). 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

[12] Table A.1 in Appendix shows a list of the variables used in this paper and their definitions.

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 in Cole (2008), the weighted descriptive statistics in Table A.2 in Appendix are classified by borrower type: non-borrowers, discouraged borrowers, approved borrowers, and denied borrowers. The pooled SSBF samples used for Table A.2 include 12,412 observations in total - 4,637 from the 1993 SSBF, 3,551 from the 1998 SSBF, and 4,224 from the 2003 SSBF.[15] By racial group, the pooled SSBF samples are broken into 2,302 minority-owned small businesses (825 African American, 671 Hispanic, and 806 other), 8,234 small businesses owned by white males, and 1,876 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.

[13] The coefficients of race dummy variables across the survey years are presented in Table A.4 in 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 10 observations whose most recent loan applications are not identified, so they are dropped from Table A.2. For the same reason, 13 observations in the 2003 SSBF are dropped. 3 observations in the 2003 SSBF are also dropped because they belong to two race categories (i.e., Hispanic and the "other" race category).

Lenders therefore are expected to assess a firm's profitability and likelihood of loan repayment based on these variables (Bostic & 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 (7 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. Grown and Bates (1992), for example, hypothesize that commercial banks compared to other financial institutions tend to approve larger loans to borrowers (p. 8), and Cole (2008) argues that specialized lenders such as finance companies and savings associations offer only specialized loans (e.g., equipment loans) (p. 16). Berger and Udell (1995) also shows 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 A.1.

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 A.2 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 A.2), 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 A.2), 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 the 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.

No Correction for Sample Selection

Regression results in Table 1 are based on the pooled SSBFs.[16] 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 percentage points 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,

[16] All coefficients for variables in the models can be found in Table A.3

we see that the relationship declines relatively little when loan and lender characteristics are controlled.

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.[17] 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 & 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,

[17] 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.

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.[18]

Model specifications, however, presented in Table 1 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 in 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 (p. 794). 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

[18] 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).

consistent estimates.[19] 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 & 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

[19] Please see Equation (17) in the paper.

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, panel A shows that black-owned small businesses have, on average, a 15 percent 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 includes the same variables 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 tend to decrease as we control for more variables. In the lower panels (E, F, G and H), we present results for equations corresponding to models 1 and 2 in Table 1, which control for fewer variables. In panels E and F when we implement a bivariate probit sample selection model based on model 1 in Table 1, the effects of selection bias seem to overestimate the marginal effects. This holds for panel G and H, as well, which present results corresponding to model 2 in Table 1. As we control for more variables, however, the effects of selection bias decrease remarkably as shown in panels A through D. Regardless of whether exclusion restrictions are implemented, 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 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.

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 Conclusion

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.

The data used in our analyses date from 1993 to 2003, but there is no evidence that the racial discrimination in the credit market has declined. In particular recent studies provide evidence that minority-owned small businesses may be discriminated against compared to their counterparts (i.e., white-owned small businesses) in obtaining loans. For example, Atkins et al. (2022) show that the Paycheck Protection Program (PPP) for small businesses, which was created by the U.S. government in response to the Covid-19 pandemic, produced different loan outcomes (i.e., small loans) for black and white small business owners.

Our findings have policy implications. First, as pointed out in Blanchard et al. (2007), 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 (p. 492).

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. 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 to 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.

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

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Chapter 2. Determinants of Racial Prejudice: A Quantile Regression Approach

Introduction

Since Becker first formalized the role of discrimination in labor markets in 1957 using a taste or preference-based model of discrimination, there has been much empirical research focused on the role of discriminatory preferences in explaining racial disparities in economic outcomes between whites and minorities (Blanchard et al., 2007; Lang and Manove, 2011; Neumark, 1999). The main focus of research in this sphere, however, has not tried to analyze how racial preferences themselves can be affected by socioeconomic factors, although there is some literature which analyzes how the changes in such preferences impact observed market discrimination in the U.S. (Charles & Guryan, 2008, 2013; Fryer & Torelli, 2010; Donohue & Heckman, 1991).

It is noteworthy that Becker (1971) admits that the amount of discrimination can change based on changes in other variables - real income per capita, educational attainment, and so on - although he does not provide a detailed discussion of the mechanisms (p. 135). However, despite the importance of racial preferences in determining racial disparities in economic outcomes, the economic literature mainly presumes that racial preferences are exogenous in explaining racial disparities.

The sociological literature on racial preferences, however, shows that racial discrimination is endogenous and should be understood as part of the structure on which the racial ideology supporting historically constituted races is based, what many social scientists have called racism (Bonacich, 1972; Bonilla-Silva, 1997; Reskin 2003; Gonzalez-Sobrino, 2016; Richeson & Sommers, 2016). The institutional perspective in the sociological literature, for example, emphasizes the social and systematic nature of racism (Wellman, 1977). From the institutional perspective, racism is defined as a combination of prejudice and power which enable the dominant group to institutionalize its dominance at all levels, economic, political, and educational (Knowles & Prewitt, 1969).

As pointed out in DeSante and Smith (2020), in this context, racial resentment has become the key measurement that can explain whites' racial attitudes in the past four decades after the Civil Rights Movement (p. 639).[21] Since we focus mainly on changes in discriminatory preferences described in Becker's model, a proxy for prejudice - a one-dimensional aggregate prejudice index suggested by Charles and Guryan (2008) - will be used to explore what factors - economic and noneconomic - can cause discriminatory preferences to vary. Although there are a few papers that try to show how racial preferences vary according to different economic conditions, most of them are focused on non-US contexts (Facchini & Mayda, 2009; Johnson & Lordan, 2016; Mayda, 2006).[22]

To analyze the determinants of racial preferences, the main theoretical assumption used in this paper is that an individual's racial preference is determined mainly through the structure of the labor market (e.g., the degree of unemployment). If individuals care only about economic self-interest (e.g., wage level) observed in the labor market, then racial preferences regarding minorities (here, black people) are determined by the sign and the magnitude of the changes in their relative wages (Mayda, 2006). The assumption that an individual's racial preference is influenced by the labor market can be supported by ethnic competition theories and the factor-endowments model. Bonacich (1972), for example, examines a labor market that is split into two groups of workers, and discriminatory preferences are considered as the result of a social process borne of the competition between a dominant group (i.e., whites) and a group that challenges their labor market dominance.

Applying these two theoretical frameworks, this paper adds to the racial preference literature by 1) combining repeated cross-sectional survey data - from multiple waves (1976-

[21] Regarding the evolution and composition of racial attitudes, see DeSante and Smith (2020, p. 639-640).

[22] Jayadev and Johnson (2017) analyze how racial preferences vary in the US, but their model specifications do not consider important variables such as regional differences and the proportion of the black population.

2018) of General Social Survey (GSS) - 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) using a quantile regression approach to show how the two theoretical frameworks can explain the variations in the distribution of racial preferences.

Literature Review

Despite the fact that changes in racial preferences are closely associated with economic outcomes (e.g., wage level or unemployment duration differences) as shown in the economic literature (Lang & Lehmann, 2012), there exist few attempts that analyze what the determinants are that can impact racial preferences (Jayadev & Johnson, 2017). The research in this area has been focused mainly on the impacts of economic conditions on racial attitudes toward African Americans in the United States (Charles & Guryan, 2008; Goldsmith et al, 2007; Jayadev and Johnson 2017) and attitudes toward migrants in non-U.S. contexts (Dustmann et al., 2005; Dustmann & Preston, 2006; Facchini & Mayda, 2009, Johnston and Lordan, 2016; Mayda, 2006).

Charles and Guryan (2008) use survey questions, which are strongly related to racially prejudiced sentiments, in the GSS dataset from multiple waves (1972-2004) to build a proxy for prejudice: a one-dimensional aggregate prejudice index.[23] The study estimates a pooled OLS regression that controls key demographic variables (e.g., age and education), and shows that an individual's racial preference is closely associated with those demographic variables (p. 785). Using the same dataset as in Charles and Guryan (2008), but with more waves (1972-2014) and a more extensive set of variables controlled, Jayadev and Johnson (2017) find that unemployment rates affect the degree of prejudice.

[23] See p. 783-785 in Charles and Guryan (2008) for details of construction of the index.

Mayda (2006), on the other hand, considers economic and noneconomic determinants in non-US contexts to analyze how they affect individual attitudes toward immigrants.[24] The author uses two data sources - the 1995 National Identity module of the International Social Survey Programme, and the third wave of the World Value Survey data set implemented in 1995-1997. Based on standard trade and labor-economics theories, this study estimates a linear (OLS) regression using a five-valued immigration attitude as the dependent variable and find that labor-market variables such as individual skill (i.e., years of education) continue to play a key role in individual attitudes toward immigrants after controlling for noneconomic factors.

Other research also finds that individual attitudes toward immigrants are affected by economic considerations. For example, Dustmann and Preston (2006) show that the public burden (e.g., the additional tax burden of immigrants) is strongly related to the overall assessment of migration.[25] Quillian (1995) defines the size of the subordinate group (i.e., immigrants) relative to the dominant group (i.e., residents in a host country) as the primary determinant of perceived threat and shows that the average degree of prejudice is strongly related to the threat perceived by dominant group residents.

As pointed out by Fosse and Winship (2019), it is noteworthy that any temporal change - racial preferences in our case - can be attributed to three time-dimensional variables - age, period, and cohort (p. 1976). Most research in the racial preference literature, however, does not consider the effects of these three variables, which can be subject to functional misspecifications that may produce biased estimates. In this context, this research considers the impacts of the three time-dimensional variables in estimating the coefficients of interest,

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[24] For example, parents' foreign citizenship, national pride, and attitudes in favor of political refugees are some of the noneconomic regressors used in Mayda (2006). For the full list of the noneconomic factors, please see section IV in Mayda (2006).
[25] See Facchini and Mayda (2009) and Jamie-Castillo et al. (2016) for more information on the public burden model.

although it is admitted that the linear effects of the three variables cannot be exactly estimated due to their linear dependence. However, we will show that the estimates of the coefficients in regression analyses are robust in the sense that the coefficients for other variables are almost identical regardless of different model specifications for the three time-dimensional variables.

Since it is widely argued in the racial preference literature that workers with low levels of education are located at the right tail of the racial preference distribution relative to highly educated ones (Charles & Guryan, 2008; Gang et al., 2013; Jayadev & Johnson, 2017), I will fit quantile regression models to better understand how the response distribution is affected by such predictors (Hao & Naiman, 2007).

Theoretical Framework

Theoretical explanations for a change in racial preference can be grouped mainly into two major streams based on which factors are emphasized in determining racial preference in the literature - cultural/ideological factors or socio-economic factors as described in Jaime-Castillo et al. (2015, p. 1090).[26] As described in the introduction section, we will mainly describe below how racial preference can change through the workings of the labor market (i.e., competition over scarce resources) based on the labor market competition theories such as ethnic competition theories and the factor endowments model. Specifically, we will analyze the impacts of unemployment and the proportion of blacks in the population in

[26] Other than the theories discussed in the main text, there are different versions of theories that explain racial preference change (e.g., social identity and group conflict theories). As described in Pardos-Prado and Xena (2019), however, these theories can be integrated in either the labor market competition or the social identity paradigms (pp. 287-288).

explaining a racial preference change (Blumer, 1958; Bonacich, 1972; Bobo, 1988; Hainmuller et al, 2015; Mayda, 2006; Scheepers et al, 2002).

There has been a variety of research in the racial preference literature that explains racial preference change based on ethnic competition dating back to the 1950s (Coser, 1956; Cox, 1948).[27] Central to ethnic competition theories is the proposition that inter-group competition over scarce resources is the catalyst that causes antagonistic attitudes to occur between ethnic groups (Scheepers et al., 2002, p. 18). Blalock (1967), for example, argued that perceptions of competition - the subjectively perceived threat by ethnic out-groups - might be caused by actual competition (e.g., competition between individuals from different ethnic groups who try to hold economic positions), which in turn may be an antecedent of unfavorable and exclusionary attitudes toward these out-groups.

The perception of such competitive threat, according to Semyonov et al. (2006), might be influenced by macro-level socio economic conditions (e.g., unemployment) and micro-level factors (e.g., the skill level of individuals who compete with out-group members for the same or similar jobs in the labor market). A variety of research shows that the perception of competitive threat can, at least, partly explain antagonistic attitudes toward out-group members (i.e., minorities) (Hainmueller & Hiscox, 2010; Mayda, 2006; Scheve & Slaughter, 2001). Bonacich (1972) also argues that a labor market is split into at least two groups (e.g., white workers vs. minorities) and tension between the two groups will be created due to competition over scare resources.

From the theoretical expectations described above, we can hypothesize that a deterioration of macro-level socioeconomic conditions such as an increase in the

[27] Among the theories based on inter-group competition, although not fully listed, see Blumer (1958), Bobo (1988, 1996), Bonacich (1972), Coser (1956), Scheepers et al. (2002).

unemployment rate can trigger competition over scarce resources in the labor market, which has a greater effect on white workers located at the low end of the skill distribution. The theories, therefore, predict during economic downturns that white workers located at the low end of the skill distribution will have stronger prejudice against black workers, compared to those with greater skills, since they will be exposed to more competition.

Several studies also emphasize material self-interests (e.g., earnings and economic opportunities) in explaining racial preference change and use the factor-endowment model to show how a change in factor proportions (e.g., skilled vs. unskilled labor) in the labor market can create antagonistic attitudes toward out-group members (Facchini & Mayda, 2009; Mayda, 2006; Scheve & Slaugheter, 2001).[28] Applying factor endowments model with the assumptions of perfect substitutability between white and black workers and perfect elasticity of capital, Mayda (2006, p. 510) argues that the skill composition of white relative to black workers will be associated with attitudes toward minorities.

What the factor endowments model predicts is that a change in factor proportions will affect factor prices if there exists a substantial shock to the factor's supply. For example, an increase in the amount of unskilled out-group members in the labor market will have a negative effect on wages of low-skilled white workers (Hainmuller et al., 2015). Extending these theoretical predictions, we expect that if the proportion black in the population changes substantially, that will affect factor prices (i.e., mostly wages) in the labor market, which will in turn affect racial preferences of white workers, in particular those who are located at the low end of the skill distribution.[29]

[28] These studies analyze social attitudes toward migrants in non-US contexts.

[29] Here, we assume that black workers are less educated (i.e., less skilled) compared to white workers. This assumption is supported by level of education by race. See the following website.

As described in the literature review section, we try to fully control age, period, and cohort variables to estimate the coefficients of interest; the previous literature examining the determinants of changes in preference has not addressed the role of these factors. Considering that any temporal change in social outcomes (discriminatory preferences in our case) can be attributed to age, period and cohort effects, as pointed out in Fosse and Winship (2019), only by controlling those three-time dimensional variables can we identify the effects of the variables of interest (i.e., unemployment rates and the proportion of black population) in our model specifications. Since unemployment rates and proportion black are measured within Census division, it is relative changes of those independent variables within division that identify the effects of these variables. We first focus on the mean relationship between discriminatory preferences and the independent variables by using an OLS method.

With a quantile regression approach, in addition to focusing on mean preferences that might miss an important part of the mechanism, we expect that if there is a substantial change in the proportion black in the population or there occurs negative economic changes such as an increase in unemployment rates, then, they are associated with a change in racial preferences of white workers, in particular those who are located at the low end of the skill distribution since they are exposed to more competition over scarce resources, while those who are located at the upper tail are less affected by these changes.

Data

Data used for this study are based on the General Social Survey (GSS) from multiple waves (1976-2018) and includes 64,785 observations in total: 52,011 whites, 9,183 blacks, and 3,591 others. The GSS is a repeated cross-sectional survey that measure the attitudes and

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https://www.brookings.edu/blog/social-mobility-memos/2017/12/04/black-women-are-earning-more-college-degrees-but-that-alone-wont-close-race-gaps/

behaviors of the survey respondents in the United States beginning in 1972 (Davis, Smith, and Marsden, 2005). In each year of the survey, multistage stratified sampling is used,[30] and a nationally representative sample of adults of age 18 and older is included (Yang & Land, 2013). In many survey years, the GSS provides survey questions from which we can infer an individual's racial preferences.

As described in Charles and Guryan (2008), there have been 26 different survey questions asked over the approximately 40 years of the GSS, and those questions can be used to identify racial feelings for the survey respondents (p. 782).[31] In each year, a different subset of the questions was asked, and as described in Jayadev and Johnson (2017), the questions asked vary from the role of government policy for black people to direct measures of racial hostility (p. 381). The 26 questions, for example, include one indicating whether the individual objects to interracial marriage, and one asking if the respondent's political party nominated a black for president, would the respondent vote for him if he was qualified for the job.

To obtain a measure of racial preference, this research follows what Charles and Guryan (2008) suggest in their paper - a standardized measure of racial preference.[32] They consider both the mean and variance within and across questions to standardize the measure of racial preference since the range of numerical values in responses differs across questions (Jayadev & Johnson, 2017). As pointed out in Charles and Guryan (2008), however, there are some questions that are more associated with the role of government rather than with racial sentiments. Among the 26 questions, for example, one focused on government expenditures

[30] For more information on the multistage sampling technique used in the GSS, please look at the document offered at the following website.
https://gss.norc.org/documents/codebook/gss_codebook.pdf

[31] For a full list of the 26 different questions and the frequency of those questions asked in each survey year, please see App. Table 1 and App. Table 2.

[32] For more information on the construction of the measure of racial preference by Charles and Guryan (2008), see their paper, in particular pp. 783-785.

for blacks is excluded in constructing the measure since the question is more related to views about the appropriate role of government (Charles & Guryan, 2008, p. 783). Five questions out of the 26 questions were excluded in the construction of the measure for this reason.[33]

In what follows, we will show trends - based on some of the racial-related questions - over the past 30 years, and we will also look at how racial preference - based on Charles and Guryan (2008) - changes across nine census regions over time. After describing the trends, we will focus on empirical analyses based on an OLS method and a quantile regression approach.

Figure 1 shows trends in response to the four racial-related questions that are standardized based on Charles and Guryan (2008), which are most commonly asked in the GSS survey from 1972 to 2018. The scale on the y-axis is structured so that higher values mean greater discriminatory preferences against blacks. Following Charles and Guryan (2008), we excluded two questions from Figure 1 that were also frequently asked, because they were more associated with the role of government.[34] In Figure 1, we can recognize a general downward trend in response to all the questions although there exist some variation in the trend. For example, there is a relatively small decline in D16 while there is a quite large decline in D21.

Figure 2 shows trends in a standardized racial preference index based on Charles and Guryan (2008) by US geographic division. There are a couple of things that can be noticed in Figure 2. First, there exists a general decline in indexes between the 1970s and the mid 1990s. Although there is an increase between the mid 1990s and 2000, a decline is observed since 2000. Second, as pointed out in Charles and Guryan (2008), the relative ranking of levels of a racial preference index is constant across regions over time. For example, the

[33] D1, D2, D5, D6, and D22 in App. Table 1 are not used in the construction of the measure.
[34] The two questions excluded are D5 and D6 in App. Table 1.

South divisions (e.g., the East South Central) are most prejudiced throughout the period while the Pacific and Mountain divisions are the least prejudiced.

Empirical Results

Table 1 presents a series of regression results showing how the coefficients of some key independent variables change based on different model specifications. Numbers in parentheses are standard errors of the coefficients. The coefficients in Model 1, for example, are obtained without age, period, and cohort variables controlled while the coefficients in Model 8 are obtained with the three-time dimensional variables controlled. Looking at the coefficients of years of education in Table 1, we see that they vary by about 15-20% as we control more variables (i.e., age, period, and cohort variables).[35] The coefficient of education in Model 8, for example, shows that one year of education is associated with a decrease in racial preference by about 0.024, which is equivalent to about 3.5 percent of a standard deviation in racial preference. The coefficients of education are relatively stable and statistically significant across different model specifications.

Looking at the coefficients of female, its range is about 10-20% as we control additional variables, and the coefficients show that women are much less likely to have discriminatory preferences than men. Also, there seem to be regional differences in racial preference as shown in the coefficients of regional variables. For example, the West region is less likely to be discriminatory than the South (i.e., the omitted region) by about 0.158 in Model 8, which is equivalent to a reduction in racial preference of about 20 percent of a

[35] Other than the model specifications shown in Table 1, we estimated all the coefficients with alternative functional forms for age and cohort variables, in particular a cubic rather a quadratic for age, and five-year cohort dummies rather than ten-year spans. We obtained almost identical coefficients for the variables shown in Model 8 of Table 1. This implies that although controlling the three-time dimensional variables matters, results are not sensitive to these differences in how they are controlled in regression analyses. Hence, when quantile regression analyses are implemented below, the model specification will be based on Model 8 in Table 1.

standard deviation, and we observe similar levels of discrimination in the Midwest and Northeast regions.

