Explaining Cross-Racial Differences in Teenage Labor Force Participation: Results from a General Equilibrium Search Model

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Abstract

White teenagers are substantially more likely to search for employment than their black counterparts. This occurs despite the fact that conditional on race individuals who come from poorer families are more likely to search and black teenagers come from poorer families. While differences in wages between white and black teenagers are small, the unemployment rate for black teenagers is forty percent higher than that of white teenagers. We develop a general equilibrium search model where firms are partially able to target their search based upon demographics. While differences in the labor market can explain some of the cross-race difference in labor force participation rates, a substantial fraction is still unexplained.

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1 Introduction

The teenage labor force participation rate for whites attending school was a little over 40% in the nineties.\(^1\) The corresponding number for blacks is much smaller at 26%. The lower labor force participation rate for black teenagers is surprising given that black teenagers on average come from poorer and less educated families, groups that typically have higher teenage labor force participation rates. We estimate a general equilibrium search model to separate out how much the differences in labor force participation rates result from different tastes for work, differences in productivity and discrimination at the wage setting stage, and differences in search rates by firms.

The potential for search discrimination to play a large role in differences in labor force participation rates follows from the much higher probabilities white teenagers have of finding work conditional on searching. Data from the Current Population Survey show that from 1989-2000 the average probability of a white teenager finding a job was over 76% while the corresponding probability for a black teenager was around 67%.\(^2\) Indeed, data from recent audit studies show that even having a black sounding name on your resume can result in a lower probability of being called in for an interview (Bertrand and Mullainathan 2004). Discrimination by searching firms can then have a magnified effect on labor market outcomes through lowering the search rates of the discriminated group.

While some theoretical work exists showing how search discrimination may lead to cross-racial differences in outcomes, empirical estimates of search models with discrimination are few. This is in part because search models have generally focused on infinite horizon models with identical individuals having a steady state reservation wage. These models are particularly cumbersome to work with and are clearly inappropriate for studies of teenage labor supply. In

\(^1\)The sample is taken from those in the outgoing rotation group of the Current Population Survey focusing in on those from southern states.

\(^2\)Much larger gaps are found when the teenagers who are not in school are added to the sample.
fact, few papers even estimate the elasticity of teenage labor supply in general, let alone across races.

For these reasons, we focus on extending the model used by Ahn, Arcidiacono, and Wessels (2005). There, individuals and firms match through a one shot game where both the labor supply of workers and the search rates of firms are endogenous and the employment level is determined by a matching function. Matched firms and workers then negotiate over the wage using generalized Nash bargaining. By having the search process over in one step, it is possible to make other parts of the model much more complicated. For example, it is easy to incorporate both endogenous labor supply and endogenous firm vacancies. The latter results from zero expected profits from posting a vacancy while the former results from workers having heterogeneous values of leisure.

A key contribution of our paper is that firms are partially able to target their search through choosing different search methods. Workers emit signals regarding their characteristics and firms can target their search based upon these signals. Since firms are identical, expected zero profit conditions must hold across signals. With black-white productivity gaps varying across locations as well as location-specific minimum wages, firms in different locations have differing incentives to target their search.

There is then a separate matching function for each signal. Whites and blacks know their probabilities of being placed in each of the matching functions and use this information in forming their decision as to whether to search. In equilibrium, firms know the number of searching workers and associated racial distributions for each of the matching functions in forming their decisions as to which method to use to post a vacancy.

In practice we do not observe the different matching functions. However, we can integrate out the probabilities of blacks and whites matching in particular markets using mixture distributions. The key features in the data which identify the distributions of blacks and whites associated with particular matching functions in particular locations are 1) the probabilities of finding a match conditional on searching, 2) how these probabilities feed into the probabilities of
searching, and 3) the productivity gap and minimum wage laws in the location.

The data we use to estimate the model comes from a twelve year band of the basic monthly outgoing rotation files of the Current Population Survey (CPS) from 1989 to 2000. We use black and white male teenagers from 16 to 19 years old during non summer months. These teenagers are enrolled in school and have primary residence in the home of their parents. We focus on southern states because of the relatively large sample of black teenagers. The data contain hourly wages, employment status and whether the individual was looking for work. Demographic characteristics such as parental marital status and parental employment are used to approximate the reservation wage.

Estimates of the model show that productivity differs significantly by race and age. However, firms are more able to target their search based upon race than based upon age. Indeed, the raw data show that black nineteen year olds earn substantially more than white seventeen year olds, yet their unemployment rates are higher. Differences in the labor market for black workers is then shown to explain over twenty percent of the difference between black and white labor force participation rates.

