Spring 5-7-2017

Race and the Labor Market: A Call for Counteractive Affirmative Action

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RACE AND THE LABOR MARKET

A Call for Counteractive Affirmative Action

University of Wyoming
ECON 4240
1.0 - Overview and Structure

Racial issues are a hard subject to address. The area of study often elicits an emotional response, and debates can quickly devolve from empirical and theoretically sound discussions to charged exchanges where alternative viewpoints are ignored and evidence loses all credence. However, the variety of issues regarding race in contemporary are very real. To deny the possibility of race based disadvantages is to ignore strong demonstrative evidence to the contrary, and these issues bring about significant consequences for minority communities. The purpose of the following research is to establish the effects of race within labor market interactions, then to analyze and offset such effects using an applicative policy model based in a solid theoretical basis. The original policy this analysis will introduce is called counteractive affirmative action, and it is based within the economic labor theory of statistical discrimination.

This analysis will be split into sections that build upon each other. Section two will briefly examine the measurable labor market discrepancies that result from the factor of race. Section three will then introduce the theory of statistical discrimination and provide evidence that such a theory fits labor market realities. Section four will establish the measurable and shared costs that are linked to statistical discrimination, thus justifying the need for a policy based solution. Section five will provide a mathematical analysis of the practice of statistical discrimination using a hypothetical, Bayesian, profit maximizing employer. This analysis will allow for the calculation of an optimal tax policy to offset the effects of statistical discrimination. Section six will introduce counteractive affirmative action, an adjustable policy framework used to approximate optimal taxation practices in the real world.

2.0 - Effects of Race in the Labor Market
2.1 - Productivity, Unemployment, and Race

Neoclassical economic theory dictates that individuals in a labor market equilibrium should be paid their value of marginal product, and that unemployed individuals are simply looking for a job at which they can earn this amount. Unemployment is treated as a homogenous state across individuals, as productivity is what dictates an individual's wage and state of employment. The first indication that race plays a significant factor in the labor market is the observable differences in unemployment levels categorized by race and educational attainment. These are illustrated in the table below:

Table 1 – 2016 US Unemployment Rates by Race and Educational Attainment

<table>
<thead>
<tr>
<th>Total</th>
<th>Less than HS Diploma</th>
<th>High School Graduate</th>
<th>Some College</th>
<th>Bachelor's Degree or More</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>3.6%</td>
<td>6.5%</td>
<td>4.5%</td>
<td>3.6%</td>
</tr>
<tr>
<td>Black</td>
<td>6.8%</td>
<td>14.1%</td>
<td>8.6%</td>
<td>6.1%</td>
</tr>
<tr>
<td>Hispanic</td>
<td>4.8%</td>
<td>5.9%</td>
<td>5.1%</td>
<td>4.3%</td>
</tr>
</tbody>
</table>


This data illustrates that unemployment is almost always consistently higher for blacks and hispanics than it is for whites, even when controlling for educational attainment among the groups. These differences would make sense in neoclassical theory if the races had differing average productivities, as these differing levels of productivity would lead to differing average labor market outcomes among the races. However, Elvira and Town (2002), using "percentage of an initial sales goal achieved" as their proxy measurement for objective performance, finds that objective performance does not statistically differ across races. Hunter and Schmidt (1998) finds that "minority and majority job applicants with equal ability scores have the same level of job performance". This evidence supports that, when controlling for other factors, there is no
productivity difference between races. If this conclusion is to be believed, then the differences in unemployment rates by race indicates that race does play a significant role in the labor market.

Labor market outcomes depend upon a plethora of determinant factors, including education, age, experience, occupational type, and region. Altonji and Blank (1999) ran a Blinder-Oaxaca regression on wage while controlling for these characteristics. A Blinder-Oaxaca regression runs a OLS regression model on two differing portions of a sample, in this case the black labor force and the white labor force, and controls for the same variables. The residual difference in this regression, not explained by the controlled characteristics, accounts for the wage difference attributable to race as a factor. Altonji and Blank (1999) found a 21% wage difference between the black and white sample, and 13% of this wage difference was attributable to race alone. Such a Blinder-Oaxaca regression is illustrated in Figure 1, found in Appendix A. The results of this study provide even stronger evidence that race plays a role in labor market outcomes.