As described in the theoretical framework section, it is argued that competition for scarce resources (e.g., the number of jobs in the labor market) tends to increase the propensity for prejudice and discrimination (Bonacich, 1972; Caselli & Coleman, 2013; Frijters, 1998; Levine & Campbell, 1972). If this theoretical expectation is correct, then unemployment rates should be associated with racial preference. Looking at Table 1, the coefficient of the unemployment rate in Model 8 implies that a one-percentage-point increase in the unemployment rate is associated with an increase in the racial preference index by about 0.014, which is equivalent to about 2 percent of a standard deviation**.**

Also, as implied in the factor-endowments model, the proportion black in the population should be associated with racial preference, since an increase in the supply of unskilled labor (i.e., the number of black workers) relative to skilled workers should have a negative effect on the factor price (i.e., wage) for low-skilled white workers. Contrary to the theoretical expectations, however, a 1 percent increase in the percentage of blacks in the population is associated with a decrease the racial preference index by about 0.002, implying that a 20 percent increase in the proportion black is associated with an increase of about 6 percent of a standard deviation.[36]

As shown in Table 1, we find that there exists a relatively robust association between racial preference and the independent variables. However, as pointed out in Jayadev and Johnson (2017), there may exist differential effects of the variables across the distribution of

[36] In the racial preference literature, there are some alternative theories that can analyze the determinants that can affect racial preference. The group contract theory, for example, argues that contact generally can foster favorable attitudes toward out-group members (Allport, 1954; Pettigrew, 1998). To test this theory, I added to the full model (i.e., model 8) the proportion in the 'other' racial category (including Hispanic) to see whether the theory's argument is supported and how it can affect the other variables. The variable itself is significant in the OLS specification, and it is also significant in some of the other percentile specifications. However, controlling for the variable does not alter any of the other coefficients in a meaningful way.

racial preference (p. 387). Since our interest also lies in how the percentiles of the racial preference distribution for low-skilled (i.e., low-educated) workers are affected by economic factors such as unemployment rates and the proportion of blacks in the population, quantile regression methods are needed to analyze the quantiles of the racial preference distribution.

Table 2 shows the coefficients from an OLS estimation and seven quantile regression estimates, and their model specifications are based on Model 8 in Table 1. Looking at the coefficients of education, level of education seems to be robust in explaining racial preference since holding the other variables fixed, its effect is strong and statistically significant even when we look across the racial preference distribution. Also, regional differences in racial preference are still observed, although the degree of those differences seems to be smaller at the right end of the racial preference distribution.

The coefficients of unemployment rate show interesting results. As described above, the mean relationship, based on an OLS method, is positive as expected in the classical labor market competition theories - competition for scarce resources tend to increase the propensity for prejudice and discrimination (Bonacich, 1972; Caselli & Coleman, 2013; Frijters, 1998; Levine & Campbell, 1972). The effect of unemployment rate also seems to increase as we move up the racial preference distribution,[37] so we observe a larger effect of unemployment rate at the upper end of the distribution.

Looking at the coefficients of the proportion black in the population (i.e., Bproportion) in Table 2, their signs seem to be not consistent with what the factor-endowments model predicts, and these are observed across the racial preference distribution. As we move up to the upper end of the distribution, however, Figure 3 - (b) shows an incremental effect of the black proportion on racial preference - in particular between .50th and .90th quantile, which is consistent with the theoretical expectation, but the coefficients are

[37] Please see Figure 3 - (a).

not statistically significant. The theoretical expectation from the factor-endowment model might be supported if we had more local variations in the black proportion, but our measure of the black proportion is at the level of census regions, not the level of state or local area.[38]

Last but not least, the coefficients of occupation skill are consistent with what the classical labor market competition theories predict. Compared to those in the occupational category where high levels of skill is required (i.e., the omitted group), those with low level of skill required (i.e., occupation_lowskill) are more likely to have discriminatory preferences while those belonging to occupation_other - mostly armed forces - are less likely to have discriminatory preference. These results suggest that the degree of competition exposed to people in the labor market can be the major determinant in explaining racial preference.

Discussion

The regression results in Table 1 are based on an OLS approach with different model specifications on the three-time dimensional variables. The coefficients of interest (e.g., education and unemployment rates) are relatively robust and statistically significant across different model specifications as long as the three-time dimensional variables are controlled. This implies that although controlling the three time-dimensional variables matters, results are not sensitive to how they are controlled. The regression results in Table 1 also show that ethnic competition theories, which argue that antagonistic attitudes are triggered by competition between group members over scarce resources in the labor market, are still useful in explaining the determinants of discriminatory preferences.

As reviewed in the section of empirical results using both OLS and quantile regression approaches, however, we didn't get regression results fully consistent with the

[38] Becker [1957] (1971) also briefly discusses the impact of the number of nonwhites on racial preference, and he admits the difficulty in finding appropriate measure of community (e.g., county, state, or census region) for the number of nonwhites (p. 123-126).

factor-endowments model – in particular, we did not find that a higher the proportion of black population led to more discriminatory preferences. One of the potential explanations for this inconsistency might be due to there being relatively small changes in the proportion of blacks, which might cause white workers not to be aware of resulting decreases in their wage levels, which are expected to trigger racial hostility. In addition, the existence of region fixed effects in the analyses captures the effects of the proportion of blacks between one region and another region. In this case, the changes in the proportion of blacks are treated as the deviations from the mean of the proportion. Therefore, the effects of the proportion of blacks may not be statistically significant because those changes in the proportion among regions are small.

While the use of an OLS approach is informative in examining the effects of the variables on the mean of the discriminatory preference distribution, it does not necessarily show us how the extremes of the distribution (i.e., upper and lower tails) are affected by the variables of interest (e.g., unemployment rates). Since white people with the low levels of education are expected to be exposed to more competition from minorities in the labor market, we can expect that those people will be likely to be located at the upper tail of the discriminatory preference distribution. If this is the case, economic factors such as unemployment rates, will have different effects at different points on the distribution of discriminatory preferences - those at the upper tails of the distribution will be more sensitive to unemployment rates. Hence, this paper used a quantile regression method to model the determinants of discriminatory preferences across the entire distribution, and our findings show that there may exist differential effects of some factors across the distribution.

Summary and Conclusion

This research is focused mainly on examining the relationships between discriminatory preferences and economic considerations based on the classical labor market competition theories. We found that the coefficients of education and unemployment rates remain stable and statistically significant across different model specifications. This paper makes contributions to the literature by 1) getting more precise estimates with a large sample (i.e., the GSS datasets from 1976-2018), 2) conducting regression analyses with considering the effects of the three-time dimensional variables based on OLS and quantile regression approaches, and 3) showing the classical labor market competition theories are still useful in explaining the determinants of discriminatory preferences.

Regardless of the model specifications used in this paper, socioeconomic factors (e.g., education and unemployment rates) are robust and statistically significant in affecting the entire distribution of discriminatory preferences, but it should be noted that our analyses do not show any causal relationships although this research depends on the theoretical predictions in explaining the determinants of discriminatory preferences. Crime rates are, for example, closely related to not only the degree of discriminatory preferences revealed by survey respondents, but also unemployment rates controlled in our research (i.e., an omitted variable bias) (Mungan, 2018). Also, this research uses a public version of the GSS datasets from 1974 to 2018. Since there is limited variation in regional variables controlled in our analyses, our failure to find the relationship between proportion of black population and discriminatory preferences as predicted by the factor-endowments model may be due to this data limitation.

Our findings have policy implications. First, as pointed out in Jayadev and Johnson (2017), our results suggest that discriminatory preferences should be treated as malleable since macroeconomic policies targeted for unemployment rates can also affect those preferences. Insofar as racial wage gaps between white and black workers increase with prejudice, as described in Becker's model, economic policies that reduce discriminatory preferences will reduce racial wage gaps in the labor market. Second, our findings show that discriminatory preferences can be seen as counter cyclical, so any economic policies designed to reduce discriminatory preferences are required to be implemented more actively especially during economic downturns. Last but not least, our findings show that there may exist differential effects of the factors that can affect discriminatory preferences across the distribution of preferences. This means that policy makers and politicians need to be more attentive to the responses of those with extreme opinions, especially individuals with the greatest levels of racial hostility. Such individuals may be more susceptible to economic competition, and policies to ease the economic burden associated with such competition may be most effective.

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Chapter 3. Determinants of Racial Prejudice: A Bounding Analysis of the Effects of Age, Period, and Cohort

Introduction

As argued in Mannheim ([1928], 1972), at important points in history, it is individuals who alter their views and cohorts with different values and beliefs that tend to make social change occur (pp. 292-302). To better understand the nature of social change (i.e., racial preference in our case), for example, it is important to investigate how the shift in racial preference derives from age, period, and cohort effects. The effects of policy on racial preference depend on the underlying mechanisms that drive changes in preferences. Hence. appropriate policies on racial preference can have important consequences on society (e.g., economic growth, redistribution earnings, and so on) (Clark and Eisenstein, 2013).[39]

The empirical results derived from the second chapter of the dissertation show that the coefficients of individual characteristics and area economic and population attributes remain stable regardless of different model specifications as long as the three time-dimensional variables (i.e., age, period, and cohort) are controlled in regression analyses. This implies that although controlling the three time-dimensional variables matters, results are not sensitive to how they are controlled in regression analyses. These analyses tell us about the personal and locational factors that affect racial preference, but the effects of the three time-dimensional variables remain indeterminate due to the linear dependence among them.

To analyze the unique contributions of age, period, and cohort on a variety of outcomes (racial preference in our case), various methods with necessary assumptions have been proposed to address the linear dependence issue (i.e., so-called Age-Period-Cohort, or APC identification

[39] This statement is based on a standard approach in the economics literature that the earnings gap between white and black workers observed in the labor market, after individual characteristics (e.g., education) are controlled, are mainly due to discriminatory preference as argued in Becker ([1957], 1972).

issue).[40] Since existing techniques to obtain point estimates for the three variables (APC) are generally based on unjustifiable theoretical assumptions (Fosse and Winship, 2019b, p. 468), this paper tries to estimate the bounds of the effects of the three variables based on constraining the size, sign, and shape of one or more of the three variables as first suggested in Fosse and Winship (2019a, 2019b).

As described above, although the three-time dimensional factors are intertwined with one another empirically, they identify conceptually different mechanisms. Since any successful policy of reducing racial disparities in economic outcomes may be directly associated with a change in racial preference, it is worthwhile to make efforts to distinguish the three effects. Applying the bounding analysis approach, this paper makes contributions to the literature by 1) trying to identify the overall effects of age, period, and cohort based on the bounds for the linear effects, 2) applying a variety of different bounding strategies to narrow the bounds for the linear effects, 3) making a weak theoretical assumption in estimating the bounds, and 4) use the APC bounding analysis developed by Fosse and Winship (2019a, 2019b) for the first time in investigating how age, period, and cohort affect racial preference.

Those seeking to modify racial attitudes need to recognize the role that each of these mechanisms plays in the process of racial prejudice formation.

Literature Review

The literature has shown that economic outcomes (e.g., wage level) are closely related to changes in racial preferences (Lang & Lehmann, 2012). Despite the important role of racial preferences in economic outcomes, it is noteworthy that there have been few attempts that

[40] One possible solution to the linear dependence, for example, is to drop one of the APC variables assuming there are no effects for the dropped variable. For more information, see Land and Yang (2016, pp. 64-68).

investigate the determinants of racial preferences (Jayadev & Johnson, 2017). The literature, which focuses on examining the determinants of racial preferences, is generally grouped into two subcategories: 1) research investigating the impacts of economic conditions on racial attitudes toward African Americans in the United States (Charles & Guryan, 2008; Goldsmith et al, 2007; Jayadev and Johnson 2017), and 2) research reviewing the impacts of socioeconomic factors on attitudes toward migrants in non-U.S. contexts (Dustmann et al., 2005; Dustmann & Preston, 2006; Facchini & Mayda, 2009, Johnston and Lordan, 2016; Mayda, 2006).

Although the racial preference literature commonly shows the importance of socioeconomic considerations (e.g., unemployment rate, years of education, and so on) in explaining racial attitudes, Fosse and Winship (2019a, 2019b) show that any temporal change - racial preferences in our case - can be attributed to three time-dimensional variables - age, period, and cohort (p. 1976). However, it is noteworthy that most research in the racial preference literature does not explicitly consider the effects of these three variables.

The literature shows that the existence of the social and cultural characteristics (i.e., cohort effects) shared by members of a generation can create differences in attitudes among different cohort groups (Jennings & Niemi, 2014, pp.118-123). Given that more recent cohorts have higher levels of education compared to previous ones, and level of education is negatively associated with discriminatory racial preferences, we might observe a decline in racial preference through the process of cohort replacement if cohort only is considered. This implies that if age and period effects are held fixed in explaining changes in racial preference, cohort replacement can reduce the level of discriminatory preference, resulting in a decrease in the earnings gap between white and black workers.

Mayer (1992) argued, however, that the distinctive patterns (e.g., differences in attitudes) observed among different cohort groups at a point in time are due not to the years when their members were born but to their position in the lifecycle (p. 146). This age explanation argues that age is responsible for any differences observed between generations and those differences will eventually disappear as younger generations replace previous ones. If we accept this explanation and assume, for example, monotonically increasing racial bias with age (Maykovich, 1975), given that older individuals generally have greater economic power, this could lead to larger racial disparities in economic outcomes than would be expected on the basis of average preferences (Blanchard et al., 2008; Charles & Guryan, 2008; Lang & Manove, 2011).

It is also possible that important moments in history - whether they are due to economic, political, or cultural factors - could affect attitudes across all generations and all ages. A negative economic climate reflected in an increase in the unemployment rate, for example, can affect the public's attitudes. During an economic downturn, for example, more competition over scarce resources is generally triggered among ethnic groups in the labor market, which can create antagonistic attitudes against minorities (Coenders et al., 2002, p. 18). This suggests that a change in racial preference may reflect period effects.

Any APC estimator for age, period, and cohort effects uses identifying constraints on regression equations to obtain point estimates, but an infinite number of solutions are possible due to the linear dependence issue (i.e., perfect multicollinearity among age, period, and cohort).[41] Fosse and Winship (2019a, 2019b), however, show that linear combinations of the effects are identifiable, although each effect is unknown due to the linear dependence issue. They

[41] A standard econometric or linear algebra textbook shows that a unique solution for an estimator can be obtained when there exists a regular inverse matrix. However, in APC analyses, there is no unique solution since there is an identical equation such that age = period - cohort (i.e., linear dependence).

also show that general bounding formulas on the effects can be derived from the linear combinations and that the range of the effects can be narrowed down with their bounding strategies (e.g., fixing the size and direction of one or more effects).

Theoretical Framework

According to Fosse and Winship (2019b), any temporal change (i.e., discriminatory preferences in our case) can be attributed to three kinds of processes: (1) age effects; (2) period effects; and (3) cohort effects. Therefore, analyzing age, period, and cohort (APC) variables can be understood as observed indicators for underlying, unobserved, causal processes (Clogg, 1982; Mason & Fienberg, 1985). Carrying this insight over to discriminatory preferences, we can express the equation (i.e., the classical APC model or C-APC) as follows.[42]

$$\text{Eq.1) } Y_{ijk} = \mu + \alpha_i + \pi_j + \gamma_k + \varepsilon_{ijk},$$

where we let $i = 1, \ldots, I$ represent the age groups, $j = 1, \ldots, J$ represent the period groups, and $k = 1, \ldots, K$ represent the cohort groups with $k = j - i + I$ and $K = I + J - 1$. Y_{ijk} is the outcome variable (i.e., discriminatory preferences), and μ is the intercept. α_i, π_j, γ_k represent the i^{th} age effect, the j^{th} period effect, and the k^{th} cohort effect, respectively.

However, Eq. (1) suffers from a fundamental identification problem due to linear dependence (i.e., $\alpha_i = \pi_j - \gamma_k$), which does not allow us to estimate the coefficients in the

[42] The presentation and the equations in this section follow closely from Fosse and Winship (2019b).

equation using conventional statistical techniques.[43] If we orthogonally decompose the linear from the nonlinear components, Eq. (1) can be written as follows.

$$\text{Eq. 2) } Y_{ijk} = \mu + \alpha(i - i^*) + \pi(j - j^*) + \gamma(k - k^*) + \widetilde{\alpha_i} + \widetilde{\pi_j} + \widetilde{\gamma_k} + \varepsilon_{ijk},$$

where the asterisks denote midpoints or referent indices $i^* = (\mathrm{I} + 1)/2$, j^*= (J+1)/2, and k^*= (K+1)/2. α, π, and γ represent the linear effects for age, period, and cohort, respectively while $\tilde{\alpha}$, $\tilde{\pi}$, and $\tilde{\gamma}$ represent the nonlinearities of effects for the three variables.[44] To make the analyses simple, for now, I assume in Eq. (2) that the nonlinearities are zero so that $\widetilde{\alpha_i} = \widetilde{\pi_j} = \tilde{\gamma}_k = 0$. Instead of obtaining point estimates, I will describe how to obtain the bounds of the linear effects for the three-time dimensional variables based on APC bounding analyses suggested by Fosse and Winship (2019a, 2019b). Following this, I will show how to narrow the bounds by specifying the direction of one or two of the slopes and considering the nonlinearities of the three variables. We will group the three variables by categories to facilitate the empirical analysis.

Supposing that the nonlinear terms are zero, then Eq. (2) can be written as follows.

$$\begin{aligned}\text{Eq. 3) } Y_{ijk} &= \mu + \alpha(i - i^*) + \pi(j - j^*) + \gamma(k - k^*) + (0) + (0) + (0) + \varepsilon_{ijk} \\ &= \mu + \alpha(age_i) + \pi\left(period_j\right) + \gamma(cohort_k) + \varepsilon_{ijk},\end{aligned}$$

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[43] As pointed out Fosse and Winship (2019a), obtaining point estimates of the three-time dimensional variables based on traditional approaches of APC analysis such as explicit constraints (e.g., drop-one variable) requires strong assumptions. For a discussion of the most commonly used methods to obtain point identification, see Fosse and Winship (2019a, p. 475-480).

[44] Eq. (2) shows that the overall age effect can be written as $\alpha_i = \alpha(i - i^*) + \widetilde{\alpha_i}$.

where age_i, $period_j$, and $cohort_k$ are the midpoint values for each of the categories.[45] If Eq. (3) is taken as an estimation equation, only two of the three variables can be included due to linear dependence among the variables. What we can observe in Eq. (3) based on actual data is only the particular sums of the slopes that identify the linear effects. Below we will show how to derive the APC bounding formulas - especially period bounds - suggested in the Fosse and Winship papers.[46]

Period Bounds

We can specify particular sums of the slopes using the following equations.

Eq. 4)

$$\alpha^* = \alpha + s$$

$$\pi^* = \pi - s$$

$$\gamma^* = \gamma + s,$$

where the asterisk indicates an arbitrary set of estimated slopes from an APC model under a particular constraint, and s is a scalar fixed to some value. α, π, and γ indicate the true effects of age, period, and cohort, respectively. Because s can take on any value from negative to positive infinity, the true slopes lie at some unknown location on the real number line. From Eq. (4), particular sums of the slopes can be written because the value of s cancels out. In particular, the following equations hold:

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[45] Fosse and Winship (2019b) shows that age_i can be converted to $i - i^*$ because $i - i^* = (age_i - age^*)/(\Delta age)$, where Δage is the width of the category interval.

[46] Fosse and Winship's papers show that we can obtain age, period, and cohort bounds, respectively. However, only the formula for period bounds will be used here since this paper uses the constraint - the estimated period effect is equal to zero - to calculate the bounds for the other effects.

Eq. 5)

$$(\alpha + s) + (\pi - s) = \alpha + \pi = \theta_1$$

$$(\gamma + s) + (\pi - s) = \gamma + \pi = \theta_2.$$

Moreover, we also know the differences $\gamma - \alpha = \theta_2 - \theta_1$ and $\alpha - \gamma = \theta_1 - \theta_2$. Since these combinations of slopes are invariant to any given constraint defined by s, we can estimate θ_1 and θ_2 from the data. Substituting $age_i + cohort_k$ for $period_j$ in Eq. (3), for example, we have the following equation.

$$\text{Eq. 6) } Y_{ijk} = \mu + (age_i)(\alpha + \pi) + (cohort_k)(\gamma + \pi) + \varepsilon_{ijk}$$

$$= \mu + (age_i)\theta_1 + (cohort_k)\theta_2 + \varepsilon_{ijk}.$$

Since there is no linear dependence in Eq. (6), θ_1 and θ_2 are identified and can be estimated from the data. To construct the formula for period bounds, I assume in explaining discriminatory preferences that people become more conservative as they age over time and that more recent cohorts become less conservative as they obtain more education. To show the bounding analysis steps (as described in Fosse and Winship, 2019a), I fix the estimated period effect (π*) to zero (i.e., $\pi^*=0$). We then obtain the constrained estimates $\alpha^*=\theta_1$, $\pi^*=0$, and $\gamma^*=\theta_2$, which have the following relationship to the true age, period, and cohort slopes.