We use the estimates of the model to simulate how removing targeted search affects the labor market outcomes for blacks and whites. Removing the targeting breaks a large portion of the tie between race and unemployment, with some gap remaining due to the average value of a match being lower with a black teenager than with a white teenager. Lower match values for blacks means pooling blacks with whites leads to higher unemployment rates for whites. This leads to a feedback effect in that whites respond to the higher unemployment rates by searching less often.

The rest of the paper proceeds as follows. Section 2 discusses the related literature. Section 3 proposes the model. Section 4 describes the data while section 5 shows how the data can be used to structurally estimate the model. Results are presented in section 6 with policy simulations conducted in section 7. Section 8 concludes.
2 Related Literature

Alternative models to the classical model for low wage labor markets have received more attention recently due in part to the findings of Card and Krueger (1994, 1995). Their research, although heavily criticized,\(^3\) points towards changes in employment levels due to minimum wage changes possibly not measuring labor demand elasticities. Search models allow other factors to impact the effect of a minimum wage on employment levels besides through labor demand. In addition to Ahn, Arcidiacono, and Wessels (2005), Lang and Kahn (1998), Flinn (2005), and van den Berg (2003) examine search models in the presence of a minimum wage. The latter two papers are in the spirit of the traditional search literature\(^4\) where workers solve dynamic optimization problems in determining their reservation wages but must trade off having firms earn positive profits and not dealing with heterogeneity in leisure values affecting the labor supply decision.

One of the distinguishing features of our model is that it allows firms to partially target their search for different types of workers based on observable characteristics. Further, this partial targeting of search comes directly out of the firm’s zero profit condition. The previous theoretical research has generally assumed either perfect targeting (Black (1995) and Arcidiacono (2003)) or a discrete choice about whether to target whites or blacks (Mailath, Samuelson, and Shaked (2000)). Satttinger (1998) presents two theoretical models. One model allows for “active” recruitment or perfect targeting whereby firms can choose which type of workers to interview. The least attractive group of workers will receive less interviews and face higher unemployment. In his alternative model firms are “passive” recruiters who can not target their search. As a result high ability workers are hurt by firms’ inability to separate them from low ability workers. The pooling of particular types of workers will drive some of the results here as well with the dating dictating what groups are pooled.

While more structural along many dimensions, the empirical search literature

\(^3\)See for example, Neumark and Wachter (2000).

\(^4\)See Eckstein and van den Berg (forthcoming) for a review.
on discrimination has generally had the offer arrival rates be a reduced form parameters as opposed to coming out of profit maximization.\textsuperscript{5} Our results are most similar to Bowlus and Eckstein (2002) in that we find a lower probability of matching with a firm (lower arrival rate) for blacks than for whites.

The treatment of unemployment and minimum wages is similar to work by Meyer and Wise (1983a, 1983b). Meyer and Wise assume that workers fall into four categories: unemployed, employed at less than the minimum wage, employed at the minimum wage, and employed above the minimum wage. Therefore, the density of the wage distribution is reduced at all points below the minimum wage and a spike in the distribution of wages occurs at the minimum. The primary difference here is that our model comes from firms and workers solving their respective optimization problems at the expense of ignoring workers who earn less than the minimum wage.

3 Model

In this section we present a two-sided search model similar to Ahn, Arcidiacono, and Wessels (2005). The key extension is that firms are able to partially target their search based upon observable characteristics: in Ahn, Arcidiacono, and Wessels either full targeting occurred (separate labor markets) or no targeting was possible. We assume that there are $K$ types of workers where $k$ indexes type. Each worker is a member of only one type. Let $N_k$ index the number of type $k$ individuals in the population. The number of workers of each type who search is endogenous as is the number of searching firms, $J$. Let $N_k$ indicate the number of searching workers of type $k$.

The different types of workers may differ in their average productivity and their attachment to the labor force. Firms then have an incentive to target their search. We assume that firms are able to at least partially target their search based upon the productivity signals of the worker where $M$ indexes the

\textsuperscript{5}See, for example, Wolpin (1992), Eckstein and Wolpin (1995, 1999) and Bowlus and Eckstein (2002).
signal. $J_m$ then indexes the number of searching firms who choose to search on signal $m$.

