Chapter 16

What We Know about Discriminatory Differentials in Labor Market Outcomes

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This chapter reviews the current learning with respect to discriminatory differentials in labor market outcomes, with a primary focus on earnings. Discriminatory differentials by race,[1] gender, and physical appearance are covered.

INTRODUCTION

The existence of raw earnings differences between different demographic groups in the United States is well established.[2] For example, in 2009, blacks who were full-time wage and salary workers had median weekly earnings of approximately 80 percent of the median weekly earnings of white full-time wage and salary workers (U.S. Department of Labor 2010). Looking across gender reveals a similar finding—women who were full-time wage and salary workers had median weekly earnings in 2009 of roughly 80 percent of the median weekly earnings of male full-time wage and salary workers (U.S. Department of Labor 2010).

On one hand, these earnings differences might reflect what are referred to as premarket differences. For example, it could be that they are the result of differences in productivity, which is typically proxied using a variety of human capital measures (e.g., years of schooling, job experience). That is to say, whites and males might earn more than blacks and females, respectively, because they have more years of schooling and more job experience. Such earnings differences could also reflect differences in occupational choice. For example, it might be that whites and males choose to enter into higher-paying occupations than blacks and females, respectively.[3]

Alternatively, these earnings differences could be the result of discrimination. Discrimination is said to exist if there are unexplained differences in earnings between people with the same premarket characteristics. For example, Hannah, a white female, and Jack, a white male, work as medical doctors in the same family medicine practice in Chicago. Hannah and Jack have equal levels of human capital (same medical school, same internship and residency, same number of years of experience, same number of years on the current job) and are equally productive in that they see the same number of patients per week. However, Jack is paid a higher salary than Hannah, which suggests discrimination.

SOURCES OF DISCRIMINATION

There are three principal sources of discrimination in the labor market—employers, customers, and coworkers (Becker 1971). Employer discrimination occurs when *employers* are prejudiced against certain groups and act on these prejudices. Such preferences might result solely from the employer's own tastes and preferences or, referring to the identity economics literature, might instead reflect social codes that tell people how they are supposed to think of themselves and how they are supposed to interact with others (Akerlof and Kranton 2010). For example, Auto Shop Owner X, who is white, pays his white mechanics more than his equally productive black mechanics. Customer discrimination occurs when *customers* are prejudiced against certain groups and act on these prejudices. For example, most of the customers of Retail Store X, which is located in a predominantly white suburb, prefer to interact with white salespeople, thus rendering white salespeople more productive in a sense than black salespeople. Based on this productivity difference, Retail Store X will pay its white salespeople more than its black salespeople, even though Retail Store X per se may not hold any prejudices. Finally, coworker discrimination occurs when *coworkers* are prejudiced against certain groups and act on these prejudices. For example, Large Factory X, which is located in a mostly white area, employs a large number of white workers who are uncomfortable working alongside their equally productive black colleagues. Thus Large Factory X, which has to employ at least some white workers due to the limited supply of nonwhite labor, pays its white workers a wage premium to keep them, even though Large Factory X per se may not hold any prejudices. The result is that Large Factory X's white workers earn more than the factory's equally productive black workers. Economic theory suggests that only employer and coworker discrimination can be eliminated by market forces (Kahn 1991), and even then, some type of government intervention would probably be necessary.

Another common source of labor market discrimination is statistical discrimination. Statistical discrimination occurs when employers judge members of a particular group based on the characteristics of the group itself. For example, Billing Department X pays college graduates more than high school graduates because college graduates are more productive, on average, than high school graduates. However, according to Darity and Mason (1998), statistical discrimination cannot persist because if average group differences are merely perceived and not real, then employers should over time learn that their beliefs are in error. On the other hand, the authors say that if average group differences are indeed real, then in a world with antidiscrimination laws employers are likely to find ways to predict the future performance of potential employees with sufficient accuracy without having to rely on group membership.