Eq. 7)

$$\theta_1 = \alpha + s$$

$$0 = \pi - s$$

$$\theta_2 = \gamma + s.$$

Since we have constrained the estimated period slope to be 0, we can interpret the arbitrary constant s as an upper or lower bound on the unknown true period slope. That is, if we let $s = \pi_{min}$ or $s = \pi_{max}$, then we have the following inequalities.

Eq. 8)

$$\begin{array}{ccc} \theta_1 - \pi_{min} \geq \alpha & & \theta_1 - \pi_{max} \leq \alpha \\ \pi_{min} \leq \pi & \text{and} & \pi_{max} \geq \pi \\ \theta_2 - \pi_{min} \geq \gamma & & \theta_2 - \pi_{max} \leq \gamma. \end{array}$$

Given that we have set bounds on the period slope, Eq. (8) indicates the corresponding bounds on the age and cohort slopes as shown in Table 1.

Since the period effect (π) can take either positive or negative infinity as its value,

we cannot obtain a set of finite bounds based on Table 1. As suggested in Fosse and Winship (2019b), however, we can narrow bounds with the sign of a slope. Even further, we can obtain a set of finite bounds with the sign of two slopes as shown in Table 2.

To understand how the bounds in Table 2 are derived, consider the case where we calculate the bounds for α based on assuming that $\pi \geq 0$ and $\gamma \geq 0$ (the first line in the lower panel of Table 2). From Table 1, we obtain the following equation.

Eq. 9) $\theta_1 - \pi_{max} \leq \alpha \leq \theta_1 - \pi_{min}$.

With the constraints $\pi \geq 0$ and $\pi_{min} \leq \pi \leq \pi_{max}$, Eq. (9) can be written as follows.

$$\text{Eq. 10) } -\infty \leq \alpha \leq \theta_1.$$

Since $\theta_1 = \alpha + \pi$ and $\theta_2 = \gamma + \pi$, then $\theta_1 = \alpha + \theta_2 - \gamma$. Therefore, $\alpha = \theta_1 - \theta_2 + \gamma$. Using this equation to substitute into Eq. (10), then we have the following equation:

$$\text{Eq. 11) } \theta_1 - \theta_2 + \gamma \leq \alpha \leq \theta_1,$$

where if we use the condition (i.e., $\gamma \geq 0$), then Eq. (11) can be written as

$$\text{Eq. 12) } \theta_1 - \theta_2 \leq \alpha \leq \theta_1.$$

Using this approach, we can obtain the other bounds in Table 2. Table 2 (in particular, the lower part) shows that with constraints based on theoretical assumptions or predictions, we can obtain finite bounds. To summarize, we can obtain the linear effects of the three-time dimensional variables by using the bounding formulas as shown in Table 1 and Table 2.

In order to use this approach, we need to have information regarding the signs for at least some of the effects we wish to estimate. To decide the signs, this paper depends on the literature on racial preferences. For example, most of the literature argues that discriminatory preferences increase with age ($\alpha \geq 0$). Consider that recent cohorts are more educated compared to older cohorts and that the level of education is expected to be negatively associated with discriminatory preferences ($\gamma \leq 0$). Together, these conditions are represented in the fifth line of the lower part Table 2 (e.g., $\alpha \geq 0$ and $\gamma \leq 0$). Following Fosse and Winship (2019b), we will first look at the scenario in which age, period, and cohort consist solely of linear effects.

As pointed out in Fosse and Winship (2019b), however, age, period, and cohort effects consist of both linear and nonlinear effects in reality (p. 1989). To further reduce the bounds derived from the constraints used in this paper, therefore, we can also consider how to use estimates of nonlinear effects, since deviations from linear effects can be fully identified.[47] In our case, we can assume that, as briefly mentioned above, the overall effect (i.e., linear and nonlinear effects considered jointly) of age follows a monotonic increasing functional form in explaining discriminatory preferences (Maykovich, 1975; Quillian, 1995). More specifically, the probability of more discriminatory preferences observed would either increase or stay the same across all the age categories.

To make sure that the overall effect of age follows a monotonic increasing functional form, for example, let us assume that we calculate the deviations from the linear effect based on the constraining the linear effect to be zero. We then find the forward differences in the deviation from the linear effect ($\Delta\tilde{\alpha}$) between any adjacent age categories in the dataset.[48] If we then observe the minimum forward difference among them, the overall difference between categories (linear plus nonlinear effects) will be the sum of the nonlinear effect forward difference ($\Delta\tilde{\alpha}$) and the linear effect (α). If we choose the linear effect to be equal to the negative of the minimum forward difference,[49] the overall effect of age is expected to be flat at this point, and it

[47] As explained in Fosse and Winship (2019b), the nonlinearities are deviations from linear effects, which in turn are unknown (p. 1995).
[48] For this example, we can imagine a specific function that the values of the identified age deviations decrease among some age categories, stay the same, or increase otherwise.
[49] In this case, the size of a linear effect can be written as (-1) $\times$ min ($\Delta\tilde{\alpha}$) if min ($\Delta\tilde{\alpha}$) < 0.

will be positive for all other forward differences. Hence, we know that if the linear age effect is at least this large, then the overall age effect is monotonically increasing. With this shape constraint of age nonlinearities, therefore, we can further narrow finite bounds for linear effects described in Table 2.

Following the approach described above by which the constraint of the age effect is used in reducing the bounds, an assumption on the shape of the cohort effect can also help us reduce the bounds. For example, historical data shows that recent cohorts are more educated compared to older cohorts.[50] The literature also shows that educational attainment is negatively associated with discriminatory preferences (Charles & Guryan, 2008; Gang et al., 2013; Jayadev & Johnson, 2017). Therefore, we can assume that the overall effect of cohort follows a monotonic decreasing functional form in explaining discriminatory preferences. In this case, contrary to the shape constraint of age, we can first find the forward differences between nonlinear deviations for adjacent cohort categories in the dataset ($\Delta\tilde{\pi}$). If we then observe the maximum forward difference and constrain the size of the linear effect of cohort to be less than or equal to the value of the maximum forward difference,[51] the overall effect of cohort is expected to be flat at that point, and so will be smaller at all other points. implying a monotonically decreasing overall effect.

To summarize, the bounding strategies described above allow us to obtain finite bounds by specifying the direction of two or more slopes of the variables in the scenario where there are no nonlinearities. In the more realistic case that considers the nonlinearities of the effects additionally, we can further narrow the bounds.

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[50] For educational attainment distribution in the United States from 1960 to 2021, visit the following website. https://www.statista.com/statistics/184260/educational-attainment-in-the-us/

[51] In this case, the size of a linear effect can be written as (-1) × max ($\Delta\tilde{\pi}$) if max ($\Delta\tilde{\pi}$) > 0.

Data

Data used for this study are based on the General Social Survey (GSS) from multiple waves (1972-2018) and includes 49,464 observations of white respondents with valid data on our measure of discriminatory preferences.[52] The GSS is a repeated cross-sectional survey that measures the attitudes and behaviors of the survey respondents in the United States beginning in 1972 (Davis, Smith, & Marsden, 2005). In each year of the survey, multistage stratified sampling is used,[53] and a sample of adults of age 18 and older is included (Yang & Land, 2013). In many survey years, the GSS provides survey questions from which we can infer an individual's racial preferences.

As described in Charles and Guryan (2008), there have been 26 different survey questions asked over the approximately 40 years of the GSS (p. 782).[54] In each year, a different subset of the questions was asked, and as described in Jayadev and Johnson (2017), the questions asked vary from those on the appropriate role of government policy supporting blacks to direct measures of racial hostility (p. 381). The 26 questions, for example, include one indicating whether the individual objects to interracial marriage, and one asking, if the respondent's political party nominated a black for president, would the respondent vote for him if he was qualified for the job.

[52] The first two paragraph below are based mainly on the data section of the second chapter. The total number of observations available in the GSS from multiple waves (1972-2018) dataset is 64,785.
[53] For more information on the multistage sampling technique used in the GSS, look at the document offered at the following website:
https://gss.norc.org/documents/codebook/gss_codebook.pdf
[54] For a full list of the 26 different questions and the frequency of those questions asked in each survey year, see App. Table 1 and App. Table 2.

This research uses a standardized measure of racial preference following from Charles and Guryan (2008).[55] They consider both the mean and variance within and across questions to standardize the measure of racial preference, since the range of numerical values in responses differs across questions (Jayadev & Johnson, 2017). As pointed out in Charles and Guryan (2008), however, there are some questions that are more associated with the role of government than with racial sentiments. Among the 26 questions, for example, one focusing on government expenditures for blacks is excluded in constructing the measure since the question is more related to views about the appropriate role of government (Charles & Guryan, 2008, p. 783). Five questions out of the 26 questions were excluded in the construction of the measure for this reason.[56]

In what follows, we will review the age-period array of the mean of discriminatory preferences based on the GSS dataset (Table 1) to see how age, period, and cohort effect can be reflected in the array. After reviewing the array, we will show the pattern graphically for the cohort in the array and focus on empirical analyses based on APC bounding analyses as reviewed in the theoretical framework section.

Table 3 shows the mean values of a standardized racial preference index across periods and ages. With age on the vertical axis and period on the horizontal axis at the top, the cohorts can be read on the diagonal axes that begins higher on the left and lower on the right. They are identified by the midpoint of the birth year in Table 3. For example, looking at the cohort indicator 1930 at the lower right, this identifies individuals born from 1926-1934, which corresponds to those age 85-89 in 2015-19.

[55] Following the approach of Charles and Guryan, the measure of racial preference used here is coded so that higher numbers indicate more discriminatory preferences. For more information on the construction of the measure of racial preference, see Charles and Guryan (2008 pp. 783-785).
[56] D1, D2, D5, D6, and D22 in App. Table 1 are not used in the construction of the measure.

If we examine Table 1 from a period perspective, there seems to be a general downward trend in the measure across all periods other than the period 1995-1999. For the age distribution, we can find almost a monotonic increase in the measure within periods.

Looking at Figure 1, we can find two remarkable characteristics. First, the mean values of a standardized racial preference index tend to decrease as an old cohort is replaced with a more recent cohort. This may be largely due to the fact that more recent cohorts have higher level of education, which is known to be negatively associated with discriminatory preferences in the literature (Charles & Guryan, 2008; Jayadev & Johnson, 2017; Mayda, 2006).[57] The discriminatory preferences are highly unstable over age, and do not seem to follow a consistent pattern for different cohorts. This suggests the possibility that period effects may be important.

Empirical Results

In this section, we will show how to obtain bounds for the APC variables based on Fosse and Winship (2019a, 2019b). We will first estimate the bounds of the linear effects for the APC variables, and then we will narrow the bounds by considering the nonlinearities.

Linear Effects

Using Eq. (6) in the theoretical framework section, we can estimate θ_1 (i.e., $\alpha + \pi$) and θ_2 ($\gamma + \pi$), which are -0.1141 and -0.3993, respectively.[58] Based on the period bounds described in the theoretical framework section, we can obtain bounds for the three-time dimensional variables as indicated in Table 4. Figure 2 provides a graphical depiction of the relationship among the three-time dimensional variables based on these estimates.

[57] See the educational attainment distribution by cohort in the United States on the following website. https://www.statista.com/statistics/184260/educational-attainment-in-the-us/

[58] They both are statistically significant at the 1% significance level.

In Figure 2, the left vertical axis refers to the values of the age slope; the top and bottom horizontal axes to the values of the period slope; and the right vertical axis to the values of the cohort slope. We can also refer to each point in the coordinate space in terms of age, period, and cohort. For example, the point on the line (0.8, -0.9146, 0.5179) refers to $\alpha = 0.8$, $\pi = -0.9146$, $\gamma = 0.5179$. As shown in Table 3 and Figure 2, we can obtain the linear relationships among the APC variables based on the values of the θs. Any combinations on the solution line in Figure 2 identifies a potential true combination of linear effects for the APC variables. However, without constraining the direction of one or more slopes, we cannot obtain finite bounds for the true values.

As shown in Table 2 in the theoretical framework section, we can specify the sign of one slope - for example either $\pi \geq 0$ or $\pi \leq 0$ - to obtain bounds with one end of interval set at zero and the other side at either negative or positive infinity. However, the constraint $\pi \geq 0$ implies that the age effect is negative (i.e., $\alpha \leq -0.1141$), which contradicts what the racial preference literature argues – that discriminatory preferences increase with age, i.e., that the age effect is monotonically increasing. If we use the constraint $\pi \leq 0$, we can obtain the bounds as shown in Table 5.

As described in Fosse and Winship (2019b), one drawback of setting the sign of one slope - in our case, $\pi \leq 0$ – is that the set of bounds we obtain is not finite. However, as described in the theoretical framework section, we can obtain finite bounds based on theoretical assumptions or predictions. For example, most of the literature argues that discriminatory preferences increase with age ($\alpha \geq 0$). Recent cohorts are more educated compared to older cohorts, and the level of education is expected to be negatively associated with discriminatory preferences ($\gamma \leq 0$). Together, these conditions are represented in the fifth line of the lower part

Table 2 (e.g., $\alpha \geq 0$ and $\gamma \leq 0$). Based on these signs, we can obtain finite bounds for the APC variables as shown in Table 6.

Nonlinear Effects

In the above section, we have reviewed the linear effects of the APC variables assuming that the nonlinear effects are equal to zero. However, as shown in Eq. (2), the effects of the APC variables generally consist of the sum of linear and nonlinear components. Since the nonlinearities (or deviations from linear effects) of the APC variables can be identified, we can further the bounds through the shape constraints of functional forms of the APC variables. As described in the theoretical framework section, to obtain tighter bounds we use the following assumptions: 1) the overall effect of age follows a monotonic increasing functional form and 2) the overall effect of cohort follows a monotonic decreasing functional form in explaining discriminatory preferences.

As Fosse and Winship (2019b) show that the bounds can be reduced further when the assumptions are used together (p. 1989-1993), we will use those two assumptions to produce narrower bounds. The educational attainment distribution in the United States shows that recent cohorts are more educated compared to older cohorts. It is also well known that educational attainment is negatively associated with discriminatory preferences (Charles & Guryan, 2008; Gang et al., 2013; Jayadev & Johnson, 2017). Combining these two characteristics with monotonically increasing racial bias with age (Maykovich, 1975), we can argue that the overall effect of cohort has a monotonic decreasing functional form while the overall effect of age has a monotonic increasing functional form.

To illustrate how we can reduce the bounds we obtained in Table 6, we can consider our dataset with $\theta_1 = -0.1141$ and $\theta_2 = -0.3993$ including the nonlinearities for the APC variables as shown in Figure 3. The nonlinearities for the cohort groups are $\tilde{\pi} = \{0.0599, 0.0704, 0.0409, \ldots, 0.0272\}$.[59] For the overall effect of cohort to be monotonically decreasing, as described in detail in the theoretical framework section, the size of the linear effects of cohort should less than or equal to the negative of the value of the maximum forward differences (i.e., $\Delta\tilde{\gamma} = 0.0703$), which is the difference between cohorts 1970 and 1975.[60] That is, if we constrain the size of the linear effect of cohort to be less than or equal to (-1) × max ($\Delta\tilde{\gamma}$) if max ($\Delta\tilde{\gamma}$) > 0, then we can obtain the overall effect of cohort that follows a monotonic decreasing functional form.

Panel (a) in Figure 4 shows the bounds for the APC variables based on Table 6. For example, the blue shaded region indicates the bound for the period slope and the green shaded region indicates the resulting bound for the age slope. With these two shaded regions, we can rule out any slopes that are not lying in the feasible region (i.e., the solid line). On the other hand, panel (b) shows that we can further reduce the bounds by considering the nonlinearities and the shape constraints of cohort and age effects - there is a feasible area that lies in the three shaded regions in panel (b) and we can obtain more reduced bounds as shown in Table 6.

Overall Effects

Incorporating the constrained slopes with the shape constraints from the nonlinearities, we can obtain the overall effects of the APC variables as shown in Figure 7 based on the assumptions that the overall effect of cohort is monotonically decreasing, and the overall effect

[59] As shown in Figure 2, there are 21 cohort groups in total since we do not include the three cohort groups (1885, 1890, 1895) in the APC analysis. Since their ages are more than 75, we can argue that they cannot show valid cohort effects. As described in Fosse and Winship (2019b), it is hard to interpret these nonlinearities because they are deviations from unknown linear effects.

[60] Rather than using the maximum forward difference for cohort, we could have applied this approach to age. In the case of age, however, we should calculate the minimum forward difference for the overall effect of age to be monotonically increasing.

of age is monotonically increasing. From the overall effects shown in Figure 5, we can make a couple of conclusions. First, the period effect seems to be negatively associated with discriminatory preferences although there was an increase between 1992 and 1997.[61] Second, although racial bias increases with age, the existence of the period and cohort effects seem to have been primary sources of a decreasing trend in discriminatory preferences over time. When information on these three effects is combined, we may conclude that although there may be temporal variations over time, discriminatory preferences in the United States will show a general downward trend due to the large effect of cohort.

Summary and Conclusion

The economic literature on the determinants of racial preference or racial attitude shows consistent results: socioeconomic factors and locational factors impact changes in racial preference. However, there are few attempts that try to investigate the effects of age, period, and cohort in explaining the shifts in racial preference despite their importance. The sociological literature, on the other hand, shows that the effects of age, period, and cohort are intertwined in their effects on social change (Mannheim [1928], 1972). This implies that age, period, and cohort have underlying mechanisms that drive changes in preference. This research adds to the literature on racial preference by 1) trying to identify the overall linear effects of age, period, and cohort based on the bounding analyses, 2) estimating narrower bounds with a variety of bounding strategies, 3) depending on weak theoretical assumptions in estimating bounds, and 4) using the APC bounding analyses for the first time in the racial preference literature.

[61] One of the potential explanations for such an increase between 1992 and 1997 may relate to the crack epidemic that occurred in major cities in the United States, which had a serious effect on African American communities (Dunlap et al., 2006).

Our findings show that using theoretical justifications or weak assumptions on the signs of effects of the three-time dimensional variables it is possible to obtain the finite bounds for the linear effects. Further, we show that using shape constraints for variable effects, it is possible to obtain tight bounds based on strong theoretical assumptions. The APC bounding analysis used in this paper confirms the view that discriminatory preferences tend to increase with age while the effects of period and cohort are negative in explaining discriminatory preferences. These findings suggest that discriminatory preferences in the United States will show a general downward trend although there may be variations over time.

Although the bounding strategies outlined in this research are very flexible in estimating the bounds for the linear effects, the constraints used in this research are based on theoretical predictions that cannot be verified. In this sense, we admit that there is no ultimate solution to the APC identification problem that does not require theoretical knowledge about at least one of the APC variables (Bell, 2020).

Our findings lead to clear conclusions. First, the age effect identified in this research - an increase in discriminatory preference with age - implies that large racial disparities in economic outcomes (e.g., employment or wages) may be observed in the labor market if older individuals have greater economic power since their preferences will be most strongly associated with economic outcomes (Borjas, 2016). Second, the period effect in our research shows that there may exist variations in racial preference over time due to the period effects. This suggests that the degree of racial preference can vary relatively easily according to, for example, macroeconomic conditions. Third, our research shows that the cohort effect displays a strong downward trend, which plays an important role in explaining racial preference. Considering the positive relationship between years of education and more recent cohorts, we may expect in the long run that our society will have less racial preference through the process of continuing cohort replacement.

In terms of policies, the findings of both strong cohort and period effects suggest that the social changes have operated both by altering the life beliefs in formative periods of personal development as well as influencing the general population across age groups. Those seeking policies to change attitudes should recognize that their activities should focus on both these mechanisms.

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Tables and Figures

Table 1-1[62]: Discrimination Estimates

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 A.3.