Workers and firms are matched using a Cobb-Douglas matching function for each search method with the restriction that the number of matches can be no greater than either the number of searching workers or the number of searching firms. Let $x_m$ index the number of matches in the signal $m$ market and is given by:

$$x_m = \min \{ AJ_m^\alpha N_m^{1-\alpha}, J_m, N_m \} \quad (1)$$

While individuals choose to search, they do not control the signal they send to the labor market. Rather, $\lambda_{mk}$, the probability of being assigned signal $m$ conditional on being the $k$th type, is taken as exogenous. The number of workers assigned to method $m$ is then given by:

$$N_m = \sum_{k=1}^{K} \lambda_{mk} N_k \quad (2)$$

and $\sum_{m=1}^{M} \lambda_{mk} = 1$ for all $k$.

We assume that, conditional on the signal, all workers have the same probability of being matched, $p_m = x_m/N_m$. With workers only knowing the probabilities of being assigned particular signals, the probability of a worker with type $k$ matching with a firm is given by:

$$p_k = \sum_{m=1}^{M} \lambda_{mk} p_m$$

Firms who search on signal $m$ also have identical probabilities of matching, $q_m = x_m/J_m$. Further, firms targeting the same signal also have identical probabilities of matching with a particular type of worker. The probability of matching with a worker of type $k$ emitting signal $m$ is then:

$$q_{mk} = q_m \Lambda_{mk}$$

where $\Lambda_{mr}$ is given by:

$$\Lambda_{mk} = \frac{\lambda_{mk} N_k}{\sum_{k'=1}^{K} \lambda_{mk'} N_{k'}}$$
Individuals are differentiated in their reservation values for not working. The $i$th individual of type $k$ has reservation value $R_{ik}$, where $R_{ik}$ is drawn from the cumulative distribution function $F_k(R)$ and has support $[0, \infty)$. This reservation value can be leisure or any outside option for workers. For instance, we may assume that $R_{ik}$ is the value of schooling for teenagers, with the treatment effect of education varying across the population and across type.

Denote $C_1$ as the search cost which is uniform across individuals and is paid whether an individual matches with a firm or not. Individuals are risk neutral and the net expected value of searching for individual $i$ of type $k$, $V_{ik}$, is given by:

$$V_{ik} = p_k E \max \{W - R_{ik}, 0\} - C_1,$$

where $W$ is the wage. Individuals search when $V_{ik} > 0$.

The number of firms in the signal $m$ market, $J_m$, is endogenous. Production from a match is given by $S$ and, like workers, firms pay a search cost, $C_2$, whether or not they find a match. Firms enter until all firms have zero expected profits the market for each of the signals. Expected profits for searching using method $m$ are then given by:

$$\sum_{k=1}^{K} q_{mk} E(\max \{S_k - W_k, 0\}) - C_2 = 0.$$  

(4)

as firms will reject matches where $S < W$. We assume that the surplus of the match is match-specific and is given by $S_{ijk}$ where $S_{ijk}$ is drawn from the cumulative distribution function $G_k(S)$, and has support $[\underline{S}, \bar{S}]$.

We now specify the wage-generating process. Matched pairs split $S$ according to generalized Nash bargaining, with the caveat that a successful match pays at least the minimum wage, $W$. The worker’s bargaining power is set at $\beta$, $\beta \in (0, 1)$. Wages for a successful match are then given by:

$$W_{ijk} = \max \{\beta S_{ijk}, W\}.$$  

(5)

with the wages of unsuccessful matches set at zero. The splitting of the surplus in this manner can generate the spike observed at the minimum wage in the

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6See Flinn (2005) for a similar specification.
data. All matches where the worker’s share of the surplus would normally be below the minimum wage will earn the same wage even if their match-specific components differ.

Contrary to the standard search literature but similar to Ahn, Arcidiacono, and Wessels, the reservation value has no effect on the wage. This is because reservation values here are not the future value of search but the value of leisure which is not verifiable and generally not something workers want to send positive signals about. With reservation values not affecting the bargaining process it may be possible to have matches with excess surplus that are rejected by the worker. Let $\epsilon_A$ give the expected value of $\epsilon$ conditional on a match being acceptable and let $\pi_A$ be the corresponding probability of an acceptable match conditional on matching. We make the same assumption as in Ahn, Arcidiacono, and Wessels which ensures that all matches are acceptable to workers:

$$A.1 \quad \pi_A \beta(S_A - \bar{S}) < C_1 \text{ for all } \{\pi_A, S_A\}$$

The model has a number of implications. First, consider the case where firms can perfectly target their search. In order for the zero profit condition to hold, workers from groups where the expected value of the surplus is high will then have higher probabilities of finding a match. These higher probabilities of finding a match then feedback into higher probabilities of looking for a job. Hence, groups with high surplus levels have higher employment levels both because demand is greater but also because of the decisions as to whether to participate in the labor market.