MEASURING LABOR MARKET DISCRIMINATION: THE REGRESSION APPROACH

As stated earlier, discrimination is said to exist if there are unexplained differences in earnings between people with the same premarket characteristics. To make such comparisons using real-world data, researchers often rely on a statistical procedure known as regression analysis. Regression analysis allows the researcher to test for a statistical relationship between an outcome measure (e.g., earnings) and a group membership indicator (e.g., white, black) while holding constant variables that measure various premarket attributes.[4] A statistically significant group membership indicator suggests discrimination, as it indicates black-white earnings differences due solely to race.[5]

A potential issue with the regression approach is that unobserved, and therefore not controlled for, differences between demographic groups might be driving observed earnings differences between the groups. For example, if the quality of schooling received by whites systematically exceeds the quality of schooling received by blacks, then a study using the regression approach that does not control for school quality will overstate the presence of discrimination.[6] As another example, consider a researcher using the regression approach to study beauty discrimination. The researcher finds a statistically significant, positive coefficient on the beauty variable, implying that more attractive people earn more than less attractive people; however, the interpretation is not as straightforward as one might think. The result might reflect discrimination on one hand, but on the other hand it might be that beauty is a proxy for other productive factors that are not easily measured and therefore not captured by the data, such as self-motivation and discipline.[7] Even if the latter can be ruled out, the researcher may have a difficult time identifying the type of discrimination.

These kinds of ambiguities are ubiquitous throughout the regression literature on discrimination. Looking first at the regression literature on racial discrimination, the extent to which the black-white raw earnings differential is attributable to discrimination versus premarket differences between blacks and whites has been widely studied. Regarding the former camp, Darity and Mason (1998), in a fairly extensive review of this literature, conclude that a standard result is that a significant portion of the earnings gap between black and white males in the United States cannot be explained by variables included to control for premarket differences between members of the two racial groups.[8] This result, which suggests discrimination, is corroborated, they say, by studies that examine the effect of within-race skin shade on earnings. The benefit of such an approach is that it minimizes the effect that unobserved differences can have on the findings. According to Darity and Mason (1998), such studies provide evidence that lighter-complexioned blacks tend to have superior incomes than darker-skinned blacks in the United States. A recent study by Goldsmith et al. (2007) further confirms this, finding that the wage difference between white workers and medium or dark-skinned blacks are considerably larger than in comparison to their lighter-skinned counterparts and that, among blacks, lightness is rewarded in the labor market. Anchoring the other camp, Neal and Johnson (1996) argue that controlling for a single measure of skill (Armed Forces Qualification Test), something that is not observable in most datasets, explains all of the black-white wage gap for young women and much of the gap for young men. The authors conclude that the black-white wage gap primarily reflects a skill gap, which in turn can be partly attributed to observable differences in family backgrounds between whites and blacks. This sentiment, which is vigorously refuted by Darity and Mason (1998), is strongly echoed by Heckman (1998) and reinforced by more recent studies by Carneiro et al. (2005), O'Neill and O'Neill (2005), and O'Neill et al. (2006).[9]

Looking next at the regression literature on gender discrimination, Blau and Kahn (2007), using two, nationally representative datasets, the Current Population Survey (CPS) and the Panel Study of Income Dynamics (PSID), find that after controlling in regression analyses for human capital, race, industry, and occupation, an unexplained gender wage gap of 9 to 17 percent remains.[10] The authors say that this unexplained gap might overstate discrimination if omitted factors such as working conditions or motivation are at play, but could understate discrimination in the presence of occupational segregation. Regarding the latter, Blau and Kahn (2007), because they include controls for occupation and industry, are essentially examining gender differences in earnings across males and females in the same occupation and industry. However, it might be that women are steered, because of discrimination, into lower-paying occupations and industries, so that looking at male-female earnings differences within occupation and industry understates the degree to which women are being discriminated against. Evidence of occupational segregation comes from looking at the Index of Dissimilarity, which is defined mathematically as follows:

$$\text{Index of Dissimilarity} = \frac{1}{2}\sum_{j=1}^{j}\left|P_j^M - P_j^W\right|$$

where P_j^M and P_j^W measure, respectively, the percentage of men and women in occupational category j. The Index value indicates the percentage of men, women, or a combination of the two that needs to shift occupations in order for the two genders to have equal occupational distributions and ranges from 0 to 100. A value of 0 means equal occupational representation by gender, whereas a value of 100 implies complete occupational segregation by gender. For example, computing the Index for two occupations, Occupation 1, in which 80 percent of males and 40 percent of females work, and Occupation 2, in which 20 percent of males and 60 percent of females work, yields the following value:

$$\text{Index of Dissimilarity} = \frac{1}{2}[|80 - 40| + |20 - 60|] = 40$$

This means that 40 percent of men, women, or a combination of percentages that adds up to 40 must shift occupations for males and females to have equal occupational distributions in this case. For example, if 20 percent of men switch from Occupation 1 to Occupation 2 and 20 percent of women switch from Occupation 2 to Occupation 1, then the Index value becomes 0:

$$\text{Index of Dissimilarity} = \frac{1}{2}[|60 - 60| + |40 - 40|] = 0$$

According to Blau and Kahn (2000), after remaining at roughly two-thirds for each Census year since 1900, the Index of Dissimilarity fell from 67.7 in 1970 to 59.3 in 1980 and 52.0 in 1990. Recent estimates by Gabriel and Schmitz (2007) indicate a 2001 index value of 31.1. The main cause of these reductions is the movement of women into predominately male jobs (Blau and Kahn 2000). The extent to which occupational segregation is due to gender differences in preferences versus discrimination remains largely unanswered (Blau and Kahn 2000).