3.0 - Theoretical Understandings of Race and Unemployment

3.1 - Statistical Discrimination

This analysis has presented evidence that indicates that race plays a role in labor market outcomes. Now the question arises—why does race affect the labor market? To answer this, one can turn to several economic theories, but perhaps the most prominent among them is the theory of statistical discrimination. This is the idea that race affects the labor market not because of prejudiced hiring preferences, but because of employer beliefs. The theory is a negative feedback loop that results in sub optimal labor market conditions for black workers.
The theory starts out by assuming that employers believe that fewer blacks are qualified for the positions they need to fill. The employer then screens potential employees and assigns them a "test score" based on this screening. The test score is a grade indicating the likelihood that the candidate is qualified to perform the job they are applying for. Because the employer has prior beliefs about the qualifications of blacks, he must assign a risk premium to the minority applicants. Because of this, fewer black applicants would be hired at the same "test score" as whites. Because of this, the return on investment for education is less for blacks than it is for whites. They are less likely to see the same employment benefits from such an investment as their white counterparts. This leads to fewer black workers investing in education, which leads to fewer blacks being qualified for higher level employment opportunities. This result reinforces the employer’s initial beliefs on black qualifications, which starts the cycle over again. This cycle is illustrated in Figure 2, found in Appendix A.

3.2 - Evidence in Support of Statistical Discrimination

Cavalluzzo, Cavalluzzo, and Wolken (2002) found evidence of behavior in line with racial statistical discrimination in the loan market for small business financing. Pager, Western, and Bonikowski (2009) found strong evidence of statistical discrimination type behavior through a controlled application survey. They found that applicants with "black sounding names" but identical resumes were much less likely to receive a job offer or follow up interview over a spectrum of employers. Both studies indicate that prior beliefs on the differences between races might play a role in individual cost benefit analyses.

4.0 - Societal Costs of Statistical Discrimination
This analysis has established the behavior of statistical discrimination within labor market interactions, but does statistical discrimination have measurable societal costs? Besides being facially unequitable, the practice does have associated costs. Statistical discrimination leads to higher levels of unemployment for the minority labor force. In Gould, Weinberg, and Mustard (2002) it was found that stagnating wages and high unemployment levels are heavily correlated with an increase in crime. This is a direct cost to society. Not only do individuals face the prospect of a more unstable society, but taxpayers also pay a heavy burden with regards to crime prevention. These costs can be broken down into two major categories. The first is individual expenses taken to avoid becoming a victim. This includes the purchase of locks, keys, cab rides, and security investments. David Anderson (1999) estimated the sum of these costs to be something like $130 billion per year in the 90s. The second category is the criminal justice system. This includes funding the police, and judicial and correctional systems. Kyckelhahn (2012) estimated these costs to be $258 billion in 2009. The resulting costs of crime are not minimal.

Krivo and Peterson (1996) found that "extremely disadvantaged neighborhoods have unusually high rates of crime". This means that the concentration of unemployment in minority neighborhoods may lead to higher overall levels of crime. Subsequently, taxpayers are spending even more financing the criminal justice system thanks to discrepancies in unemployment by race. If a solution to statistical discrimination could be found, this would help alleviate such associated costs to society.

5.0 - Analysis of Statistical Discrimination

5.1 - Bayesian Probability Model of A Hypothetical Employer
So far, it has been established that race is indeed a significant factor within the labor market, and that this reality is likely due to the implicit practice of statistical discrimination by employers. Statistical discrimination results from the employers’ prior beliefs about the portion of minority populations that are qualified for the position they are hiring for. To conduct a proper analysis on the effects of statistical discrimination, one must create a hypothetical employer with a set of differing prior beliefs on race, who operates under rational, profit maximizing behaviors.

