“Hate at First Sight”: Evidence of Consumer Discrimination Against African-Americans in the US

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‘Hate at First Sight’: Evidence of Consumer Discrimination Against African-Americans in the US*

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Abstract

The paper runs the customer discrimination test provided by Combes et al. (2013) on US data. This test is based on a two-sector matching model with racial sector-specific preferences or abilities, employer discrimination and customer discrimination. The strategy makes it possible to disentangle customer from employer discrimination. My results prove the existence of discrimination against African-Americans at job entry from both employers and consumers in the US. It also reports that racial prejudice has a quantitative effect on the relative employment and contact probabilities of blacks. A decrease in the intensity of discrimination by one standard deviation raises the raw employment rate of blacks by 15 percent and increases the proportion of blacks in jobs in contact with customers by 20 percent.

JEL classification: J15, J61, R23

Keywords: Customer Discrimination, Racial Prejudice, Search Model

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1 Introduction

The employment rate gap between African-Americans and white Americans has been increasing over the past thirty years in the US and is considered by public policy makers as a significant challenge. Today, low-skilled black men are 10 percent more likely to be unemployed than their white counterparts, after controlling for individual characteristics and location. There is reason to believe that discrimination driven by prejudice plays a part in explaining this residual gap. The starting point of racial prejudice is that some people have a negative feeling when interacting with people of another race. In his seminal work, Becker (1957) represents negative sentiment as a disutility stemming from cross-racial interaction between employers and/or customers, and minority employees. While there is a sizable literature explaining the impact of prejudice on the wage gap between whites and blacks, such as Charles and Guryan (2008), no previous empirical studies have explored the presence of discrimination at job entry and specifically in jobs which involve being in contact with customers. This paper explores this relationship by running the test strategy provided by Combes et al. (2013) which was the first to identify employer and consumer discrimination both theoretically and empirically. This present paper adds to the existing literature by providing empirical support to explain why blacks are both less likely to be employed and to occupy a contact job in the presence of prejudice against them from employers and customers.

Combes et al. (2013) provide a test strategy of customer discrimination which is run on French data. Their paper allows distinguishing customer discrimination from two other competing explanations : employer discrimination and ethnic-specific preferences in some occupations. This model predicts that if the racial differential unemployment probability, namely unemployment for blacks minus unemployment for whites, is positively affected by the proportion of prejudice, then there is racial (employer and/or customer) discrimination. Second, there is customer discrimination if there is racial discrimination and if the racial differential probability of working in a contact job is negatively impacted by the proportion of prejudiced individuals. Using French data, the authors provide evidence of the existence of customer discrimination against African immigrants. A few other studies prove the existence of consumer discrimination against minorities in contact jobs in the US[1]. Similarly to the previous paper, these analyses use the racial composition of residents in a geographical area as a proxy for the consumer composition of the firms located in that area. Holzer and Ihlanfeldt (1998) analyze the effect of consumer racial composition on the race of newly hired employees, whereas Giuliano et al. (2010) study the impact of this racial composition on firms' sales. There have also been a number of experimental contributions to the customer discrimination literature: Ihlanfeldt and Young (1994) and Kenney and Wissoker (1994). All these papers suggest empirical evidence that minority workers are excluded from jobs involving substantial interaction with majority customers.

[1] A large part of the literature on this source of discrimination uses data from professional sports leagues which include detailed measurements of athletes' performances (see for instance Kahn and Sherer (1988) and Nardinelli and Simon (1990) and Kahn (1991) for a literature review.)

The empirical analysis provided by Combes et al. (2013) has three main drawbacks. First, they focus on African immigrants, but the French Constitution forbids the collection of data on ethnic groups. Therefore, the authors use an indirect method to circumvent this issue by using individuals' citizenship and country of birth. Their categorization distinguishes first-generation immigrants from the rest of the population. Second-generation immigrants are spuriously considered in the group of French natives, which is harmful to the authors' empirical analysis. Second, they use the local demographic composition to assess the presence of customer discrimination. All the other empirical papers using US data which are mentioned above identify customer discrimination based on the same assumption. The ethnic composition of customers is certainly different from the spatial distribution of prejudiced customers. This assumption may bias the results in these papers. Third, they do not observe whether individuals work in a contact job or not. In order to compute the probability of working in a job in contact with consumers for each occupation, Combes et al. (2013) use a survey in which employed individuals are asked whether they are in contact with consumers in their job. With this information, the authors assign each occupation the empirical proportion of contact in a given job. Relying on a small survey to compute the probability of being in contact with customers may however lead to measurement issues.

This present paper solves the three problems raised above. First, I use US Census (IPUMS) that gives precise information on the race of individuals which allows me to separate the majority (whites) from the minority (blacks). Second, instead of using the local ethnic composition of individuals as a pool of discriminating employers and consumers, I am able to measure the share of racial prejudice accurately by using the General Social Survey (GSS) as the source for data on racial prejudice. This representative dataset elicited responses from survey questions about matters strongly related to racially prejudiced sentiments. I compute the share of prejudiced individuals for each local area based on white respondents' answers to questions about race. Third, to measure how important contact is for a given occupation, I use job task data from the Dictionary of Occupational Titles which is administered by the US Department of Labor. This data provides an index of how important working with the public is in a given occupation.

Using the Integrated Public Use Microdata Series (2000), I develop a two-step procedure to examine how the individual probability of being unemployed and the individual probability of working in a contact job respond to the share of racial prejudice at the local labor market level (Commuting Zones). The first probability is corrected for selection based on mobility, as proposed by Dahl (2002) and implemented by Beaudry et al. (2012), whereas the second one is corrected for sample selection bias using Heckman (1979)'s procedure. I derive a careful strategy that controls for possible reverse causality and endogeneity of racial prejudice by instrumenting the share of racial prejudice by the share of prejudice against communists and homosexuals. I also assess the quantitative impact of my estimates and carry out several counterfactual experiments. I find that the residual racial unemployment rate differential is greater in commuting zones where the proportion of racial prejudice is high. I also find that the residual racial differential in the probability of occupying a contact job is smaller in commuting zones where the share of racial prejudice is large. These empirical results are robust to instrumentation and to other robustness checks. Following the theoretical predictions of Combes et al. (2013), my empirical results strongly support the hypothesis that consumer discrimination exists in the US. Finally, I show that racial prejudice has a quantitative effect on both the relative employment and contact probabilities of blacks. A decrease in the intensity of discrimination by one standard deviation raises the raw employment rate of blacks by 15 percent and increases the proportion of blacks in jobs in contact with customers by 20 percent.

The remainder of the paper is organized as follows : Section 2 briefly amends the theoretical model used by Combes et al. (2013), Section 3 tests theoretical predictions on US data and Section 4 concludes.

2 Test of Customer Discrimination: Model and Predictions

In this section, I briefly expose the two-sector static matching model provided by Combes et al. (2013). I slightly amend the model in two different directions. First, I rely on the local share of racial prejudice instead of the local ethnic composition of individuals. Second, I include some equilibrium effects, in the sense that whites are better off in the labor market if they are located in areas characterized by a high share of racially prejudiced individuals. Except for these two changes, my model follows the original one.

Sector 1 is composed of jobs in which there is no consumer contact, while sector 2 comprises contact jobs. With probability p, the job is from sector 2. Job seekers are either black or white (j= B,W respectively). Job seekers are homogeneous, except as regards their observable racial group and through their preferences with respect to the various jobs. Job seekers have sector-specific preferences whose distribution possibly differs between ethnic groups. Let ϕ_i^j denote the proportion of individuals j who accept an offer from sector i. Search frictions forbid workers from finding a job with certainty. The probability of locating an available job is m. Matching is random and therefore job seekers cannot perfectly observe the type of employer or consumer in terms of prejudice.

Some whites have a disutility towards African-American employees, and therefore discriminate against them. As Combes et al. (2013), I disentangle the disutility which comes from hiring a black employee (employer discrimination) from that which derives from being in contact with a black worker (customer discrimination). Let α_e be the proportion of available jobs whose corresponding employer has a taste for discrimination and refuses to hire black employees as a result. Also, let α_c be the proportion of available sector-2 jobs whose customers refuse to interact with a black employee. Unlike blacks, whites do not suffer from discrimination of any kind. On the contrary, they benefit from the presence of racial discrimination in the sense that they occupy jobs from which blacks are excluded. Therefore, α_e and α_c are the proportions of jobs and contact jobs respectively available to whites only. Therefore, an increase in prejudice against blacks favors employment prospects for whites. We observe that the employment rate of both whites and blacks is affected by the global availability of jobs, sectorial preferences and racial discrimination. For a group-j individual, let

q^j be the probability of employment in sector 2 conditional on being employed, and let e^j be the group-j employment rate.

For white workers, the employment rate is:

$$e^W = (1-p)m\phi_1^W(1+\alpha_e) + pm\phi_2^W(1+\alpha_e)(1+\alpha_c) \tag{1}$$

When $\alpha_e > 0$ and/or $\alpha_c > 0$, whites benefit from racial discrimination which increases their employment probabilities. Discrimination may be due to employers (in both sectors) or consumers (in sector 2 only). The probability of employment in sector 1 is $\pi_1^W = (1-p)m\phi_1^W(1+\alpha_e)$, while it is $\pi_2^W = pm\phi_2^A(1+\alpha_e)(1+\alpha_c)$ in sector 2.

The conditional probability q^W is:

$$q^W = \frac{pm\phi_2^W(1+\alpha_c)}{(1-p)m\phi_1^W + pm\phi_2^W(1+\alpha_e)(1+\alpha_c)} \tag{2}$$

This probability depends on the relative supply of sector-2 jobs, on whites' absolute preferences ϕ_2^W/ϕ_1^W for contact jobs and on advantages from racial discrimination.

Black workers may be discriminated against, thus reducing their employment probabilities. The probability of employment in sector 1 is $\pi_1^B = (1-p)m\phi_1^B(1-\alpha_e)$, while it is $\pi_2^B = pm\phi_2^B(1-\alpha_e)(1-\alpha_c)$ in sector 2. The unemployment rate of African-Americans is:

$$e^B = (1-p)m\phi_1^B(1-\alpha_e) + pm\phi_2^B(1-\alpha_e)(1-\alpha_c) \tag{3}$$

The conditional probability q^B is then given by:

$$q^B = \frac{pm\phi_2^B(1-\alpha_e)(1-\alpha_c)}{(1-p)m\phi_1^B(1-\alpha_e) + pm\phi_2^B(1-\alpha_e)(1-\alpha_c)} \tag{4}$$

As for whites, this probability depends on the relative supply of sector-2 jobs and on blacks' absolute preferences for contact jobs, but unlike whites, it is negatively affected by racial discrimination.