Consider, lastly, the regression literature on physical appearance discrimination. Anchoring this literature is the seminal piece by Hamermesh and Biddle (1994), which uses data from two broad household surveys for the United States and Canada. In all three surveys, the interviewer was asked to rate or categorize the survey respondent's physical appearance on a five-point scale (1 = Strikingly Beautiful or Handsome, 2 = Above Average for Age [Good Looking], 3 = Average for Age, 4 = Below Average for Age [Quite Plain], 5 = Homely). The authors combine categories "1" and "2" and call it "Above-Average" and combine categories "4" and "5" and call it "Below-Average," with category "3" remaining "Average." Hamermesh and Biddle (1994) find that there is a 7 to 9 percent earnings penalty for being below-average looking and a 5 percent earnings premium for being above-average looking. Looking across gender, the 9 percent penalty and 5 percent premium for men are at least as great as the 5 percent penalty and 4 percent premium for women. The likely culprit, according to the authors, is either employer or coworker discrimination. However, the authors also find evidence, albeit weak, that the labor market sorts the best-looking people into occupations where their looks are productive, suggesting that customer discrimination might also play a role.

In sum, the consensus from the regression literature on racial discrimination seems to be that black males earn between 5 and 19 percent less than white males and that black females earn anywhere from 9 percent less to 7 percent more than white females, while the consensus from the regression literature on gender discrimination appears to be that females earn between 7 and 17 percent less than males.[11] Given the much smaller size of the physical-appearance discrimination regression literature, the Hamermesh and Biddle (1994) finding of a 7 to 9 percent earnings penalty for being below-average looking and a 5 percent earnings premium for being above-average looking acts as an appropriate consensus finding for beauty discrimination. Regarding height- and weight-based discrimination, Mitra (2001) finds no effect of height and weight on male earnings and no effect of weight on female earnings. Mitra (2001) does, however, find that an additional inch of height increases the earnings of female professionals and managers by roughly 2.5 percent.

MEASURING LABOR MARKET DISCRIMINATION USING OCCUPATION-SPECIFIC DATA

To deal with the ambiguities of the regression approach, researchers sometimes look at narrowly defined occupations, the benefits of which are threefold. First, controlling for productivity is often easier because either such data are readily available for the occupation in question or because focusing on a specific occupation makes it easier to identify an appropriate set of productivity proxies. Second, while for many occupations there are many actors (employers, customers, coworkers), for some occupations there is but a sole actor. For occupations that fall into the latter category, the matter of identifying the source of discrimination is straightforward. Finally, because members of a particular occupation are more similar than members of different occupations, focusing on a particular occupation should lessen (but will not completely eliminate) the effect of differences in unobserved or omitted factors across members.

One oft-studied occupation, for which detailed productivity data are available, is professional sports. For example, Kahn and Sherer

(1988) examine racial differences in 1985–86 salaries of individual professional basketball players and find that although white and black players earn similar mean compensation, white players have a higher conditional mean compensation. That is, the authors find that after controlling for productivity and other differences between players in a regression analysis, white players earn 20 percent more than black players, which suggests discrimination.[12] Kanazawa and Funk (2001) examine Nielsen ratings data for locally televised NBA games and find that even after controlling for a variety of factors that might impact ratings, viewership increases when there is greater participation by white players. Combining this with another finding by the authors that higher ratings generate more advertising revenue suggests that white players have a higher marginal revenue product than that of comparable black players. This, the authors say, can explain much of the race-based earnings gap that exists in professional basketball, such as the 20 percent differential found in Kahn and Sherer (1988).

Using unique survey data collected outside of five Virginia restaurants, and controlling for (subjective) server productivity, as well as a variety of other factors, Parrett (2011) compares the tip earnings of male and female servers and finds evidence of customer discrimination, but only among those customers who frequent the restaurant the least.[13] More specifically, Parrett (2011) finds that female servers earn comparable tips to male servers when the service quality they produce is exceptional (high quality), but for any lower service quality their tips are smaller, suggesting that female servers are being held to a very high standard and that if this standard is not met, they are treated unfavorably in comparison to male servers who produce the same level of service quality. Additionally, Parrett (2011) finds that it is male customers driving these results.