Rational employers hire candidates based on the probability that they believe the candidate is qualified. The probability that a candidate is qualified can be denoted mathematically by the term Pr(q). Now, in this model it will be assumed that this hypothetical employer will make a positive profit if he hires a qualified candidate, while he incurs a loss if he hires an unqualified candidate. This analysis will denote profit as π. As long as the payoffs based on qualification are positive for qualified candidates and negative for unqualified candidates, then such an analysis will work; however, this model will assume that the employer will make $1500 in profit for a qualified candidate, and -$1000 in profit for an unqualified candidate. To simplify the analysis, it will be assumed that this employer is risk neutral in his hiring decisions. This means that the employer will hire any candidate with a probability of qualification (Pr(q)=x) that averages a profit payout of $0. This can be modeled with the equation:

\[ 1500 \times x + (-1000) \times (1 - x) = 0 \]

Solving this equation for the employer’s risk neutral hiring threshold gives:
Pr(q) = x = .4

This means that the employer will hire any candidate that they believe has a 40% chance of being qualified for the position. Now, the question arises—how does an employer formulate their belief on any candidate’s probability of qualification? The theory of statistical discrimination holds that employers are Bayesian observers whose beliefs depend upon prior beliefs of qualification related to a candidate’s race, as well as a signal of qualification. In labor market practices this signal can come from a candidate's resume, the interview process, or a test that measures the likelihood of qualification for a job. In this model, a test will be used as the signal that informs an employer's belief on candidate qualification.

Before moving forward, this model will denote the employer’s prior beliefs based on race. The model will hold as long as the employer believes that minority groups are less qualified overall than white candidates. For the sake of simplicity, this analysis will assume that only white candidates and black candidates applied for positions. This model will assume hypothetical employer believes that 50% of the white population is qualified for the positions he is hiring for, while he believes that only 25% of the black population is qualified. The model will also assume that there is a population of 32 white applicants, and 32 black applicants. These are arbitrary numbers that can be changed and will have no effect on the model, I simply chose these populations to illustrate the effects of statistical discrimination. With this employer’s prior beliefs, and without the signal of the employment test, he would believe that 16 white candidates were qualified, while only 8 black candidates were qualified. The employer’s prior beliefs can be denoted mathematically as:
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\[(\Pr_{p}\mid \text{white}) = 0.5\]

\[(\Pr_{p}\mid \text{black}) = 0.25\]

The employer also uses an employment test as a signal of qualification. It will be assumed that this employer's test will have three grade outcomes, either A, B, or C. The probability of any candidate getting these grades will depend on whether the candidate is qualified or unqualified. Below are the grade probability distributions for both qualified and unqualified candidates.

<table>
<thead>
<tr>
<th>Qualified Candidates</th>
<th>Unqualified Candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade</td>
<td>Probability</td>
</tr>
<tr>
<td>A</td>
<td>.5</td>
</tr>
<tr>
<td>B</td>
<td>.5</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
</tr>
</tbody>
</table>

Again, these grade distributions are arbitrary. The model will hold as long as qualified candidates have a higher chance of getting higher grades, while unqualified candidates have a higher chance of getting lower grades. It should also be noted that these grade distributions are not affected by race. A qualified black candidate will have the same grade distribution as a qualified white candidate.

So, within this model the white candidates and the black candidates will take the test and receive their grades. The employer will then use these grades, as well as the candidates' race, based on his prior beliefs on qualification, in order to formulate his beliefs on the candidates' probability of qualification. To combine these two signals, this model will use Bayes Theorem, which can be written:

\[\Pr (q \mid \text{grade, race}) = (\Pr(\text{grade}|q)) /\]
\[(\Pr(\text{grade}|q)\Pr_p(q|\text{race})) + (\Pr(\text{grade}|\text{unq})\Pr_p(1-q|\text{race}))\]

This is an equation that gives the employers final belief on a candidate’s probability of qualification, given the test score they received and their race. Because the employed knows the grade distributions for both qualified and unqualified candidates, his final beliefs can now be calculated. First, we will look at the white applicants. One must remember the employer believes that \(\Pr_p(q|\text{white}) = .5\), so the first equation will show his probability of qualification for whites who got A's. The second equation will correspond to whites who got B's, and the third equation will correspond to whites who got C's.

\[
\Pr (q| A,\text{white}) = (0.5) / ((0.5*0.5) + (0.25*(1-0.5)))
\]

\[
\Pr (q| B,\text{white}) = (0.5) / ((0.5*0.5) + (0.375*(1-0.5)))
\]

\[
\Pr (q| C,\text{white}) = (0) / ((0*0.5) + (0.375*(1-0.5)))
\]