The employment rate racial gap, $\Delta e = e^B - e^W$, and the conditional probability racial differential, $\Delta q = q^B - q^W$, are given by:

$$\Delta e = m[(1-p)[\phi_1^B(1-\alpha_e) - \phi_1^W(1+\alpha_e)] + p[\phi_2^B(1-\alpha_e)(1-\alpha_c) - \phi_2^W(1+\alpha_e)(1+\alpha_c)]] \tag{5}$$

and:

$$\Delta q = \frac{p(1-\alpha_c)\phi_2^B}{p(1-\alpha_c)\phi_2^B + (1-p)\phi_1^B} - \frac{p\phi_2^W(1+\alpha_c)}{(1-p)\phi_1^W + p\phi_2^W(1+\alpha_c)} \tag{6}$$

Equations (5) and (6) provide a way to identify ethnic discrimination, and differentiate customer from employer discrimination.

The impact of α_e, the local share of employers' racial prejudice, on the employment rate differential is given by:

$$\frac{\partial \Delta e}{\partial \alpha_e} = m[-(1-p)(\phi_1^B + \phi_1^W) - p(\phi_2^B(1-\alpha_c) + \phi_2^B(1+\alpha_c))] \tag{7}$$

The impact of α_c, the local share of consumers' racial prejudice, on the employment rate differential is given by:

$$\frac{\partial \Delta e}{\partial \alpha_c} = m[-p(\phi_2^B(1-\alpha_e) + \phi_2^W(1+\alpha_e))] \tag{8}$$

An increase in the share of prejudiced employers or in the share of prejudiced consumers decreases the employment rate differential. As long as $\alpha_e > 0$ and/or $\alpha_c > 0$, racial discrimination exists, but this relationship does not enable us to disentangle customer from employer discrimination.

As Combes et al. (2013) do, I use the second gap to identify customer from employer discrimination unambiguously:

$$\frac{\partial \Delta q}{\partial \alpha_c} = -\frac{p(1-p)\phi_1^B\phi_2^B}{\left[(1-p)\,\phi_1^B + p\,(1-\alpha_c)\,\phi_2^B\right]^2} - \frac{p(1-p)\phi_1^W\phi_2^W}{\left[(1-p)\,\phi_1^W + p(1+\alpha_c)\phi_2^W\right]^2} \tag{9}$$

This derivative is negative if and only if there is customer discrimination.

Combes et al. (2013) provide theoretical arguments to show how the predictions of the model are robust to relaxing some assumptions. Their goal is to exclude any potential explanation other than customer discrimination (like sector-specific employer discrimination, statistical discrimination and ethnic networks) which could explain the predictions of the model. They also examine alternative settings like building a directed search model instead of a random search model and accounting for wage creation. All these specifications provide similar predictions. The robustness checks on the theoretical model are not detailed in this paper and the readers who are interested in these checks should have a look at Combes et al. (2013).

3 Data, Empirical Strategy and Estimations

This section tests the previous model of both employer and consumer discrimination on US data. I empirically estimate the effect of the share of racial prejudice coming from employers α_e and from consumers α_c on the individual probability of employment e and on the conditional probability of being in contact with customers q. First, I introduce datasets, then I discuss the econometric methodology, and finally I present the results.

3.1 Data

This analysis draws on the Census Integrated Public Use Micro Series (Ruggles et al. (2004)) for the year 2000. It provides a large sample size (5% of the U.S. population) which is essential for an analysis of local labor markets. It also gives extensive information on individual data, which is useful to assess outcomes on the labor market[2].

3.1.1 Commuting Zones

By providing local geographic information, IPUMS allows the construction of *Commuting Zones* (CZs) in the US. This concept of CZs comes from Tolbert and Sizer (1996). CZs are particularly suitable for this analysis of local labor markets for two main reasons. First, they are based primarily on economic geography rather than factors such as minimum population. Second, they can be consistently constructed using Census Public Use Micro Areas. Each CZ approximates a local labor market, which can be considered as the smallest geographic area where most residents work and most workers reside. Tolbert and Sizer (1996) describe the identification of CZs using county-level commuting data from the 1990 Census. Each CZ is a collection of counties (or a single county) with strong commuting links which covers both urban and rural areas. However, CZs have hardly been used in empirical economic research on the US, probably because this geographic unit is not reported in publicly accessible micro data. The most detailed geographic units in IPUMS data (US Census) are defined to comprise between 100,000 and 200,000 residents each. These Census-defined places are called Public Use Microdata Areas (PUMAs) and do not cross state lines. This definition does not allow the perfect matching of boundaries for all CZs. In order to overcome this issue, I assign individuals to CZs. I split every individual observation into multiple parts whenever an individual's PUMA cannot be uniquely assigned to a CZ. The adjusted person weights in the resulting dataset multiply the original census weights 'PERWT' to the ratio between the number of residents in the overlap between PUMA and CZ and the number of residents in each PUMA. This ratio is simply the probability that a resident of a specific PUMA lives in a particular CZ for each Census year. The CZs in the sample were chosen based on having at least 100 black wage-earning respondents in the IPUMS census data. Therefore, this analysis includes 193 CZs (instead of 722) which cover the contiguous US (both metropolitan and rural areas), excluding Alaska, Hawaii and Puerto Rico. See Appendix A for more details on the construction of CZs at the individual level.

3.1.2 Proportion of Contact for Each Occupation

In order to test evidence of customer discrimination, the empirical analysis requires measuring how important contact is for a given occupation. The decennial IPUMS details occupations at the three-digit level, but does not indicate whether the worker is in contact with the public or not. I use job task data from the Dictionary of Occupational Titles (DOT - US Department of Labor, Employment and Training Administration, 1977) to characterize the share of contact in an occupation. This Occupation information network (O*NET) gives details for each occupation

[2] The Current Population Survey is often preferred to IPUMS since it provides detailed information on individual earnings every month. The drawback of this database is the lack of precise geographic information on the location of individuals: it contains state-level geographic identifiers only.

by using the *SOC* occupational classification. The network provides more than 275 standardized descriptors of skills, knowledge, tasks, occupation requirements, and worker abilities, interests, and values for 974 occupations. As a measure of a contact job, I use the index for how important 'Working directly with the Public' is in a given occupation. This index is part of work activities. The exact definition is: 'Performing for people or dealing directly with the public'. This includes serving customers in restaurants and stores, and receiving clients or guests. The importance indexes take values between 1 and 98. Table 11 in Appendix B enumerates the indexes for each occupation category and gives more information on the construction of the occupational classification. I match the importance index of customer contact from the US Department of Labor's DOT with the corresponding Census occupation classification to measure contact by occupation.

Table 1 shows the proportion of contact jobs in 6 distinctive job categories. It clearly suggests that the tertiary sector (represented in the first three lines) provides many more contact jobs than the agricultural and industrial sectors.

Table 1: Proportion of Contact Jobs In 6 Job Categories

Job Categories	**Mean**	**Std Dev**	**Min**	**Max**
Managerial and Professional Occupations	53.8	22.7	5	98
Technicians, Sales & Related Support Occupations	52.3	23.4	5	95
Service Occupations	66.6	20.5	26	98
Farming, Forestry and Fishing Occupations	28.1	17.3	6	56
Precision Production, Craft & Repair Occupations	38.0	19.3	6	79
Operators, Fabricators & Laborers	28.3	20.4	1	96

Source: Occupation information network (O*NET).

3.1.3 Share of Racial Prejudice

Measuring the share of racial prejudice at the local level is paramount to identifying both employer and customer discrimination against blacks. Combes et al. (2013) test their theoretical model on French data based on the assumption that discrimination depends on the ethnic composition of local residents. The authors rely on this relatively strong assumption since they cannot accurately measure the level of prejudice across local areas. Unlike them, I use the General Social Survey (GSS) for the years 1996 to 2004 as the source of data on racial prejudice at the local level. This nationally representative dataset elicited responses from survey questions about matters strongly related to racially prejudiced opinions. Using this survey has three main drawbacks. The first one is that none of these questions perfectly captures the disutility which an employer or a customer may have from a cross-racial interaction. However, a person's probability of responding to these questions in a racially intolerant way is strongly correlated with the racial prejudice felt by employers and customers towards blacks. I use the question "Do you think there should be laws against marriages between blacks and whites?" and compute the share of prejudiced individuals for each commuting zone as the percentage of white respondents who answered positively[3]. This question is particularly suited to my purpose as it reveals the true prejudice individuals may have interacting with blacks[4]. The second concern is that this question does not differentiate between employers' and consumers' racial prejudice. Hence, I assume the share of racial prejudice has the same value for both α_e and α_c. Finally, the last problem is GSS provides information on prejudice at the state level only. As PUMAs do not cross state lines, I can allocate the share of prejudice at the state level to the PUMA level. Then, I convert this share at the PUMA level to the CZ level by assigning a PUMA to a CZ based on the population weight of the PUMA in the CZ. If a PUMA overlaps several counties, I match PUMAs to counties assuming that there is the same probability for all residents of a PUMA of living in a given county. See Appendix C for more details on the construction of racial prejudice at the CZ level. Some states have missing values or do not have enough observations to accurately measure the proportion of white respondents to the question of interest on interracial marriage. For these states, I use the answers of contiguous states. For each table of results, I provide two geographical definitions of the share of racial prejudice: uncorrected at the state level and corrected at the CZ level. Table 2 provides some summary statistics on the share of racial prejudice at both geographical levels. Both definitions present similar statistics.