Finally, Biddle and Hamermesh (1998) study the effect of beauty on earnings using longitudinal data on a large sample of graduates from a highly selective law school they denote Law School X. Beauty for each graduate in the sample is measured by a panel of four persons, each of whom independently provides a rating of the graduate's matriculation photograph on a five-point scale similar to that used in Hamermesh and Biddle (1994). Because each entering law school class was rated by a different panel of four observers, each graduate's average beauty rating was standardized within the graduate's entering class.[14] Biddle and Hamermesh (1998) find that better-looking attorneys who graduated in the 1970s earned more than others after five years of practice, an effect that grew with experience. The authors rule out employer discrimination as a culprit based on an absence of larger returns to beauty among employed versus self-employed lawyers. That attorneys in the private sector are better looking than public sector attorneys, that attorneys switch between the public and private sectors based partly on looks, that the monetary return to beauty rises rapidly in the private versus public sector, and that men who are more attractive have a greater chance of making partner early all suggest, according to Biddle and Hamermesh (1998), that the likelier culprit is customer (client) discrimination.

THE AUDIT STUDY APPROACH TO MEASURING LABOR MARKET DISCRIMINATION

Another way of dealing with the ambiguities of the regression approach is to rely on audit studies. Audit studies typically focus not on discriminatory differentials in earnings but instead in hiring. In an audit study, employers with advertised job openings are approached by people from two different groups (e.g., male and female) posing as applicants. The applicants' work histories and resumés are constructed by the researcher so as to make it that the only difference between the applicants is their group affiliation. If members of one group are treated differently than members of the other group, like if female applicants receive fewer callbacks than male applicants, then discrimination is said to exist. Despite offering greater control over differences in premarket attributes between the groups being studied, audit study results, just like regression study results, can also be driven by unobserved differences between the groups, making drawing conclusions more difficult.

A survey of audit studies of racial discrimination by Darity and Mason (1998) reveals that relative to whites, blacks (1) are less likely to receive an interview, (2) are less likely to receive a job offer, conditional on receiving an interview, and (3) are offered less pay and are steered toward lower-level positions, conditional on receiving an offer. However, as alluded to previously, and as pointed out by Heckman (1998) and acknowledged by Darity and Mason (1998), audit study results could be getting driven by unobserved differences between the groups being studied, such as the ability to make a first impression. Hence the use of correspondence tests in which researchers send fictitious letters of inquiry or resumés from prospective "applicants" to employers whereby the letter or resumé signals the applicant's membership to a particular group. The letters and resumés are designed so as to demonstrate comparable credentials and skills across the members of the groups being studied. Like with the audit study approach, if members of one group are treated differently than members of the other group, for example if black applicants receive fewer callbacks than white applicants, then discrimination is said to exist. In a recent correspondence test study, Bertrand and Mullainathan (2004) send fictitious resumés to help-wanted ads in Boston and Chicago newspapers, whereby resumés are randomly assigned African American- or white-sounding names in order to manipulate perceived race. The authors find that relative to African American-sounding names, white-sounding names receive 50 percent more callbacks for interviews.

Neumark (1996) reports the results of an audit study of gender discrimination in which comparably matched pairs of males and females apply for jobs as waiters and waitresses at various Philadelphia restaurants. Neumark finds that for female applicants to high-priced restaurants, their probabilities of receiving an interview and an offer are approximately 35 and 40 percentage points lower than the probability of a male applicant receiving an interview and an offer, respectively.

THE EXPERIMENTAL APPROACH TO MEASURING LABOR MARKET DISCRIMINATION

A final way that the ambiguities of the regression approach have been addressed is through the use of the experimental approach. Roughly speaking, an experiment works as follows. There are two groups, the treatment and the control, the latter of which does not receive the treatment. Subjects are randomly assigned to one of the two groups, which ensures that differences in the outcome measure between the two groups are due solely to the treatment. For example, Mobius and Rosenblat (2006) examine the beauty wage gap using laboratory experiments in which "employers" determine wages of "workers" who perform a maze-solving task that is independent of beauty.[15] The authors find a sizable beauty premium, which they attribute to three things—more attractive workers are more confident, more attractive workers are considered more able by employers (controlling for confidence), and more attractive workers have better oral skills (controlling for confidence).

