HARRIS SCHOOL WORKING PAPER
SERIES 08.13

SPEECH PATTERNS AND RACIAL WAGE INEQUALITY

Jeffrey Grogger

Speech Patterns and Racial Wage Inequality

Jeffrey Grogger
Harris School of Public Policy
University of Chicago
1155 E. 60th St.
Chicago, IL 60637
jgrogger@uchicago.edu
(773) 834-0973

June 2008
Revised September 2009

Abstract

Speech patterns differ substantially between whites and many African Americans. I collect and analyze speech data to understand the role that speech may play in explaining racial wage differences. Among blacks, speech patterns are highly correlated with measures of skill such as schooling and AFQT scores. They are also highly correlated with the wages of young workers. Even after controlling for measures of skill and family background, black speakers whose voices were distinctly identified as black by anonymous listeners earn about 12 percent less than whites with similar observable skills. Indistinctly identified blacks earn essentially the same as comparable whites. I discuss a number of models that may be consistent with these results and describe the data that one would need to distinguish among them.

The author thanks two anonymous referees, Kerwin Charles, Matt Gentzkow, Fabian Lange, Steve Levitt, Jens Ludwig, and Dan Nagin for helpful comments, along with seminar participants at Berkeley, Chicago, Harvard, St. Gallen, Texas, and the NLSY97 10th Year Anniversary Conference. Ben Dietrich, Dan Kreisman, and Joonsik Yoon provided excellent research assistance. Special thanks are due to Dan Black for his extraordinary efforts in making the speech data available. Any errors are the sole responsibility of the author.

I. Introduction

Racial wage inequality is persistent. After declining between 1940 and 1980, the black-white wage gap has remained roughly constant. In 1980, black men earned an average of 73 cents for every dollar earned by white men. In 2000, the number was 70 cents (Neal 2006). One question is whether these persistent differences in wages can be explained by persistent differences in behavior.

One such difference involves speech patterns. Linguists have documented substantial differences between Standard American English (SAE), variants of which are spoken by whites (and many blacks) in the US, and African American English (AAE), variants of which are spoken by many African Americans. These differences arise at almost every level of linguistic analysis, including syntax (e.g., negation rules), morphology (e.g., rules for subject-verb agreement), phonology (e.g., the resolution of various consonant clusters), and even acoustics (e.g., vocal harmonics).[1]

At the same time, research shows that almost no one speaks a pure form of either SAE or AAE. Rather, regardless of their primary dialect, speakers mix standard and non-standard features. The mix varies among speakers, but also within individual speakers as a function of the setting (e.g., the level of formality). Furthermore, many speakers of AAE use SAE features in their speech (Labov 1972).

Despite such variation, race is a salient characteristic of speech. Listeners can identify a speaker's race from their speech, even small amounts of it (Thomas and Reaser 2004). For example, Purnell, Idsardi, and Baugh (1999) played a standardized single-sentence speech clip for listeners that varied only in its dialectical "guise," that is, in

[1] See Bailey and Thomas 1992; Clopper and Pisoni 2004; Green 1992; Labov 1972, 1992; Martin and Wolfram 1992; Mufwene 1992; Rickford and Rafal 1996; Thomas and Reaser 2004; Walton and Orlikoff 1994; Washington and Craig 2002; Wolfram 1969, 1991.

whether the speaker delivered the sentence using typically SAE or AAE forms. Their listeners identified the African-American guise with 75 to 90 percent accuracy.

Furthermore, listeners act on racial information in speakers' voices. Purnell, Idsardi, and Baugh (1999) and Massey and Lundy (2001) have conducted audit studies in which black- and white-sounding callers are randomly assigned to inquire by phone regarding apartments that have been advertised for rent. Black-sounding callers are more likely then white-sounding callers to be told that the apartment is already rented.

My question in this paper is whether racial differences in speech patterns help explain racial differences in wages. To address the question I collected audio data from validation interviews administered to respondents from the 1997 cohort of National Longitudinal Survey of Youth (NLSY). The NLSY is a large, nationally representative longitudinal survey of the labor market behavior of youths who were aged 12 to 16 in 1997. It interviews respondents annually.

The validation interviews are carried out by telephone a few weeks after the main interview. They ask a few hundred randomly chosen respondents about five minutes' worth of questions in order to gauge the quality of key data elements collected during the main interviews. During the 2006-2007 interview round the validation interviews were recorded. I excerpted unidentifiable samples of speech from these recordings, then recruited listeners to listen to them and answer questions about their perceptions of the speakers, including the speaker's race. I then merged the listener responses to the rest of the NLSY data on the speakers. The data show strong links between speech patterns, education, and test scores. They also show a strong correlation between wages, race and speech, even after controlling for measures of skill and family background.

This is not the first study to ask whether language affects labor market performance. Numerous studies have analyzed the role that language plays in the wages earned by immigrants.[2] Virtually by definition, those studies concern the worker's second language. This study is distinctive in that it focuses on the worker's native language in his home country, rather than a second language in a foreign country. I ask whether language differences can explain racial wage differences among natives.

This question has received some theoretical attention from Lang (1986), who provides a model of language minorities, but this is the first empirical analysis of the link between native-language differences and racial wage inequality. The paper also relates to recent work on ethnic identity, since speech patterns are widely viewed as an important element of ethnic identification (Fordham and Ogbu 1986; Baugh 1992; Pattillo 1999). Theoretical work in the field has focused on how certain aspects of behavior may simultaneously be viewed as favorable signals in the labor market but as unfavorable signals in the peer group (Akerlof and Kranton 2000; Austen-Smith and Fryer 2005). Recent empirical studies have analyzed such phenomena as naming conventions and academic achievement (Bertrand and Mullainathan 2004, Cook and Ludwig 1998; Fryer and Levitt 2004, Fryer and Torelli 2005). This paper is the first to analyze the link between race, speech patterns, and wages.

The next section describes my data. Section III presents results. In Section IV I discuss a number of models that could explain the observed associations among race, speech patterns, skill, and wages. Section V concludes.

[2] See, e.g., McManus, Gould, and Welch 1983; Chiswick 1991; Trejo 1997, and Bleakley and Chin 2004.

II. Data

A. Background on the NLSY

The NLSY is an annually administered, nationally representative longitudinal survey of youths who were 12 to 16 years old in 1997. Early rounds of the survey focused on respondents' educational experiences, whereas recent rounds have focused on their labor market experiences. Most respondents took the Armed Services Vocational Aptitude Battery (ASVAB) in the first year of the survey. The Armed Forces Qualifying Test (AFQT), which is constructed from the ASVAB, has been shown to be an important correlate of wages and racial wage differences (Altonji and Pierret 2001; Cameron and Heckman 1993; Farber and Gibbons 1996; Grogger 1998; Neal and Johnson 1996).

B. Speech Data from the Validation Interviews

After every interview, a small random sample of respondents is chosen to participate in a short follow-up interview, the goal of which is to assess the quality of key data elements collected in the main interview. These validation interviews are carried out by telephone. In late 2006 and early 2007, the validation interviews were recorded in their entirety.[3] Technicians under my direction then excerpted samples from the raw audio (.wav) files. The excerpts were played to listeners to obtain their perceptions regarding characteristics of the speaker.