Table 2: Different Measures of the Share of Racial Prejudice

2000	**Mean**	**Std Dev**	**Min**	**Max**
$\%Prejudice_{ST}$	0.13	0.084	0.029	0.39
$\%Prejudice_{CZ}$	0.14	0.092	0.001	0.42

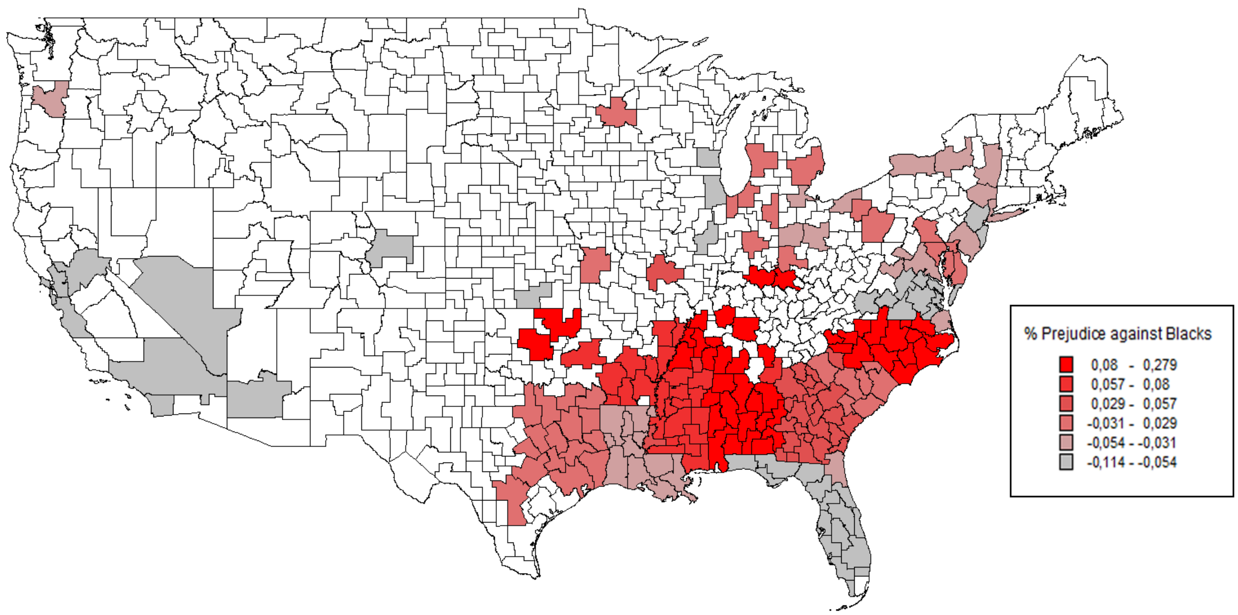
Source: GSS 1996-2004.

[3]Using the same survey, Charles and Guryan (2008) focus on testing whether an association between racial prejudice and blacks' wages implied by the Becker prejudice model can be found in the data. Using responses to a number of racial questions, the authors create an individual prejudice index among whites in a given state and identify different percentile points in that prejudice distribution, differentially by state. They pool all observations over all years in the data to measure various percentiles of the distribution of prejudice in each state. The goal of this paper is to link the average residual wage gap experienced by blacks in a state to the white prejudice distribution in that state in order to test Becker's predictions.

[4]Other questions are linked to statistical discrimination like "Blacks have worse jobs, income and housing than white people. Do you think these differences are because most blacks have less in-born ability to learn?", or "Do you think most blacks just don't have the motivation or will power to pull themselves up out of poverty?" , and to housing discrimination "Do you think White people have a right to keep Blacks out of their neighborhoods if they want to?", or "Suppose there is a community-wide vote on the general housing issue. There are two possible laws to vote on. Law A says that a homeowner can decide for himself whom to sell his house to, even if he prefers not to sell to Blacks. Law B says that a homeowner cannot refuse to sell to someone because of their race or color. Which law would you vote?".

Figure 1 maps the spatial distribution of racial prejudice in 2000. It clearly shows that the proportion of prejudiced whites is high in the South East. The commuting zones which are characterized

Figure 1: Proportion of White Respondents Prejudiced Against African-Americans by County Zone



Notes: (i) the proportion of racial prejudice is computed from the General Social Survey on the 1996-2004 time period; (ii) the map consists of 193 CZs; (iii) white CZs are dropped from the analysis; and (iv) the share of racial prejudice is centered with respect to the mean.

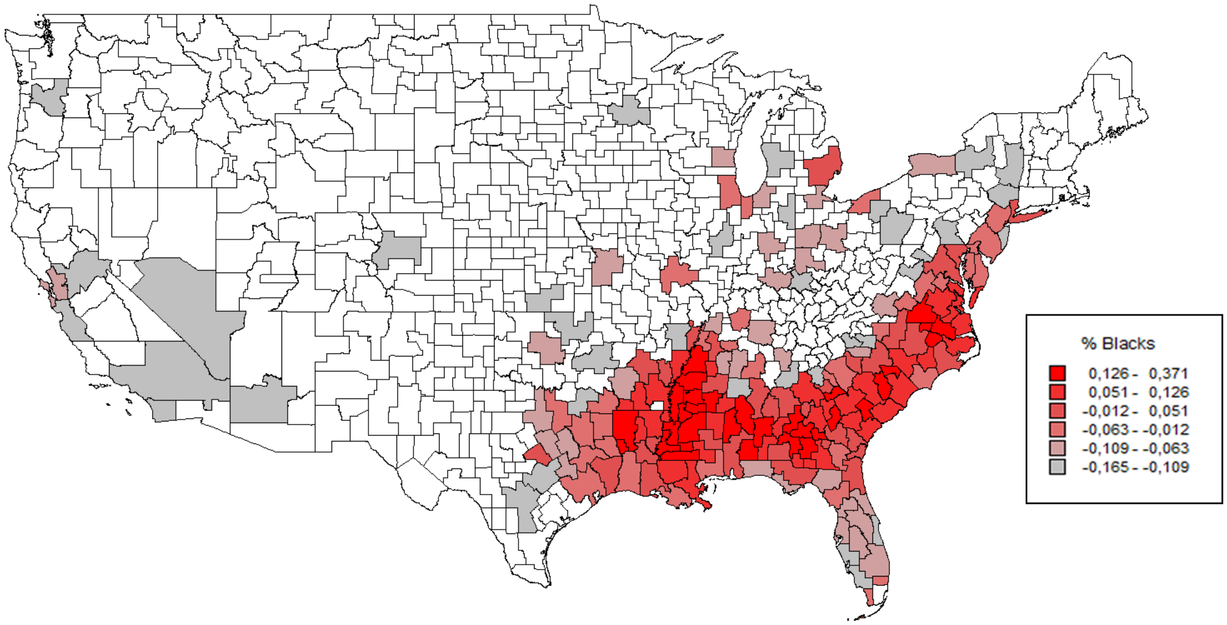
by the highest levels of prejudice are also the areas with the highest share of African-Americans. Figure 2 shows the spatial distribution of African-Americans is relatively high in the South East[5] The correlation between these two shares is 0.3. In the US, prejudice against African-Americans is deeply rooted in the slavery period. Counties where Blacks constitute a large share of the workforce used to be plantation farming areas and are still influenced today by a strong tradition of hierarchical race relations (see Sundstrom (2007)).

3.2 Econometric Methodology

In order to disentangle customer from employer discrimination, I study the relationship between the employment and contact probabilities of black men and the share of racial prejudice. I focus on males to avoid a number of questions related to family arrangements, residential choices, and female labor market outcomes and more specifically on males who have at most a high school diploma since differentials among highly skilled male workers are barely present. The sample includes all low-skilled males aged 25-65 not living in group quarters. All calculations are made using the sample weights provided and the CZ weights. For the contact regression, I focus on wage and salary workers

[5]The fraction of the population that is black is calculated by summing the relevant subpopulation in the IPUMS.

Figure 2: Proportion of African-Americans by County Zone



Notes: (i) the proportion of African-Americans is computed from the 2000 Census; (ii) the map consists of 193 CZs; (iii) white CZs are dropped from the analysis; and (iv) the share of racial prejudice is centered with respect to the mean.

with positive wages, working full time (usual hours worked per week 35 or more and weeks worked per year 40 or more).

As Combes et al. (2013) do, I adopt a two-step procedure. In the first step, I regress an individual-level regression of both employment and contact probabilities (e_i and q_i) on a set of common individual characteristics (categorical education variables, age and its quadratic) and on a set of individual characteristics specific to each regression (marital status and the presence of children for the employment regression, and occupation dummies for the contact regression). Both regressions also include a full set of racial CZ cell dummies, and their coefficients are used to construct the dependent variable in the second-stage regression. I eliminate all racial CZ cells which include fewer than 100 individuals.

$$e_i = \gamma_0 + \gamma_1 X_i + \gamma_2 Black_i + \sum_{k(i)} \left(\psi^1_{k(i)} CZ_{k(i)} + \varphi^1_{k(i)} CZ_{k(i)}.Black_i \right) + \epsilon_i \tag{10}$$

$$q_i = \beta_0 + \beta_1 \chi_i + \beta_2 Black_i + \sum_{k(i)} \left(\psi^2_{k(i)} CZ_{k(i)} + \varphi^2_{k(i)} CZ_{k(i)}.Black_i \right) + \rho\sigma\widehat{\lambda}_i + \varepsilon_i \tag{11}$$

where e_i is a variable that captures the probability of being unemployed for individual i, q_i is the observed probability of being in contact with consumers if individual i works, k is the corresponding location, $Black_i$ is a dummy variable equal to 1 for blacks and 0 otherwise, and X_i and χ_i are the vectors of observed individual characteristics specific to each first-step regression. Model (10) is estimated for both OLS and probit. The estimation of model (10) is corrected for selection based on mobility since employment is closely related to individuals' mobility. More specifically, the distribution of unobserved skills in a CZ may be correlated with the share of racial prejudice. This would imply a non-zero coefficient on the coefficient of interest, which does not reflect evidence of discrimination. The potential bias due to the endogenous residential location generates a correlation between the density of unavailable jobs and potential black workers' unobserved characteristics. For example, suppose that the most able workers move from the South where racial prejudice is high, then employment outcomes for blacks are lower. To address the issue of selection on the unobservables of workers across local labor markets, I implement a Heckman-type two-step procedure as proposed by Dahl (2002) and implemented by Beaudry et al. (2012).

The estimation of model (11) is corrected for sample selection bias (see Heckman (1979)), since occupying a contact job is conditional on being employed. The dual model is identified thanks to the introduction into the selection equation of variables regarding the marital status and the presence of children. The coefficients of the CZ-black interactions $\varphi^1_{k(i)}$ and $\varphi^2_{k(i)}$ are the adjusted estimates of both racial unemployment and contact gaps in each CZ. These effects are then taken as dependent variables in the second step of the estimation. Following the theoretical framework, I regress them on the share of racial prejudice ($\%Prejudice_k$):

$$\hat{\varphi^1}_k = \alpha^1 \%Prejudice_k + \upsilon^1_k \tag{12}$$

$$\hat{\varphi^2}_k = \alpha^2 \%Prejudice_k + \upsilon^2_k \tag{13}$$

Given that the second-step dependent variables are estimated in the first step, errors in the second-step regressions υ^1_k and υ^2_k are heteroskedastic. Following Card and Krueger (1992), I use the inverse of the square root of the standard errors of each race-CZ cell from the first step to form the weights for the second-stage estimation and therefore to take this measurement error into account.