As firms become less able to target their search, those from groups with low surplus values benefit. Because they are pooled with groups with higher surplus values, demand is higher. In contrast, those groups with higher surplus values are hurt as targeting decreases because they are begin pooled with groups with low surplus values. This effect is magnified with endogenous labor supply. By partially removing targeting, members of the groups with high surplus values become less likely to participate while members of groups with low surplus values benefit.
surplus values become more likely to participate. These effects further lower the equilibrium probabilities of both groups finding employment.

The size of the groups also matter. If groups with low surplus values are relatively small, they will have little impact on the labor market outcomes of those groups with high surplus values. As long as targeting is not perfect, groups with low surplus values prefer to be outnumbered by those from groups with high surplus values.

4 Data

In this section, we present the data we use. We use twelve years of the basic monthly outgoing rotation groups, (ORG) survey files of the Current Population Survey (CPS) from 1989 to 2000. The CPS ORG is ideal for our estimation as the hourly wage variable is obtained from direct reports of hourly wages. We use black and white male teenager workers ages 16 to 19 during non summer months to look for discrimination at the employment stage. These teenagers are matched with their parents to obtain household characteristics. The sample then contains data only on teenagers that still live in their parents’ household and are still enrolled in school.

From the CPS, we collect hourly wage, the individuals’ employment status, whether the individual is looking for work, and demographic characteristics such as parental weekly income, and whether the teenager comes from a single parent home. All income variables are adjusted to 2000 dollars using the CPI. To correct for misreporting of the hourly wages, if a teenagers’ reported wage is below the minimum wage but within twenty-five cents, we attribute the minimum wage to them. Teenagers who report an hourly wage more than twenty-five cents below the minimum wage, and those who report being employed but do not report an hourly wage, are excluded from our sample.

We focus our analysis on data from southern states as defined by the CPS due to the much larger percentage of blacks in this area. The southern states are defined by the CPS are Alabama, Arkansas, Delaware, the District

\footnote{The southern states are defined by the CPS are Alabama, Arkansas, Delaware, the District}
tive statistics by race for three groups of southern teenagers: the entire sample, those who are classified as searchers, and those who are employed. Since matching is the result of a one-shot game, searchers are both the unemployed plus the employed, with the employed being those who successfully matched.

Particularly relevant for the teenage labor market is the minimum wage. In all of the southern states, the binding minimum wage is the federal minimum wage. In nominal terms, the minimum wage was $3.35 in 1989. The federal minimum wage increased to $3.80 April 1st, 1990 and increased again on April 1st, 1991 to $4.25. The minimum wage was increased again on October 1st, 1996 to $4.75, with the final minimum wage change over the sample period occurring on September 1st, 1997 to $5.15.

The full southern sample shows that blacks are a little less than two and a half times more likely to come from a single parent family, with slightly less than half of blacks in the sample coming from a single parent family. Conditional on reporting parents reporting weekly income, parents of black teenagers make sixty-two percent of the amount of their white counterparts. Blacks and whites are equally likely to not report parental income, but for very different reasons. Almost fifteen percent of white households report that the father is employed but do not report his income. The corresponding number for blacks is four percent. In contrast, black households do not report income because there is no individual working over twenty percent of the time. The corresponding number for whites is a little over eight percent.

The most surprising feature of the descriptive statistics are that blacks are thirty-five percent less likely to be in the labor force than their white counterparts. Given that black teenagers are coming from worse family situations, we would suspect that black teenagers would be more likely to search than whites. The fact that is not so is suggestive that blacks are facing substantially different labor markets than their whites.

Support for the black teenage labor market being different from the white
teenage labor market can be found in the second column of Table 1 where the descriptive statistics are reported for searching workers. Here we see that blacks have unemployment rates that are forty percent higher than those of whites. Conditional on race, we also see that individuals who come from single parent families and who have lower household incomes are less likely to participate in the labor market.

The third column of Table 1 examines the characteristics of those who were able to find work. Wages for blacks are lower than their white counterparts with whites earning about five percent (twenty-seven cents an hour) more than blacks. However, this five percent difference is small relative to the large differences in employment rates.

To investigate the differences in employment outcomes in more detail, Table 2 breaks out the descriptive statistics by age. White teenagers are more likely to search as age is increased and this may be because of better labor market outcomes due to increases in their own skill level. Unemployment rates are fifty-five-percent higher for sixteen year old whites than nineteen year old whites. Sixteen year old whites who do find jobs have wages that are on average wages eighty-six cents lower than their nineteen year old counterparts.