When solved these equations yield:

\[
\Pr (q| A,\text{white}) = 0.666666 = 66.667% 
\]

\[
\Pr (q| B,\text{white}) = 0.571428 = 57.143% 
\]

\[
\Pr (q| C,\text{white}) = 0 = 0% 
\]

So, this analysis shows that such an employer would believe that whites who got A's have a 67\% chance of being qualified, whites who got B's have a 57\% chance of being qualified, and whites who got C's have a 0\% chance of being qualified. Within this analysis, this employer will hire anyone with above a 40\% chance of qualification. So, the employer will hire any white candidate who gets an A or a B.
The same calculations can be done for the black candidates. It is important to remember here that the employer believes \( \Pr_p(q|\text{black}) = 0.25 \), so the final beliefs will differ for this population.

\[
\Pr (q| A,\text{black}) = \frac{(0.5)}{((0.5*0.25) + (0.25*(1-0.25)))}
\]

\[
\Pr (q| B,\text{black}) = \frac{(0.5)}{((0.5*0.25) + (0.375*(1-0.25)))}
\]

\[
\Pr (q| C,\text{black}) = \frac{(0)}{((0*0.25) + (0.375*(1-0.25)))}
\]

Solving for these equations gives:

\[
\Pr (q| A,\text{black}) = 0.4 = 40\%
\]

\[
\Pr (q| B,\text{black}) = 0.307692 = 30.769\%
\]

\[
\Pr (q| C,\text{black}) = 0 = 0\%
\]

The results above indicate that such an employer would hire blacks who got A's, but not blacks who got B's or C's. This is a perfect illustration of statistical discrimination, because the employer, is hiring white candidates who got B's, but not black candidates who got B's. This was purely a result of the employer's prior beliefs on qualifications based only on the observable characteristic of race. So, now that differential treatment is established, how will this effect investment in education for each race? This is also something illustratable within this model.

To do this the model must establish the value of employment, the cost of education, and the value of education for the candidates. The value of employment is obviously the wages received throughout the term of employment, but the value of employment must be measured relative to the cost of education. This is the real value of employment, and it can be thought of
as the premium the job brings to the candidate. It is an exogenous factor, so for the sake of simplicity this model will set the value of employment equal to 1. Thus:

\[ V_j = 1 \]

The model must also establish the cost of education in order to derive the value of education. The cost of education will differ for every person, but in order for anyone to invest the cost must be below the value of the job. So, this model will assume that the cost of education ranges from 0.125 to 0.625. The model will also assume that the cost is evenly distributed among the population, so 25% of the population have an education cost of between 0.125 and 0.25. Another 25% have a cost between 0.25 and 0.375. The next 25% have a cost between 0.375 and 0.5, and the last 25% have a cost between 0.5 and 0.625.

So, now the model must derive the value of education. This can be taken as the value one gains from becoming qualified for the job when they were previously unqualified. To calculate this, one should take the probability that any qualified candidate will get a grade at which the employer will hire him or her and subtract the probability that they would get those same grades while being unqualified. They should then take this probability gain that comes from education and multiply it by the value of the job they are going for. Written mathematically:

\[ V_e = (Pr_{\text{hire \ grade}}|q) - (Pr_{\text{hire \ grade}}|\text{unq}) \times V_j \]

Now, it must be noted that within this model the employer will hire whites with differing grades than blacks. As such, the model must calculate the value of education for white candidates and black candidates separately. First, the white group:

\[ V_{e|\text{white}} = ((Pr(A)+Pr(B)|q) - (Pr(A)+Pr(B)|\text{unq})) \times V_j \]
\[ V_{\text{white}} = ((0.5+0.5) - (0.25+0.375)) \times 1 = 0.375 \]

This means that the value of education relative to this job is 0.375 for white candidates.

In our cost of education distribution 50% of the population had a cost of between 0.125 and 0.375. This result means that 50% of the white population will have the proper incentive to go become qualified for the job. Now let's look at the black population:

\[ V_{\text{black}} = (\text{Pr}(A|q) - \text{Pr}(A|\text{unq})) \times V_j \]

\[ V_{\text{black}} = ((0.5) - (0.25)) \times 1 = 0.25 \]

So, the value of education is less for black candidates than it is for white candidates. Within this model, 25% of candidates have a cost of education between 0.125 and 0.25, so 25% of the black population will be incentivized to go become qualified. This difference in education investment results from the statistical discrimination practiced by the employer. However, as a result of the differing hiring practices, the employer’s prior beliefs are verified and the cycle continues.