The audio excerpts were constructed with three goals in mind. The first was to ensure speaker anonymity. The second was to standardize the samples as much as possible. The third was to preserve as much language as possible. The first objective was straightforward, since it required simply that identifying information be removed.

[3] Interviews were recorded over IP telephones manufactured by Cisco. The recordings were sampled at a rate of 8KHz and the sample size was 11 bits.

The second two were sometimes in conflict. The validation interviews are highly scripted, which aids in standardization. At the same time, however, many of the questions called for short, one- or two-word responses. As a result, complete-sentence responses were fairly rare. Because sentences convey more linguistic information than shorter utterances, I retained them whenever possible, even though they tended to reduce the standardization of the speech samples across speakers. The resulting audio excerpts were short, 15- to 20-second files that mixed responses to standardized questions and whatever short sentences were available.

The validation interviews yielded a total of 520 usable audio excerpts. Of these, 402 speakers were black or white; the remaining 108 were Hispanic, Asian, or of other race or ethnicity. Since the goal of this paper is to understand the role of speech patterns in explaining the wage gap between blacks and whites, I focus only on those speakers here. I refer to these 402 speakers as the "speech sample."

On several important dimensions, the speech sample closely resembles black and white respondents in the full NLSY. Table 1 reports means for both samples. The sex ratio is the same in the two samples and the age and race distributions are similar. The AFQT score is obtained by normalizing the percentile scores to have mean zero and standard deviation of one. Mean AFQT scores are similar between the two samples. They differ from zero because they were standardized over the full NLSY sample, not just the sample of blacks and whites.

About one-fifth of both samples were enrolled in 2006, owing to the young age range of NLSY respondents. Average completed schooling is similar between the samples at about 13 years. The share of southerners, who may speak with a regionally distinctive accent, is similar between the speech sample and the broader NLSY. The speech sample is a bit more urban than the full sample.

C. Listeners' Perceptions of Speaker Characteristics

As indicated above, listeners were recruited to listen to the audio excerpts and provide their perceptions about a number of speaker characteristics. Listeners also provided limited demographic information about themselves. Most of the listeners were students in a graduate degree program at a selective Midwestern university. Table 2 shows that their characteristics reflect the program's enrollment. They are disproportionately female and white. A plurality was raised in the Midwest. Three non-native speakers took part, despite my attempts to limit participants to native speakers.

Listeners listened to the speakers' audio excerpts via an offline web-based interface. The interface first prompted listeners for their demographic information, then prompted the listener to play the first audio file. After the audio file played, the listener was prompted through screens on which he or she was asked to indicate the speaker's sex, race (White, Black, Hispanic, or Other), education level (Less than high school, High school, Some college, College or more), and region of origin (Northeast, Midwest, South, West, or Outside the US). Listeners were then prompted to repeat the process until they had listened to a total of 20 files. The entire process lasted an average of about 15 minutes. Listeners listened to the audio files using headphones throughout.[4] Of the 130 listeners, about 80 percent listened to a single 20-file batch, whereas the remainder participated more than once, listening to an average of about 3 batches each. The 20-file batches were structured in such a way that 5 different listeners listened to each speaker.

---

[4] Most listeners used Listen Technologies LA-165 stereo headphones. A small number at the beginning of the study used Sony MDR-D777 headphones.

Table 3 reports the accuracy with which listeners were able to ascertain the characteristics of speakers from the audio files. Since multiple listeners provided data for each speaker, the unit of observation here is the speaker-listener pair. Accurate identification of sex was nearly universal. Identification of race was fairly high as well. Nearly 84 percent of white speakers were accurately identified by the listeners, as were about 77 percent of black speakers. These numbers are similar to those reported elsewhere in the literature (Thomas and Reaser 2004).

Listeners were less successful in identifying speakers' education level and region of origin. Speakers lacking a high school diploma were accurately identified only 5 percent of the time; this very low identification rate may have been the result of socially correct reporting on the part of listeners. Nearly half of college-educated speakers were accurately identified by listeners, but accuracy rates for the other two educational categories were less than 30 percent. Listeners were more successful in identifying the region of origin of speakers from the Midwest and South than of those from the Northeast and West, but even for speakers from the South, where regional dialects are relatively strong, the accuracy rate was less than 50 percent.

Table 4 presents a regression analysis of factors that explain the accuracy of listeners' reports of the speaker's race. As before, the unit of observation is the listener-speaker pair. The dependent variable is a dummy equal to one if the listener accurately perceived the speaker's race. I divide explanatory factors into three groups: speaker characteristics, listener characteristics, and technical factors. The table reports coefficients and standard errors from a least-squares regression. The standard errors are clustered by speaker and account for arbitrary forms of heteroscedasticity.

Black speakers are less likely to be accurately perceived by listeners, consistent with the data in Table 3. Other characteristics of the speaker do not influence the listeners' perceptions of the speaker's race. I had no reason to expect otherwise, but included these variables because they appear in the wage regressions below.

As for listener characteristics, black listeners more accurately perceived the speaker's race than did listeners of other race or ethnic groups (Asian listeners constitute the base group).[5] Older listeners were less likely to perceive the speaker's race accurately, all else equal, whereas listeners from the Western US had higher accuracy rates. Repeat listeners did no better or worse than listeners who listened to only a single batch of audio clips. Listeners were asked how well they understood each speaker, on a scale of 1 to 5. Those who reported being better able to understand the speaker perceived race somewhat more accurately.

Among technical factors, the number of phrases in the audio clip did not affect the accuracy of listeners' perceptions. In results not reported here, I found that the size of the audio file, which provides a measure of its length, similarly had no effect on listener accuracy. Three technicians prepared excerpts from the raw audio files; clips prepared by two of them were perceived somewhat more accurately by listeners than the clips prepared by the other one. Finally, the technicians rated the audio quality of each clip as low, medium, or high. Quality varied largely due to telephone line noise and the quality of cellular connections. Audio quality had no significant effect on the accuracy of listeners' perceptions. The last column of the Table reports results from a regression that included all three sets of variables.

[5] Further analysis indicated that black listeners were particularly adept at identifying white speakers.

D. Speaker-Level Measures of Speech

Whereas Tables 3 and 4 analyze perception data at the level of the speaker-listener pair, what I require for the wage regressions below is speaker-level data. I initially consider three different speaker-level measures of the accuracy of listeners' perceptions of the speaker's race. The first is simply the number of correct reports of the speaker's race.

The second measure is a "recognizability index" that adjusts the race perceptions for potential listener effects. To construct it I first regressed the dependent variable from Table 4 (a dummy equal to one if the listeners' perception of the speaker's race was correct) on a full set of listener dummies. The average of the residuals from this regression for each speaker constitutes the recognizability index.

The first row in each panel of Table 5 reports the mean of the recognizability index by the number of correct reports of the speaker's race. The recognizability index is highly correlated with the number of correct reports, independent of race. The final column suggests that white speakers are somewhat more recognizable than black speakers, consistent with the data from Table 3.