On the plus side, experiments provide the researcher with almost complete control over potential confounds. However, there are downsides to the experimental approach. One such downside is that due to their controlled nature, experiments often lack proper context. Another drawback to the experimental approach is that the subject pool almost always consists entirely of undergraduate students whose behavior may or may not generalize to the greater population. Such downsides, though, typically apply more to laboratory settings and less so to field settings, like the one examined by Goldin and Rouse (2000), who look at the impact of the adoption of blind auditions by symphony orchestras in which a screen is used to conceal the candidate's identity from those evaluating the candidate. Using data from actual auditions, the authors find that the screen increases the probability that a female will be advanced and hired.

CONCLUSION

Taken together, the findings from the discrimination literature strongly suggest the presence of discriminatory differentials in hiring and earnings based on race, gender, and physical appearance. This begs the question of what explains their existence. Standard economic theory suggests that because of market forces, employer, coworker, and statistical discrimination cannot persist. The implication, then, is either that the main culprit is customer discrimination or that market forces are somehow being impeded. Regarding the latter, it might be that employers do not profit maximize, which, according to Heckman (1998, 112), is sustainable, saying that "if a bigoted employer prefers whites, the employer can indulge that taste as long as income is received from entrepreneurial activity, just as a person who favors an exotic ice cream can indulge that preference by being willing to pay the price." However, regardless of source, the persistence of such differentials indicates a continued need for government involvement.

NOTES

1. The focus here will be on black-white discriminatory differentials, as these are by far the most widely studied racial groups in the literature.
2. Unfortunately, raw earnings data by physical appearance are not readily available.
3. Of course, differences in productivity or occupational choice across demographic groups could reflect discrimination.

4. For example, running a regression analysis of earnings (dependent variable) on the independent variables race (black/white) and years of schooling allows the researcher to examine black-white differences in earnings holding constant years of schooling. That is, it allows the researcher to examine black-white differences in earnings across blacks and whites with the same number of years of schooling. Regression analyses are typically run via computer using statistical software such as STATA or Eviews. Microsoft Excel also has regression capabilities.

5. Sometimes researchers who use the regression approach apply what is known as the Blinder-Oaxaca decomposition procedure. This procedure, which involves running additional regression analyses, allows the researcher to sort out the extent to which earnings differences between two groups are due to (1) differences in premarket attributes between the two groups and (2) discrimination, and generally leads to the same conclusion originally reached using the regression approach (Darity and Mason 1998).

6. Continuing with the example in the fourth endnote, if school quality is unobserved in the dataset (and thus not included as an independent variable), positively related to earnings, and systematically differs between blacks and whites as described here, then school quality will not get held constant in examining black-white differences in earnings. Thus some of the observed difference in black-white earnings, even after holding years of schooling constant, will reflect black-white differences in school quality. This will result in an overestimate of the impact of race on earnings and thus an overestimate of discrimination.

7. Being beautiful takes work—exercise, diet, learning the various beauty tips, etc.

8. According to Neal (2004), much of the existing literature reveals that black-white wage gaps among working women remain quite small compared to the corresponding gaps among men and that black-white gaps in potential wages are much larger among men than women—hence the heavier focus in the black-white labor market discrimination literature on black and white males.

9. It should be noted that the black-white skill gap could itself be the result of discrimination.

10. O'Neill and O'Neill (2005) obtain similar results using nationally representative data.

11. These figures come from the studies cited here in this chapter.

12. Thus looking across equally productive white and black players (holding productivity constant), black players earn less than white players. Combining this with the fact that white and black players earn similar amounts in the raw data suggests that black players are more productive than white players. Thus, in the raw data, the increase in earnings blacks receive for being more productive is essentially offset by a decrease in black earnings due to discrimination.

13. Detecting discrimination is difficult. Even more difficult is detecting the source of discrimination. In this setting, it is easy to infer customer discrimination because the customer (other than the server) is the sole actor.

14. Each graduate i in entering class j receives four beauty ratings—B_{ij1}, B_{ij2}, B_{ij3}, B_{ij4}. To create a single beauty measure for each graduate i in entering class j: (1) for each entering class j, the mean (μ_j) and standard deviation (σ_j) across all beauty ratings for all graduates of entering class j was computed; (2) graduate i's beauty

ratings were standardized as follows: $b_{ij1} = [B_{ij1} - \mu_j] / \sigma_j$, $b_{ij2} = [B_{ij2} - \mu_j] / \sigma_j$, $b_{ij3} = [B_{ij3} - \mu_j] / \sigma_j$, $b_{ij4} = [B_{ij4} - \mu_j] / \sigma_j$; and (3) finally, graduate i's single beauty measure was computed as the average of b_{ij1}, b_{ij2}, b_{ij3}, and b_{ij4}.

15. Note that the experiments were conducted in Argentina.

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