These two second-step equations allow me to disentangle customer from employer discrimination in the US. If $\alpha^1 < 0$, then there is evidence of discrimination against blacks. If $\alpha^1 < 0$ and $\alpha^2 < 0$, then there is evidence of consumer discrimination against blacks.

3.3 Results

First, I comment on the estimates of the equations, then use them to quantify the magnitude of the discriminatory forces on both racial unemployment and contact gaps.

First-step regressions. Table 3 presents the results for the employment equation (10), while Table 4 presents the results for the contact probability equation (11).

Columns 1 and 2 report the estimates of a linear probability model, while columns 3 and 4

Table 3: Probability of Employment: First-Step Results

	OLS		Probit	
	(1)	(2)	(3)	(4)
Black	-0.133^a	-0.095^a	-0.142^a	-0.106^a
	(0.001)	(0.018)	(0.000)	(0.005)
Age	0.036^a	0.036^a	0.033^a	0.033^a
	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared	-0.000^a	-0.000^a	-0.000^a	-0.001^a
	(0.000)	(0.000)	(0.000)	(0.000)
Education 8th Grade	-0.188^a	-0.187^a	-0.219^a	-0.213^a
	(0.002)	(0.001)	(0.000)	(0.000)
Education 9th-10th Grade	-0.129^a	-0.129^a	-0.144^a	-0.146^a
	(0.001)	(0.001)	(0.000)	(0.000)
Education 11th Grade	-0.103^a	-0.101^a	-0.114^a	-0.113^a
	(0.002)	(0.002)	(0.000)	(0.000)
Children	0.035^a	0.036^a	0.043^a	0.045^a
	(0.001)	(0.001)	(0.000)	(0.000)
Married	0.103^a	0.099^a	0.108^a	0.105^a
	(0.001)	(0.001)	(0.000)	(0.000)
Constant	0.149^a	0.171^a	-0.397^a	
	(0.006)	(0.010)	(0.003)	
CZ fixed effects				
Inter-decile		[−0.064-0.006]		[−0.20-0.047]
# (share) > mean (signif. at 5%)		89 (45.4%)		95 (48.5%)
# (share) < mean (signif. at 5%)		100 (51.0%)		99 (50.5%)
CZ fixed effects X 'Black'				
Inter-decile		[−0.096-0.21]		[−0.21-0.046]
# (share) > mean (signif. at 5%)		94 (47.9%)		100 (48.8%)
# (share) < mean (signif. at 5%)		84 (42.8%)		102 (49.8%)
R^2	0.13	0.14		
Observations	1,106,304	1,106,304	1,106,304	1,106,304

Notes: (i) marginal effects are reported; standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively; (ii) columns 1 and 2 are a linear probability model and columns 3 and 4 a probit model; (iii) individual controls are age and age squared, education dummies, marital status, and presence of children.

those of a probit model. The individual characteristics have the expected effects in the employment regression. The OLS and probit estimates show similar results. Education and age increase exposure to employment. Married men and individuals with children are more employed than single men and men without children. An African-American has a lower probability of being employed, even after taking individual and location characteristics into account. The inclusion of CZ fixed effects in columns (2) and (4) reduces the black-white difference in employment from over 13-14 percentage points with no fixed effects to around 10 percentage points.

Table 4: Probability of Being in Contact: First-Step Results

	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.007^a	0.009	0.003^a	-0.004	0.009^a	0.005
	(0.001)	(0.015)	(0.001)	(0.013)	(0.001)	(0.012)
Age	-0.000^a	-0.003^a	-0.001^b	-0.003^a	-0.001^a	-0.002^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared	0.000^b	0.000^a	0.000^a	0.000^a	0.000^a	0.000^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education 8th Grade	-0.073^a	-0.064^a	-0.033^a	-0.027^a	-0.023^a	-0.021^a
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Education 9th-10th Grade	-0.052^a	-0.041^a	-0.013^a	-0.007^a	-0.012^a	-0.008^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education 11th Grade	-0.041^a	-0.031^a	-0.008^a	-0.003^a	-0.009^a	-0.006^a
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.478^a	0.501^a	0.557^a	0.574^a	0.617^a	0.629^a
	(0.007)	(0.010)	(0.007)	(0.009)	(0.006)	(0.008)
Lambda	0.079^a	0.033^a	0.020^b	-0.014^a	-0.003	-0.022^a
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
# Occupation dummies	0	0	5	5	12	12
CZ fixed effects						
Inter-decile		[−0.025-0.069]		[−0.018-0.051]		[−0.025-0.032]
# (share) > mean (signif. at 5%)		96 (49.0%)		97 (49.5%)		91 (46.4%)
# (share) < mean (signif. at 5%)		95 (48.5%)		87 (44.4%)		95 (48.5%)
CZ fixed effects X 'Black'						
Inter-decile		[−0.035-0.037]		[−0.023-0.037]		[−0.021-0.23]
# (share) > mean (signif. at 5%)		86 (43.9%)		82 (41.8%)		81 (41.3%)
# (share) < mean (signif. at 5%)		84 (42.9%)		83 (42.3%)		70 (35.7%)
R^2	0.01	0.03	0.17	0.19	0.37	0.37
Observations	488,257	488,257	488,257	488,257	488,257	488,257

Notes: (i) marginal effects are reported; standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively; (ii) specifications are corrected for sample selection bias; (iii) individual controls are age and age squared, education dummies, and occupation dummies in columns (3) to (6).

For the contact regression, I present three sets of estimations, without and with occupation dummies (5 and 12). Controlling for occupation may be justified if individuals sort across job types depending on their preferences independently from the presence of discrimination. When occupations are chosen, anticipating possible discrimination and controlling for occupation can create interpretation problems and endogeneity issues. While the two latter options largely increase the first-step explanatory power of the model, the second-step estimates are mainly left unchanged as we will see below. Other individual characteristics have the expected effects in this second regression. A higher level of education increases the probability of being in contact with consumers, while age decreases it. Black men are more likely to be employed in contact jobs than whites. When fixed effects are included, the latter probability is no longer significant. These results come from the fact that blacks are more likely to live where contact jobs are over-represented, mainly in large cities.

On the bottom part of both tables, summary statistics for CZ fixed effects are reported. Area fixed effects do not increase the explanatory power of both models much, but they are highly significant (and therefore precisely estimated), and large. A black man moving from the CZ at the first decile to the CZ at the last decile of fixed effects would increase his employment rate by 21% points and increase his contact probability by 4 to 7% points in comparison with a white man.

Second-step regressions. Table 5 presents second-step regression results. Columns (1) to (4) are estimated using a first-step linear probability model, while columns (5) to (8) are estimated using a first-step probit model. The results report both measures of prejudice: at the state level and at the CZ level. All these different specifications show similar results. The share of racial prejudice has a significant negative effect on black employment. Following the theoretical model, this result proves that there is racial discrimination at job entry on the US labor market. At the state level, the estimated coefficients indicate that a one-standard-deviation increase in the proportion of prejudiced individuals increases the employment rate gap by about .22-.28 of its standard deviation. At the CZ level, a one-standard-deviation increase in prejudice increases the employment rate gap by about .15-.22 of its standard deviation. The share of blacks in the population is also included to control for its strong correlation with the share of racial prejudice. Columns (2), (4), (6) and (8) reveal that the share of blacks also has a negative effect on the racial employment gap. The inclusion of racial composition mitigates the effect of prejudice on the employment of blacks, but does not change the significance of the estimates.

Table 6 reports the second-step regression results from the first-step contact regression. The share of racial prejudice has a significant negative effect on the adjusted racial differential probability of working in a contact job. Specifications for different geographic definitions of the share of prejudice show similar results. Controlling for occupation in addition to education in the first step reduces the significance of the coefficients of interest. But overall, it barely affects the conclusion. In the first four columns, the estimated coefficients indicate that a one-standard-deviation increase in the proportion of prejudiced individuals widens the adjusted racial contact gap by .23-.28 of its standard deviation. In the next four columns, a one-standard-deviation increase in prejudice widens the adjusted racial contact gap by about .18-.22 of its standard deviation. In the last four columns, a one-standard-deviation increase in prejudice widens the adjusted racial contact gap by about .10-.13 of its standard deviation. Following the theoretical model, this negative impact can be interpreted as evidence of customer discrimination against African-Americans on the US labor market. As in the previous table, the share of blacks in the population is included to capture the potential correlation with prejudice. Overall, it reveals that the share of blacks has a non-significant

Table 5: Probability of Employment: Second-Step Results

	Differential employment gap							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\%Prejudice_{ST}$	-0.105^a	-0.095^a			-0.300^a	-0.263^a		
	(0.033)	(0.034)			(0.091)	(0.095)		
$\%Prejudice_{CZ}$			-0.094^a	-0.073^b			-0.245^a	-0.191^b
			(0.032)	(0.034)			(0.091)	(0.094)
%Blacks		-0.027		-0.049^b		-0.092		-0.127^b
		(0.027)		(0.023)		(0.074)		(0.064)
Constant	-0.033^a	-0.033^a	-0.033^a	-0.033^a	-0.100^a	-0.100^a	-0.100^a	-0.098^a
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.008)	(0.008)
R^2	0.060	0.066	0.042	0.065	0.063	0.072	0.037	0.056
obs.	163	163	193	193	163	163	193	193

Notes: (i) weighted least-square regressions using as weights the inverse of the estimated variance of the coefficients from the first-step regression reported in Table 3; (ii) the share of prejudice is centered with respect to Blacks' means; (iii) columns (1) and (2) are estimated using a first-step linear probability model in Table 3 (column (2)) and columns (3) and (4) are estimated using a first-step probit model in Table 3 (column (4)); (iv) in columns (1), (2), (5) and (6), the share of prejudice is computed as the raw share at the state level, while in columns (3), (4), (7) and (8), the share of prejudice is corrected using contiguous areas at the CZ level; and (v) standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively.

effect on the racial contact gap. Therefore, controlling or not for the share of African-Americans in this second step does not affect the estimates.