The motivation for my third speaker-level measure of speech patterns stems from the second row of each panel of Table 5, which presents mean AFQT scores by the number of correct reports. These data show a sharp non-linearity in the relationship between the number of correct reports and test scores among blacks. Black speakers perceived as black by four or more listeners have mean AFQT scores that are much lower than those of black speakers who are correctly classified by three or fewer listeners. If the link between wages and the number of correct reports follows a similar relationship, then a speech measure which captures the non-linearity may perform better than either the number of correct reports or the recognizability index. For this reason I construct a binary indicator of the racial distinctiveness of the speaker's speech. I classify as distinctly identified those speakers whose race was correctly perceived by four or more listeners, and classify as indistinctly identified those speakers who race was correctly perceived by three or fewer listeners. According to this measure, 82 percent of whites, and 67 percent of blacks, were distinctly identified by their speech.[6]

E. Speech Patterns and Speaker Characteristics

The first two rows of Table 6 illustrate the relationship between race, the racial distinctiveness of the speaker's speech, and measures of speaker skill. The entries in columns (3) and (6) of the first row show that the mean AFQT score for blacks is 0.85 standard deviations lower than the mean for whites. This is similar to the racial differences that appear in many standardized tests (Jencks and Phillips, 1998). Indistinctly identified whites score 0.16 standard deviations lower on the AFQT than distinctly identified whites. The difference is greater for blacks. Distinctly identified blacks score .66 standard deviations lower than indistinctly identified blacks.

It comes as no surprise that test scores differ between distinctly and indistinctly identified blacks, since test scores were used to define the distinctiveness of the speaker's speech. What is surprising is the magnitude of the difference. To put it in perspective, the speech-related test-score gap among blacks amounts to three quarters of the gap that exists between blacks and whites.

[6] I also tallied whether speakers were distinctly identified as to sex, education level, and region of origin. Distinct sex identification was nearly universal. Otherwise, 23 percent of college graduates and 30 percent of southerners were distinctly identified by their speech. Listeners identified speakers of other education levels and regions of origin at rates no better than chance.

Similarly large differences appear in years of schooling, which was not used to define the speech categories. Mean highest grade completed among indistinctly identified whites is 12.84 years, compared to 13.52 years among distinctly identified whites. Indistinctly identified blacks average 13 years of schooling, compared to 12 years for distinctly identified blacks. The speech-related schooling gap among blacks is almost as large as the 1.07-year gap between blacks and whites.[7]

The rest of Table 6 further characterizes the speakers by race and speech pattern. Ideally, we would like to see how speakers differ with respect to characteristics that influence speech patterns. Since dialect acquisition is influenced by the speaker's peer group when the speaker is about 10 years old (Labov 1972), I would ideally report data on the speaker's pre-adolescent peer group. Since the NLSY contains no such measures, I consider variables that may be correlated with peer-group characteristics. These include family structure at age 12, parental education, and household income in 1997, when the speaker was 12 to 16 years old. Table 6 shows that the family backgrounds of whites are more advantaged than those of blacks on each of these measures. Within race, indistinctly identified blacks fare better on each of these measures than their distinctly identified counterparts. Indistinctly identified blacks are also more likely to attend private or parochial schools than their distinctly identified counterparts, which may also be correlated with peer group differences.

---

[7] Since many speakers are still enrolled in school, the differences in highest grade completed do not necessarily reflect differences in completed education. If anything, however, the gaps reported here may understate the ultimate differences that will arise among the groups. The reason is that, among whites, 27 percent of distinctly identified speakers were enrolled as of 2006 (the most recent year for which enrollment data are available), as compared to 21 percent among indistinctly identified whites. Among blacks, 22 percent of indistinctly identified speakers were enrolled, compared to 13 percent of distinctly identified speakers. Thus educational attainment is likely to grow more in the future among those groups which currently have higher levels of attainment.

In summary, differences in speech are associated with other differences that may influence wages. Distinctly identified whites and indistinctly identified blacks fare better than their counterparts not only in terms of schooling and test scores, but also in terms of family background and private/parochial school attendance. Since previous work has shown such traits to predict wages, it will be important to control for them when I estimate the link between wages and speech patterns in the next section.

III. Regression Results

A. Wage data

As I have already noted, the speakers in the speech sample are young. Their youth accounts for a number of features evident in Table 7, which displays summary statistics for the survey years 2004 through 2006. First, annual employment rates are fairly low.[8] Nevertheless, 86 percent of the sample, or 345 speakers, report at least one wage observation over the 2004-2006 period.

Not surprisingly, the wages paid to these young workers are fairly low. The mean hourly wage over the three-year period is $12.76, although growth is fairly substantial. Mean wages grew $0.84, or nearly 11 percent, between 2004 and 2005, and by $1.10, or 8.4 percent, between 2005 and 2006.

Speech sample members range in age between 20 and 26, with a mean of 23. Many are still enrolled in school. The enrollment rate was 27 percent in 2004, but fell to

[8] Wages are defined as the hourly wage on the most recent job held at each annual interview. I exclude wages from self-employment and reported hourly wages that were less then $1 or greater than $60. The apparent decrease in employment between 2004 and 2005 is likely the result of NLSY data collection procedures. Survey respondents who are not interviewed in one year are re-contacted in the following year. In that following year, data are collected covering not only the most recent period, but all previous non-interview periods. Accounting for these survey procedures, respondents have been at greater "risk" for reporting their 2004 wage than for 2005 wage.

17 percent in 2006 as the speakers left school for work. I discuss how I treat these observations in the next section.

B. Estimation

To maximize precision given my small sample, I pool data from 2004 to 2006. Most of the wage regressions make use of the binary measure of the racial distinctiveness of the speaker's speech. They take the form

$$\text{(1)} \quad \begin{aligned} \ln w_{it} &= \beta_0 + \beta_1 BLACK_i * DISTINCT_i + \beta_2 BLACK_i * INDISTINCT_i \\ &+ \beta_3 WHITE_i * INDISTINCT_i + X_{it}\delta + \alpha_i + \varepsilon_{it} \end{aligned}$$

where w_{it} is the wage of the ith speaker in year t. The key explanatory variables are interactions between race and speech patterns. The variables $WHITE_i$ and $BLACK_i$ are race dummies, equal to 1 if speaker i is white or black, accordingly, and equal to zero otherwise. The variable $INDISTINCT_i$ is a dummy equal to 1 if the ith speaker's race was indistinctly identified by the listeners, that is, if three or fewer listeners accurately assessed his race. The variable $DISTINCT_i$ is a dummy equal to 1 if the ith speaker's race was distinctly identified by the listeners, that is, if four or more listeners accurately assessed his race. The omitted group in this regression model consists of whites who were distinctly identified as white by listeners.

Other regressors included in the model, represented by X_{it}, include controls for observable measures of skill. In the initial specifications, these include the speaker's highest grade completed and potential labor market experience, both of which vary over time. The model also includes a sex dummy to control for otherwise unexplained differences in the wages of young men and women. Since I include enrolled workers in most of my regressions in order to maximize the sample size, I also include a time-varying dummy variable that is equal to one if speaker i is enrolled in school at time t and equal to zero otherwise. This accounts for the fact that young workers who are enrolled in school tend to earn less than young out-of-school workers (see, e.g., Borjas, Grogger, and Hanson 2008).