This model has a population of 32 white candidates and 32 black candidates. If the costs of education are evenly distributed between the population, and 50% of whites will get qualified while 25% of blacks will get qualified, then a total of 16 whites will be qualified while 8 blacks will be qualified.

**5.2 - Offsetting Statistical Discrimination with an Optimized Tax**

So, within the framework of this model the employer hires races differently due to prior beliefs about qualification probabilities. It is unlikely that these prior beliefs can be changed
through policy, but the employer payouts can be changed through a taxation policy. The racial
discrepancy that must be fixed is that white candidates are being hired with B grades, while
black candidates are not. This is because the employer believes that whites who get a B have a
57.143% chance of being qualified, while blacks with B's only have a 30.769% chance of being
qualified. The employer will only hire if he believes a candidate has a 40% chance of being
qualified, given his risk neutral profit payouts.

However, we can change his profit payouts. For this policy to offset the discriminatory
practice one would have to get the qualification probability threshold down to the qualification
belief for blacks who got a B—so 0.30769. The policy will initiate a tax, set at amount Z, for
every black who gets a B that the employer does not hire. We add this tax to the negative
payout, as avoiding it will offset possible profit losses due to hiring unqualified candidates. Now
the employers risk neutral profit payouts can be written as:

\[ $1500 (0.30769) + (-$1000 + Z) (1 - 0.30769) = 0 \]

\[ Z = $333.33 \]

So, in order to offset the statistical discrimination of this employer, a policy would have
to be put in place that would tax him $333.33 for every black candidate who got a B that he
didn't hire. In doing this, if he responds rationally and optimally, he would hire all whites who
get A's or B's, and all blacks who get A's or B's. This would equalize the value of education for
the races, so more blacks would become educated, which would offset the employer’s prior
beliefs over time. This policy, in the long run, would break the cycle of statistical discrimination
in the labor market.
6.0 - A Tax Incentive Model for the Real World

Within the analysis section, it was shown that given the correct information it would be possible to calculate an optimal tax that would offset the effects of statistical discrimination. This tax would be levied for any minority candidate that the employer did not hire, and who received an equal qualification score in the employee screening process. However, the employee screening process is most often a private affair, and employers are not required to disclose their hiring procedures. Even if employers were required to disclose their hiring practices, the qualification test is often not an objective test. More often than not, the qualification signal that employers use in making their decisions is a subjective interview process. Beyond this complication, calculating an optimal tax for every employer would require knowing their profit payouts, their level of risk aversion, and their prior beliefs on qualification by race. Collecting this data is very difficult, as direct measurements are not available. Beyond collection complications, the employer could lie about his prior beliefs based on race—as there would be a social pressure to appear non-discriminatory. Finally, it would not be legal to apply separate tax rates to each individual employer, which would be required for optimal taxation. So, if applying the optimal tax is not feasible in reality, how can the practice of statistical discrimination be remedied in the real world?

6.1 - Counteractive Affirmative Action

The applicative viability of this analysis hinges on replicating optimal tax incentives for employers. The solution is an incentive based tax model that follows the logic of affirmative action programs. Affirmative Action is the practice of meeting diversity quotas within public
institutions. The practice is applied only in the public sphere, so it is not common practice or legally enforceable in the private market. Chay (1998) found that the implementation of Affirmative Action has had a positive impact on minority communities. If the concept of Affirmative Action could be applied to the private sphere, then minority wages and employment levels would receive a positive boost. In the private market the legal incentive behind affirmative action programs cannot be enforced so the solution must be one based in tax incentives.

This paper will now propose a tax incentive model, that will prompt firms to meet diversity quotas by following their own self-interest. The policy is called Counteractive Affirmative Action. The model works by a seven-step process:

1. Determine the Initial Tax Level
2. Determine the Maximum Surplus Tax
3. Determine the Racial Composition of the Firm
4. Determine the Demographic Imbalances of the Firm
5. Calculate the Firm's Effective Surplus Tax
6. Sum the Initial and Effective Surplus Tax Rates

Each step will now be explained in detail. There are two different variations of this tax policy, that differ in how one determines whether a firm is discriminatory in its hiring practices. These two versions of the tax will be described within step four.