Similar age trends are seen for blacks. Nineteen year old blacks are almost two times more likely to be in the labor market than sixteen year old blacks. Conditional on finding a job, sixteen year old blacks earn on average sixty-six cents less than nineteen year old blacks.

The most striking feature of Table 2, however, are comparing across races. Table 2 debunks the notion that the differences in employment rates are driven solely by differences in productivity by blacks and whites. Nineteen year old blacks earn forty cents more an hour than seventeen year old whites and yet face slightly higher unemployment rates. The data suggest that search may

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8Recall that searching workers refers to both the employed and those who report looking for work.

9These patterns were even more pronounced when we included all teens that lived with their parents, instead of here, where we only include male teenagers in school.
Table 1: Sample Statistics for Southern States by Race

<table>
<thead>
<tr>
<th></th>
<th>Entire Sample</th>
<th>Searching</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Black</td>
<td>White</td>
<td>Black</td>
</tr>
<tr>
<td>Age</td>
<td>17.10 (1.01)</td>
<td>17.15 (1.03)</td>
<td>17.33 (1.02)</td>
</tr>
<tr>
<td>Weekly Household Head Income ($)</td>
<td>346 (344)</td>
<td>558 (548)</td>
<td>374 (346)</td>
</tr>
<tr>
<td>Parent Income Not Reported</td>
<td>0.041</td>
<td>0.150</td>
<td>0.050</td>
</tr>
<tr>
<td>Parent Not Working</td>
<td>0.201</td>
<td>0.082</td>
<td>0.148</td>
</tr>
<tr>
<td>Single Parent</td>
<td>0.446</td>
<td>0.188</td>
<td>0.435</td>
</tr>
<tr>
<td>Pr(Search)</td>
<td>0.261</td>
<td>0.406</td>
<td></td>
</tr>
<tr>
<td>Pr(Emp.</td>
<td>Search)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hourly Wage</td>
<td></td>
<td></td>
<td>5.74 (1.977)</td>
</tr>
</tbody>
</table>

be an important explanation in the differences in black-white outcomes with firms more easily able to target their search based upon race than based upon age.

5 Empirical Specification

In this section we show how to estimate the structural model. Estimation is similar to Ahn, Arcidiacono, and Wessels with the extension that firms now can partially target their search. The partial targeting of search occurs on the basis of age and race. Hence \( K \) is the set of all possible age-race combinations.

Estimation has three components. First, for those individuals who successfully match we observe wages. Second, we need to estimate the parameters of
the zero profit condition. Although we do not observe the probability of a firm
finding a match, we are able to rewrite the zero profit condition as a function
of the individual’s probability of finding a match. Finally, we observe decisions
by individuals as to whether to search. We can use these decisions to estimate
the supply side parameters.

5.1 Parameterizing Wages

We assume that $\ln(S_{ijk})$ is given by:

$$\ln(S_{ijk}) = X_{ik} \theta + \epsilon_{ij}$$  \hspace{1cm} (6)$$

where $X_{ik}$ are characteristics of individual $i$’s market and type\textsuperscript{10} and $\theta$ is the
set of parameters to be estimated. We assume that the $\epsilon$’s are drawn from
one of three normal distributions where both the means and the variances are

\textsuperscript{10}As discussed in the data section, a market is defined at the age, race, state, month, and
year level.
allowed to vary across distributions. The probability of the draw coming from the \( r \)th distribution is then given by \( \pi_r \).

Since the wage generating process is given by: \( W_{ijk} = \max\{\beta S, W\} \), without a minimum wage log wages would be given by:

\[
\ln(W_{ijk}) = X_{ik}\theta + \ln(\beta) + \epsilon_{ij} \tag{7}
\]

In the presence of a minimum wage the wage distribution is then distributed truncated log-normal with censoring at the minimum wage. The truncation occurs when the match value is so low that the firm rejects the match. This occurs whenever \( W > S_{ijk} \). There are then three relevant regions for the quality of the match:

\[
\begin{align*}
\beta S_{ijk} \geq W & \quad \Rightarrow \quad \{W_{ijk} = \beta S_{ijk}\} \\
S_{ijk} \geq W > \beta S_{ijk} & \quad \Rightarrow \quad \{W_{ijk} = W\} \\
W > S_{ijk} & \quad \Rightarrow \quad \{\text{No match}\}
\end{align*}
\]