I control as well for the listener and technician characteristics that predict the accuracy of listeners' assessments of the speaker's race, as shown in Table 4. These controls include speaker-level means of listener age, the share of black listeners, the share of listeners from the Western US; the listeners' rating of their understanding of the speaker; and technician dummies. These variables account for the possibility that some of my listeners were better able than others to judge the race of the speakers. Results from models that excluded them were generally a bit less significant. The coefficients for these variables are not shown in order to save space.

The unobservable disturbance term in the regression has two components. The term α_i is a time-invariant person-specific component. The term ε_{it} is a time-varying component. The term α_i generates dependence among the worker's wage observations, rendering the usual OLS standard errors inconsistent. I deal with this dependence by clustering the standard errors at the person level.

C. Results

Table 8 reports estimated wage regressions. Although most of the wage regressions take the form specified in equation (1) above, I begin with three that differ in their characterization of race and speech patterns. The first contains no information about speech patterns, but rather includes only the $BLACK_i$ dummy and the other X_{it} variables. This is presumably the specification that one would estimate in the absence of the speech data. The estimated coefficient on the $BLACK_i$ dummy shows that blacks earn almost ten percent less than similarly skilled whites, on average. This is roughly similar to estimated wage gaps based on other samples of young workers (Grogger 1996; Altonji and Pierret 2001).

The next regression includes the $BLACK_i$ dummy and an interaction between the $BLACK_i$ dummy and the number of correct listener reports of the speaker's race. To simplify interpretation and make these results more comparable to those based on the recognizability index, I center the number of correct responses at three, which is roughly the midpoint of the range. To capture speech variation among whites, the regression also includes an interaction between the $WHITE_i$ dummy and the (centered) number of correct reports. Given the centering, the base group here consists of whites whose race was correctly perceived by three of the listeners, whereas the coefficient on the $BLACK_i$ dummy is an estimate of the mean wage difference between the base group and black workers whose race was correctly perceived by three of the listeners.

The $BLACK_i$ coefficient is -0.083 but insignificant. The interaction between the $BLACK_i$ dummy and the number of correct listener reports shows that black workers' wages fall as the number of listeners who correctly perceive their race rises. Moreover, the coefficient is significant. The estimates show that black workers correctly identified by all five listeners face a wage penalty of -0.171 (=-0.083-0.044(5-3)) as compared to the base group. The standard error of this estimate is 0.058. In contrast, blacks correctly identified by a single listener face a wage premium of 0.005 (standard error=0.058). The coefficient on the interaction between the $WHITE_i$ dummy and the number of correct listener reports shows that white workers' wages are largely independent of the number of correct perceptions.

The regression in column (3) includes the $BLACK_i$ dummy and interactions between the race dummies and the recognizability index. The coefficient on the $BLACK_i$ dummy shows that black workers with a value of zero on the recognizability index (whose race was correctly identified by three to four listeners, on average, according to Table 5) suffer a wage penalty of -0.087 as compared to similar white workers. The coefficient on the interaction between the $BLACK_i$ dummy and the recognizability index is negative and significant. These estimates show that black workers with a recognizability index of 0.284 (the mean for blacks correctly identified by all five listeners; see Table 5) suffer a wage penalty of -0.146 (0.053). In contrast, black workers with a recognizability index of -0.443 (the mean for a black worker identified by only one listener) earn a wage premium of 0.006 (0.060).

The fourth column reports estimates of the specification given by equation (1), which makes use of the binary indicator of the racial distinctiveness of the speaker's speech. The estimates show that distinctly identified black workers earn wages that are nearly 19 percent lower than similarly skilled whites who were distinctly perceived as white. In sharp contrast, the wage penalty paid by indistinctly identified blacks is only 2.3 percent. Whereas the wage penalty paid by distinctly identified blacks is significant, the wage penalty for indistinctly identified blacks is not. The t-statistic for the test of equality between these two parameters is 2.59. Indistinctly identified whites likewise suffer only an insignificant wage penalty.

Another way to interpret these estimates is to note that the racial wage gap estimated by the conventional specification in column (1) masks two very different groups of black workers. One group, with racially distinctive speech, suffers a substantial wage penalty. The other, with indistinctive speech, enjoys virtual wage parity with whites. The racial wage penalty is greater, the more distinctive the worker's speech.

The other regressors in the table largely perform as expected. Schooling and experience have positive, significant effects on wages. Workers who are enrolled in school earn less than their counterparts who are not enrolled. Males generally earn more than similarly skilled females. Residents of the South earn lower wages, but the difference is not significant. The one surprise is that urban dwellers earn less than their non-urban counterparts, although again, those coefficients are insignificant.

Of course, Table 6 showed that other speaker traits are correlated with race and speech patterns. If those traits are also correlated with wages, they might explain the speech-related wage gap in Table 8. Table 9 adds a number of variables to the basic wage regression. I report results only from the specifications that involve the binary speech distinctiveness measure. Results based on other specifications of the speech variable were generally similar, though sometimes less significant.

The regression in column (1) of Table 9 adds to the specification from column (4) of Table 8 the speaker's AFQT score, on the grounds that speech patterns may merely be standing in for more general measures of labor market skill.[9] The AFQT score is positive and significant. Adding it to the regression reduces the wage gap between distinctly and indistinctly identified black workers, but the difference is still 14 percent and significantly different from zero, as indicated by the t-statistic in the next-to-last row of the table.[10]

[9] Because roughly 20 percent of the NLSY respondents did not take the AFQT, I also include a dummy equal one for those respondents (I set the missing AFQT scores to zero).

[10] Considering the strong correlation between AFQT and racially distinctive speech, one might wonder how their effects are independently identified. An analysis of speech patterns by AFQT quartile shows

The next four columns add variables that may influence the speaker's speech pattern, as discussed above. Family structure, parental education, household income, and private schooling are all associated with higher wages. Household income and the private-school dummy are significant at the 10 percent level. All of these variables reduce the wage gap between distinctly and indistinctly identified black workers, although the gap remains sizable and significantly different from zero. Column (6) adds a dummy equal to one if the speaker's voice was distinctly identified as Southern. Many Southern dialects and AAE share features in common (Fasold 1981), so the effect that I attribute to racially distinctive speech patterns could instead be attributable to regionally distinctive speech. The coefficient on the Southern accent dummy is negative but not significant. Adding the Southern accent dummy has little effect on the coefficients of the race-speech pattern interactions.

The last column in the table adds all the additional variables at once. Only the AFQT and household income are individually significant, but the set is highly jointly significant, with an F-statistic of 3.44. Adding the full set of background variables reduces the estimated race- and speech-related wage differences. The least restrictive estimates, in column (7) of Table 9, show that distinctly identified blacks earn 12.4 percent less than distinctly identified whites. This compares with an estimate of 18.8 percent in the most restrictive regression, reported in column (4) of Table 8. The speech-related wage gap among blacks falls as well, from 16.5 percent in the most restrictive model to 11.7 percent in the least restrictive model. Although the speech-related wage

that, among black workers in the lowest quartile, 82 percent have racially distinctive speech. In the next quartile, the number is 72 percent, indicating that more than a quarter have racially indistinctive speech. In the top half of the AFQT distribution, 46 percent of black workers have distinctive speech. In other words, above the lowest quartile, there is a fair amount of variability in speech, even controlling for AFQT.

gap falls by more than a quarter, at almost 12 percent it remains substantial, and its t-statistic is 1.93. The wage difference between indistinctly identified blacks and distinctly identified whites is less than one percent.