Table 6: Probability of Being in Contact: Second-Step Results

	Differential contact gap											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\%Prej_{ST}$	-0.093^a	-0.078^a			-0.049^b	-0.049^b			-0.022	-0.025		
	(0.023)	(0.024)			(0.019)	(0.020)			(0.015)	(0.016)		
$\%Prej_{CZ}$			-0.103^a	-0.095^a			-0.057^a	-0.064^a			-0.030^c	-0.038^b
			(0.023)	(0.024)			(0.020)	(0.020)			(0.015)	(0.016)
%Blacks		-0.036^c		-0.020		-0.000		0.016		0.006		0.019^c
		(0.019)		(0.016)		(0.016)		(0.014)		(0.013)		(0.011)
Constant	-0.007^a	-0.007^a	-0.008^a	-0.008^a	0.004^b	0.004^b	0.004^b	0.003^c	0.002	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.091	0.113	0.095	0.103	0.038	0.038	0.043	0.049	0.013	0.014	0.019	0.035
obs.	163	163	193	193	163	163	193	193	163	163	193	193

Notes: (i) weighted least-square regressions using as weights the inverse of the estimated variance of the coefficients from the first-step regression reported in Table 4; (ii) the share of prejudice is centered with respect to Blacks' means; (iii) columns (1) to (4), columns (5) and (8) and columns (9) and (12) are estimated using column (2), column (4) and column (6) of the first-step regression in Table 4 respectively; (iv) in columns (1), (2), (5), (6), (9) and (10), the share of prejudice is computed as the raw share at the state level, while in columns (3), (4), (7), (8), (11) and (12), the share of prejudice is corrected using contiguous areas at the CZ level; and (v) standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively.

In Appendix D, I add region dummies to tables (12) and (13) to capture any location effects not taken into account in CZs. This does not change my results qualitatively. Both tables prove the presence of both employer and customer discrimination against blacks.

3.4 IV results

In the previous tables, endogeneity issues may affect the estimates of racial prejudice through two effects. First, blacks' labor market outcomes may affect racial prejudice against them. This would create a reverse causality issue in the second-step estimations and therefore it would overestimate the presence of both types of discrimination. Second, some factors may affect both blacks' labor market outcomes and racial prejudice. Bound and Holzer (1993) and Wilson (1987) have stressed that the significant decline of manufacturing activity has disproportionately affected blacks' employment compared to whites. Moreover, the *Spatial Mismatch Hypothesis* postulated by Kain (1968) claims that the large supply of low-skilled workers in inner cities depreciates the labor market performances of black workers (see also Wilson (1996)). To circumvent these two potential problems, I pursue an instrumental approach that isolates exogenous spatial variation in prejudice to measure the unbiased prejudice effect. In this case, a viable IV should influence the severity of racial prejudice, but should not have an independent influence on racial gaps. For each local area, I instrument the share of racial prejudice with the share of prejudice against Communists and against homosexuals. As for the share of racial prejudice, I use the General Social Survey to compute these two shares of prejudice. For the share of prejudice against Communists, I use the two following questions: "Suppose a man who admits he is a Communist wanted to make a speech in your community. Should he be allowed to speak, or not?" and "Suppose a man who admits he is a Communist is teaching in a college. Should he be fired, or not?" and compute the share of individuals prejudiced against Communists for each commuting zone as the percentage of white respondents who answered intolerantly: "Not allowed" and "Yes" respectively. For the share of prejudice against homosexuals, I use the two following questions: "Suppose a man who admits that he is a homosexual wanted to make a speech in your community. Should he be allowed to speak, or not?" and "Should a man who admits that he is a homosexual be allowed to teach in a college or university, or not?" and compute the share of individuals prejudiced against homosexuals for each commuting zone as the percentage of white respondents who answered intolerantly: "Not allowed" to both questions.

Table 7 provides some summary statistics on the share of prejudice against homosexuals and Communists for both geographical definitions. The shares of both types of prejudice are higher than those of prejudice against blacks.

Both figures 3 and 4 show the shares of prejudice against homosexuals and against Communists, respectively. These figures reveal a spatial distribution similar to that of racial prejudice. The

Table 7: Different Measures of the Share of Prejudice

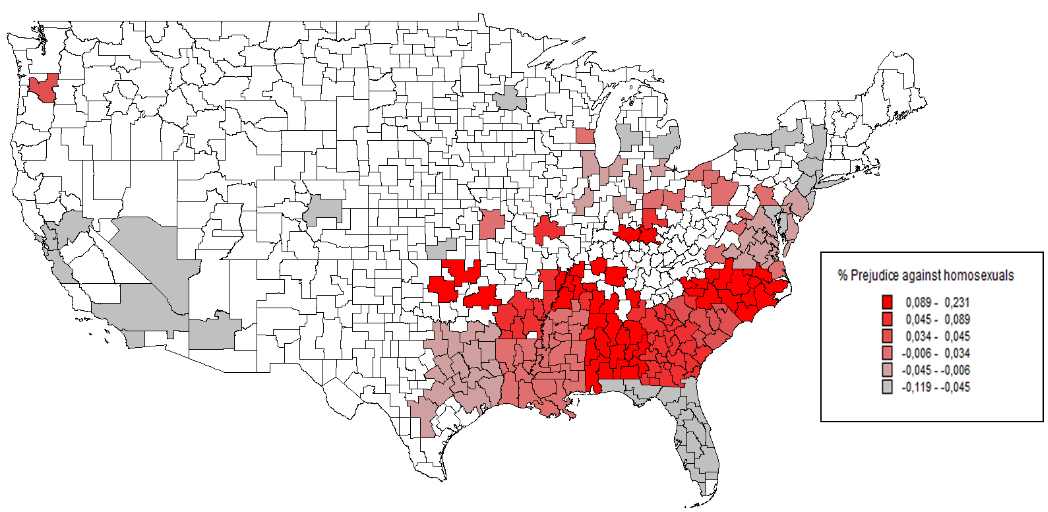
2000	**Mean**	**Std Dev**	**Min**	**Max**
%Prejudice against Communists (ST)	0.34	0.078	0.20	0.49
%Prejudice against Communists (CZ)	0.35	0.086	0.008	0.54
%Prejudice against homosexuals (ST)	0.20	0.086	0.088	0 .41
%Prejudice against homosexuals (CZ)	0.21	0.091	0.004	0.44

Source: GSS 1996-2004.

highest rates of prejudice against these two groups are located in the South East. The correlations between the share of racial prejudice and both shares of prejudice against homosexuals and Communists were around 0.8 in 2000. Prejudice against homosexuals, Communists and blacks typically comes from the same people. These two shares give two valid instruments since they are highly correlated to the share of racial prejudice, and have no influence on blacks' labor market outcomes.

In both tables 8 and 9, I check whether the effect that racial prejudice has on both black-white

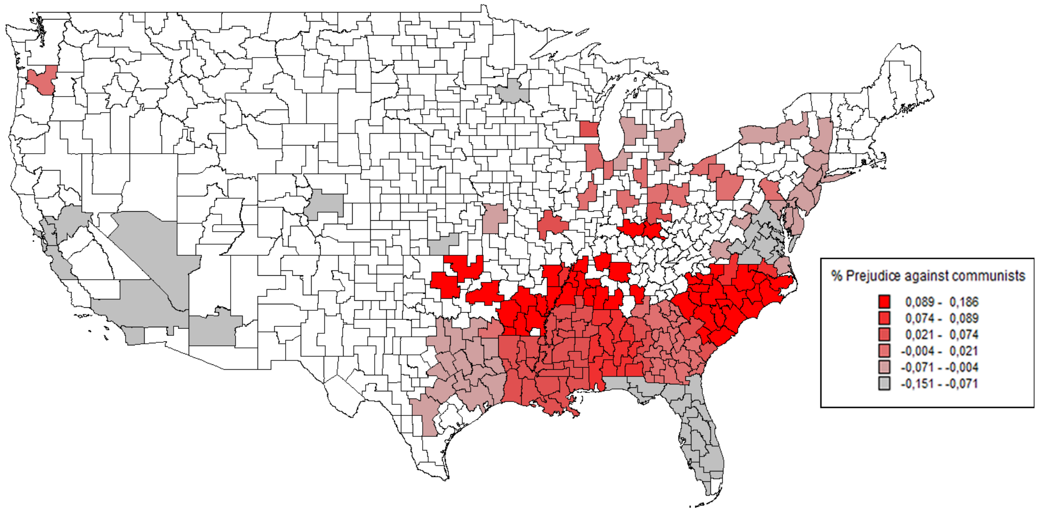
Figure 3: Proportion of White Respondents Prejudiced Against Homosexuals by County Zone



Notes: (i) the proportion of racial prejudice is computed from the General Social Survey on the 1996-2004 time period; (ii) the map consists of 193 CZs; and (iii) white CZs are dropped from the analysis.

gaps is robust to instrumentation. For all columns in the employment regressions, the instrumental variable estimates are of greater magnitude than the OLS ones. At both state and CZ levels, the estimated coefficients indicate that a one-standard-deviation increase in the proportion of prejudiced individuals increases the employment rate gap by about .22-.32 of its standard deviation. In second-step contact regressions, the magnitude of the coefficients is similar when occupations are excluded in the first step, but are somewhat lower when 5 occupations are included and the effect

Figure 4: Proportion of White Respondents Prejudiced Against Communists by County Zone



Notes: (i) the proportion of racial prejudice is computed from the General Social Survey on the 1996-2004 time period; (ii) the map consists of 193 CZs; and (iii) white CZs are dropped from the analysis.

Table 8: Probability of Employment: Second-Step Results - IV

	Differential employment gap							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\%Prejudice_{ST}$	-0.138^{a}	-0.121^{a}			-0.370^{a}	-0.324^{a}		
	(0.035)	(0.037)			(0.096)	(0.101)		
$\%Prejudice_{CZ}$			-0.129^{a}	-0.102^{a}			-0.349^{a}	-0.292^{a}
			(0.035)	(0.036)			(0.098)	(0.102)
%Blacks		−0.029		-0.049^{b}		-0.078		-0.100^{c}
		(0.025)		(0.021)		(0.069)		(0.060)
Constant	-0.025^{a}	-0.026^{a}	-0.025^{a}	-0.027^{a}	-0.077^{a}	-0.081^{a}	-0.076^{a}	-0.080^{a}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.010)	(0.008)	(0.009)
Shea p. R^2	0.85	0.84	0.84	0.82	0.85	0.84	0.84	0.82
J-stat p-value	0.03	0.04	0.06	0.11	0.13	0.15	0.45	0.59
Cragg-Donald	462.0	432.7	487.0	437.6	462.0	432.7	487.0	437.6
obs.	163	163	193	193	163	163	193	193

Notes: (i) weighted least-square regressions using as weights the inverse of the estimated variance of the coefficients from the first-step regression reported in Table 3; (ii) the share of prejudice is centered with respect to Blacks' means; (iii) columns (1) and (2) are estimated using a first-step linear probability model in Table 3 (column (2)) and columns (3) and (4) are estimated using a first-step probit model in Table 3 (column (4)) ; (iv) in columns (1), (2), (5) and (6), the share of prejudice is computed as the raw share at the state level, while in columns (3), (4), (7) and (8), the share of prejudice is corrected using contiguous areas at the CZ level; (v) the share of racial prejudice is instrumented by the shares of prejudice against Communists and against homosexuals; and (vi) standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively.