We then observe successful matches for those who are employed either at or above the minimum wage. Let \( N_{11k} \) and \( N_{12k} \) indicate the number of individuals of type \( k \) who have wage observations above and at the minimum wage respectively. The likelihood for these observations then follows:

\[
\mathcal{L}_1 = \left( \prod_{k=1}^{K} \prod_{i=1}^{N_{11k}} \sum_{r=1}^{3} \pi_r \phi \left( \frac{W_i - X_{ik}\theta - \ln(\beta) - \mu_r}{\sigma_r} \right) / \sigma_r \right) \times \left( \prod_{k=1}^{K} \prod_{i=1}^{N_{12k}} \sum_{r=1}^{3} \pi_r \left( 1 - \Phi \left( \frac{\ln(W) - X_{ik}\theta - \ln(\beta) - \mu_r}{\sigma_r} \right) \right) \right)
\]

where \( X_{ik} \) includes the characteristics of the market for the \( i \)th individual. In particular, \( X_{ik} \) includes age, race, quarter, and year indicator variables. \( \Phi \) and \( \phi \) are then the cdf and pdf of the standard normal distribution.

5.2 Parameterizing Firms

Although we have no information on the firm, we can infer the parameters of the profit function by rewriting the zero profit condition as a function of an
individual’s probability of finding a match. We first show that we can rewrite the zero profit condition as a function of $p_m$, the probability of a worker finding a match after being assigned signal $m$, rather than as a function of $q_m$. Next, we show what the distributional assumptions imply for the expected values of $S$ and $W$ given that a match is acceptable. With these expressions and the expressions for $p_m$, we can then rewrite the expression with respect to what we actually observe in the data, $p_k\psi_k$, where $p_k$ is the probability that a worker of $k$th type receives a match and $\psi_k$ is the probability that the match is successful.

The probability of finding a match for firms and workers who are in the signal $m$ market is given by:

$$q_m = A \left( \frac{N_m}{J_m} \right)^{1-\alpha} \quad p_m = A \left( \frac{J_m}{N_m} \right)^{\alpha}$$

implying that we can write $q_m$ as:

$$q_m = A^{1/\alpha} p_m^{\alpha - 1}$$

Substituting for $q_m$ as a function of $p_m$ in the zero profit condition yields:

$$A^{1/\alpha} p_m^{\alpha - 1} E(\max\{S_m - W_m, 0\}) - C_2 = 0$$

Solving for $p_m$ yields:

$$p_m = \delta E(\max\{S_m - W_m, 0\})^{\frac{\alpha}{1-\alpha}}$$

where:

$$\delta = C_2^{1-\alpha} A^{1/\alpha}$$

We can now substitute for $E(\max\{S_m - W_m, 0\})$ with the corresponding probabilities and expected values conditional on type:

$$p_m = \delta \left( \sum_{k=1}^{K} \Lambda_{mk} E(\max\{S_k - W_k, 0\}) \right)^{\frac{\alpha-1}{\alpha}} \quad (8)$$

We model the probability of begin assigned a particular signal as an ordered logit. Order the possible signals from 1 to $M$ with $M$ being the highest. For $m > 1$, we then specify $\lambda_{mk}$ as:

$$\lambda_{mk} = \frac{\exp(Z_k\zeta + \rho_m)}{1 + \exp(Z_k\zeta + \rho_m)} - \frac{\exp(Z_k\zeta + \rho_{m-1})}{1 + \exp(Z_k\zeta + \rho_{m-1})}$$
where $\rho_M = \infty$ and $\lambda_{1k}$ given by:

$$\lambda_{1k} = \frac{\exp(Z_k \zeta + \rho_1)}{1 + \exp(Z_k \zeta + \rho_1)}$$

Since we do not actually observe the markets, we assign the cut points (the $\rho_m$’s). As the number of observations increases, more and more cut points become possible and we move towards a continuous signal with the market clearing for all signals. For our data, we use four cut points with the cut points set up such that if a coefficient for a particular group is zero then that groups will have equal probabilities of being assigned each signal. We normalize the probability of emitting signal one to one for white nineteen year olds. The extent of targeting is then given by $\zeta$ with large in magnitude $\zeta$’s implying much targeting.