D. Specification Issues

The first two columns of Table 10 speak to two important specification issues. Because my sample size is so small, the regressions reported in Tables 8 and 9 include workers who were enrolled in school, along with a dummy variable indicating that they were enrolled. Column (1) reports a wage regression akin to that reported in column (7) of Table 9, from which observations have been deleted during periods when the speaker was enrolled in school or college. Although the speech-related wage gap among blacks is not significant in this regression, it remains fairly sizeable at 9.4 percent. The wage difference between distinctly identified blacks and distinctly identified whites is a significant 13.6 percent.

The second column deals with possible self-selection into employment. Following Neal, Johnson, and Kitamura (2000), I impute a low wage value (specifically, the lowest value observed in the sample), to speakers during years when they do not report wages. I then estimate the model via median regression. The motivation for this approach is a simple model of labor supply, in which the consumer works if and only if her offered wage exceeds her reservation wage. This model implies that non-workers have low offered wages; median regression helps to reduce the sensitivity of the estimates to the particular value imputed to the non-workers. This approach suggests that, if anything, the OLS wage regressions reported above understate both race- and speech-related wage differences. Of course, this approach is valid only if the assumptions of the simple labor supply model are valid. If non-workers in my young sample are students who will soon face favorable employment options, they this approach may not provide a valid correction to the sample-selection problem.

The next two columns report regressions of enrollment and employment status, respectively, on all of the variables included in column (7) of Table 9. These are of substantive interest and also help explain the findings in the first two columns of Table 10. Column (3) shows that there are no significant differences in enrollment status by race or speech pattern. This explains why the estimated wage equations are relatively insensitive to the inclusion of enrolled workers. Column (4), in contrast, shows that distinctly identified blacks work significantly less than speakers in the other race and speech categories. This explains why the imputed wage regression in column (2) produces larger speech-related wage gaps among black workers than the OLS wage regressions. Distinctly identified blacks are more likely to have missing wage data, so under the simple labor supply model, speech-related differences in offered wages exceed speech-related differences in observed wages.

An issue for which there is no direct evidence concerns the possibility of code-switching. Many African-Americans speak both AAE and SAE, and switch between the two depending on context. Research shows that bi-dialectical speakers are more likely to speak AAE when speaking with other African-Americans, and are more likely to speak SAE, the more formal the context (Labov 1972). Thus among bi-dialectical speakers, there may be a difference between the language used on the job and the language used in the NLSY validation interview.

The interviewer for the validation interview was an African American woman. By itself, this may have prompted some speakers who speak SAE on the job to speak AAE during the interview. This should bias my coefficient for sounding distinctly black toward zero, since some speakers who sounded distinctly black during the interview would sound indistinctly black at work. However, if speakers adopt a more formal style for telephone interviews than they do on the job, then the bias could go the other way.

IV. Interpretation

The above results show that speech patterns are highly correlated with wages among young African American workers. This raises the question of what explains that correlation. Here I discuss some alternative explanations and the data one would need to distinguish among them. Although much of the data is currently unavailable, understanding the different possibilities is important, because they have different implications for policy.

The results are consistent with two broad categories of models: one in which speech plays a causal role, and another in which speech serves as a signal of unobserved productivity. Causal models themselves fall into two groups: one in which speech raises productivity, and one in which speech affects discrimination. Lang (1986) provides an example of the former. In Lang's model, language differences among workers raise production costs. In equilibrium, a subset of minority-language speakers chooses to become bilingual. They become supervisors of monolingual minority members and earn a wage premium to compensate for the cost of learning the majority language. Thus Lang's model predicts that bilingual minority workers should earn a wage premium relative to monolingual minority workers, as we observed above. It also predicts that monolingual minority workers should disproportionately occupy jobs where many workers share a single supervisor, in order to minimize the costs of language learning.

Another causal explanation stems from a model of differentiated racial prejudice. If employers are prejudiced against blacks, as in (Becker 1971), but bigoted employers are less averse to blacks who do not sound distinctly black as compared to those who do, then indistinctly identified blacks should suffer a lower wage penalty than their distinctly identified counterparts. A distinctive feature of Becker's model is that the extent of wage discrimination is reduced by workplace segregation.[11] In a world where bigoted employers discriminate on the basis of both skin color and speech, such a relationship presumably should be flatter for indistinctly identified blacks than for distinctly identified blacks.

In signaling models, speech patterns do not raise productivity, but rather signal the worker's underlying skill. If the cost of acquiring the speech signal falls with skill, these models can generate the speech-related wage differences observed above. Adding measures of labor market productivity to the regression should also cause the speech-related wage gap to fall, as in Table 9.

One such signaling model is that of Lang and Manove (2006). In their model, blacks overinvest in a signal (in their case, education) due to statistical discrimination. Speech could serve a similar purpose.

Another example is Austen-Smith and Fryer's (2000) ethnic identity model. Their model involves a "two-audience" signaling problem, in which individuals gain utility both from wages, which are a function of skill, and from acceptance by the peer group. Each individual is a two-dimensional type, where one dimension is labor market skill and

[11] Charles and Guryan (2008) provide empirical evidence along these lines.

the other is a binary indicator of acceptability. Highly acceptable but low-skilled types obtain little if any education, which signals their acceptability. Highly skilled types obtain education independent of their acceptability. They signal their skill, rather than their acceptability, because the opportunity cost of forgoing education is too high. Replacing education in their model with a (continuous) speech signal would presumably lead to similar conclusions: high skill workers would obtain the speech signal to signal their skill, independent of acceptability, whereas low-skill, high-acceptability workers would forego the speech signal.

Another model in which speech could signal productivity is that of Altonji and Pierret (2001; hereafter, AP), who add employer learning along the lines of Farber and Gibbons (1996) to a model of statistical discrimination. In their model, workers are characterized by a variable s, which is fully observed at the beginning of the worker's career (such as speech), and a vector of variables z, which is largely unobservable at the beginning of the worker's career, but about which the competitive employer observes a noisy signal each period. If firms statistically discriminate on the basis of s, and s and z are positively correlated, then the effect of z on the worker's wage should rise over time as the firm acquires signals about the worker's value of z. At the same time, as the firm acquires information about z, s should exert less effect on the worker's wage.