Table 9: Probability of Being in Contact: Second-Step Results - IV

	Differential contact gap											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\%Prej_{ST}$	-0.101^a	-0.072^b			-0.045^b	-0.039			-0.004	-0.001		
	(0.027)	(0.028)			(0.023)	(0.024)			(0.019)	(0.020)		
$\%Prej_{CZ}$			-0.104^a	-0.083^a			-0.052^b	-0.053^b			-0.016	-0.020
			(0.027)	(0.029)			(0.023)	(0.024)			(0.019)	(0.020)
%Blacks		-0.047^b		-0.037^b		-0.010		0.001		-0.005		0.007
		(0.019)		(0.017)		(0.016)		(0.014)		(0.013)		(0.012)
Constant	-0.010^a	-0.013^a	-0.012^a	-0.014^a	0.000	-0.000	-0.001	-0.001	-0.001	-0.002	-0.003^c	-0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Shea p. R^2	0.85	0.84	0.84	0.82	0.85	0.84	0.84	0.82	0.85	0.84	0.84	0.82
J-stat p-value	0.36	0.27	0.65	0.87	0.14	0.13	0.79	0.80	0.07	0.07	0.75	0.81
Cragg-Donald	461.9	432.7	487.0	437.6	461.9	432.7	487.0	437.6	462.0	432.7	487.0	437.6
obs.	163	163	193	193	163	163	193	193	163	163	193	193

Notes: (i) weighted least-square regressions using as weights the inverse of the estimated variance of the coefficients from the first-step regression reported in Table 4; (ii) the share of prejudice is centered with respect to Blacks' means; (iii) columns (1) to (4), columns (5) and (8) and columns (9) and (12) are estimated using column (2), column (4) and column (6) of the first-step regression in Table 4 respectively; (iv) in columns (1), (2), (5), (6), (9) and (10), the share of prejudice is computed as the raw share at the state level, while in columns (3), (4), (7), (8), (11) and (12), the share of prejudice is corrected using contiguous areas at the CZ level; (v) the share of racial prejudice is instrumented by the shares of prejudice against Communists and against homosexuals; and (vi) standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively.

of prejudice turns out to be insignificant with the inclusion of 12 occupations. To assess the quality of the instrumentation for both second-step regressions, I report the Shea partial R^2, the p-value of the over-identification test (Hansen J Statistic) and the Cragg-Donald statistics that check the statistical validity of the instruments. Concerning the employment outcome, the value above 0.8 of the Shea partial R^2 shows that the two instruments are strong predictors of the endogenous variable. In 5 cases out of 8, over-identification tests do not reject the null hypothesis that the instruments are exogenous at the 10% level. Moreover, high Cragg-Donald values confirm that the instruments are not weak. Concerning the contact outcome, the value above 0.8 of the Shea partial R^2 shows that the two instruments are strong predictors of the endogenous variable. In 10 cases out of 12, over-identification tests do not reject the null hypothesis that the instruments are exogenous at the 10% level. Moreover, high Cragg-Donald values confirm that the instruments are not weak. In both second-step regressions, the results and tests allow me to conclude that the share of racial prejudice is robust to instrumentation.

3.5 Quantitative Implication

To better assess the impact of the share of racial prejudice on both blacks' outcomes, I perform a counterfactual experiment that isolates the impact of racial prejudice on labor market outcomes. I decrease the intensity of discrimination, i.e. the coefficients α^1 in equation (12), by one standard error and compute the impact on the black employment rate. I use the same method on the contact equation: I decrease the coefficients α^2 in equation (13), by one standard error and compute the impact on the black contact rate. By definition, the black employment rate is:

$$e = \sum_k F_k e_k, \tag{14}$$

where F_k is the weight of blacks in area k, and e_k is the local employment rate. From equation (12), the change in the employment rate when α^1 varies by $\Delta\alpha^1$ is:

$$\Delta e = \sum_k F_k [\Delta\alpha^1 \% Prejudice_k] \tag{15}$$

By definition, the black contact rate is:

$$q = \sum_k F_k q_k, \tag{16}$$

where q_k is the local contact rate. From equation (13), the change in the contact rate when α^2 varies by $\Delta\alpha^2$ is:

$$\Delta q = \sum_k F_k [\Delta\alpha^2 \% Prejudice_k] \tag{17}$$

Table 10: Counterfactual Experiment: Isolating the Impact of Discrimination Intensity

Raw Rates		Differential $\%Prejudice_{ST}$		Differential $\%Prejudice_{CZ}$	
		OLS	IV	OLS	IV
Employment	0.89	0.105 (12%)	0.138 (16%)	0.094 (11%)	0.129 (14%)
Contact	0.45	0.105 (23%)	0.101 (22%)	0.103 (23%)	0.104 (23%)

Notes: (i) the various figures measure the changes in employment rate and contact rate as given by equations (15) and (17) when the parameters α^1 and α^2 are decreased by one standard deviation; (ii) the estimates are taken from Tables 5 and 8 for employment and Tables 6 and 9 for contact; and (iii) the raw number is in percentage points, whereas the number in brackets gives the percentage variation.

Table 10 reports the results of the quantitative analysis. A decrease in discrimination intensity by one standard deviation raises the raw employment rate by 11-16% (or 0.09-0.14 percentage points). A decrease in discrimination intensity by one standard deviation raises the raw contact rate by 22-23% (or 0.10-0.11 percentage points).

Conclusion

In this paper, I examine the link between prejudicial attitudes towards African-Americans and the racial gap in employment and contact probabilities. This paper runs the test strategy of customer discrimination provided by Combes et al. (2013). It also overcomes issues inherent to Combes et al. (2013) in three different ways: it allows identifying racial groups accurately, measuring the level of racial prejudice at the local level, and computing the probability of contact for a given occupation. My results indicate that there is customer discrimination at job entry on the US labor market, and that racial discrimination explains a substantial part of both residual unemployment and contact disparities. A one-standard-deviation increase in whites' average prejudice increases the residual employment rate gap by between .15 and .32 of its standard deviation, depending on specifications. A one-standard-deviation increase in whites' average prejudice widens the adjusted racial contact gap by between .10 and .28 of its standard deviation, depending on specifications. I also run a counterfactual experiment to assess the quantitative effect of racial prejudice on both the relative employment and contact probabilities of blacks. A decrease in the intensity of discrimination by one standard deviation raises the raw employment rate of blacks by 15 percent and increases the proportion of blacks in jobs in contact with customers by 20 percent.

The inability for African-Americans to have access to customer contact jobs is detrimental to their labor market prospects since the expansion of the service sector has significantly contributed to the growth of these types of jobs in recent decades in most industrialized countries.

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Appendix

A Construction of Commuting Zones - Individual Level

Since the Census data do not identify commuting zones for individuals, I have to construct commuting zones based on the PUMAs defined in 2000. In order to assign individuals to CZs, I split every individual observation into multiple parts whenever an individual's PUMA cannot be uniquely assigned to a CZ. The adjusted person weights in the resulting dataset multiply the original census weights 'PERWT' to the probability that a resident of a particular PUMA lives in a specific CZ.

Figure 5 shows a simple example that assumes a uniformly distributed population. Commuting Zone X (CZ X) is in red and is composed of two PUMAs: PUMA 1 and PUMA 2. Commuting Zone Y (CZ Y) is in blue and is composed of three PUMAs: PUMA 1, PUMA 3 and PUMA 4. An individual who lives in P1 has a 1/6 % chance of living in CZ X. I assign living in CZ X with a weight of 0.166 to this individual. He has a 1/3 % chance of living in CZ Y. I assign living in CZ Y with a weight of 0.333 to this individual. An individual who lives in P2 has a 100 % chance of living in CZ X. I assign living in CZ X with a weight of 1 to this individual.

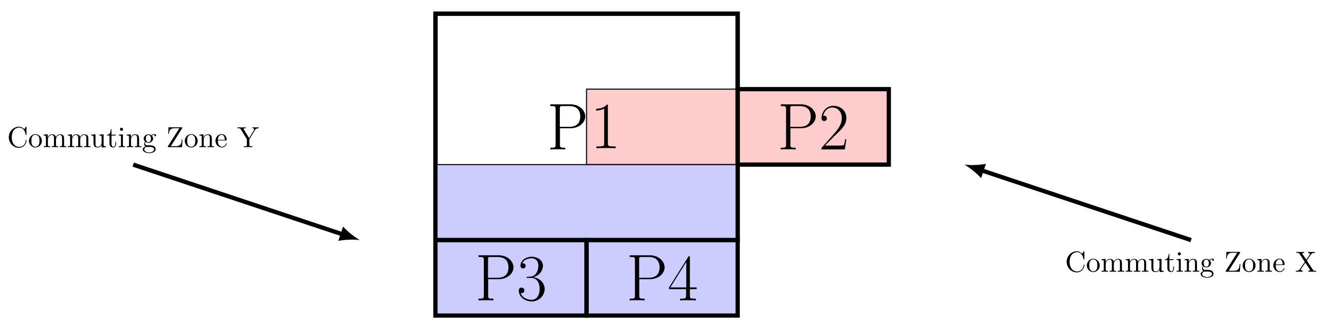

Figure 5: Example 1

B Proportion of Contact Jobs by Occupation

The US Census records the detailed titles of workers' occupations. The *occ1990* occupational classification is provided for census 2000. This occupation system provides 386 occupation codes which are based on the 1990 Census occupation system. I use job task data from the Dictionary of Occupational Titles (DOT - US Department of Labor, Employment and Training Administration, 1977) to characterize the share of contact for a given occupation. O*NET gives details for each occupation using the *SOC* occupational classification. I match the 1998 Standard Occupational Classification (SOC) system with the *occ1990* occupational classification. Table 11 lists all *occ1990* occupations, and details the share of contact for each category. This table distinguishes 6 major occupation groups: "Managerial & Professional Specialty Occupations", "Technicians, Sales & Related Support Occupations", "Service Occupations" "Farming, Forestry, & Fishing Occupations", "Precision production, Craft & Repair Occupations" and "Operators, Fabricators, & Laborers".