Table 1-2: Estimates from Different Bivariate Probit Sample Selection Models in Loan Denial Equations with Pooled SSBFs Data

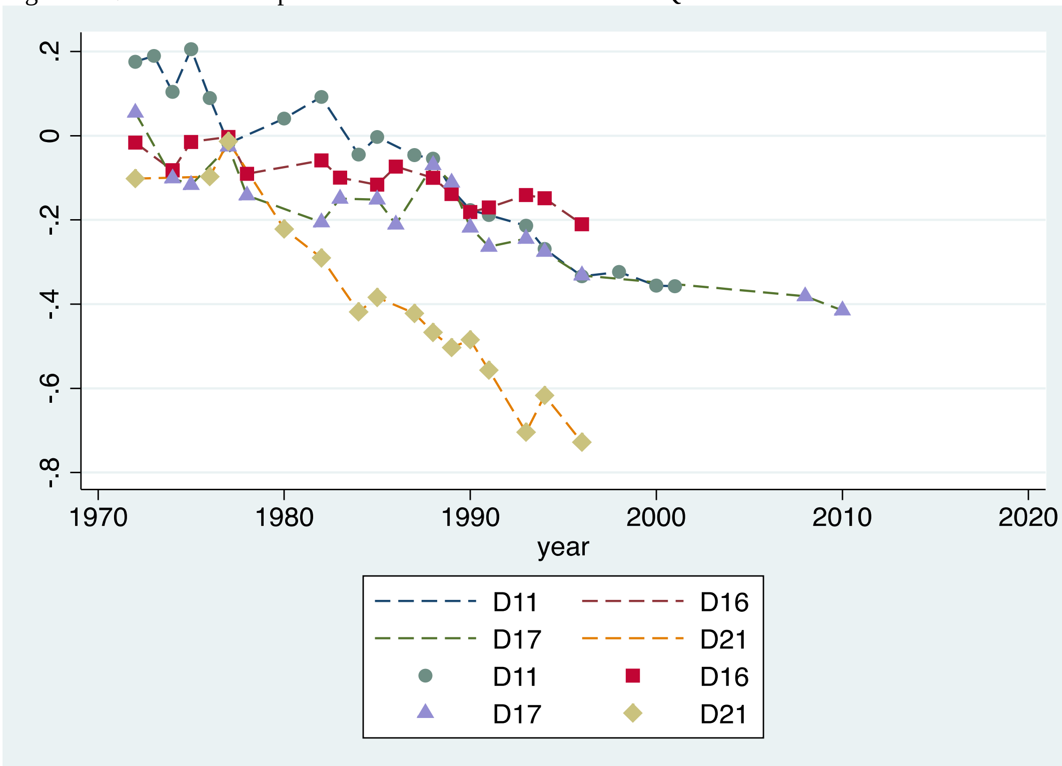
Model Specification	African American	Hispanic	Other	White Women	No. of Observations
Panel A: Bivariate probit sample selection model [a]	Outcome equation: same as model 8 in Table 1: loan and lender characteristics included Selection equation: loan and lender characteristics excluded with identifying variables				
Denial	0.1490*** (0.0411)	0.0585* (0.0322)	0.1489*** (0.0331)	0.0187 (0.0242)	N = 12,198
Apply (Selection Equation)[b]	0.0354 (0.0248)	-0.0130 (0.0224)	-0.0646*** (0.0192)	-0.0364*** (0.0132)	N = 12,198
Correlation between error terms in estimation equations	-0.8843***				
Panel B: Bivariate probit sample selection model	Outcome equation: As table 8 in Table 1 except loan and lender characteristics excluded Selection equation: loan and lender characteristics excluded with identifying variables				
Denial	0.1485*** (0.0560)	0.0501 (0.0318)	0.1157*** (0.0329)	0.0225 (0.0211)	N = 12,349
Apply (Selection Equation)	0.0354 (0.0248)	-0.0130 (0.0224)	-0.0646*** (0.0192)	-0.0364*** (0.0132)	N = 12,349
Correlation between error terms in estimation equations	-0.8871***				
Panel C: Bivariate probit sample selection model	Outcome equation: loan and lender characteristics included Selection equation: loan and lender characteristics excluded without identifying variables				

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

Denial	0.1475*** (0.0360)	0.0609* (0.0314)	0.1461*** (0.0314)	0.0179 (0.0243)	N = 12,198
Apply (Selection Equation)	0.0331 (0.0250)	-0.0153 (0.0224)	-0.0692*** (0.0192)	-0.0369*** (0.0133)	N = 12,198
Correlation between error terms in estimation equations	-0.8800***				
Panel D: Bivariate probit sample selection model 4	Outcome equation: loan and lender characteristics excluded Selection equation: loan and lender characteristics excluded without identifying variables				
Denial	0.1495*** (0.0431)	0.0520* (0.0302)	0.1132*** (0.0297)	0.0216 (0.0213)	N = 12,349
Apply (Selection Equation)	0.0331 (0.0250)	-0.0153 (0.0224)	-0.0692*** (0.0192)	-0.0369*** (0.0133)	N = 12,349
Correlation between error terms in estimation equations	-0.8788***				
Panel E: Bivariate probit sample selection model	Outcome equation: the same as model 1 in Table 1 Selection equation: loan and lender characteristics excluded with identifying variables				
Denial	0.4042*** (0.0682)	0.0872** (0.0371)	0.1132** (0.0468)	0.0233 (0.0224)	N = 12,349
Apply (Selection Equation)	0.1320* (0.0789)	-0.0325 (0.0734)	-0.2122*** (0.0686)	-0.1131** (0.0440)	N = 12,349
Correlation between error terms in estimation equations	0.2477				
Panel F: Bivariate probit sample selection model	Outcome equation: the same as model 1 in Table 1 Selection equation: loan and lender characteristics excluded without identifying variables				
Denial	0.3870*** (0.0700)	0.0804** (0.0350)	0.1092** (0.0442)	0.0198 (0.0206)	
Apply (Selection Equation)	0.1287 (0.0789)	-0.0367 (0.0730)	-0.2243*** (0.0685)	-0.1126** (0.0440)	N = 12,349
Correlation between error terms in estimation equations	0.3104				N = 12,349
Panel G: Bivariate probit sample selection model	Outcome equation: the same as model 2 in Table 1 Selection equation: loan and lender characteristics excluded with identifying variables				
Denial	0.2787*** (0.0592)	0.0726** (0.0309)	0.0903** (0.0351)	0.0152 (0.0180)	
Apply (Selection Equation)	0.1172 (0.0764)	-0.0361 (0.0728)	-0.2132*** (0.0683)	-0.1126** (0.0439)	
Correlation between error terms in estimation equations	0.3209				N = 12,349
Panel H: Bivariate probit sample selection model	Outcome equation: the same as model 2 in Table 1 Selection equation: loan and lender characteristics excluded without identifying variables				
Denial	0.2609*** (0.0562)	0.0660** (0.0284)	0.0809** (0.0326)	0.0123 (0.0164)	
Apply (Selection Equation)	0.1096 (0.0767)	-0.0414 (0.0724)	-0.2251*** (0.0682)	-0.1123** (0.0439)	
Correlation between error terms in estimation equations	0.3877				N = 12,349

[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 the all selection equations are regression estimates, not marginal effects.

Figure 2-1: Trends in Response to Some GSS Racial-Related Questions



Note: For descriptions of the questions used, please see App. Table 1.

Figure 2-2: Trends in a Racial Preference Index by Census Region

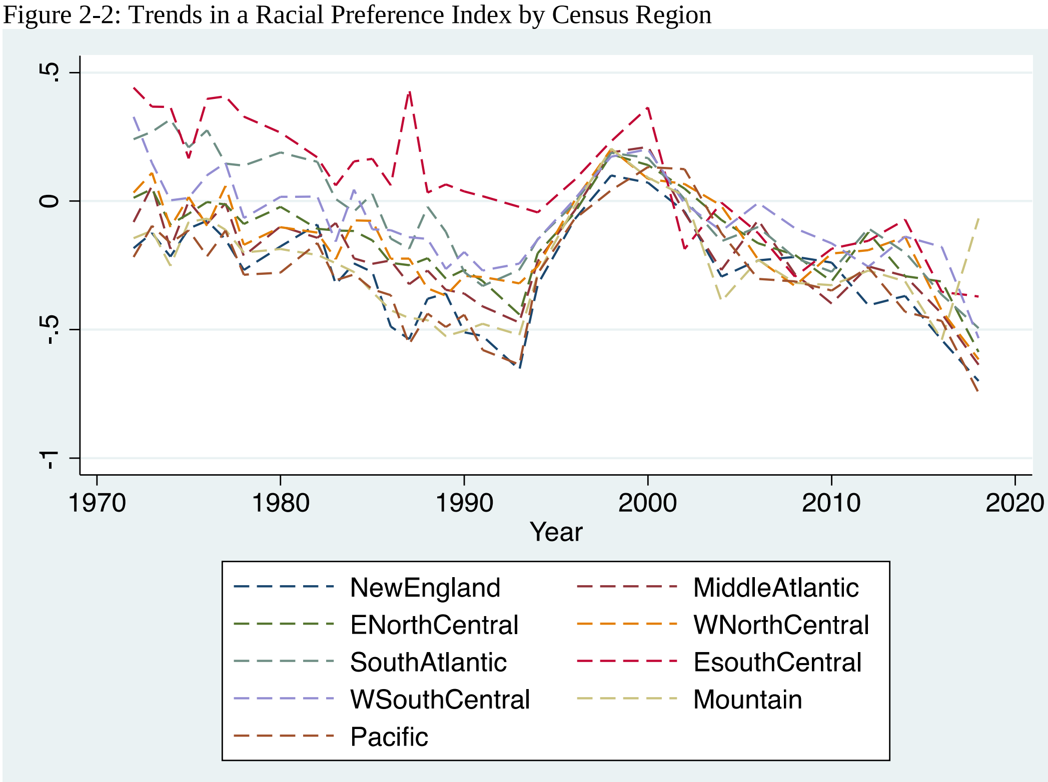


Table 2-1: OLS Regression Results based on Different Model Specifications: Pooled GSSs Data[a]

	Aggregate Index of Individual Racial Preference							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of education	-0.0300***[b]	-0.0287***	-0.0274***	-0.0246***	-0.0254***	-0.0243***	-0.0242***	-0.0242***
	(0.00142)	(0.00143)	(0.00138)	(0.00144)	(0.00139)	(0.00144)	(0.00140)	(0.00140)
Female	-0.0587***	-0.0548***	-0.0526***	-0.0475***	-0.0470***	-0.0479***	-0.0468***	-0.0466***
	(0.00742)	(0.00744)	(0.00712)	(0.00740)	(0.00713)	(0.00739)	(0.00712)	(0.00712)
West	-0.138***	-0.145***	-0.151***	-0.0982***	-0.157***	-0.0819***	-0.157***	-0.158***
	(0.0190)	(0.0191)	(0.0204)	(0.0191)	(0.0204)	(0.0193)	(0.0204)	(0.0204)
Midwest	-0.0638***	-0.0685***	-0.0741***	-0.0479***	-0.0785***	-0.0395***	-0.0794***	-0.0796***
	(0.0140)	(0.0140)	(0.0145)	(0.0140)	(0.0145)	(0.0141)	(0.0145)	(0.0145)
Northeast	-0.107***	-0.114***	-0.123***	-0.105***	-0.132***	-0.0990***	-0.132***	-0.132***
	(0.0136)	(0.0136)	(0.0138)	(0.0136)	(0.0138)	(0.0136)	(0.0138)	(0.0138)
Unemployment Rates[c]	-0.000880	-0.000208	0.0134***	-0.00929***	0.0140***	-0.0122***	0.0142***	0.0142***
	(0.00174)	(0.00174)	(0.00317)	(0.00177)	(0.00315)	(0.00183)	(0.00315)	(0.00315)
Proportion of Black Population[c]	-0.00265**	-0.00303***	-0.00250**	0.000186	-0.00270**	0.00127	-0.00271**	-0.00272**
	(0.00116)	(0.00116)	(0.00124)	(0.00117)	(0.00124)	(0.00119)	(0.00124)	(0.00124)
Occupation_other	-0.131***	-0.115***	-0.111***	-0.103***	-0.0887**	-0.111***	-0.0869**	-0.0857**
	(0.0390)	(0.0392)	(0.0366)	(0.0387)	(0.0367)	(0.0387)	(0.0365)	(0.0365)
Occupation_lowskill	0.0276***	0.0341***	0.0263***	0.0418***	0.0353***	0.0396***	0.0358***	0.0364***
	(0.00802)	(0.00805)	(0.00766)	(0.00801)	(0.00769)	(0.00800)	(0.00768)	(0.00769)
Age[d]	-	X	-	-	X	X	-	X
Year	-	-	X	-	X	-	X	X
Cohort[e]	-	-	-	X	-	X	X	X
Number of obs.	47,150	47,073	47,150	47,073	47,073	47,072	47,073	47,072
R-squared	0.054	0.057	0.128	0.068	0.132	0.069	0.133	0.134

[a] This table reports average marginal effects of the coefficients. All the estimates shown above are calculated with weights.
[b] ***, **, and * represents 1%, 5%, and 10% significance level, respectively.
[c] These two variables are obtained from the FRED and the Census websites, respectively.
[d] In Table 1, age variable is controlled in the form of the linear and quadratic terms.
[e] Cohort is a dummy variable and ten-year cohort interval is used in Table 1.

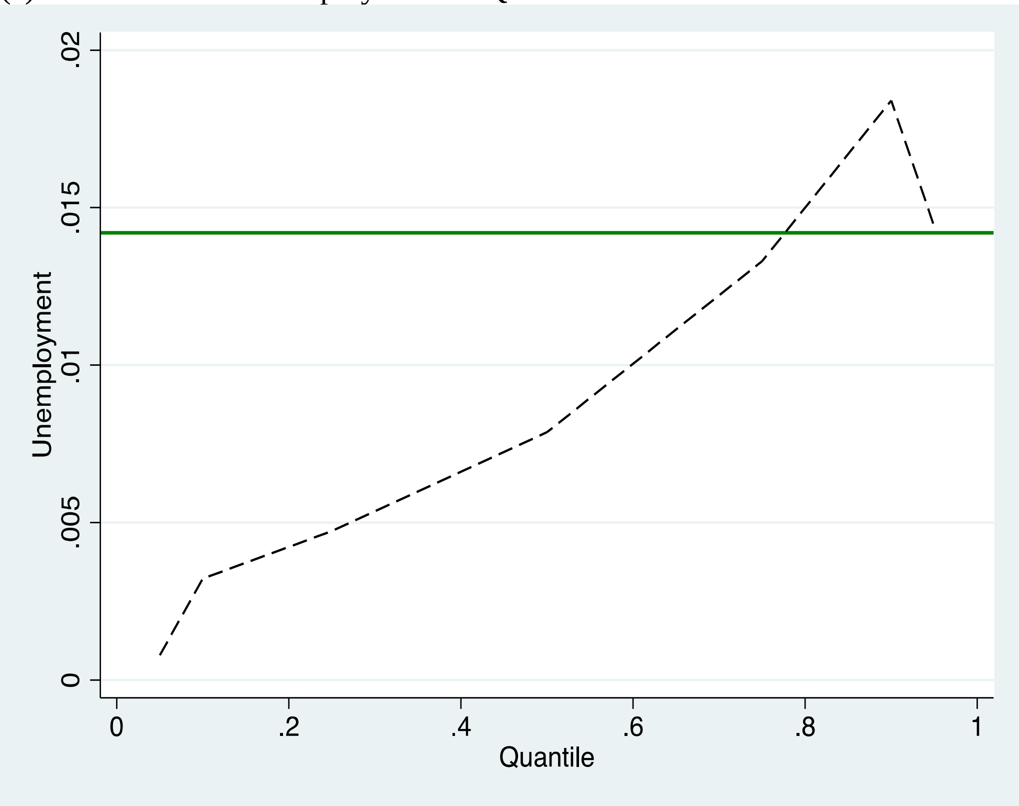
Table 2-2: OLS and Quantile Regression Results: Pooled GSSs Data[a]

	Aggregate Index of Individual Racial Preference							
	OLS	Q(.05)	Q(.1)	Q(.25)	Q(.5)	Q(.75)	Q(.9)	Q(.95)
Years of Education	-0.0242***[b]	-0.00152**	-0.00342***	-0.0115***	-0.0215***	-0.0322***	-0.0317***	-0.0218***
	(0.00140)	(0.000672)	(0.000676)	(0.000972)	(0.00142)	(0.00167)	(0.00106)	(0.00101)
Female	-0.0466***	-0.00538*	-0.0133***	-0.0298***	-0.0393***	-0.0443***	-0.0217***	-0.0302***
	(0.00712)	(0.00307)	(0.00314)	(0.00501)	(0.00750)	(0.00855)	(0.00626)	(0.00332)
West	-0.158***	-0.00668	-0.0275***	-0.0925***	-0.158***	-0.190***	-0.151***	-0.115***
	(0.0204)	(0.00868)	(0.00937)	(0.0124)	(0.0222)	(0.0268)	(0.0208)	(0.0129)
Midwest	-0.0796***	-0.000364	-0.00888	-0.0402***	-0.0740***	-0.105***	-0.0907***	-0.0753***
	(0.0145)	(0.00626)	(0.00628)	(0.00970)	(0.0157)	(0.0194)	(0.0117)	(0.00733)
Northeast	-0.132***	-0.00743	-0.0241***	-0.0774***	-0.131***	-0.159***	-0.130***	-0.105***
	(0.0138)	(0.00565)	(0.00654)	(0.00958)	(0.0149)	(0.0180)	(0.0122)	(0.00881)
Unemployment Rates	0.0142***	0.000787	0.00322**	0.00473**	0.00787**	0.0133***	0.0184***	0.0144***
	(0.00315)	(0.00111)	(0.00137)	(0.00188)	(0.00311)	(0.00424)	(0.00462)	(0.00401)
Proportion of Black	-0.00272**	-0.000114	-0.000973*	-0.00274***	-0.00255*	-0.000844	0.0000839	-0.00100
Population	(0.00124)	(0.000528)	(0.000509)	(0.000821)	(0.00132)	(0.00160)	(0.00109)	(0.000674)
Occupation_other	-0.0857**	-0.0113	-0.0469*	-0.0685**	-0.0675	-0.0773*	-0.0566	-0.0438***
	(0.0365)	(0.0273)	(0.0249)	(0.0287)	(0.0623)	(0.0454)	(0.0507)	(0.0113)
Occupation_lowskill	0.0364***	0.00340	0.00271	0.000819	0.0165**	0.0481***	0.0428***	0.0181***
	(0.00769)	(0.00295)	(0.00321)	(0.00531)	(0.00798)	(0.00945)	(0.00797)	(0.00398)
Age	X	X	X	X	X	X	X	X
Year	X	X	X	X	X	X	X	X
Cohort	X	X	X	X	X	X	X	X
Number of obs.	47,072	47,072	47,072	47,072	47,072	47,072	47,072	47,072
R-squared[c]	0.134	0.214	0.175	0.125	0.094	0.088	0.092	0.057

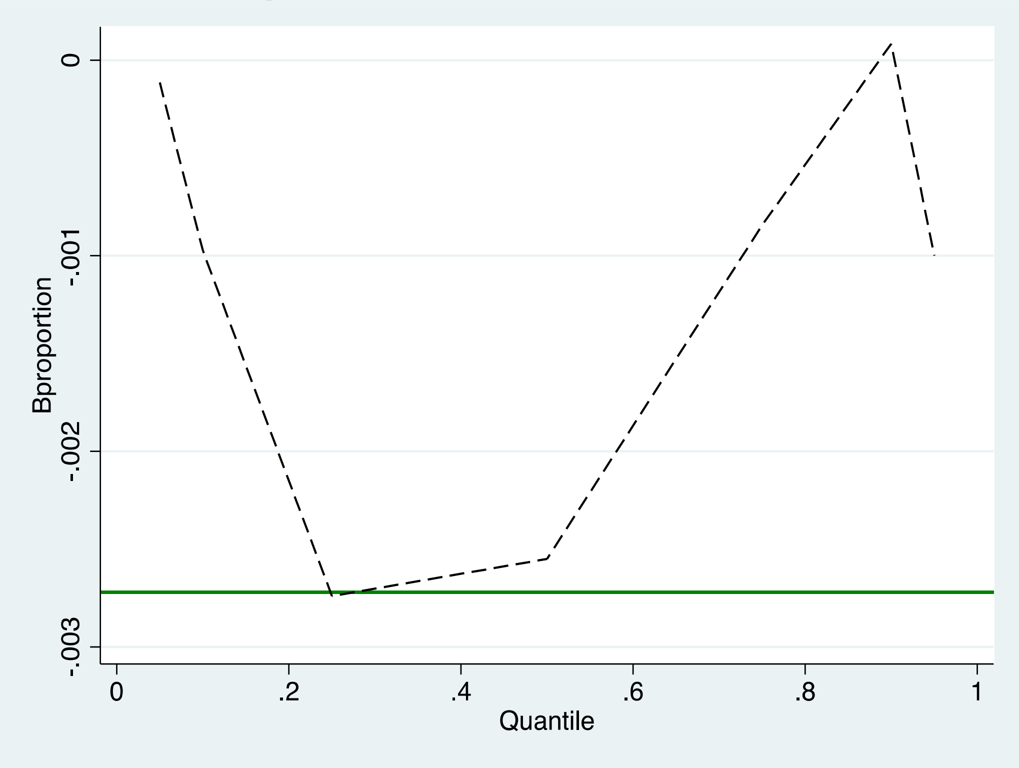
[a] All the coefficients are obtained based on Model 8 in Table 1. All the estimates shown above are calculated with weights.
[b] ***, **, and * represents 1%, 5%, and 10% significance level, respectively.
[c] R-squared for quantile regression models are based on pseudo R-squared.