6.1 - Determine the Initial Tax Level

Counteractive Affirmative Action is a system based within corporate income tax. The basic idea is that a company that is determined to be statistically discriminating against minority
candidates will be taxed at a higher rate than a company that seems to be hiring without putting influence on race. It is important to keep in mind that the goal of this program is to bring down minority unemployment to near equal levels of the white portion of the labor force. This, beyond seeming inherently fairer, will lower the concentration of unemployment in minority neighborhoods which will help to alleviate the phenomena of street vice concentration. This will reduce criminal justice costs imposed on society.

Corporate income tax is a tax paid by all private firms, levied out of their profits. It is set at a percentage level, and all firms pay that percent of their profit before deductions. This policy will use the corporate income tax as a tool of incentive. The first step of this model is to determine the initial corporate income tax level. The policy treats this figure as exogenous. It can be thought of as the minimum corporate income tax that a firm will have to pay, discounting any deductions. A firm that is found to have no demographic imbalances will not have to pay any additional tax, so this initial tax level can be thought of as the government fund raising tool that it usually serves as. Again, the government could set this at any level it sees fit and it should not affect the effectiveness of the policy.

6.2 - Determine the Maximum Surplus Tax

There will be an additional portion of corporate income tax levied on any firm that is determined to be statistically discriminating in its hiring practices. This policy will refer to the additional portion of tax as the "surplus tax". The surplus tax will also be a percentage of profit that the firm must pay, and the more severe a firm’s discrimination in hiring, the higher the surplus tax will be. The surplus tax can be thought of as a range of possible taxation. The first
step is to determine the level that such a range of taxation would take. This decision would be up to policy makers, and should be adjusted according to policy outcomes.

For the sake of discussion, this analysis will look at a hypothetical maximum surplus tax, set at 2%. This would mean that a firm could have to pay anywhere from 0% to 2% of its profits depending on the severity of its discriminatory hiring practices. In this hypothetical situation, the initial corporate income tax is set at 13%. This would mean that all firms would face a minimum tax level, discounting deductions, of 13% and a maximum tax level of 15%.

6.3 - Determine the Firm's Racial and Ethnical Composition

This tax policy would require a measurement of the racial composition of each firm's workforce. Firms already provide a plethora of tax information regarding their employees, so measuring racial demographics would not require a substantial amount of additional effort. Each employer would have to include a list of their employees categorized by their self-identified race or ethnicity. These categories would include the recognized races and ethnicities found on the US Census. The firm’s demographic reports could be cross referenced with individual tax returns, or medical records to account for the accuracy of measurement.

6.4 - Determine a Firm's Demographic Imbalances

It has been stated that a firm will pay a portion of the maximum surplus tax based on how severe their discriminatory hiring practices are, but how can discriminatory hiring practices be observed? This policy answers this question with the concept of demographic imbalances. A demographic imbalance simply references when there is a large discrepancy between a firm's racial and ethnical employee composition and the expected or "proper" composition as
determined by national averages. Measuring these discrepancies requires a bit of subjective judgement, as determining the benchmark for what the expected racial composition of a firm should be is a difficult task. This analysis will offer two baseline policy options for determining what constitutes a demographic imbalance. These models will be called the population proportion model and the demographics by occupation model.

**Population Proportion Model**

The question now arises, how can one determine whether a firm is statistically discriminating based on race? The practical answer is to use regional demographic comparisons. The regions used for analysis will be US census tracts, as these are the most local units of analysis at which consistent race data is available. To analyze whether a firm is discriminating or not, one must look for demographic imbalances. However, defining a demographic imbalance takes some subjective choices. This first definition of demographic imbalances defines the term as any significant difference between an firms workforce demographics and the surrounding communities demographics. Roughly put, the firm should hire proportionally from the human capital of its surrounding pool of candidates.