Given the assumed distribution of $S$ and the parameters of the wage-generating process, we can calculate $E(\max\{S_k - W_k, 0\})$, the expected surplus from matching with a particular worker type. This surplus can be broken down into three parts for each type of worker: 1) when the match value is high enough such that the minimum wage does not bind, $\tilde{S}_{1k}$, 2) when the match value is such that the minimum wage binds, $\tilde{S}_{2k}$, and 3) when the match value is so low that the firm rejects the match. The last of these parts yields an expected surplus of zero. The first and second parts are then given by:

$$\tilde{S}_{1k} = \sum_{r=1}^{3} \pi_r \left[ \exp(X_k \theta + \ln(1 - \beta) + \mu_r + \sigma_r^2/2) \Phi \left( \frac{\sigma_r^2 - \ln(W) + X_k \theta + \ln(\beta) + \mu_r}{\sigma_r} \right) \right]$$

$$\tilde{S}_{2k} = \sum_{r=1}^{3} \pi_r \left[ \exp(X_k \theta + \mu_r + \sigma_r^2/2) B_{rk} \right. - \left. \Phi \left( \frac{\ln(W) - X_k \theta - \mu_r - \ln(\beta)}{\sigma_r} \right) \right] \left[ W \right]$$

where:

$$B_{rk} = \Phi \left( \frac{\sigma_r^2 - \ln(W) + X_k \theta + \mu_r}{\sigma_r} \right) - \Phi \left( \frac{\sigma_r^2 - \ln(W) + X_k \theta + \ln(\beta) + \mu_r}{\sigma_r} \right)$$

We then define $\tilde{S}_k$ such that:

$$\tilde{S}_k = E(\max\{S_k - W_k, 0\}) = \tilde{S}_{1k} + \tilde{S}_{2k}$$

(9)
The probability of employment for an individual of the $k$th type matching is:

$$p_k = \sum_{m=1}^{M} \lambda_{mk} p_m$$

What we observe in the data is $p_k \psi_k$ where $\psi_k$ gives the probability of a successful match conditional on matching:

$$\psi_k = \sum_{r=1}^{2} \pi_r \left( 1 - \Phi \left( \frac{\ln W - X_k \theta - \mu_r}{\sigma_r} \right) \right)$$

Substituting in for the $p_m$ in the expression for $p_k$ and multiplying by $\psi_k$ yields:

$$p_k \psi_k = \psi_k \sum_{m=1}^{M} \lambda_{mk} \delta \left( \sum_{k=1}^{K} \Lambda_{mk} \tilde{S}_k \right)^{\frac{\alpha}{1-\alpha}}$$

Positive search outcomes for workers are then Bernoulli draws from $p_k \psi_k$.

The likelihood function is then given by:

$$L_2 = \prod_{k=1}^{K} \prod_{i=1}^{N_{2k}} \left( \psi_k \sum_{m=1}^{M} \lambda_{mk} \delta \left( \sum_{k=1}^{K} \Lambda_{mk} \tilde{S}_k \right)^{\frac{\alpha}{1-\alpha}} \right)^{y_{ik}=1} \left( 1 - \psi_k \sum_{m=1}^{M} \lambda_{mk} \delta \left( \sum_{k=1}^{K} \Lambda_{mk} \tilde{S}_k \right)^{\frac{\alpha}{1-\alpha}} \right)^{y_{ik}=0}$$

where $y_{ik}$ indicates whether or not the $i$th worker was matched and $N_{2k}$ is the number of searching workers of the $k$th type.

Identification of $\beta$ at the state level separately from $\delta$ occurs because of the differences in the binding rates of the minimum wage and how these differences affect the corresponding probability of unemployment. If the $\beta$ for a given state is close to one, then there will be few individuals whose productivity places them right at the minimum wage.

Estimation of the firm parameters requires data on the number of white and black searchers at each age for each state-quarter combination. We use census data combined with reduced form estimates of the probability of searching to
form the number of searching workers in each group. The census data provided forecasts of the size of each of our eight groups. We then forecasted the share of each group that would be in school and living with their parents. Given our actual data, we estimated a probit on the probability of being in the labor force using year, year squared, state dummies, quarter dummies, and age dummies as regressors. We estimated the probit separately for blacks and whites and then used the fitted values in forming the expected number of each group in the labor force for each state-quarter combination.

5.3 Parameterizing the Individual

We now turn to the decision by individuals as to whether or not to search which follows directly from Ahn, Arcidiacono, and Wessels (2005). Recall that an individual searches if:

$$p(E(W) - R_i) - C_1 > 0.$$ 

where search costs may now be heterogeneous as well. With the estimates from the previous two stages it is possible to calculate expected wages and the probability of employment for each individual. We now need to parameterize the reservation values. In particular, we parameterize $R_i$ such that all workers have positive reservation values:

$$R_i = \exp(Z_1 \gamma_1 + \epsilon_i)$$

$Z_i$ is then a vector of demographic characteristics which affect the individual’s outside option, the $\gamma_1$’s are the coefficients to be estimated, and $\epsilon_i$ is the unobserved portion of the reservation value. We also allow the search costs to vary where:

$$C_{1i} = Z_2 \gamma_2$$

and all search costs are constrained to be positive.