Figure 2-3: Coefficients

(a) Coefficients of Unemployment as Quantile Varies



(b) Coefficients as Proportion Black as Quantile Varies



Note: the black dotted lines above are the quantile regression estimates for unemployment rate and the proportion black in the population, respectively. The green lines are the OLS estimates.

Table 3-1: The Formula for Period Bounds

Age (α)	$\theta_1 - \pi_{max} \leq \alpha \leq \theta_1 - \pi_{min}$
Period (π)	$\pi_{min} \leq \pi \leq \pi_{max}$
Cohort (γ)	$\theta_2 - \pi_{max} \leq \gamma \leq \theta_2 - \pi_{min}$

Table 3-2: Bounds Given by Setting the Sign of One or Two Slopes

Sign of One Slope			
	Age (α)	Period (π)	Cohort (γ)
$\pi \geq 0$	$-\infty \leq \alpha \leq \theta_1$	$0 \leq \pi \leq \infty$	$-\infty \leq \gamma \leq \theta_2$
$\pi \leq 0$	$\theta_1 \leq \alpha \leq +\infty$	$-\infty \leq \pi \leq 0$	$\theta_2 \leq \gamma \leq +\infty$
Sign of Two Slopes			
	Age (α)	Period (π)	Cohort (γ)
$\pi \geq 0$ and $\gamma \geq 0$	$(\theta_1 - \theta_2) \leq \alpha \leq \theta_1$	$0 \leq \pi \leq \theta_2$	$0 \leq \gamma \leq \theta_2$
$\pi \leq 0$ and $\gamma \leq 0$	$\theta_1 \leq \alpha \leq (\theta_1 - \theta_2)$	$\theta_2 \leq \pi \leq 0$	$\theta_2 \leq \gamma \leq 0$
$\pi \geq 0$ and $\alpha \geq 0$	$0 \leq \alpha \leq \theta_1$	$0 \leq \pi \leq \theta_1$	$(\theta_2 - \theta_1) \leq \gamma \leq \theta_2$
$\pi \leq 0$ and $\alpha \leq 0$	$\theta_1 \leq \alpha \leq 0$	$\theta_2 \leq \pi \leq 0$	$\theta_2 \leq \gamma \leq (\theta_2 - \theta_1)$
$\alpha \geq 0$ and $\gamma \leq 0$	$0 \leq \alpha \leq (\theta_1 - \theta_2)$	$\theta_2 \leq \pi \leq \theta_1$	$(\theta_2 - \theta_1) \leq \gamma \leq 0$
$\alpha \leq 0$ and $\gamma \geq 0$	$(\theta_1 - \theta_2) \leq \alpha \leq 0$	$\theta_1 \leq \pi \leq \theta_2$	$0 \leq \gamma \leq (\theta_2 - \theta_1)$

Figure 3-1: Discriminatory Preferences within Cohorts in the GSS Dataset

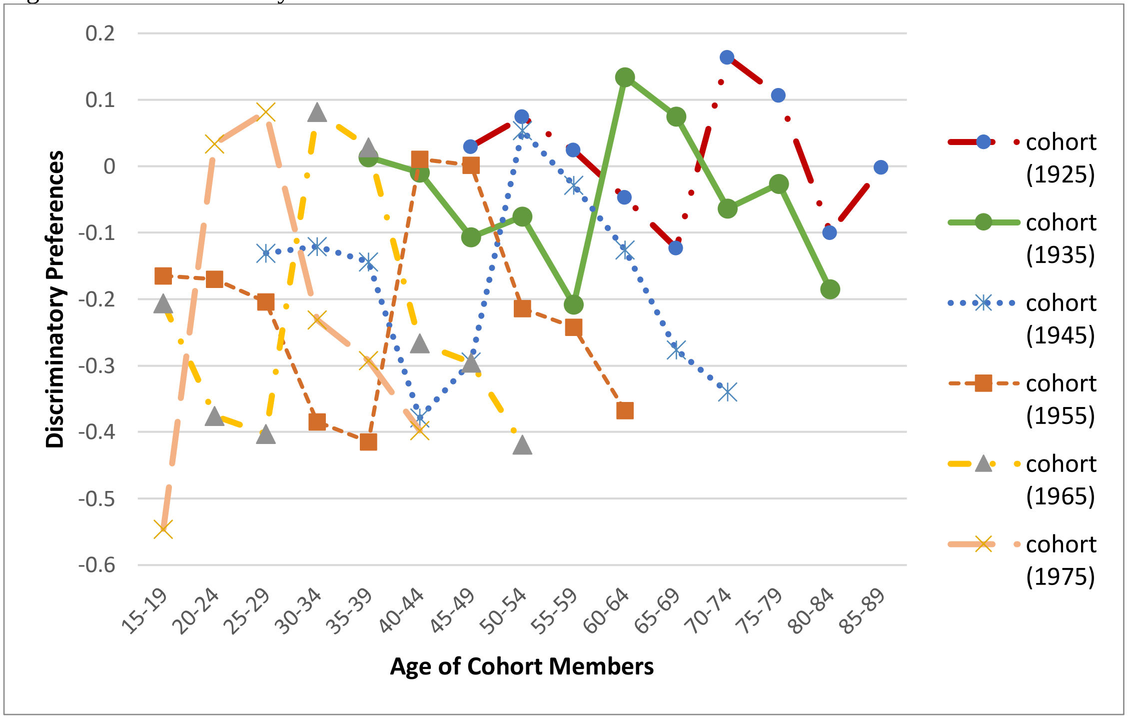


Table 3-3[63]: Age-Period Array of a Standardized Measure of a Racial Preference in the GSS Dataset

Age \ **Period**	1970-1974	1975-1979	1980-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019	**Cohort**
15-19	-0.1647	-0.2361	-0.2064	-0.4190	-0.5455	0.0933	0.1053	-0.3280	-0.2961	-0.6161	2000
20-24	-0.1199	-0.1694	-0.2240	-0.3753	-0.4291	0.0336	0.0890	-0.3014	-0.2864	-0.6171	1995
25-29	-0.1304	-0.1688	-0.2038	-0.4173	-0.4027	0.0244	0.0819	-0.3267	-0.3432	-0.6273	1990
30-34	-0.0150	-0.1211	-0.2059	-0.3843	-0.3933	0.0814	0.0244	-0.2310	-0.3280	-0.6680	1985
35-39	0.0136	-0.0302	-0.1434	-0.3769	-0.4143	0.0461	0.0292	-0.2481	-0.2921	-0.5483	1980
40-44	-0.0097	-0.0089	-0.1124	-0.3785	-0.3907	0.0107	0.0441	-0.2666	-0.3172	-0.3978	1975
45-49	0.0294	0.0406	-0.1064	-0.2467	-0.2942	0.0178	0.0016	-0.1927	-0.2951	-0.4745	1970
50-54	0.0842	0.0740	-0.0547	-0.0753	-0.2810	0.0533	-0.0090	-0.2143	-0.2603	-0.4181	1965
55-59	0.0950	0.0564	0.0242	-0.0823	-0.2083	0.0891	-0.0289	-0.2095	-0.2422	-0.4499	1960
60-64	0.1104	0.1604	0.0339	-0.0473	-0.1310	0.1344	0.0893	-0.1261	-0.2629	-0.3672	1955
65-69	0.2092	0.1328	0.1083	0.0226	-0.1232	0.0654	0.0753	-0.1338	-0.2758	-0.4237	1950
70-74	0.3051	0.2605	0.1925	0.0518	-0.0483	0.1640	0.0388	-0.0632	-0.1363	-0.3392	1945
75-79	0.3042	0.2243	0.1884	0.1445	-0.0178	0.2127	0.1061	0.0322	-0.0269	-0.4095	1940
80-84	0.3182	0.3316	0.1206	0.1122	0.1068	0.2261	0.0642	-0.1000	-0.0967	-0.1848	1935
85-89	0.1541	0.3505	0.0764	0.2783	0.1067	0.1800	0.1154	0.1782	-0.0023	-0.2384	1930
Cohort	1885	1890	1895	1900	1905	1910	1915	1920	1925	1930	

Note: cohort axes indicate midpoint birth year for each age-period cell.

[63] The format is based on Fosse and Winship (2019b)

Table 3-4: Bounds for APC Variables

Age (α)	$\theta_1 - \pi_{max} \leq \alpha \leq \theta_1 - \pi_{min} \Leftrightarrow -0.1141 - \pi_{max} \leq \alpha \leq -0.1141 - \pi_{min}$
Period (π)	$\pi_{min} \leq \pi \leq \pi_{max}$
Cohort (γ)	$\theta_2 - \pi_{max} \leq \gamma \leq \theta_2 - \pi_{min} \Leftrightarrow -0.3993 - \pi_{max} \leq \gamma \leq -0.3993 - \pi_{min}$

Figure 3-2: 2D-APC Graph of the Solution Line

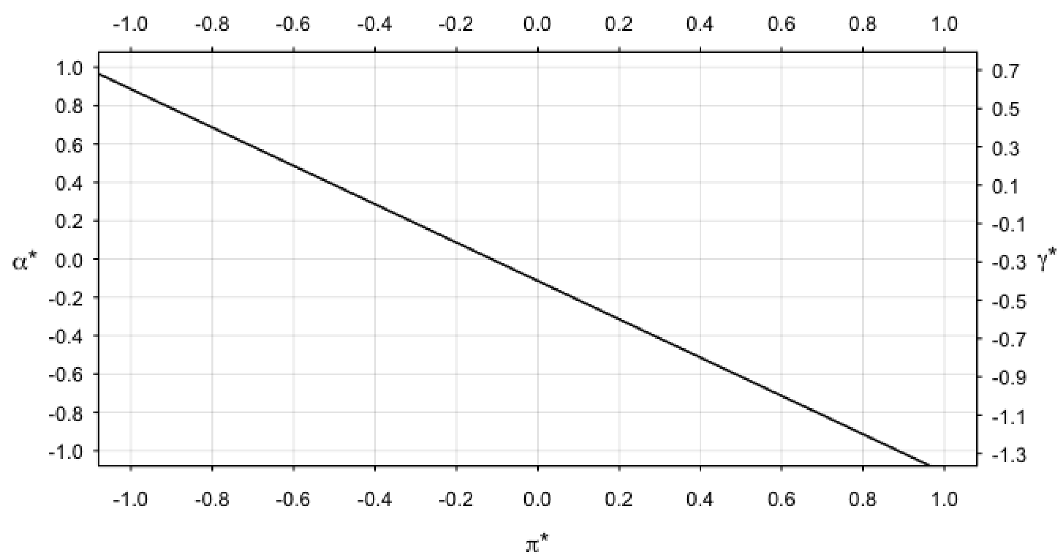


Table 3-5: Bounds for APC Variables with the Constraint, $\pi \leq 0$

Age (α)	$\theta_1 \leq \alpha \Leftrightarrow -0.1141 \leq \alpha$
Period (π)	$\pi \leq 0$
Cohort (γ)	$\theta_2 \leq \gamma \Leftrightarrow -0.3993 \leq \gamma$

Table 3-6: Finite Bounds for APC Variables with the Sings of the Two Slopes, $\alpha \geq 0$ and $\gamma \leq 0$

Age (α)	$0 \leq \alpha \leq (\theta_1 - \theta_2) \Leftrightarrow 0 \leq \alpha \leq 0.2852$
Period (π)	$\theta_2 \leq \pi \leq \theta_1 \Leftrightarrow -0.3993 \leq \pi \leq -0.1141$
Cohort (γ)	$(\theta_2 - \theta_1) \leq \gamma \leq 0 \Leftrightarrow -0.2852 \leq \gamma \leq 0$

Figure 3-3: The Nonlinearities of the APC Variables[64]

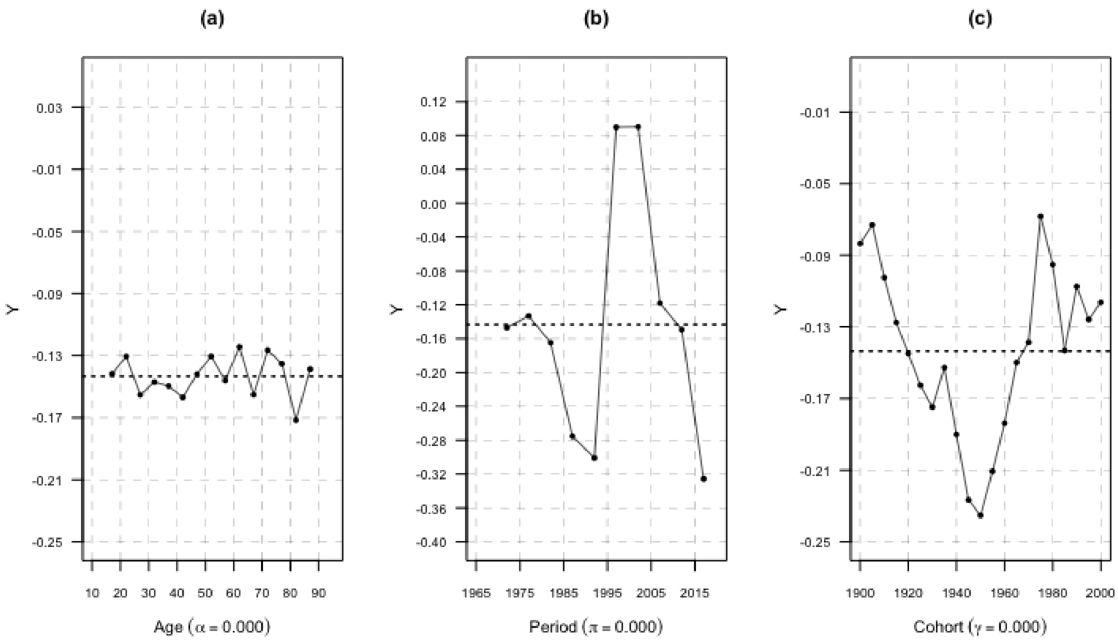


Figure 3-4: Upper and Lower Bounds of 2D-APC Graph When Monotonic Conditions Are Considered

(a) (b)

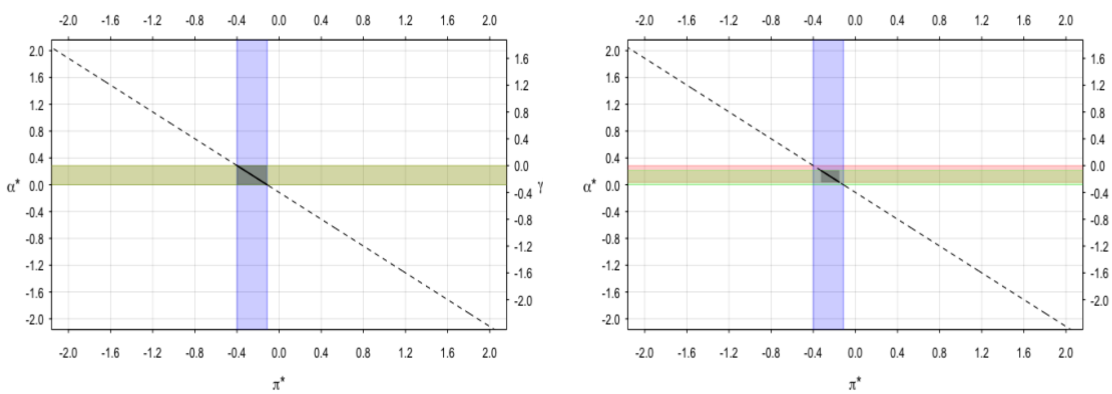


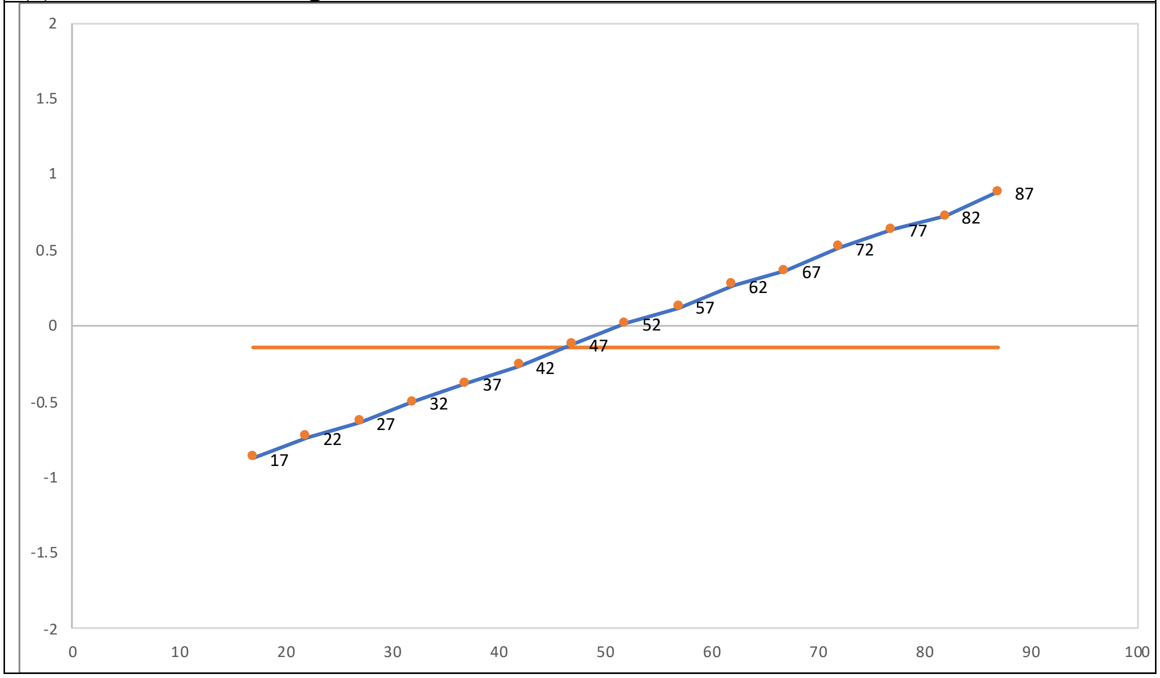
Table 3-7: Finite Bounds for APC Variables with the Shape Constraints

Age (α)	$0.04 \leq \alpha \leq 0.21$
Period (π)	$-0.3241 \leq \pi \leq -0.1541$
Cohort (γ)	$-0.2452 \leq \gamma \leq -0.0752$

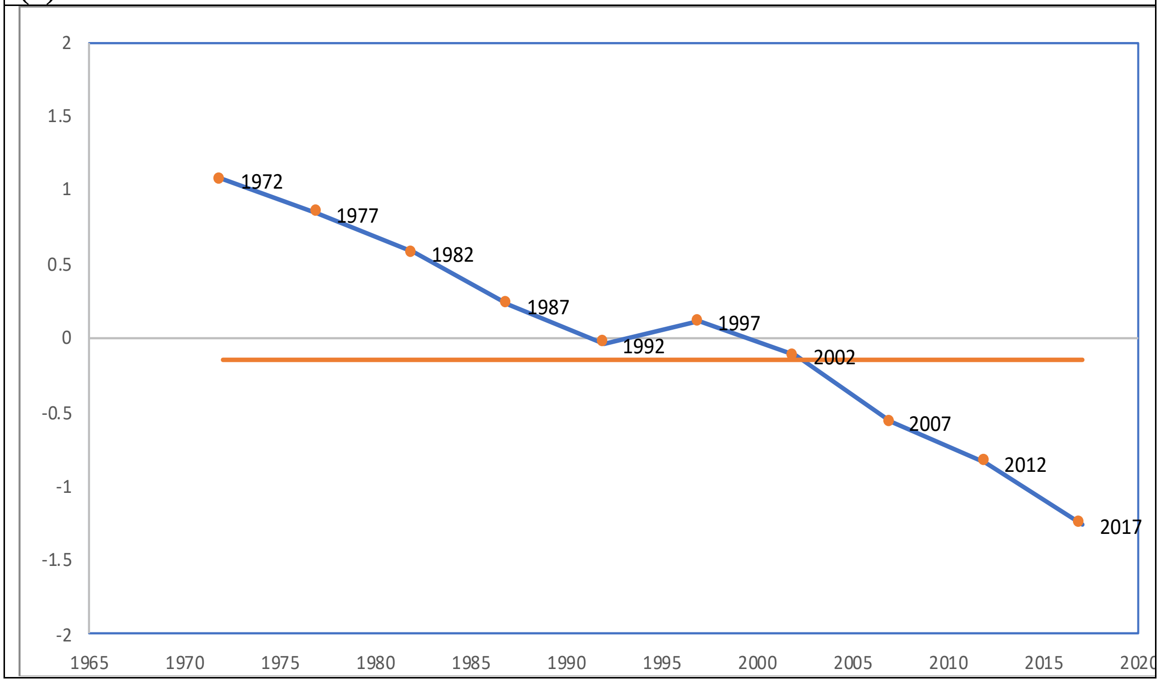
[64] Panel a, b, and c show the identifiable nonlinearities of the APC variables, with the horizontal dashed line indicating the overall mean (= -0.1434) in the data.