Table 11: Proportion of Contact Jobs by Occupation

OCC1990	Occupation	% Contact	OCC1990	Occupation	% Contact
Managerial & Professional Specialty Occupations			418	Police, detectives, & private investigators	89
3	Legislators	51	423	Sheriffs, correctional institution officers	98
4	Chief executives & public administrators	41	425	Crossing guards & bridge tenders	70
7	Financial managers	89	426	Guards, watchmen, doorkeepers	62
8	Human resources & labor relations managers	42	427	Protective services, n.e.c.	86
13	Managers in marketing, & public relations	56	434	Bartenders	96
14	Managers in education & related fields	79	435	Waiter/waitress	82
15	Managers of medicine & health occupations	64	436	Cooks, variously defined	64
16	Postmasters & mail superintendents	59	438	Food counter & fountain workers	84
17	Managers of food-serving & lodging establishments	79	439	Kitchen workers	26
18	Managers of properties & real estate	60	443	Waiter's assistant	58
19	Funeral directors	88	444	Misc food prep workers	26
21	Managers of service organizations, n.e.c.	61	445	Dental assistants	73
22	Managers & administrators, n.e.c.	61	446	Health aides, except nursing	29
23	Accountants & auditors	28	447	Nursing aides, orderlies, & attendants	67
24	Insurance underwriters	30	448	Supervisors of cleaning & building service	65
25	Other financial specialists	28	453	Janitors	50
26	Management analysts	19	454	Elevator operators	57
27	Personnel, HR & labor relations specialists	67	455	Pest control occupations	84
28	Purchasing agents & buyers, of farm products	67	456	Supervisors of personal service jobs, n.e.c.	80
29	Buyers, wholesale & retail trade	58	457	Barbers	89
33	Purchasing managers, agents & buyers, n.e.c.	31	458	Hairdressers & cosmetologists	89
34	Business & promotion agents	10	459	Recreation facility attendants	83
35	Construction inspectors	73	461	Guides	80
36	Inspectors & compliance officers, outside construction	69	462	Ushers	68
37	Management support occupations	50	463	Public transportation attendants & inspectors	64
43	Architects	51	464	Baggage porters	75
44	Aerospace engineer	12	465	Welfare service aides	45
45	Metallurgical & materials engineers	23	468	Child care workers	38
47	Petroleum, mining, & geological engineers	16	469	Personal service occupations, nec	71
48	Chemical engineers	27	**Farming, Forestry, & Fishing Occupations**		
53	Civil engineers	51	473	Farmers (owners & tenants)	6
55	Electrical engineer	16	474	Horticultural specialty farmers	18
56	Industrial engineers	15	475	Farm managers, except for horticultural farms	32
57	Mechanical engineers	24	476	Managers of horticultural specialty farms	18

Continued on Next Page

Table 11 – Continued

OCC1990	Occupation	% Contact	OCC1990	Occupation	% Contact
59	Not-elsewhere-classified engineers	23	479	Farm workers	6
64	Computer systems analysts & computer scientists	28	483	Marine life cultivation workers	16
65	Operations & systems researchers & analysts	29	484	Nursery farming workers	38
66	Actuaries	21	485	Supervisors of agricultural occupations	18
67	Statisticians	18	486	Gardeners & groundskeepers	44
68	Mathematicians & mathematical scientists	5	487	Animal caretakers except on farms	52
69	Physicists & astronomers	33	488	Graders & sorters of agricultural products	22
73	Chemists	10	489	Inspectors of agricultural products	52
74	Atmospheric & space scientists	58	496	Timber, logging, & forestry workers	56
75	Geologists	34	498	Fishers, hunters, & kindred	16
76	Physical scientists, n.e.c.	33	**Precision Production, Craft & Repair Occupations**		
77	Agricultural & food scientists	30	503	Supervisors of mechanics & repairers	56
78	Biological scientists	30	505	Automobile mechanics	40
79	Foresters & conservation scientists	72	507	Bus, truck, & stationary engine mechanics	44
83	Medical scientists	61	508	Aircraft mechanics	25
84	Physicians	66	509	Small engine repairers	25
85	Dentists	85	514	Auto body repairers	40
86	Veterinarians	81	516	Heavy equipment & farm equipment mechanics	34
87	Optometrists	85	518	Industrial machinery repairers	16
88	Podiatrists	78	519	Machinery maintenance occupations	7
89	Other health & therapy	79	523	Repairers of industrial electrical equipment	16
95	Registered nurses	67	525	Repairers of data processing equipment	65
96	Pharmacists	78	526	Repairers of household appliances & power tools	79
97	Dietitians & nutritionists	76	527	Telecom & line installers & repairers	75
98	Respiratory therapists	78	533	Repairers of electrical equipment, n.e.c.	16
99	Occupational therapists	71	534	Heating, AC, & refrigeration mechanics	54
103	Physical therapists	77	535	Precision makers, repairers, & smiths	51
104	Speech therapists	64	536	Locksmiths & safe repairers	78
105	Therapists, n.e.c.	73	538	Office machine repairers & mechanics	71
106	Physicians' assistants	83	539	Repairers of mechanical controls & valves	65
113	Earth, environmental, & marine science instructors	58	543	Elevator installers & repairers	57
114	Biological science instructors	54	544	Millwrights	17
115	Chemistry instructors	29	549	Mechanics & repairers, n.e.c.	16
116	Physics instructors	25	558	Supervisors of construction work	66
118	Psychology instructors	58	563	Masons, tilers & carpet installers	49
119	Economics instructors	58	567	Carpenters	33

Continued on Next Page

Table 11 – Continued

OCC1990	Occupation	% Contact	OCC1990	Occupation	% Contact
123	History instructors	55	573	Drywall installers	50
125	Sociology instructors	50	575	Electricians	36
127	Engineering instructors	43	577	Electric power installers & repairers	75
128	Math instructors	57	579	Painters, construction & maintenance	35
139	Education instructors	52	583	Paperhangers	45
145	Law instructors	54	584	Plasterers	38
147	Theology instructors	44	585	Plumbers, pipe fitters, & steamfitters	62
149	Home economics instructors	65	588	Concrete & cement workers	30
150	Humanities profs/instructors, college, nec	55	589	Glaziers	46
154	Subject instructors (HS/college)	55	593	Insulation workers	36
155	Kindergarten & earlier school teachers	43	594	Paving & surfacing equipment operators	64
156	Primary school teachers	60	595	Roofers & slaters	32
157	Secondary school teachers	46	596	Sheet metal duct installers	37
158	Special education teachers	55	597	Structural metal workers	27
159	Teachers , n.e.c.	51	598	Drillers of earth	14
163	Vocational & educational counselors	64	599	Construction trades, n.e.c.	36
164	Librarians	71	614	Drillers of oil wells	25
165	Archivists & curators	75	615	Explosives workers	49
166	Economists & survey researchers	29	616	Miners	9
167	Psychologists	65	617	Other mining occupations	9
168	Sociologists	37	628	Production supervisors or foremen	22
169	Social scientists, n.e.c.	44	634	Tool & die makers & die setters	21
173	Urban & regional planners	61	637	Machinists	12
174	Social workers	79	643	Boilermakers	57
175	Recreation workers	65	644	Precision grinders & filers	37
176	Clergy & religious workers	88	645	Patternmakers & model makers	11
178	Lawyers	72	646	Lay-out workers	18
179	Judges	94	649	Engravers	47
183	Writers & authors	45	653	Tinsmiths & sheet metal workers	37
184	Technical writers	5	657	Cabinetmakers & bench carpenters	19
185	Designers	63	658	Furniture & wood finishers	50
186	Musician or composer	96	659	Other precision woodworkers	35
187	Actors, directors, producers	75	666	Dressmakers & seamstresses	61
188	Art makers: painters, sculptors, craft-artists	47	667	Tailors	61
189	Photographers	57	668	Upholsterers	14
193	Dancers	96	669	Shoe repairers	30

Continued on Next Page

Table 11 – Continued

OCC1990	Occupation	% Contact	OCC1990	Occupation	% Contact
194	Art/entertainment performers & related	64	674	Other precision apparel & fabric workers	42
195	Editors & reporters	76	675	Hand molders & shapers, except jewelers	24
198	Announcers	98	677	Optical goods workers	38
199	Athletes, sports instructors, & officials	69	678	Dental & medical appliance technicians	26
200	Professionals, n.e.c.	50	679	Bookbinders	20
Technicians, Sales & Related Support Occupations			684	Other precision & craft workers	27
203	Clinical laboratory technologies & technicians	31	686	Butchers & meat cutters	65
204	Dental hygenists	86	687	Bakers	51
205	Health record tech specialists	49	688	Batch food makers	26
206	Radiologic tech specialists	83	693	Adjusters & calibrators	42
207	Licensed practical nurses	67	694	Water & sewage treatment plant operators	56
208	Health technologists & technicians, n.e.c.	63	695	Power plant operators	6
213	Electrical & electronic (engineering) technicians	30	696	Plant & system operators, stationary engineers	32
214	Engineering technicians, n.e.c.	30	699	Other plant & system operators	11
215	Mechanical engineering technicians	24		**Operators, Fabricators, & Laborers**	
217	Drafters	5	703	Lathe, milling, & turning machine operatives	11
218	Surveyors, mapping scientists & technicians	42	706	Punching & stamping press operatives	9
223	Biological technicians	13	707	Rollers, roll hands, & finishers of metal	16
224	Chemical technicians	20	708	Drilling & boring machine operators	20
225	Other science technicians	20	709	Grinding, abrading, buffing, & polishing workers	6
226	Airplane pilots & navigators	65	713	Forge & hammer operators	8
227	Air traffic controllers	75	717	Fabricating machine operators, n.e.c.	12
228	Broadcast equipment operators	26	719	Molders, & casting machine operators	1
229	Computer software developers	27	723	Metal platers	5
233	Programmers of numerically machine tools	15	724	Heat treating equipment operators	15
234	Legal assistants, paralegals, legal support, etc	46	726	Wood lathe, routing, & planing machine operators	10
235	Technicians, n.e.c.	42	727	Sawing machine operators & sawyers	8
243	Supervisors & proprietors of sales jobs	81	728	Shaping & joining machine operator (wood)	8
253	Insurance sales occupations	84	729	Nail & tacking machine operators (wood)	8
254	Real estate sales occupations	84	733	Other woodworking machine operators	8
255	Financial services sales occupations	82	734	Printing machine operators, n.e.c.	15
256	Advertising & related sales jobs	68	735	Photoengravers & lithographers	20
258	Sales engineers	34	736	Typesetters & compositors	20
274	Salespersons, n.e.c.	52	738	Winding & twisting textile/apparel operatives	25
275	Retail sales clerks	91	739	Knitters, loopers, & toppers textile operatives	12
276	Cashiers	82	743	Textile cutting machine operators	29