In AP's model, if employers do *not* statistically discriminate on the basis of race (because such discrimination is illegal, for example), then race is essentially a z variable. As such, it should have relatively little effect on the worker's wage at the beginning of his career. If race and productivity are negatively correlated, as suggested by the negative correlation between race and AFQT scores, then the effect of race should become increasingly negative over time. Moreover, if firms statistically discriminate on the basis of speech, which is observable, then at the beginning of the worker's career, black workers with the favorable signal should earn higher wages than black workers without it. This is consistent with the results above. However, over time, the favorable speech signal should have less effect on wages as the labor market acquires signals about the worker's true productivity. Thus under the assumptions of AP, we would expect speech-related wage gaps to be temporary. Indeed, Lange's (2007) findings suggest they may disappear quickly.

Understanding why speech patterns are correlated with wages is important, since different models have different implications for policy. In Lang's (1986) model, speech differences reduce productivity, so interventions that lower the cost of becoming bi-dialectical should raise output. In signaling models, the speech signal has distributional consequences, but does not affect output. The same is true for models of discrimination along the lines of Becker (1971). In principle, it should be possible to distinguish among these models empirically, but to do so would require new data collection.

Of course, there is another possibility, which is that speech is correlated with the worker's productivity, but in contrast to the usual assumptions of signaling models, it is correlated with aspects of productivity that are already observable to the employer, even if they are not generally observable to the analyst. In this case, the results above identify a group of African American workers who suffer almost no wage disadvantage in comparison to similarly qualified whites. Other such groups have been found before (Bound and Freeman 1992), but they are rare. Understanding why indistinctly identified blacks have achieved wage equality with whites may help provide insights into the considerable inequality that remains.

V. Conclusions

Speech patterns are correlated with racial wage differences. Among blacks, speech patterns are correlated with skill, measured by either schooling or AFQT scores. Yet even controlling for schooling and test scores, speech patterns predict racial wage gaps. Black workers whose speech is distinctly identified as black earn 12 percent less than comparably skilled whites. Their indistinctly identified counterparts earn essentially the same as whites.

There are many potential explanations for the speech-related wage gaps reported here. Some are causal, but others are not. It would be useful to distinguish among them, since different models have different implications for policy. More generally, better understanding how one group of African Americans has achieved wage equality may help to explain the substantial inequality that persists.

References

Akerlof, George A. and Rachel E. Kranton. “Economics and Identity.” Quarterly Journal of Economics 115 (3), 2000, 715-753.

Altonji, J. G. & Pierret, C. R. (2001). Employer Learning and Statistical Discrimination. Quarterly Journal of Economics, 464 (February), pp. 313-350.

Austen-Smith, David, and Roland G. Fryer, Jr. “An Economic Analysis of ‘Acting White.’” Quarterly Journal of Economics, 2005, 551-583.

Bailey, Guy and Erik Thomas. “Some Aspects of African American Vernacular Phonology.” In Mufwene, Salikoko S, John R. Rickford, Guy Bailey, and John Baugh, eds., African American English: Structure, History, and Use. London: Routledge, 1998.

Baugh, John. “Hypocorrection: Mistakes in Pronunciation of Vernacular African American English as a Second Dialect.” Language and Communication 12 (3/4), 1992, 317-326.

Becker, Gary S. The Economics of Discrimination. Chicago: The University of Chicago Press, 2nd edition, 1971.

Bertrand, Marianne and Sendhil Mullainathan. “Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination.” American Economic Review 94(4), 2004, 991-1013.

Bleakley, Hoyt and Aimee Chin. “Language Skills and Earnings: Evidence from Childhood Immigrants.” Review of Economics and Statistics 86 (2), 2004, 481-496.

Borjas, George J., Jeffrey Grogger, and Gordon H. Hanson. “Imperfect Substitution Between Immigrants And Natives: A Reappraisal.” NBER Working Paper 13887, March 2008.

Bound, John, and Richard B. Freeman. "What Went Wrong? The Erosion of Relative Earnings and Employment Among Young Black Men in the 1980s." Quarterly Journal of Economics 107, (February 1992), 201-232.

Cameron, Steven and James J. Heckman. "The Nonequivalence of High School Equivalents." Journal of Labor Economics 11, (January 1993), 1-47.

Charles, Kerwin K. and Jon Guryan. “Prejudice and the Economics of Discrimination.” NBER Working Paper 13661, December 2007.

Chiswick, Barry R. “Speaking, Reading, and Earnings among Low-Skilled Immigrants.” Journal of Labor Economics 9 (2), 1991, 149-170.

Clopper, Cynthia G., and David B. Pisoni. "Some Acoustic Cues for the Perceptual Categorization of American English Regional Dialects." Journal of Phonetics 32, 2004, 111-140.

Cook, Phillip, and Jens Ludwig. "Weighing The "Burden Of 'Acting White'": Are There Race Differences In Attitudes Towards Education? Journal of Public Policy and Analysis, 16, 1997, 256-278.

Farber, H. S. & Gibbons, R. (1996). Learning and Wage Dynamics. Quarterly Journal of Economics 111:1007-47.

Fasold, Ralph W. "The Relation Between Black and White Speech in the South." American Speech 56, 163-189.

Fordham, Signithia and John U. Ogbu. "Black Students' School Success: Coping with the 'Burden of "Acting White."' The Urban Review 18 (3), 1986, 176-206.

Fryer, Roland G. Jr., and Steven D. Levitt. "The Causes and Consequences of Distinctly Black Names." Quarterly Journal of Economics 119, 2004, 767-805.

Fryer, Roland G. Jr., and Paul Torelli. "An Empirical Analysis of 'Acting White.'" NBER Working Paper 11334, May 2005.

Green, Lisa. "Aspect and predicate Phrases in African American Vernacular English." In Mufwene, Salikoko S, John R. Rickford, Guy Bailey, and John Baugh, eds., African American English: Structure, History, and Use. London: Routledge, 1998.

Grogger, J. "Does School Quality Explain the Recent Black-White Wage Trend?" Journal of Labor Economics 14 (1996), 231-253.

Grogger, J. (1998). Market Wages and Youth Crime. Journal of Labor Economics 16, no. 4, October 1998, 756-791.

Labov, William. Language in the Inner City: Studies in the Black English Vernacular. Philadelphia: University of Pennsylvania Press, 1972.

Labov, William. "Co-existent Systems in African American Vernacular English." In Mufwene, Salikoko S, John R. Rickford, Guy Bailey, and John Baugh, eds., African American English: Structure, History, and Use. London: Routledge, 1998.

Lang, Kevin. "A Language Theory of Discrimination." Quarterly Journal of Economics 101 (2), 1986, 363-382.

Lange, Fabian. "The Speed of Employer Learning." Journal of Labor Economics 25 (1), January 2007.

Martin, Stefan and Walt Wolfram. "The Sentence in African American Vernacular English." In Mufwene, Salikoko S, John R. Rickford, Guy Bailey, and John Baugh, eds., African American English: Structure, History, and Use. London: Routledge, 1998.

Massey, Douglas S. and Garvey Lundy. "Use of Black English and Racial Discrimination in Housing Markets." Urban Affairs Review 36 (4), 2001, 452-469.

McManus, Walter, William Gould, and Finis Welch. "Earnings of Hispanic Men: The Role of English Language Proficiency." Journal of Labor Economics 1 (2), 1983, 101-130.