Figure 3-5[65]: Overall Effects of the APC Variables

(a) Overall Effect of Age

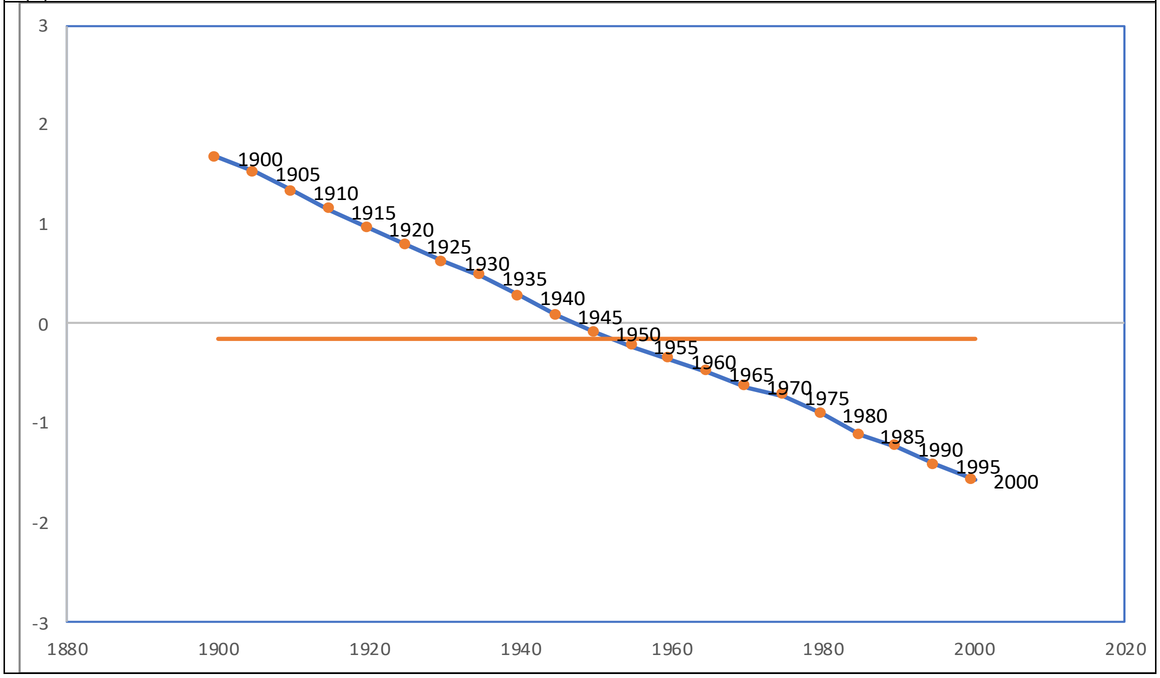


(b) Overall Effect of Period



[65] The orange line in each graph represents the overall mean (= -0.1434) in the data, and the dotted lines indicate the ranges of the possible true values.

(c) Overall Effect of Cohort



APPENDIX

Table A1-1: Variable Definitions

Dependent Variable	
Denied	Whether the most recent loan application was denied
Credit History	
Delinquent_personal	Whether the firm owner had delinquent personal obligations within the past three years
Judgement	Whether the firm or owner had any judgements rendered against them within the past three years
Owner_bankrupt	Whether the firm or the owner declared bankruptcy within the past seven years
Firm Characteristics	
Log_sales	Log of total sales for current fiscal year
Log_profit	Log of total profit for current fiscal year
Log_networth	Log of total net worth of the firm
Firm_age	The age of the firm
Firm_age_square	The square of firm_age
Totemp	Total number of workers
Totemp_square	The square of total number of workers
Organization type	The firm's type - three dummy variables (i.e., corporation, partnership, or proprietorship)
Business_delinquent	Whether delinquent on business obligations within the past three years
Firm's industry	Dummies for seven categories (i.e., mining, manufacture, transportation, whole trade, retail trade, finance, or service)
Owner Characteristics	
Education level	The owner's education level - dummy variables for five categories (i.e., less than high school, high school graduate, some college, college degree, or postgraduate)
Exper	Years of the owner's experience - how many years of experience the principal owner has had managing or owning a business
Owner_age	Owner's age
Loan Characteristics	
Type of loan	The most recent approved or denied loan - dummy variables for six categories (i.e., line of credit, capital, mortgage, vehicle, equipment, other)
Lender Characteristics	
Type of lender	Financial institution which approved or denied the most recent loan - dummy variables for four categories (i.e., commercial bank, savings bank, finance company, or other)
Year_withlender	Total years with financial institution that approved or denied the most recent loan
Type of primary financial institution	The firm's primary institution for financial services - dummy variables for four categories (i.e., commercial bank, savings bank, finance company, or other)
Geographic Variables	
MSA	Whether the firm was in a Metropolitan Statistical Area
Region	The firm's location - dummy variables for nine U.S. subregions (i.e., New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific)
Additional Variables	
Survey-year fixed effects	Dummy variables for years (i.e., the year of 1993, 1998, or 2003)
HHI	The Herfindahl-Hirschman Index - the level of concentration in the banking industry at which the firm's headquarters is located - defined at MSA or county

Table A1-2: Descriptive Statistics for the Full Sample for the 1993, 1998, and 2003 SSBFs (N = 12,412)

	1993 SSBF (N = 4,637)				**1998 SSBF (N = 3,551)**				**2003 SSBF (N = 4,224)**			
Variables	Non-Borrower	Discouraged Borrower	Approved Borrower	Denied Borrower	Non-Borrower	Discouraged Borrower	Approved Borrower	Denied Borrower	Non-Borrower	Discouraged Borrower	Approved Borrower	Denied Borrower
Observations (%)	1990 (42.91)	640 (13.80)	1695 (36.55)	312 (6.72)	2099 (59.11)	500 (14.08)	713 (20.07)	239 (6.73)	2013 (47.65)	330 (7.81)	1693 (40.08)	188 (4.45)
Credit History												
Business Delinquency (%)	9.83 (0.80)[b]	39.00 (2.40)	20.24 (1.32)	41.59 (3.31)	6.69 (0.62)	27.09 (2.25)	14.85 (1.66)	40.41 (3.82)	8.49 (0.77)	36.36 (3.01)	18.80 (1.49)	38.02 (4.57)
	Avg: 19.02 (0.72)				Avg: 13.37 (0.67)				Avg: 15.78 (0.75)			
Across Comparison[a]	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} \neq D_{1998}^{***}$											
Personal Delinquency (%)	7.71 (0.73)	32.19 (2.35)	10.05 (1.01)	31.22 (3.18)	6.01 (0,60)	29.43 (2.30)	10.67 (1.50)	36.15 (3.74)	6.46 (0,68)	40.38 (3.15)	9.39 (1.26)	33.50 (4.42)
	Avg: 13.43 (0.64)				Avg: 12.34 (0.65)				Avg: 12.10 (0.69)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
Bankruptcy (%)	1.07 (0.26)	9.03 (1.43)	1.54 (0.38)	6.00 (1.73)	1.01 (0.23)	8.08 (1.34)	0.11 (1.10)	9.22 (2.36)	1.41 (0.36)	11.19 (2.03)	0.77 (0.31)	4.87 (1.78)
	Avg: 2.67 (0.30)				Avg: 2.48 (0.30)				Avg: 2.40 (0.32)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
Judgments (%)	3.05 (0.46)	12.67 (1.63)	3.37 (0.58)	11.28 (2.16)	2.41 (0.38)	6.34 (1.16)	2.71 (0.86)	13.73 (2.82)	0.79 (0.22)	5.93 (1.51)	2.74 (0.82)	6.67 (2.16)
	Avg: 5.07 (0.40)				Avg: 3.79 (0.38)				Avg: 2.17 (0.33)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$											
Firm Characteristics												
Sales[c] *(Millions)*	0.82 (0.04)	0.47 (0.03)	2.63 (0.12)	0.75 (0.07)	1.04 (0.08)	0.35 (0.03)	2.17 (0.25)	0.77 (0.09)	0.60 (0.03)	0.22 (0.01)	2.33 (0.12)	0.67 (0.08)
	Avg: 1.27 (0.04)				Avg: 1.11 (0.06)				Avg: 1.07 (0.04)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{**}$											
Profit[c] *(Millions)*	0.08 (0.01)	0.02 (0.01)	0.12 (0.05)	0.02 (0.11)	0.13 (0.01)	0.09 (0.03)	0.27 (0.03)	0.02 (0.05)	0.14 (0.02)	0.01 (0.00)	0.30 (0.03)	0.06 (0.01)
	Avg: 0.08 (0.01)				Avg: 0.14 (0.01)				Avg: 0.17 (0.01)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{***}$											
Net Worth[c] *(Millions)*	0.19 (0.01)	0.06 (0.01)	0.50 (0.04)	0.11 (0.02)	0.22 (0.02)	0.03 (0.02)	0.22 (0.04)	0.06 (0.07)	0.18 (0.02)	0.02 (0.02)	0.45 (0.03)	0.01 (0.10)
	Avg: 0.26 (0.01)				Avg: 0.18 (0.01)				Avg: 0.23 (0.02)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{*}$ / $D_{1993} \neq D_{1998}^{***}$											
Total Employment	6.20 (0.18)	4.52 (0.18)	14.90 (0.26)	7.83 (0.42)	8.20 (0.33)	5.32 (0.45)	13.10 (0.75)	8.19 (0.66)	5.80 (0.16)	4.58 (0.29)	15.25 (0.43)	8.83 (0.92).

	Avg: 8.49				Avg: 8.57				Avg: 8.57			
	(0.12)				(0.25)				(0.16)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
Firm Age (Years)	15.69	11.33	14.16	10.22	14.67	11.04	12.15	9.46	15.01	9.17	15.39	10.91
	(0.34)	(0.41)	(0.34)	(0.56)	(0.30)	(0.47)	(0.41)	(0.56)	(0.31)	(0.45)	(0.39)	(0.81)
	Avg: 14.28				Avg: 13.36				Avg: 14.32			
	(0.21)				(0.21)				(0.22)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{***}$											
Sole Proprietorship (%)	48.84	48.10	31.21	39.60	52.21	50.66	37.97	49.19	50.52	56.88	30.50	34.46
	(1.31)	(2.41)	(1.57)	(3.46)	(1.26)	(2.51)	(2.36)	(3.84)	(1.35)	(3.20)	(1.78)	(4.56)
	Avg: 43.21				Avg: 49.40				Avg: 44.58			
	(0.91)				(0.98)				(1.00)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{***}$											
Partnership (%)	8.58	6.57	8.55	4.24	6.50	6.99	8.46	7.46	9.18	7.07	8.67	6.67
	(0.75)	(1.26)	(0.95)	(1.38)	(0.65)	(1.34)	(1.44)	(1.86)	(0.85)	(1.77)	(1.08)	(2.06)
	Avg: 8.00				Avg: 6.97				Avg: 8.70			
	(0.50)				(0.52)				(0.60)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} = D_{1998}$											
Corporation (%)	42.56	45.31	60.22	56.15	41.27	42.33	53.55	43.33	40.28	36.03	60.81	58.86
	(1.28)	(2.36)	(1.63)	(3.47)	(1.23)	(2.48)	(2.39)	(3.78)	(1.30)	(3.04)	(1.84)	(4.61)
	Avg: 48.77				Avg: 43.62				Avg: 46.72			
	(0.90)				(0.97)				(0.99)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} \neq D_{1998}^{***}$											
Firm Mining or Construction (%)	13.56	13.71	15.08	16.24	11.41	12.16	13.23	12.07	9.91	11.09	15.80	11.72
	(0.94)	(1.77)	(1.23)	(2.74)	(0.87)	(1.77)	(1.66)	(2.48)	(0.86)	(2.07)	(1.57)	(3.03)
	Avg: 14.18				Avg: 11.87				Avg: 11.84			
	(0.67)				(0.68)				(0.71)			
Across Comparison	$D_{2003} \neq D_{1993}^{**}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{**}$											
Firm Manufacturing (%)	7.64	5.98	9.48	9.88	7.19	9.72	9.42	12.85	6.11	4.73	9.49	9.15
	(0.67)	(1.05)	(0.87)	(2.05)	(0.63)	(1.52)	(1.35)	(2.70)	(0.61)	(1.16)	(0.95)	(2.64)
	Avg: 8.05				Avg: 8.32				Avg: 7.10			
	(0.46)				(0.53)				(0.47)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{*}$ / $D_{1993} = D_{1998}$											
Firm Transportation, Communications, Electric, Gas, or Sanitation (%)	2.13	3.78	3.05	4.21	3.08	4.64	5.39	3.00	3.41	2.94	4.22	4.60
	(0.34)	(0.90)	(0.49)	(1.49)	(0.45)	(1.12)	(1.04)	(1.49)	(0.59)	(1.24)	(0.72)	(2.05)
	Avg: 2.76				Avg: 3.70				Avg: 3.65			
	(0.27)				(0.38)				(0.42)			
Across Comparison	$D_{2003} \neq D_{1993}^{*}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{**}$											
Firm Wholesale Trade (%)	6.36	10.76	10.60	10.62	7.16	6.39	9.13	3.96	5.28	4.67	7.88	3.39
	(0.61)	(1.50)	(0.99)	(2.24)	(0.67)	(1.26)	(1.47)	(1.47)	(0.58)	(1.41)	(0.87)	(1.36)
	Avg: 8.46				Avg: 7.16				Avg: 5.88			
	(0.49)				(0.53)				(0.44)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{*}$ / $D_{1993} \neq D_{1998}^{*}$											
Firm Retail Trade (%)	21.71	19.99	21.85	24.79	18.95	20.07	18.93	16.77	18.38	18.65	17.21	25.27
	(1.08)	(1.97)	(1.38)	(3.12)	(0.99)	(2.03)	(1.87)	(2.81)	(1.02)	(2.44)	(1.42)	(4.08)
	Avg: 21.70				Avg: 18.98				Avg: 18.40			

		(0.76)				(0.77)				(0.77)		
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{**}$											
Firm Finance, Insurance, or Real Estate (%)	8.11	5.24	7.01	3.46	6.92	4.39	7.62	4.52	8.59	3.71	6.31	3.94
	(0.67)	(1.06)	(0.81)	(1.07)	(0.63)	(1.04)	(1.35)	(1.59)	(0.83)	(1.15)	(0.84)	(1.66)
		Avg: 7.09				Avg: 6.49				Avg: 7.20		
		(0.45)				(0.48)				(0.54)		
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
Firm Service (%)	40.47	40.50	32.89	30.77	45.24	42.60	36.24	46.79	48.29	54.18	39.07	41.89
	(1.32)	(2.43)	(1.60)	(3.35)	(1.27)	(2.47)	(2.32)	(3.83)	(1.36)	(3.24)	(1.83)	(4.57)
		Avg: 37.73				Avg: 43.43				Avg: 45.90		
		(0.91)				(0.98)				(1.01)		
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{*}$ / $D_{1993} \neq D_{1998}^{***}$											
Owner Characteristics												
High school Dropout (%)	5.62	5.07	2.55	4.73	2.56	5.31	3.79	4.73	1.56	1.36	2.69	0.00
	(0.61)	(1.04)	(0.52)	(1.56)	(0.42)	(1.34)	(0.94)	(1.52)	(0.33)	(0.65)	(0.67)	
		Avg: 4.62				Avg: 3.33				Avg: 1.79		
		(0.38)				(0.38)				(0.27)		
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$											
High School Graduate (%)	25.62	24.78	20.12	17.55	19.49	21.04	21.15	21.56	18.14	21.57	19.24	24.35
	(1.16)	(2.17)	(1.35)	(2.84)	(1.02)	(2.06)	(2.03)	(3.19)	(1.08)	(2.71)	(1.53)	(4.26)
		Avg: 23.44				Avg: 20.14				Avg: 19.11		
		(0.79)				(0.80)				(0.82)		
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{***}$											
Some College (%)	23.50	25.37	26.63	33.96	28.15	30.64	26.00	27.52	29.69	41.17	33.22	39.45
	(1.13)	(2.11)	(1.49)	(3.39)	(1.15)	(2.31)	(2.12)	(3.46)	(1.24)	(3.28)	(1.80)	(4.39)
		Avg: 25.32				Avg: 28.13				Avg: 32.36		
		(0.81)				(0.89)				(0.95)		
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$											
College Degree (%)	24.58	25.58	29.95	25.72	30.73	27.15	31.00	29.74	28.14	20.71	25.10	24.30
	(1.14)	(2.16)	(1.49)	(3.04)	(1.17)	(2.23)	(2.21)	(3.49)	(1.24)	(2.67)	(1.57)	(3.85)
		Avg: 26.30				Avg: 30.16				Avg: 26.31		
		(0.81)				(0.90)				(0.89)		
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{***}$											
Postgraduate Degree (%)	20.66	19.17	20.73	18.02	19.05	15.83	18.04	16.42	22.44	15.17	19.72	11.88
	(1.09)	(1.98)	(1.33)	(2.67)	(0.99)	(1.82)	(1.83)	(2.76)	(1.11)	(2.21)	(1.46)	(3.18)
		Avg: 20.29				Avg: 18.22				Avg: 20.40		
		(0.75)				(0.75)				(0.80)		
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} \neq D_{1998}^{*}$											
Owner Age	51.16	47.18	48.12	45.96	51.49	48.82	48.04	45.68	52.97	46.91	50.99	47.86
	(0.32)	(0.50)	(0.33)	(0.70)	(0.29)	(0.47)	(0.48)	(0.75)	(0.32)	(0.68)	(0.38)	(1.05)
		Avg: 49.40				Avg: 50.13				Avg: 51.52		
		(0.21)				(0.22)				(0.23)		
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$											
Business Experience (Years)	19.95	16.42	18.80	16.32	19.30	16.07	17.32	14.93	19.95	14.91	20.03	16.66
	(0.31)	(0.48)	(0.33)	(0.62)	(0.31)	(0.48)	(0.45)	(0.65)	(0.32)	(0.64)	(0.40)	(0.97)
		Avg: 18.88				Avg: 18.19				Avg: 19.30		
		(0.20)				(0.22)				(0.23)		

Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$											
Loan Characteristics												
Loan New Line of Credit (%)	N/A	N/A	52.44 (1.66)	40.96 (3.57)	N/A	N/A	30.11 (2.21)	56.23 (3.73)	N/A	N/A	59.85 (1.83)	34.23 (8.78)
	Avg: 50.30 (1.51)				Avg: 37.36 (1.97)				Avg: 58.79 (1.80)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{***}$											
Loan Capital Lease (%)	N/A	N/A	2.51 (0.51)	2.22 (0.80)	N/A	N/A	5.37 (1.08)	8.23 (2.19)	N/A	N/A	1.39 (0.51)	0.14 (0.01)
	Avg: 2.46 (0.44)				Avg: 6.17 (0.99)				Avg: 1.33 (0.49)			
Across Comparison	$D_{2003} \neq D_{1993}^{*}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{***}$											
Loan Mortgage (%)	N/A	N/A	11.27 (1.06)	10.80 (2.35)	N/A	N/A	12.30 (1.61)	6.58 (1.79)	N/A	N/A	10.07 (1.09)	20.56 (7.40)
	Avg: 11.19 (0.97)				Avg: 10.71 (1.27)				Avg: 10.50 (1.09)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
Loan Vehicle (%)	N/A	N/A	9.58 (1.01)	4.79 (1.58)	N/A	N/A	19.69 (1.96)	4.11 (1.54)	N/A	N/A	11.70 (1.21)	19.80 (9.75)
	Avg: 8.69 (0.88)				Avg: 15.37 (1.50)				Avg: 12.03 (1.23)			
Across Comparison	$D_{2003} \neq D_{1993}^{**}$ / $D_{2003} \neq D_{1998}^{*}$ / $D_{1993} \neq D_{1998}^{***}$											
Loan Equipment (%)	N/A	N/A	10.06 (1.00)	11.40 (2.26)	N/A	N/A	15.58 (1.64)	7.77 (1.79)	N/A	N/A	9.40 (1.05)	14.81 (5.29)
	Avg: 10.31 (0.91)				Avg: 13.41 (1.29)				Avg: 9.63 (1.04)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} \neq D_{1998}^{*}$											
Loan Other (%)	N/A	N/A	14.10 (1.17)	29.80 (3.40)	N/A	N/A	16.92 (1.86)	17.05 (2.89)	N/A	N/A	7.56 (1.17)	10.42 (4.34)
	Avg: 17.03 (1.15)				Avg: 16.95 (1.56)				Avg: 7.68 (1.14)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} = D_{1998}$											
Lender Characteristics												
Lender Commercial Bank (%)	N/A	N/A	80.33 (1.35)	81.22 (2.93)	N/A	N/A	68.15 (2.28)	71.34 (3.52)	N/A	N/A	74.16 (1.70)	82.01 (3.24)
	Avg: 80.49 (1.22)				Avg: 69.03 (1.91)				Avg: 75.27 (1.55)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} \neq D_{1998}^{***}$											
Lender Savings Bank, Loan Association or Credit Union (%)	N/A	N/A	7.02 (0.92)	5.80 (1.85)	N/A	N/A	9.03 (1.46)	6.98 (1.93)	N/A	N/A	11.84 (1.23)	8.00 (2.32)
	Avg: 6.78 (0.82)				Avg: 8.46 (1.18)				Avg: 11.30 (1.11)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{*}$ / $D_{1993} = D_{1998}$											
Lender	N/A	N/A	5.25 (0.73)	3.36 (1.18)	N/A	N/A	12.30 (1.58)	6.33 (1.77)	N/A	N/A	8.47 (1.04)	5.81 (2.00)