To analyze this model in practice, one can take a hypothetical firm and its hypothetical surrounding community. Now, this hypothetical community is made up of a population of 40% whites, 30% blacks, and 30% Hispanics. A non-discriminatory firm would likely hire around these demographic proportions for their workforce, assuming that candidates from all races are equally represented in application pool. However, for analysis sake, this hypothetical employer's
workforce consists of 58% whites, 21% blacks, and 21% Hispanics. This employer is now a bit astray from the population demographics.

Remember that a demographic imbalance consists of a "significant" deviation from expected demographics, as it is likely that one would observe some deviation from population demographics in each firm. So, how do we define a significant deviation? This policy proposes setting margins of error for defining demographic imbalances. The margins could be adjustable, but this analysis will set the margins at 10% in either direction. This means that if any workforce race demographic is more that 10% away from the expected demographic then that demographic of employees would be categorized as a demographic imbalance. Setting margins of errors on both sides of each racial demographic will keep the policy from either over incentivizing or under incentivizing proportional minority hiring. There is also no rule that the margins have to be equal on both sides of the demographic. If a policy maker were more worried about under incentivizing minority hiring than over incentivizing it, then he or she could set the lower margin closer to the expected demographic proportion while setting the upper margin further away. This would provide a larger incentive to hire minority workers. It is also reasonable to assume that census tracts with smaller populations will have larger deviations in demographics, as each individual worker accounts for a higher percentage of the local workforce. The margins of error for determining demographic imbalances could be made sensitive to population size by adjusting for the population of each census tract.

Back to the hypothetical employer within the population proportion model. We have just established our margins of error for significant demographic deviations at 10% in either direction. The employer has a workforce of 58% whites, 21% blacks, and 21% Hispanics. The
surrounding population is 40% white, 30% black and, 30% Hispanic. Under the margins of error, the white portion of this employer’s workforce would be categorized as a demographic imbalance. Within this step of the process, all the policy analyst must do is recognize demographic imbalances.

One criticism of this model for categorizing demographic imbalances is that it ignores the fact that firms can source their workforce from outside of their surrounding communities in order to find the most qualified candidates. One possible response to this criticism is that most low skilled occupations draw from local candidates. As such, the population proportion model would still help in reducing minority unemployment, and it would incentivize employers to bring in workers in proportion to the communities in which they are situated. However, there is another model for determining imbalances.

**Demographics by Occupation**

The second model for determining demographic imbalances that this model will introduce is called Demographics by Occupation. This model starts with the assumption that races are inherently distributed in a certain way among certain occupational types. There may be a higher portion of minorities that are qualified for social work than there are for tax services. As such, it would not make sense to define a demographic imbalance in hiring based off population proportions, as the population proportion is not representative of qualification distributions. These qualification distributions could be proxied by average national proportions of the workforce separated by race. Now, the expected proportion of each racial demographic based on the type of occupation would be determined by national averages in those occupations.
A demographic imbalance under these definitions would be an employer who hires in relative conjunction with national averages in their occupational category. This model avoids the trap of punishing firms that do not have a large minority pool of applicant to draw from initially. This model would have to discount the local demographics, as national averages are the only way to identify the expected composition of a firm by occupational type.

One major criticism of this model is that it would disincentive minorities from investing in education for occupations in which they do not make up a large portion of national average demographics. It may act as a psychological type of "pre-distribution" among occupations by race. It could have distortionary effects on educational investments.

Whether a policy maker opts to use the population proportion model, or the demographics by occupation model, the important aspect of this step of the process is identifying demographic imbalances within firms that indicate discrimination in hiring.

6.5 - Determine the Severity of a Firm's Demographic Imbalances

Within Counteractive Affirmative Action, once a firm’s demographic imbalances are identified, then the level of those imbalances must be quantified. To do this, the policy takes the difference between the expected demographic percentage and the firms actual demographic percentage. The policy then sums these severities to get the firms total level of calculated demographic imbalance.

To illustrate this, this section will look at an extreme case using the population proportion model with margins of error set at 10% in either direction for all racial demographic groups. Now, imagine a hypothetical employer who has a workforce that is 100% white. His firm is
located in a census tract that is 50% white and 50% black. He falls outside of the 10% margin of error in both the black and white categories, so he has two demographic imbalances. The expected proportion for whites is 50%, so calculating the severity of the demographic imbalance we get:

\[
\left|\frac{\text{expected white demographic proportion} - \text{actual white demographic proportion}}{50\% - 100\%}\right| = 50
\]

And for the black demographic imbalance we get:

\[
\left|\frac{\text{expected black demographic proportion} - \text{actual black demographic proportion}}{50\% - 0\%}\right| = 50
\]

And finally, the policy would sum the total demographic imbalances:

\[50 + 50 = 100\]

Note that this is an example of the most extreme case of discriminatory hiring. It is not possible, under this model, to receive a total demographic imbalance score of over 100. The hypothetical employer from section 6.4 would only have a score of 18.