Mufwene, Salikoko S. "The Structure of the Noun Phrase in African American Vernacular English." In Mufwene, Salikoko S, John R. Rickford, Guy Bailey, and John Baugh, eds., African American English: Structure, History, and Use. London: Routledge, 1998.

Neal, Derek. "Black-White Labour Market Inequality in the United States." In Steven Durlauf and Lawrence Blume, eds., New Palgrave Dictionary of Economics, 2006

Neal, D. A. and Johnson, W. R. (1996). The Role of Premarket Factors in Black-White Wage Differences. The Journal of Political Economy, Vol. 104, No. 5 (Oct., 1996), pp. 869-895.

Neal, D. A., Johnson, W. R. and Kitamura. "Evaluating a Simple Method for Estimating Black-White Gaps in Median Wages." American Economic Review 90, (May 2000), 339-343.

Jencks, Christopher, and Meredith Phillips. "The Black-White Test Score Gap: An Introduction." In Jencks, Christopher, and Meredith Phillips. eds., The Black-White Test Score Gap. Washington, DC: Brookings Institution Press, 1998.

Pattillo, Mary. Black Picket Fences: Privilege and Peril Among the Black Middle Class. Chicago" University of Chicago Press, 1999.

Purnell, Thomas, William Idsardi, and John Baugh. "Perceptual and Phonetic Experiments on American English Dialect Identification." Journal of Language and Social Psychology 18 (1), 1999, 10-30.

Rickford, John R. and Christine Theberge Rafal. "Preterite Had + V-Ed in the Narratives of African-American Preadolescents." American Speech 71 (3), 1996, 227-254.

Thomas, Erik R. "Sociophonetic Applications of Speech Perception Experiments." American Speech 77 (2), 2002, 115-147.

Thomas, Erik R., and Jeffrey Reaser. "Delimiting Perceptual Cures Used for the Ethnic Labeling of African American and European American Voices." Journal of Sociolinguistics 8 (1), 2004, 54-87.

Trejo, Stephen J. "Why Do Mexican Americans Earn Low Wages?" Journal of Political Economy 105 (6), 1997, 1235-1268.

Walton, Julie H. and Robert F. Orlikoff. "Speaker Race Identification from Acoustic Cues in the Vocal Signal." Journal of Speech and Hearing Research 37 (4), 1994, 738-746.

Washington, Julie A. and Holly K. Craig. "Morphosyntactic Forms of African American English Used by Young Children and their Caregivers." Applied Psycholinguistics 23, 2002, 209-231.

Wolfram, Walt. "Black-White Speech Differences Revisited." in Wolfram, Walt and Nona H. Clarke, eds., Black White Speech Relationships. Washington, DC: Center for Applied Linguistics, 1971.

Wolfram, Walt. Dialects and American English. Englewood Cliffs, NJ: Prentice Hall, 1991.

Table 1: Summary Statistics for Blacks and Whites in the Speech Sample and the Full NLSY

Variable	Speech sample	Full NLSY
Male	0.51	0.51
Age, 2006	23.1	23.0
Race		
White	0.69	0.67
Black	0.31	0.33
AFQT	0.06	0.08
Share enrolled, 2006	0.17	0.20
Highest grade completed, 2006	13.1	13.0
Southern residence, 2006	0.42	0.43
Urban residence, 2006	0.71	0.63
Sample size [a]	402	7,000

a - Due to item non-response, sample sizes for ASVAB are 330 and 5317.

Table 2: Listener Characteristics

Sex	N	Percent
Female	79	61
Male	51	39
Total	130	100
Race/ethnicity		
White	98	75
Black	12	9
Hispanic	6	5
Asian	11	8
Other	3	2
Total	130	100
Region of residence, age 6		
Northeast	27	21
Midwest	50	38
South	22	17
West	22	17
Outside US	9	7
Total	130	100
Native language		
English	127	98
Spanish	2	2
Other	1	1
Total	130	100

Table 3: Accuracy of Listeners' Perceptions of Speaker Characteristics

Speaker characteristic	Percent correct listener responses
Sex	
Male	98.3
Female	97.8
Race/ethnicity	
White	83.6
Black	77.1
Education	
Less than high school	5.3
High school	28.3
Some college	29.6
College or more	48.3
Region of origin	
Northeast	27.5
Midwest	39.6
South	47.0
West	24.4

Note: Number of speaker-listener pairs is 2010.

Table 4: Determinants of the Accuracy of Listeners' Perceptions of Speaker's Race
Dependent variable is a dummy equal to one if listener's perception of speaker's race is correct

Variable	(1)	(2)	(3)	(4)
A. Speaker characteristics				
Black	-0.089			-0.087
	(0.036)			(0.036)
Male	-0.034			-0.036
	(0.026)			(0.027)
Age, 2006	0.012			0.011
	(0.010)			(0.009)
Enrolled, 2006	-0.054			-0.050
	(0.043)			(0.043)
Highest grade, 2006	0.007			0.007
	(0.008)			(0.008)
Midwest	0.020			0.023
	(0.047)			(0.046)
South	0.068			0.064
	(0.045)			(0.045)
West	-0.044			-0.040
	(0.057)			(0.056)
AFQT	-0.001			-0.003
	(0.019)			(0.020)
B. Listener characteristics				
Male		0.009		0.007
		(0.018)		(0.018)
Black		0.099		0.091
		(0.044)		(0.043)
Hispanic		-0.010		-0.022
		(0.056)		(0.057)
Other race		-0.038		-0.030
		(0.065)		(0.063)
White		0.041		0.026
		(0.032)		(0.032)
Age		-0.009		-0.009
		(0.003)		(0.003)
Graduate degree		-0.013		-0.021
		(0.026)		(0.026)
Midwest		-0.008		-0.003
		(0.023)		(0.023)
South		-0.001		0.001
		(0.029)		(0.030)
West		0.071		0.071
		(0.028)		(0.028)
Outside US		0.041		0.029
		(0.042)		(0.041)
Repeat listener		-0.020		-0.011
		(0.032)		(0.031)
Understood clip (1-5 scale)		0.022		0.014
		(0.010)		(0.011)
C. Technical factors				
Phrase count			-0.006	-0.005
			(0.007)	(0.008)
Technician 1			0.062	0.057
			(0.044)	(0.044)
Technician 2			0.061	0.047
			(0.030)	(0.031)
Medium quality			0.005	-0.024
			(0.033)	(0.034)
High quality			0.030	0.009
			(0.045)	(0.044)
Observations	2010	2010	2010	2010
R-squared	0.027	0.016	0.008	0.046

Notes: Standard errors, in parentheses, are clustered by speaker. In addition to the variables shown, all regressions include missing value flags for speaker's enrollment status, highest grade, region of residence, and ASVAB score. Missing value flags equal one if the corresponding variable is missing and zero otherwise. The missing values of the corresponding variable are recoded to zero.