Finance Company (%)	Avg: 4.90 (0.64)				Avg: 10.65 (1.25)				Avg: 8.09 (0.94)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{***}$											
Lender Other (%)	N/A	N/A	7.39	9.55	N/A	N/A	10.51	15.34	N/A	N/A	5.51	4.16
			(0.90)	(2.22)			(1.51)	(2.92)			(1.07)	(1.45)
	Avg: 7.79 (0.83)				Avg: 11.85 (1.37)				Avg: 5.32 (0.94)			
Across Comparison	$D_{2003} \neq D_{1993}^{**}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$											
Lender's Relation with the Firm (Year)	N/A	N/A	7.79	5.54	N/A	N/A	5.55	3.98	N/A	N/A	8.18	4.79
			(0.25)	(0.46)			(0.36)	(0.38)			(0.32)	(0.59)
	Avg: 7.37 (0.22)				Avg: 5.11 (0.28)				Avg: 7.70 (0.29)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{***}$											
Primary Lender Commercial Bank (%)	81.91	75.40	86.28	79.30	81.24	78.67	85.45	77.43	93.53	92.19	90.47	82.48
	(1.03)	(2.21)	(1.19)	(2.92)	(0.99)	(1.98)	(1.73)	(3.22)	(0.68)	(1.63)	(1.05)	(4.14)
	Avg: 82.02 (0.72)				Avg: 81.30 (0.77)				Avg: 91.92 (0.56)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} = D_{1998}$											
Primary Lender Savings Bank, Loan Association or Credit Union (%)	9.49	12.10	8.86	6.08	10.75	9.24	6.79	9.29	6.10	7.02	9.00	14.38
	(0.79)	(1.58)	(1.01)	(1.71)	(0.80)	(1.41)	(1.22)	(2.28)	(0.64)	(1.53)	(1.02)	(3.78)
	Avg: 9.47 (0.56)				Avg: 9.76 (0.59)				Avg: 7.44 (0.52)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
Primary Lender Finance Company (%)	0.67	2.51	2.17	2.32	1.06	2.58	2.96	4.07	0.00	0.00^{d}	0.39	1.64
	(0.20)	(0.77)	(0.45)	(1.16)	(0.24)	(0.76)	(0.81)	(1.55)		(0.02)	(0.21)	(1.63)
	Avg: 1.47 (0.21)				Avg: 1.81 (0.25)				Avg: 0.19 (0.10)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} = D_{1998}$											
Primary Lender Other (%)	3.74	5.28	2.66	10.16	2.22	5.34	4.78	9.19	0.00	0.43	0.12	1.48
	(0.51)	(1.08)	(0.55)	(2.1)	(0.35)	(1.06)	(1.08)	(2.16)		(0.34)	(0.11)	(1.39)
	Avg: 4.08 (0.37)				Avg: 3.58 (0.35)				Avg: 0.15 (0.08)			
Across Comparison	$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} = D_{1998}$											
Geographic Characteristics												
MSA (%)	78.40	88.60	73.38	84.45	80.34	82.87	74.65	81.42	80.58	84.99	74.13	85.84
	(0.17)	(0.36)	(0.29)	(0.59)	(1.03)	(1.91)	(2.12)	(3.10)	(0.64)	(1.39)	(1.05)	(1.94)
	Avg: 78.87 (0.14)				Avg: 79.85 (0.81)				Avg: 79.41 (0.50)			
Across Comparison	$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$											
East North Central (%)	15.68	12.71	19.14	11.70	15.65	13.83	12.84	9.26	13.63	10.69	17.30	9.57
	(0.20)	(0.64)	(0.35)	(0.83)	(0.91)	(1.74)	(1.59)	(2.30)	(0.39)	(0.78)	(0.71)	(0.86)
	Avg: 15.96				Avg: 14.49				Avg: 14.20			

		(0.18)				(0.69)					(0.31)	
Across Comparison						$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{**}$						
East South Central (%)	3.84	3.80	6.75	2.25	5.74	4.44	6.62	2.56	5.29	5.47	5.02	6.03
	(0.11)	(0.34)	(0.20)	(0.37)	(0.60)	(1.11)	(1.20)	(1.32)	(0.26)	(0.57)	(0.24)	(0.53)
		Avg: 4.55				Avg: 5.48					Avg: 5.27	
		(0.09)				(0.46)					(0.17)	
Across Comparison						$D_{2003} \neq D_{1993}^{*}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{*}$						
Middle Atlantic (%)	15.53	18.96	12.36	19.03	14.28	14.44	10.08	15.77	14.08	17.44	11.36	15.65
	(0.27)	(0.69)	(0.34)	(0.88)	(0.95)	(1.89)	(1.50)	(2.81)	(0.43)	(0.88)	(0.49)	(1.07)
		Avg: 15.37				Avg: 13.70					Avg: 13.71	
		(0.20)				(0.72)					(0.30)	
Across Comparison						$D_{2003} \neq D_{1993}^{**}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{**}$						
Mountain (%)	5.82	4.18	6.38	6.87	6.36	5.03	7.83	10.24	7.51	6.37	8.44	7.93
	(0.13)	(0.29)	(0.21)	(0.45)	(0.63)	(1.02)	(1.29)	(2.23)	(0.31)	(0.78)	(0.46)	(0.51)
		Avg: 5.80				Avg: 6.64					Avg: 7.69	
		(0.10)				(0.49)					(0.23)	
Across Comparison						$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{*}$/ $D_{1993} = D_{1998}$						
New England (%)	7.23	8.48	5.56	7.10	5.21	5.14	5.68	4.41	6.42	5.71	5.57	3.78
	(0.10)	(0.49)	(0.24)	(0.77)	(0.60)	(1.15)	(1.17)	(1.51)	(0.23)	(0.51)	(0.39)	(0.48)
		Avg: 6.94				Avg: 5.22					Avg: 5.97	
		(0.12)				(0.46)					(0.18)	
Across Comparison						$D_{2003} \neq D_{1993}^{**}$ / $D_{2003} = D_{1998}$ / $D_{1993} \neq D_{1998}^{***}$						
Pacific (%)	19.22	22.32	14.27	18.81	18.92	24.88	17.85	24.11	18.77	17.70	12.83	14.76
	(0.28)	(0.71)	(0.39)	(0.71)	(0.97)	(2.16)	(1.88)	(3.37)	(0.41)	(0.81)	(0.60)	(1.50)
		Avg: 18.26				Avg: 20.00					Avg: 16.74	
		(0.21)				(0.78)					(0.31)	
Across Comparison						$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{***}$ / $D_{1993} \neq D_{1998}^{**}$						
South Atlantic (%)	14.94	13.93	14.64	16.86	16.43	18.21	16.74	17.49	18.56	19.72	17.63	30.63
	(0.22)	(0.66)	(0.35)	(0.58)	(0.91)	(1.88)	(1.77)	(2.87)	(0.42)	(0.96)	(0.61)	(1.79)
		Avg: 14.83				Avg: 16.83					Avg: 18.99	
		(0.19)				(0.72)					(0.32)	
Across Comparison						$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} \neq D_{1998}^{**}$ / $D_{1993} \neq D_{1998}^{**}$						
West North Central *(%)*	7.96	5.52	10.27	6.55	7.32	5.22	9.67	4.72	6.06	4.65	9.82	3.19
	(0.12)	(0.27)	(0.23)	(0.26)	(0.66)	(1.19)	(1.47)	(1.76)	(0.24)	(0.26)	(0.45)	(0.84)
		Avg: 8.16				Avg: 7.22					Avg: 6.88	
		(0.10)				(0.52)					(0.20)	
Across Comparison						$D_{2003} \neq D_{1993}^{***}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$						
West South Central *(%)*	9.74	10.04	10.59	10.77	10.05	8.77	12.65	11.41	9.62	12.21	11.98	8.40
	(0.19)	(0.56)	(0.26)	(0.86)	(0.74)	(1.37)	(1.53)	(2.18)	(0.31)	(0.99)	(0.59)	(0.67)
		Avg: 10.09				Avg: 10.37					Avg: 10.52	
		(0.15)				(0.58)					(0.26)	
Across Comparison						$D_{2003} = D_{1993}$ / $D_{2003} = D_{1998}$ / $D_{1993} = D_{1998}$						

Notes. There are a few variables (e.g., Exper) that have missing values, but their ratios are less than 1%.

[a] This is calculated based on a linear regression in which each variable in Table ? is used as the dependent variable and the survey year dummy variables are used as the independent variables.

[b] Numbers in parenthesis are standard deviations for variables.

[c] These nominal variables are converted to real variables, based on the year of 2003 as a base year.

[d] They are not equal to zero, but virtually close to it.

[*] 10% significance level.

[**] 5% significance level.

[***] 1% significance level.

Table A1-3: Estimated Results for the Full Model of Loan Denial Based on a Standard Probit Approach

Independent variable	Marginal effect	Standard error	P value
African American	0.1552	0.0451	0.001
Hispanic	0.0495	0.0257	0.054
Other (e.g., Pacific Islander, Native American)	0.0977	0.0315	0.002
White women	-0.0097	0.0177	0.582
Delinquent_personal	0.0979	0.0229	0.000
Judgement	0.0736	0.0328	0.025
Owner_bankrupt	0.2906	0.0554	0.000
Log_sales	-0.0776	0.0161	0.000
Log_profit	-0.0672	0.0241	0.005
Log_networth	-0.1406	0.0640	0.028
Firm_age	-0.0037	0.0014	0.010
Firm_age_square	0.0000	0.0000	0.012
Totemp	1.2176	0.5079	0.017
Totemp_square	-2.9001	1.6177	0.073
Proprietorship	0.0200	0.0154	0.195
Partnership	-0.0427	0.0211	0.043
Business_delinquent	0.0746	0.0178	0.000
Mining	-0.0055	0.0204	0.786
Manufacture	0.0138	0.0223	0.536
Transportation	-0.0358	0.0247	0.148
Whole_trade	0.0035	0.0246	0.885
Retail_trade	0.0226	0.0187	0.226
Finance	-0.0311	0.0252	0.218
Lessthanhigh	0.0194	0.0372	0.602
Highschool	-0.0086	0.0192	0.653
Somecollege	0.0152	0.0174	0.381
Postgraduate	-0.0151	0.0174	0.386
Exper	0.0008	0.0009	0.384
Owner_age	-0.0013	0.0008	0.099
Loan_captial	0.0119	0.0341	0.727
Loan_mortgage	-0.0002	0.0211	0.727
Loan_vehicle	-0.0571	0.0212	0.007
Loan_equipment	-0.0090	0.0203	0.657
Loan_other	0.0333	0.0191	0.081
Lender_commercial	0.0562	0.0233	0.016
Lender_finance	-0.0349	0.0326	0.284
Lender_other	0.0348	0.0381	0.362
Year_withlender	-0.0015	0.0011	0.172
Primary_savings	0.0478	0.0309	0.122
Primary_finance	0.0959	0.0464	0.039
Primary_other	0.0965	0.0436	0.027
MSA	0.0489	0.0144	0.001
East_Ncentral	-0.0488	0.0189	0.010
East_Scentral	-0.0567	0.0236	0.017
Mid_Atlan	0.0190	0.0227	0.402
Mountain	0.0059	0.0248	0.811
New_England	-0.0155	0.0281	0.581
South_Atlan	0.0314	0.0228	0.169
West_Ncentral	-0.0623	0.0197	0.002
West_Scentral	-0.0113	0.0227	0.617
Survey_2003	-0.1242	0.0134	0.000
Survey_1998	0.0452	0.0150	0.003
HHI	0.0276	0.0135	0.041
N = 4,644			
F-statistic = 9.90			
Pseudo R squared = 0.27			

Table A1-4: Coefficients of Race Dummy Variables across the Survey Years: Comparisons

Independent variable	1993	1998	2003
African American	0.1409 (0.0435)	0.1908 (0.0658)	0.0994 (0.0662)
Across Comparison[a]	$\beta_{1998} = \beta_{2003}$ / $\beta_{1998} = \beta_{1993}$ / $\beta_{1993} = \beta_{2003}$		
Hispanic	-0.0173 (0.0433)	0.2097 (0.0639)	0.0220 (0.0364)
Across Comparison	$\beta_{1998} = \beta_{2003}$ / $\beta_{1998} \neq \beta_{1993}^{***}$ / $\beta_{1993} = \beta_{2003}$		
Other (e.g., Pacific Islander, Native American)	0.0653 (0.0514)	0.2106 (0.0620)	0.0685 (0.0380)
Across Comparison	$\beta_{1998} = \beta_{2003}$ / $\beta_{1998} \neq \beta_{1993}^{*}$ / $\beta_{1993} = \beta_{2003}$		
White Women	0.0153 (0.0317)	-0.0271 (0.0415)	0.0011 (0.0181)
Across Comparison	$\beta_{1998} = \beta_{2003}$ / $\beta_{1998} = \beta_{1993}$ / $\beta_{1993} = \beta_{2003}$		
Firm Characteristics	X	X	X
Owner Characteristics	X	X	X
Geographic Characteristics	X	X	X
SIC Codes	X	X	X
Loan Characteristics	X	X	X
Lender Characteristics	X	X	X
N (Number of Observations)	1,987	952	1,673
F-statistic	4.75	4.80	3.16
Pseudo R squared	0.2089	0.3209	0.3564

Notes. The coefficients of race dummy variables are based on model 8 in Table 1.
[a] This shows that the coefficients of African American are within sampling errors.
[b] Numbers in parenthesis are standard errors for variables.
[*] 10% significance level.
[**] 5% significance level.
[***] 1% significance level.

Table A2-1: GSS Questions Used to Measure Racial Preference[66]

AFFRMACT (D1)	Do you oppose a preference in hiring and promotion?
BUSING (D2)	In general, do you favor the busing of black and white children from one school district to another?
CLOSEBLK (D3)	In general, how close do you feel to blacks?
FEELBLKS (D4)	In general, how warm or cool do you feel toward blacks?
HELPBLK (D5)	Agree? The government is obligated to help blacks.
NATRACE (D6)	Agree? We are spending too much money improving the condition of blacks.
RACAVOID (D7)	If you were driving through neighborhoods in a city, would you go out of your way to avoid going through a black section?
RACCHNG (D8)	If you and your friends belonged to a social club that would not let blacks join, would you try to change the rules?
RACDIN (D9)	How strongly would you object if a family member brought a black friend home for dinner?
RACJOB (D10)	Do you think blacks should have as good a chance as anyone to get any kind of job, or do you think white people should have the first chance at any kind of job?
RACMAR* (D11)	Do you think there should be laws against marriages between blacks and whites?
RACMAREL (D12)	How would it make you feel if a close relative of yours were planning to marry a black?
RACMARPR (D13)	Agree? You can expect special problems with marriages between blacks and whites.
RACOBJCT (D14)	If a black with the same income and education as you have moved in to your block, would it make any difference to you?
RACOPEN (D15)	Would you vote for a law that says a homeowner can refuse to sell to blacks, or one that says homeowners cannot refuse to sell based on skin color?
RACPEERS* (D16)	Aggregation of three questions about whether you would object to sending your kids to a school that had few/half/most black students.
RACPRES* (D17)	If your party nominated a black for president, would you vote for him if he were qualified for the job?
RACPUSH (D18)	Agree? Blacks shouldn't push themselves where they're not wanted.
RACQUIT (D19)	If yes to RACCHNG: If you could not get the rules changed, do you think you would resign from the club, even if your friends didn't?
RACSCHOL (D20)	Do you think white students and black students should go to the same schools or separate schools?

[66] The format of the table is based on Table. A1 in Charles and Guryan (2008). Also the questions with an asterisk are used for Figure 1., and the questions in red are used to build a racial preference index.

RACSEG* (D21)	Agree? White people have the right to keep black people out of their neighborhoods and blacks should respect the right.
RACSUBGV (D22)	Do you think the city government in white suburbs should encourage black people to buy homes in the suburbs, discourage them, or leave it to private efforts?
RACSUBS (D23)	Do you oppose voluntary (religious/private business) efforts to integrate white suburbs?
RACSUPS (D24)	Agree? You can expect special problems with black supervisors getting along with workers who are mostly white.
RACTEACH (D25)	Agree? A school board should not hire a person to teach if that person belongs to an organization that opposes school integration.
WRKWAYUP (D26)	Agree? Italians, Jews, and other minorities overcame prejudice and worked their way up. Blacks should do the same without special favors.

Table 2A-2: The Frequency of the GSS Questions Asked in Each Survey Year

Year	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D11**	**D12**	**D13**	**D14**	**D15**	**D16**	**D17**	**D18**	**D19**	**D20**	**D21**	**D22**	**D23**	**D24**	**D25**	**D26**
1972		X							X	X	X			X		X	X	X		X	X					
1973						X			X		X				X			X								
1974		X				X			X		X					X	X									
1975		X			X	X					X				X	X	X	X								
1976		X				X			X		X				X			X		X	X					
1977		X				X	X	X	X		X	X	X			X	X	X	X	X	X	X	X	X	X	
1978		X				X									X	X	X									
1980						X			X		X				X			X		X	X					
1982		X				X			X		X					X	X	X		X	X					
1983		X			X	X									X	X	X									
1984					X	X			X		X				X			X		X	X					
1985		X				X		X	X		X					X	X	X		X	X					
1986		X			X	X		X							X	X	X									
1987					X	X					X				X						X					
1988		X			X	X		X			X				X	X	X				X					
1989		X			X	X		X			X				X	X	X				X					
1990		X			X	X		X			X				X	X	X				X					
1991		X			X	X		X			X				X	X	X				X					
1993		X			X	X		X			X				X	X	X				X					
1994	X	X			X	X		X			X				X	X	X	X			X					X
1996	X	X	X		X	X					X				X	X	X	X			X					X
1998	X		X		X	X					X							X								X
2000	X		X		X	X					X							X								X
2002	X		X	X	X	X					X							X								X
2004	X		X		X	X									X											X
2006	X		X		X	X									X											X
2008	X		X		X	X									X		X									X
2010	X		X		X	X									X		X									X
2012	X		X		X	X									X											X
2014	X		X		X	X									X											X
2016	X		X		X	X									X											X
2018	X				X	X									X											X
N (=32)	13	17	11	1	23	31	1	9	9	1	21	1	1	1	24	16	18	14	1	7	15	1	1	1	1	13

Table A2-3: Variable Definitions

Dependent Variable	
Racial_Index	A standardized measure of racial preference that considers both mean and variance within and across questions.
Three-Time Dimensional Variable	
Age	A survey respondent's age
Age_sq	The square term of Age
Dumyear_1977 - Dumyear_2018	Dummy variables for years - the base year is 1976 (i.e., omitted)
Cohort1 - Cohort21	Dummy variables for cohorts - the base cohort is a cohort group who was born between 1950 and 1960 (i.e., omitted)
Demographic Variable	
Years of Education	A survey respondent's years of education
Family_income_adjusted	It is measured in constant dollars (base year = 1986) - the variable was divided by 10000
Female	Whether a survey respondent is a female (=1)
Marital Status	A survey respondent's marital status - five dummy variables (i.e., widowed, divorced, separated, never married, and married (i.e., omitted))
Political and Religious Variable	
Political Affiliation	A survey respondent's political ideology - four dummy variables (i.e., republican, democrat (i.e., omitted), independent, and other party)
Religious Preference	A survey respondent's religious preference - three dummy variables (i.e., protestant, catholic (i.e., omitted), and other)
Employment Variable	
Working Status	A survey respondent's working status - five dummy variables (i.e., working (i.e., omitted), not working, retired, in school, and other)
Occupation Type	A survey respondent's occupation type based on skill level described in International Standard Classification of Occupations (i.e., ISCO08) - three dummy variables (low skilled, high skilled (i.e., omitted), and other)
Geographic Variable	
Region	A survey respondent's location - four dummy variables (i.e., West, South (i.e., omitted), Midwest, and Northeast)
Additional Variable	
Unemployment Rates	each year's unemployment rates for nine census divisions - measured in percentage point units
Proportion of Black Population	each year's proportion of black population for nine census divisions - measured in percentage point units.