**6.6 - Calculate the Firm's Effective Surplus Tax**

The effective surplus tax is the portion of surplus tax that a firm must pay for their demographic imbalances. To calculate this, you take the firms demographic imbalance severity score from the last section, you divide it by 100 to put it into decimal form. You then take the
decimal form of that severity score and multiply it by the maximum surplus tax to get the firms effective surplus tax.

This portion of analysis will draw back to the hypothetical employer found in section 6.4 under the population proportion model. This employer had a demographic imbalance severity score of 18, and the decimal version of this score would be 0.18. Assuming that the maximum surplus tax is set at 2%, which again is an arbitrary level for this analysis, this firm would have an effective surplus tax of 0.18 * 2 = 0.36%, which means that they would have to pay 0.36% of their profits as corporate income tax due to their hiring practices.

6.7 - Total Corporate Income Tax

To calculate a firm’s total corporate tax burden, discounting deductions, one would take the initial tax level—which is exogenous to the policy—and sum it with the firm's effective surplus tax.

6.8 - Optimal Responses and Why CAA Remedies Statistical Discrimination

Now, to understand the incentive drivers of this model, we must look at the optimal responses for employers within it. An employer should be doing a cost benefit analysis within this system. In order to avoid a higher tax burden, he must hire a more proportional level of minority employees. However, in doing this the employer might hire minority employees who are not qualified for their positions. This will negatively impact the employer’s profits and offset the tax benefit. It is therefore up to each employer to evaluate their hiring practices. If the surplus tax rate is set high enough to where some employers hire minorities in line with proportional demographics then this will increase the return on investment to education for
minorities. This will cause more minorities to invest and become qualified for employment opportunities, which will counteract the employer’s prior beliefs in tandem with the tax incentive. This model is illustrated in Figure 3, found in Appendix A.

The red portion of this graphic is the original cycle of statistical discrimination. The green components are the addition of counteractive affirmative action. This starts with the implementation of the incentive of the surplus tax, accounted for next to test scores. The beauty of this policy, is that it is adjustable. Say that a government sets the maximum surplus tax too low. At this point employers believe that the higher tax burden is still a better option than the losses that will occur from changing their hiring practices. If this is the case then the tax incentive will follow the red arrow to hiring decision 1, and statistical discrimination will continue. At this point, the government could increase the maximum surplus tax, to make it a bigger incentive. If the surplus tax incentive is large enough, then employers will follow the green arrow paths to hiring decision 2. At this point they will believe that the potential losses from hiring minority employees will be outweighed by the tax break. This will counteract and eliminate the employer’s prior beliefs on minority qualifications. Now, it is likely that every employer will respond to different levels of tax incentive. This policy can be adjusted until national employment levels match national population demographics.

7.0 - Conclusions

This analysis has indicated that labor market outcomes are influenced by race, and that this observation is likely due to the practice of statistical discrimination. This is a detrimental cycle that promotes disparate and sub-optimal hiring practices. As a result, minority populations experience higher than average levels of unemployment.
The tax incentive policy of counteractive affirmative action was introduced as an adjustable framework solution. The policy, inspired by affirmative action programs in the public sphere, incorporates tax incentives to reverse the prior beliefs regarding race and productivity that lead to statistical discrimination. It is politically malleable, and if implemented correctly it would incentivize proportional hiring practices. The policy is fluid enough to account for population concentrations and shifts. In the long run, such a policy would contribute to the elimination of concentrated unemployment linked to higher levels of crime. This would save billions of dollars in tax revenue currently directed towards crime prevention. Counteractive affirmative action provides a solution that combats labor market discrimination while maintaining the freedom of hiring practices for employers.
Appendix A – Figures

Figure 1
Figure 2
Works Cited