Table 5: Recognizability of Speech and Mean AFQT Scores, by Race and Number of Correct Listener Reports of Race

Number of correct listener reports:	0	1	2	3	4	5	Total
A. White							
Recognizability index	-0.639	-0.486	-0.280	-0.116	0.091	0.267	0.117
AFQT	-0.132	-0.379	0.252	0.448	0.176	0.427	0.314
Cell size	10	5	13	23	73	154	278
B. Black							
Recognizability index	-0.688	-0.443	-0.282	-0.138	0.108	0.284	0.061
AFQT	-0.153	0.480	-0.298	-0.060	-0.852	-0.721	-0.536
Cell size	10	3	10	18	14	69	124

Note: Cell size is for recognizability index. Cell sizes for AFQT add to 330 due to item non-response.

Table 6: Means of Skill Measures and Family Background, by Race and Distinctiveness of Speech

Race:	White			Black		
Speech pattern:	Indistinct	Distinct	Total	Indistinct	Distinct	Total
Variable	(1)	(2)	(3)	(4)	(5)	(6)
AFQT	0.18	0.34	0.31	-0.08	-0.74	-0.54
Highest grade	12.84	13.52	13.39	13.00	11.99	12.32
Two parents, age 12	0.58	0.57	0.57	0.33	0.14	0.20
Parent's schooling	13.3	14.27	14.09	13.24	12.43	12.69
HH income ($1,000s)	4.65	5.9	5.69	4.01	2.8	3.15
Private/parochial school	0.06	0.07	0.07	0.12	0.04	0.06

Table 7: Summary Wage, Age, and Enrollment Data, by Year

Period Variable	2004 (2)	2005 (3)	2006 (1)	Total (4)
Share reporting wages	0.63	0.60	0.75	0.86 [a]
Mean wage (s.d.)	11.77	12.61	13.71	12.76
	(5.96)	(7.36)	(7.24)	(6.93)
Age				
Mean	22.1	23.1	24.1	23.1
Min	20	21	22	19
Max	24	25	26	25
Share enrolled	0.27	0.25	0.17	0.23

a - Share reporting wages at least once between 2004 and 2006.

Table 8: Wage Regression Results

Dependent variable is the speaker's log hourly wage

Variable	(1)	(2)	(3)	(4)
Black	-0.099	-0.083	-0.087	
	(0.047)	(0.051)	(0.043)	
Black*(no. correct-3)		-0.044		
		(0.020)		
White*(no. correct-3)		0.005		
		(0.018)		
Black*recog. index			-0.209	
			(0.098)	
White*recog. index			0.079	
			(0.090)	
Black*distinct				-0.188
				(0.057)
Black*indistinct				-0.023
				(0.057)
White*indistinct				-0.023
				(0.051)
Highest grade comp.	0.106	0.104	0.104	0.105
	(0.012)	(0.012)	(0.012)	(0.012)
Experience	0.053	0.051	0.053	0.051
	(0.011)	(0.011)	(0.011)	(0.011)
Enrolled	-0.108	-0.114	-0.109	-0.112
	(0.047)	(0.049)	(0.047)	(0.048)
Male	0.118	0.111	0.119	0.114
	(0.039)	(0.039)	(0.039)	(0.039)
South	-0.071	-0.065	-0.062	-0.063
	(0.041)	(0.041)	(0.041)	(0.041)
Urban	-0.061	-0.070	-0.063	-0.068
	(0.047)	(0.047)	(0.047)	(0.047)
Constant	0.529	0.636	0.935	0.636
	(0.502)	(0.492)	(0.201)	(0.493)
Observations	786	786	786	786
Adj. R-squared	0.181	0.187	0.181	0.188

Note: Figures in parentheses are standard errors, clustered by individuals. Sample size is 786. Number of individuals is 345. In addition to the variables shown, the regressions in columns (2) and (4) include a set of listener and technician characteristics that predict the accuracy of listeners' perceptions of the speaker's race: the share of listeners from the western U.S.; the share of black listeners; mean listener age, mean listener understanding, and technician dummies.

Table 9: Additional Wage Regressions

Dependent variable is the speaker's log hourly wage							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black, distinct	-0.152	-0.161	-0.173	-0.155	-0.191	-0.195	-0.124
	(0.057)	(0.057)	(0.057)	(0.056)	(0.057)	(0.057)	(0.057)
Black, indistinct	-0.013	-0.010	-0.010	-0.010	-0.031	-0.028	-0.007
	(0.057)	(0.057)	(0.056)	(0.055)	(0.060)	(0.057)	(0.054)
White, indistinct	-0.027	-0.028	-0.010	-0.011	-0.023	-0.034	-0.031
	(0.050)	(0.050)	(0.051)	(0.049)	(0.051)	(0.052)	(0.049)
AFQT	0.063						0.067
	(0.024)						(0.025)
Two parents, age 12		0.079					0.039
		(0.047)					(0.049)
Parent's schooling			0.014				-0.002
			(0.009)				(0.010)
HH income, 1997				0.017			0.015
				(0.009)			(0.008)
Private school					0.143		0.118
					(0.082)		(0.080)
South, distinct						-0.068	-0.068
						(0.054)	(0.053)
t-statistic for H_0: Black, distinct=Black, indistinct	2.19	2.40	2.57	2.30	2.49	2.64	1.93
Adj. R-squared	0.198	0.198	0.192	0.205	0.193	0.189	0.219

Note: Figures in parentheses are standard errors, clustered by individuals. Sample size is 786. Number of individuals is 345. In addition to the variables shown, each regression includes all of the variables shown in column (4) of Table 8 and a set of listener and technician characteristics that predict the accuracy of listeners' perceptions of the speaker's race. These include the share of listeners from the western U.S.; the share of black listeners; mean listener age, mean listener understanding, and technician dummies. The regressions that include the variables AFQT, Two parents, Parent's schooling, and HH income also include missing value flags. The flag takes the value one if the value for the variable is missing and zero otherwise. The missing value for the variable is set to zero.

Table 10: Additional regressions

Dependent variable:	Log wage	Imputed log wage	Enrolled	Employed
Variable	(1)	(2)	(3)	(4)
Black, distinct	-0.136	-0.208	-0.015	-0.112
	(0.062)	(0.063)	(0.042)	(0.045)
Black, indistinct	-0.042	0.026	-0.006	0.003
	(0.066)	(0.069)	(0.045)	(0.037)
White, indistinct	0.027	-0.011	-0.023	0.026
	(0.055)	(0.062)	(0.051)	(0.038)
t-statistic for H_0: Black, distinct=Black, indistinct	1.38	3.44	0.20	2.30
Observations	600	1092	1092	1051
Adj. R-squared	0.263		0.223	0.063
Drop enrolled speakers	Yes			
Median regression		Yes		

Note: Figures in parentheses are standard errors, clustered by individuals. Standard errors in column (2) are bootstrapped. In addition to the variables shown, each regression includes all of the variables shown in column (7) of Table 9 and a set of listener and technician characteristics that predict the accuracy of listeners' perceptions of the speaker's race. These include the share of listeners from the western U.S.; the share of black listeners; mean listener age, mean listener understanding, and technician dummies. The regressions also include missing value flags for the variables AFQT, Two parents, Parent's schooling, and HH income. The flag takes the value one if the value for the variable is missing and zero otherwise. The missing value for the variable is set to zero. In columns (2) and (3), sample size is less than 1206 (=402*3) due to missing data on educational attainment. In column (4), sample size is smaller still due to missing data on employment status.