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Table 11 – Continued

OCC1990	Occupation	% Contact	OCC1990	Occupation	% Contact
277	Door-to-door sales, street sales, & news vendors	79	744	Textile sewing machine operators	16
283	Sales demonstrators / promoters / models	73	745	Shoemaking machine operators	26
303	Office supervisors	66	747	Pressing machine operators (clothing)	28
308	Computer & peripheral equipment operators	27	748	Laundry workers	37
313	Secretaries	67	749	Misc textile machine operators	25
314	Stenographers	46	753	Cementing & gluing maching operators	30
315	Typists	46	754	Packers, fillers, & wrappers	14
316	Interviewers, enumerators, & surveyors	70	755	Extruding & forming machine operators	5
317	Hotel clerks	81	756	Mixing & blending machine operatives	21
318	Transportation ticket & reservation agents	91	757	Separating & filtering machine operators	32
319	Receptionists	65	759	Painting machine operators	14
323	Information clerks, nec	65	763	Roasting & baking machine operators (food)	18
326	Correspondence & order clerks	37	764	Washing & pickling machine operators	8
328	Human resources clerks, except payroll	48	765	Paper folding machine operators	26
329	Library assistants	75	766	Furnace & oven operators (apart from food)	9
335	File clerks	47	768	Crushing & grinding machine operators	23
336	Records clerks	23	769	Slicing & cutting machine operators	24
337	Bookkeepers, accounting & auditing clerks	31	773	Motion picture projectionists	44
338	Payroll & timekeeping clerks	25	774	Photographic process workers	50
343	Cost & rate clerks (financial records processing)	20	779	Machine operators, n.e.c.	23
344	Billing clerks & related financial records processing	57	783	Welders & metal cutters	24
345	Duplication/office machine operators	71	784	Solderers	24
346	Mail & paper handlers	70	785	Assemblers of electrical equipment	10
347	Office machine operators, n.e.c.	71	789	Hand painting & decorating occupations	45
348	Telephone operators	42	796	Production checkers & inspectors	73
349	Other telecom operators	42	799	Graders & sorters in manufacturing	13
354	Postal clerks, excluding mail carriers	70	803	Supervisors of motor vehicle transportation	41
355	Mail carriers for postal service	72	804	Truck, delivery, & tractor drivers	78
356	Mail clerks, outside of post office	70	808	Bus drivers	75
357	Messengers	70	809	Taxi cab drivers & chauffeurs	81
359	Dispatchers	72	813	Parking lot attendants	96
361	Inspectors, n.e.c.	13	823	Railroad conductors & yardmasters	28
364	Shipping & receiving clerks	39	824	Locomotive operators (engineers & firemen)	27
365	Stock & inventory clerks	52	825	Railroad brake, coupler, & switch operators	31
366	Meter readers	66	829	Ship crews & marine engineers	49
368	Weighers, measurers, & checkers	23	834	Water transport infrast tenders & crossing guards	67

Continued on Next Page

Table 11 – Continued

OCC1990	Occupation	% Contact	OCC1990	Occupation	% Contact
373	Material recording, production & expediting clerks	20	844	Operating engineers of construction equipment	41
375	Insurance adjusters, examiners, & investigators	58	848	Crane, derrick, winch, & hoist operators	11
376	Customer service reps, investigators, except insurance	64	853	Excavating & loading machine operators	26
377	Eligibility clerks for government programs	95	859	Misc material moving occupations	26
378	Bill & account collectors	57	865	Helpers, constructions	25
379	General office clerks	59	866	Helpers, surveyors	42
383	Bank tellers	74	869	Construction laborers	36
384	Proofreaders	19	874	Production helpers	7
385	Data entry keyers	30	875	Garbage & recyclable material collectors	59
386	Statistical clerks	18	876	Materials movers: longshore workers	45
387	Teacher's aides	43	877	Stock handlers	45
389	Administrative support jobs, n.e.c.	41	878	Machine feeders & off bearers	13
	Service Occupations		883	Freight, stock & materials handlers	45
405	Housekeepers, maids & lodging cleaners	41	885	Garage & service station related occupations	35
407	Private household cleaners & servants	50	887	Vehicle washers & equipment cleaners	48
415	Supervisors of guards	40	888	Packers & packagers by hand	48
417	Fire fighting, prevention, & inspection	86	889	Laborers outside construction	45

Notes: (i) Job Categories are in bold; and (ii) Source: O*NET.

C Construction of Commuting Zones - Share of Prejudice at the CZ level

Since the General Social Survey is available at the state level only, I have to construct the share of racial prejudice at the commuting-zone level based on the PUMAs defined in 2000. I approximate CZ averages using PUMA averages. I calculate averages of the share of prejudice for each PUMA and take a population-weighted average of PUMA averages that make up each CZ.

Figure 6 shows the same simple example as before. CZ X is composed of 50% of P1 and 50% of P2. I compute the share of prejudice in P1 and in P2, and weight them by 0.5 each to obtain the share of prejudice in CZ X. CZ Y is composed of 50% of P1, 25% of P3 and 25% of P4. I compute the share of prejudice in P1, P3 and P4, and weight them by 0.5, 0.25 and 0.25 respectively to obtain the share of prejudice in CZ Y.

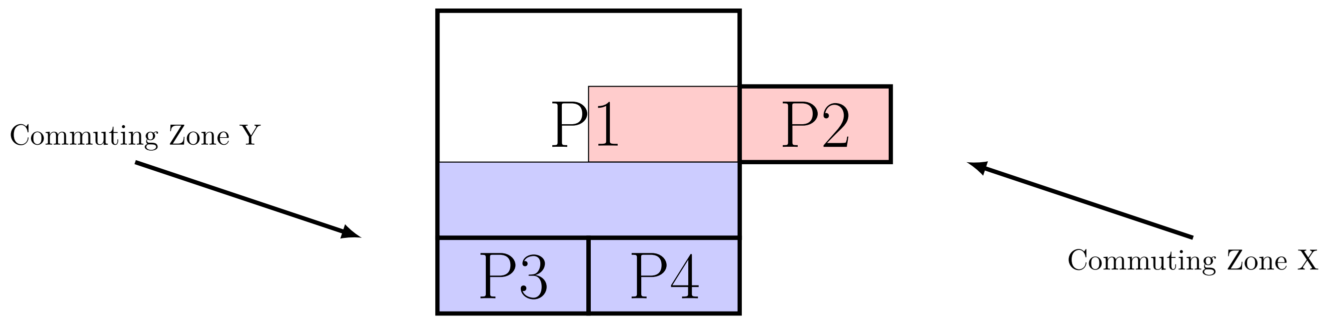

Figure 6: Example 2

D Robustness: Inclusion of Region Dummies

Table 12: Probability of Employment: Second-Step Results

	Differential employment gap							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\%Prejudice_{ST}$	-0.203^a	-0.176^a			-0.476^a	-0.407^a		
	(0.045)	(0.040)			(0.135)	(0.124)		
$\%Prejudice_{CZ}$			-0.175^a	-0.185^a			-0.488^a	-0.516^a
			(0.041)	(0.035)			(0.121)	(0.110)
%Blacks		-0.140^a		-0.146^a		-0.362^a		-0.361^a
		(0.021)		(0.018)		(0.065)		(0.057)
Region Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.012	-0.039	-0.006	-0.040	-0.230^a	-0.269^a	-0.243^a	-0.280^a
	(0.031)	(0.028)	(0.032)	(0.028)	(0.049)	(0.046)	(0.051)	(0.047)
R^2	.44	.57	.38	.54	.36	.47	.30	.42
obs.	163	163	193	193	163	163	193	193

Notes: (i) weighted least-square regressions using as weights the inverse of the estimated variance of the coefficients from the first-step regression reported in Table 3; (ii) the share of prejudice is centered with respect to Blacks' means; (iii) columns (1) and (2) are estimated using a first-step linear probability model in Table 3 (column (2)) and columns (3) and (4) are estimated using a first-step probit model in Table 3 (column (4)); (iv) in columns (1), (2), (5) and (6), the share of prejudice is computed as the raw share at the state level, while in columns (3), (4), (7) and (8), the share of prejudice is corrected using contiguous areas at the CZ level; and (v) standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively.

Table 13: Probability of Being in Contact: Second-Step Results

	Differential contact gap											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\%Prej^{ST}$	−0.059	−0.059			−0.026	−0.030			0.027	0.023		
	(0.038)	(0.039)			(0.033)	(0.033)			(0.026)	(0.027)		
$\%Prej^{CZ}$			-0.083^{b}	-0.082^{b}			-0.060^{b}	-0.058^{c}			−0.009	−0.007
			(0.035)	(0.035)			(0.030)	(0.030)			(0.024)	(0.023)
%Blacks		−0.001		0.003		0.020		0.029^{c}		0.017		0.032^{a}
		(0.020)		(0.018)		(0.017)		(0.016)		(0.014)		(0.012)
Region Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.008	0.007	0.006	0.006	0.004	0.008	0.001	0.007	0.004	0.006	0.004	0.008
	(0.025)	(0.026)	(0.015)	(0.015)	(0.022)	(0.022)	(0.022)	(0.022)	(0.010)	(0.010)	(0.010)	(0.010)
R^2	0.20	0.20	0.15	0.15	0.12	0.13	0.07	0.09	0.08	0.09	0.04	0.08
obs.	163	163	193	193	163	163	193	193	163	163	193	193

Notes: (i) weighted least-square regressions using as weights the inverse of the estimated variance of the coefficients from the first-step regression reported in Table 4; (ii) the share of prejudice is centered with respect to Blacks' means; (iii) columns (1) to (4), columns (5) and (8) and columns (9) and (12) are estimated using column (2), column (4) and column (6) of the first-step regression in Table 4 respectively; (iv) in columns (1), (2), (5), (6), (9) and (10), the share of prejudice is computed as the raw share at the state level, while in columns (3), (4), (7), (8), (11) and (12), the share of prejudice is corrected using contiguous areas at the CZ level; and (v) standard errors in brackets; significance levels a, b, c: 1%, 5%, and 10%, respectively.

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