Table A2-4: Estimated Results for the Full Model Based on a Standard OLS Approach

Independent variable	Marginal effect	Standard error	P value
Years of Education	-0.0241	0.0013	0.000
Female	-0.0465	0.0071	0.000
West	-0.1575	0.0203	0.000
Midwest	-0.0795	0.0144	0.000
Northeast	-0.1322	0.0138	0.000
Unemployment Rates	0.0141	0.0031	0.000
Proportion of Black Population	-0.0027	0.0012	0.028
Occupation_other	-0.0857	0.0364	0.019
Occupation_lowskill	0.0364	0.0076	0.000
Republican	0.1881	0.0073	0.000
Independent	0.1137	0.0103	0.000
Other_party	0.1520	0.0300	0.000
Notworking	-0.0240	0.0145	0.098
Retired	-0.0020	0.0145	0.887
Inschool	-0.0071	0.0249	0.773
Other[e]	0.0027	0.0106	0.797
Family_income_adj	-0.0027	0.0013	0.040
Widowed	0.0094	0.0144	0.514
Divorced	-0.0154	0.0112	0.172
Separated	-0.0996	0.0195	0.000
Not_married	-0.0463	0.0100	0.000
Protestant	-0.0378	0.0079	0.000
Other_relig	-0.0649	0.0109	0.000
Age	0.0032	0.0018	0.080
Age_sq	-0.0000	0.0000	0.557
Dum_year1977	0.0106	0.0193	0.582
Dum _year1978	-0.0797	0.0227	0.000
Dum _year1980	-0.0135	0.0206	0.513
Dum _year1982	-0.0909	0.0203	0.000
Dum _year1983	-0.1675	0.0236	0.000
Dum _year1984	-0.0840	0.0210	0.000
Dum _year1985	-0.1199	0.0222	0.000
Dum _year1986	-0.2280	0.0254	0.000
Dum _year1987	-0.3212	0.0263	0.000
Dum _year1988	-0.2195	0.0273	0.000
Dum _year1989	-0.2494	0.0277	0.000
Dum _year1990	-0.2553	0.0273	0.000
Dum _year1991	-0.3442	0.0274	0.000
Dum _year1993	-0.3512	0.0285	0.000
Dum _year1994	-0.1325	0.0280	0.000
Dum _year1996	0.0656	0.0310	0.035
Dum _year1998	0.2440	0.0343	0.000
Dum _year2000	0.2352	0.0372	0.000
Dum _year2002	0.1952	0.0383	0.000
Dum _year2004	-0.1103	0.0448	0.014
Dum _year2006	-0.0639	0.0429	0.136
Dum _year2008	-0.1827	0.0432	0.000
Dum _year2010	-0.2716	0.0452	0.000
Dum _year2012	-0.1786	0.0495	0.000
Dum _year2014	-0.2188	0.0501	0.000
Dum _year2016	-0.3009	0.0522	0.000
Dum _year2018	-0.4865	0.0572	0.000
Cohort1	0.1751	0.0834	0.036
Cohort2	0.1736	0.0621	0.005
Cohort3	0.1357	0.0478	0.005
Cohort4	0.1123	0.0366	0.002
Cohort5	0.0813	0.0256	0.002
Cohort6	0.0267	0.0149	0.073
Cohort8	0.0190	0.0151	0.209

Cohort9	0.0581	0.0262	0.027
Cohort10	0.0121	0.0389	0.756
Cohort11	0.0517	0.0570	0.364
	N = 47,072		
	F-statistic = 110.79		
	R squared = 0.13		

[a] This table reports average marginal effects of the coefficients. All the estimates shown above are calculated with weights.

Table 2A-5: Estimated Results for the Full Model Based on a Standard Quantile Regression Approach

	Aggregate Index of Individual Racial Preference						
	Q(.05)	Q(.1)	Q(.25)	Q(.5)	Q(.75)	Q(.9)	Q(.95)
Years of Education	-0.0015** (0.0006)	-0.0034*** (0.0006)	-0.0115*** (0.0009)	-0.0215*** (0.0014)	-0.0322*** (0.0016)	-0.0317*** (0.0010)	-0.0218*** (0.0010)
Female	-0.0053* (0.0030)	-0.0133*** (0.0031)	-0.0298*** (0.0050)	-0.0393*** (0.0075)	-0.0443*** (0.0085)	-0.0217*** (0.0062)	-0.0302*** (0.0033)
West	-0.00668 (0.0086)	-0.0275*** (0.0093)	-0.0925*** (0.0124)	-0.158*** (0.0222)	-0.190*** (0.0268)	-0.151*** (0.0208)	-0.115*** (0.0129)
Midwest	-0.00036 (0.0062)	-0.00888 (0.0062)	-0.0402*** (0.0097)	-0.0740*** (0.0157)	-0.105*** (0.0194)	-0.0907*** (0.0117)	-0.0753*** (0.0073)
Northeast	-0.0074 (0.0056)	-0.0241*** (0.0065)	-0.0774*** (0.0095)	-0.131*** (0.0149)	-0.159*** (0.0180)	-0.130*** (0.0122)	-0.105*** (0.0088)
Unemployment Rates	0.0007 (0.0011)	0.0032** (0.0013)	0.0047** (0.0018)	0.0078** (0.0031)	0.0133*** (0.0042)	0.0184*** (0.0046)	0.0144*** (0.0040)
Proportion of Black Population	-0.0001 (0.0005)	-0.0009* (0.0005)	-0.00274*** (0.0008)	-0.00255* (0.0013)	-0.0008 (0.0016)	8.39e-05 (0.0010)	-0.0010 (0.0006)
Occupation_other	-0.0113 (0.0273)	-0.0469* (0.0249)	-0.0685** (0.0287)	-0.0675 (0.0623)	-0.0773* (0.0454)	-0.0566 (0.0507)	-0.0438*** (0.0113)
Occupation_lowskill	0.0034 (0.0029)	0.0027 (0.0032)	0.0008 (0.0053)	0.0165** (0.0079)	0.0481*** (0.0094)	0.0428*** (0.0079)	0.0181*** (0.0039)
Republican	0.0277*** (0.0064)	0.0505*** (0.0054)	0.111*** (0.0051)	0.168*** (0.0078)	0.169*** (0.0088)	0.0835*** (0.0072)	0.0406*** (0.0046)
Independent	0.0220*** (0.0058)	0.0373*** (0.0058)	0.0702*** (0.0066)	0.0989*** (0.0102)	0.0907*** (0.0123)	0.0453*** (0.0094)	0.0282*** (0.0050)
Other_party	0.0201 (0.0174)	0.0445*** (0.0164)	0.0818*** (0.0144)	0.150*** (0.0269)	0.116** (0.0497)	0.0948*** (0.0267)	0.0327*** (0.0120)

Notworking	-0.0057 (0.0051)	-0.0129** (0.0056)	-0.0131 (0.0118)	-0.0356*** (0.0119)	-0.0388 (0.0249)	-0.00261 (0.0168)	0.00572 (0.0078)
Retired	-0.0006 (0.0053)	-0.0046 (0.0077)	-0.0065 (0.0110)	0.0003 (0.0149)	0.0122 (0.0183)	0.0093 (0.0102)	0.0210*** (0.0069)
Inschool	-0.0024 (0.0183)	-0.0110 (0.0174)	0.0109 (0.0090)	-0.0122 (0.0385)	-0.0144 (0.0193)	0.0013 (0.0297)	0.0232 (0.0191)
Other[e]	-0.0016 (0.0043)	-0.0019 (0.0042)	0.0027 (0.0070)	-0.0033 (0.0108)	-0.0002 (0.0138)	-0.0020 (0.0082)	0.0100 (0.00628)
Family_income_adj	-0.0008 (0.0006)	-0.0008 (0.0005)	-0.0012 (0.0010)	-0.0027* (0.0014)	-0.0037** (0.0016)	-0.0011 (0.00140)	-0.0015*** (0.0005)
Widowed	-0.0009 (0.0059)	-0.0065 (0.0069)	0.0101 (0.0127)	0.0165 (0.0140)	0.0349 (0.0225)	0.0166* (0.0101)	0.0080 (0.0060)
Divorced	-0.0128* (0.0065)	-0.0166*** (0.0039)	-0.0233*** (0.0087)	-0.0132 (0.0122)	-0.0003 (0.0136)	0.0081 (0.0091)	0.0067 (0.0049)
Separated	-0.0156 (0.0095)	-0.0318*** (0.0060)	-0.0554*** (0.0166)	-0.0927*** (0.0194)	-0.0922*** (0.0152)	-0.0694*** (0.0136)	-0.0463*** (0.0150)
Not_married	-0.0080* (0.0048)	-0.0218*** (0.0044)	-0.0324*** (0.0068)	-0.0422*** (0.0109)	-0.0201* (0.0120)	-0.0161* (0.0088)	-0.0125** (0.0054)
Protestant	-0.00812** (0.0038)	-0.0176*** (0.0038)	-0.0343*** (0.0050)	-0.0367*** (0.0080)	-0.0187** (0.0094)	0.0012 (0.0073)	-0.0041 (0.0046)
Other_relig	-0.0189*** (0.0064)	-0.0377*** (0.0058)	-0.0566*** (0.0081)	-0.0679*** (0.0109)	-0.0237* (0.0126)	-0.0114 (0.0097)	0.0003 (0.0059)
Age	-0.0015 (0.0010)	-0.0016 (0.0010)	0.0015 (0.0011)	0.0026 (0.0020)	0.0073*** (0.0022)	0.0145*** (0.0018)	0.0075*** (0.0012)
Age_sq	1.86e-05** (9.19e-06)	2.77e-05** (1.08e-05)	5.21e-06 (1.02e-05)	-3.19e-06 (1.73e-05)	-4.53e-05** (1.80e-05)	-0.0001*** (1.60e-05)	-7.10e-05*** (1.17e-05)
Dum_year1977	0.00230 (0.0420)	0.0255** (0.0107)	0.0995*** (0.0151)	0.0692*** (0.0188)	0.0121 (0.0287)	-0.155*** (0.0322)	-0.271*** (0.0527)
Dum _year1978	-0.0757*** (0.0099)	-0.206*** (0.0060)	-0.244*** (0.0147)	0.0134 (0.0226)	-0.0590* (0.0303)	-0.0582 (0.0635)	-0.0722* (0.0381)

Dum _year1980	-0.0156**	-0.0748***	0.0247	0.0072	-0.0088	-0.125***	-0.0930**
	(0.0066)	(0.0187)	(0.0152)	(0.0221)	(0.0287)	(0.0417)	(0.0413)
Dum _year1982	0.0549***	0.0178***	0.0375**	-0.0436**	-0.177***	-0.324***	-0.349***
	(0.0211)	(0.0063)	(0.0148)	(0.0188)	(0.0279)	(0.0451)	(0.0951)
Dum _year1983	-0.0800***	-0.224***	-0.283***	-0.0800**	-0.102***	-0.0795	-0.130***
	(0.0104)	(0.0085)	(0.0139)	(0.0394)	(0.0362)	(0.0831)	(0.0504)
Dum _year1984	-0.0184***	-0.0955***	-0.0229	-0.0417**	-0.0976***	-0.234***	-0.280***
	(0.0068)	(0.0168)	(0.0183)	(0.0205)	(0.0314)	(0.0404)	(0.0796)
Dum _year1985	-0.0839***	-0.188***	-0.139***	-0.118***	-0.133***	-0.201***	-0.164**
	(0.0075)	(0.0103)	(0.0183)	(0.0227)	(0.0303)	(0.0490)	(0.0726)
Dum _year1986	-0.187***	-0.322***	-0.365***	-0.238***	-0.179***	-0.156***	-0.154***
	(0.0094)	(0.0077)	(0.0141)	(0.0317)	(0.0376)	(0.0421)	(0.0560)
Dum _year1987	-0.389***	-0.520***	-0.553***	-0.442***	-0.162***	-0.00313	-0.0501
	(0.0099)	(0.0085)	(0.0150)	(0.0376)	(0.0426)	(0.0560)	(0.0638)
Dum _year1988	-0.377***	-0.463***	-0.368***	-0.262***	-0.150***	-0.0965**	-0.133***
	(0.0079)	(0.0136)	(0.0199)	(0.0376)	(0.0441)	(0.0399)	(0.0506)
Dum _year1989	-0.376***	-0.465***	-0.363***	-0.281***	-0.187***	-0.161***	-0.141**
	(0.0082)	(0.0134)	(0.0201)	(0.0297)	(0.0374)	(0.0529)	(0.0570)
Dum _year1990	-0.196***	-0.325***	-0.364***	-0.276***	-0.197***	-0.242***	-0.314***
	(0.0091)	(0.0092)	(0.0168)	(0.0332)	(0.0387)	(0.0456)	(0.0934)
Dum _year1991	-0.379***	-0.478***	-0.404***	-0.386***	-0.319***	-0.263***	-0.201***
	(0.0101)	(0.0118)	(0.0179)	(0.0314)	(0.0358)	(0.0628)	(0.0706)
Dum _year1993	-0.377***	-0.478***	-0.419***	-0.413***	-0.309***	-0.242***	-0.284***
	(0.0098)	(0.0122)	(0.0205)	(0.0292)	(0.0428)	(0.0573)	(0.0614)
Dum _year1994	-0.330***	-0.296***	-0.145***	-0.0824***	-0.0985***	-0.201***	-0.266***
	(0.0186)	(0.0117)	(0.0252)	(0.0287)	(0.0371)	(0.0427)	(0.0528)
Dum _year1996	-0.286***	-0.204***	0.0178	0.143***	0.189***	0.205***	0.0393
	(0.0338)	(0.0166)	(0.0236)	(0.0319)	(0.0421)	(0.0444)	(0.0399)
Dum _year1998	-0.380	-0.208***	0.278***	0.351***	0.475***	0.376***	0.115***
	(0.300)	(0.0232)	(0.0263)	(0.0352)	(0.0451)	(0.0423)	(0.0408)

Dum _year2000	-0.902***	-0.241***	0.243***	0.377***	0.520***	0.388***	0.133***
	(0.0874)	(0.0168)	(0.0315)	(0.0379)	(0.0468)	(0.0447)	(0.0413)
Dum _year2002	-0.557***	-0.266***	-0.0140	0.309***	0.520***	0.651***	0.422***
	(0.0278)	(0.0131)	(0.0477)	(0.0389)	(0.0516)	(0.0440)	(0.0401)
Dum _year2004	-0.911***	-0.790***	-0.360***	-0.0705	0.270***	0.315***	0.109***
	(0.0211)	(0.0996)	(0.0440)	(0.0619)	(0.0699)	(0.0462)	(0.0409)
Dum _year2006	-0.895***	-0.861***	-0.309***	0.0446	0.332***	0.349***	0.106**
	(0.0227)	(0.0764)	(0.0350)	(0.0530)	(0.0555)	(0.0491)	(0.0423)
Dum _year2008	-0.811***	-0.665***	-0.271***	-0.107**	0.00157	-0.115**	-0.124
	(0.0188)	(0.0613)	(0.0332)	(0.0526)	(0.0545)	(0.0526)	(0.0928)
Dum _year2010	-0.797***	-0.681***	-0.310***	-0.164***	-0.104*	-0.270***	-0.365***
	(0.0199)	(0.0694)	(0.0385)	(0.0482)	(0.0551)	(0.0481)	(0.0560)
Dum _year2012	-0.891***	-0.957***	-0.385***	-0.106*	0.207***	0.273***	0.0417
	(0.0263)	(0.0254)	(0.0418)	(0.0566)	(0.0750)	(0.0488)	(0.0424)
Dum _year2014	-0.920***	-0.978***	-0.502***	-0.138**	0.155**	0.267***	0.0542
	(0.0194)	(0.0200)	(0.0463)	(0.0581)	(0.0656)	(0.0519)	(0.0435)
Dum _year2016	-0.982***	-1.004***	-0.617***	-0.245***	0.0577	0.245***	0.0648
	(0.0833)	(0.0203)	(0.0421)	(0.0575)	(0.0673)	(0.0559)	(0.0448)
Dum _year2018	-1.222***	-1.051***	-0.962***	-0.638***	0.0676	0.281***	0.0469
	(0.0220)	(0.0301)	(0.0367)	(0.0731)	(0.0887)	(0.0558)	(0.0463)
Cohort1	0.0336	0.0558	0.147*	0.111	0.208*	0.457***	0.363***
	(0.123)	(0.0357)	(0.0788)	(0.0757)	(0.108)	(0.0728)	(0.0442)
Cohort2	-0.00853	-0.0215	0.0490	0.151**	0.263***	0.441***	0.386***
	(0.0241)	(0.0246)	(0.0455)	(0.0646)	(0.0846)	(0.0582)	(0.0389)
Cohort3	0.00485	0.00283	0.0477	0.119**	0.156***	0.289***	0.303***
	(0.0187)	(0.0196)	(0.0339)	(0.0493)	(0.0595)	(0.0473)	(0.0366)
Cohort4	0.0118	0.0132	0.0328	0.104***	0.107**	0.188***	0.154***
	(0.0156)	(0.0154)	(0.0258)	(0.0378)	(0.0451)	(0.0335)	(0.0258)
Cohort5	0.0126	0.00962	0.0277	0.106***	0.0755**	0.100***	0.0793***
	(0.0113)	(0.0109)	(0.0178)	(0.0269)	(0.0311)	(0.0233)	(0.0175)

Cohort6	0.0107	0.0106*	0.0108	0.0267*	0.0125	0.0267*	0.0186**
	(0.0070)	(0.0056)	(0.0100)	(0.0161)	(0.0173)	(0.0148)	(0.0082)
Cohort8	-2.80e-05	0.0106*	0.0168*	0.0118	0.0167	0.0351**	0.00519
	(0.0069)	(0.0057)	(0.0101)	(0.0171)	(0.0188)	(0.0141)	(0.0084)
Cohort9	-0.0108	0.00854	0.0351*	0.0582**	0.0494	0.0840***	0.0349**
	(0.0123)	(0.0095)	(0.0211)	(0.0284)	(0.0329)	(0.0219)	(0.0142)
Cohort10	-0.0183	0.0088	0.0155	-0.0490	0.0290	0.112***	0.0451**
	(0.0168)	(0.0181)	(0.0291)	(0.0465)	(0.0494)	(0.0340)	(0.0202)
Cohort11	0.0032	0.0589	0.0891**	-0.0389	0.0286	0.173***	0.0621**
	(0.0290)	(0.0397)	(0.0359)	(0.0640)	(0.0777)	(0.0492)	(0.0266)
constant	-0.621***	-0.469***	-0.308***	-0.0098	0.261***	0.443***	0.890***
	(0.0265)	(0.0272)	(0.0354)	(0.0590)	(0.0665)	(0.0659)	(0.0586)
				N = 47,072			
Pseudo R-squared[c]	0.21	0.17	0.12	0.09	0.08	0.09	0.05

[a] This table reports average marginal effects of the coefficients. All the estimates shown above are calculated with weights.

VITA

Jeonghun Kim (hereafter Kim) was born and raised in Seoul, South Korea. Before attending the Truman School of Government and Public Affairs, he attended Korea University. He got a Bachelor of Art in Economics in 2009, and also got a Master of Arts in Economics in 2012.

His academic training in public policy/administration, including two years spent as an economics doctoral student, helped him to develop his analytical skills and to understand policy issues from different perspectives. His dissertation examines the relationships between racial preferences and economic outcomes, and changes in racial preferences over time, which are conducted with advanced quantitative

Kim worked as a research assistant at the Institute of Public Policy at the University of Missouri where he was actively involved in all aspects of the research process, including data collection/management, analyzing results, giving an advice on quantitative methods, and writing evaluation reports for policy issues. He also gained invaluable teaching experience at the University of Missouri. He taught and acted as a teaching assistant for a number of courses (including advanced quantitative methods for graduate students) through the University of Missouri: the Department of Economics and the Truman School.

Currently, Kim is preparing for his next step as an economist and a public policy scholar by extending his research areas - how racial prejudice can affect economic, health, and educational outcomes. His research will make contributions to reducing systematic differences among racial groups observed in our society.