As in Ahn, Arcidiacono, and Wessels (2005), individuals who come from high income families may have high reservation values, making search less likely.
However, these same individuals may also have lower search costs. What separates search costs from reservation values is how individuals react to the probability of finding a job. In particular, those with low search costs but high reservation values will be more willing to trade off higher expected wages conditional on matching for lower probabilities of employment. In contrast, those with high search costs but low reservation values prefer lower wages coupled with higher match probabilities.

Substituting in and solving for $\epsilon_i$ shows that an individual will search when:

$$
\epsilon_i < \ln\left( \frac{E(W) - Z_2\gamma_2}{p} \right) - Z_1\gamma_1
$$

We assume that the $\epsilon$’s are distributed $N(0,\sigma^2)$. Note that because of the log any coefficient on $E(W)$ will be factored into the intercept term of the reservation values. Since we do not observe the $\epsilon$’s, the likelihood function is then given by:

$$
\mathcal{L}_3 = \prod_{i=1}^{N_3} \Phi \left( \frac{1}{\sigma} \ln\left( E(W) - \frac{Z_2\gamma_2}{p} \right) - Z_1\gamma_* \right)_{s_i=1} \times \left( 1 - \Phi \left( \frac{1}{\sigma} \ln\left( E(W) - \frac{Z_2\gamma_2}{p} \right) - Z_1\gamma_* \right) \right)_{s_i=0}
$$

where $N_3$ is the total number of potential searchers, $s_i$ is an indicator for whether the $i$th individual chose to search, and $\Phi$ is the standard normal cdf. In the standard probit, all coefficients are relative the variance term. Here we can actually estimate $\sigma$ as there is no other natural interpretation for the coefficient on the expression inside the log. The $\gamma^*$’s are then the $\gamma$’s divided by the standard deviation of the $\epsilon$’s, $\sigma$.

While it is possible to estimate all three stages simultaneously, the additive separability of the log likelihood function makes it possible to estimate the parameters in stages. In practice, we estimate the parameters of the wage generating process and of the zero profit condition jointly. Taking these parameters as given, we then estimate the parameters of individual’s decision to search.
6 Results

Estimates of the wage generating process with the exception of the generalized Nash bargaining parameter, $\beta$, are given in Table 3. Teenage wages are negatively impacted by the prime age male unemployment rate which operates as our exclusion restriction as a variable which affects wages but not the value of leisure. Nineteen year olds generate surplus values twelve percent higher than sixteen year olds while blacks have surplus values that are almost six percent lower than whites.\(^{11}\)

The parameters of the zero profit condition are given in Table 3. These parameters are estimated jointly with the parameters of the wage distribution. A generalized Nash bargaining parameter, $\beta$, was estimated for each state. The range was 0.74 to 0.79 suggesting that the market for teenage workers is fairly competitive. $\alpha$, which measures how sensitive the matching function is to the number of searching firm versus the number of searching workers, was set at 0.5, the standard estimate from the macroeconomics literature of 0.5 (Petrongolo and Pissarides 2001).\(^{12}\)

Of more interest are the targeting parameters. Recall that these are logit parameters embedded in the zero profit condition. What these parameters imply is that firms are able to almost fully target their search by race with little targeting by age. Table 4 gives these results. With the exception of white sixteen year olds, all whites were assigned the same signal. Sixteen year old whites were assigned to all signals with 38% assigned to signal four, the signal to which all sixteen and seventeen year old blacks were also assigned. Eighteen year old blacks were also assigned across all signals, however, signal one has the largest probability with 37%. There was significant pooling of nineteen year old blacks with non sixteen year old whites, as 62% of nineteen year old blacks are assigned to signal one.

\(^{11}\)Surplus values refer to the total surplus which would include any compensation the firm would take for not wanting to hire blacks.  
\(^{12}\)We attempted to estimate $\alpha$ but separately identifying both $\alpha$ and the targeting parameters proved difficult.
Table 3: Wage and Zero Profit Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prime Age Male Unemployment Rate</td>
<td>-0.345</td>
<td>0.215</td>
</tr>
<tr>
<td>Age=17</td>
<td>0.039</td>
<td>0.005</td>
</tr>
<tr>
<td>Age=18</td>
<td>0.083</td>
<td>0.006</td>
</tr>
<tr>
<td>Age=19</td>
<td>0.124</td>
<td>0.007</td>
</tr>
<tr>
<td>Black</td>
<td>-0.055</td>
<td>0.007</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>1.590</td>
<td>0.014</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>0.087</td>
<td>0.005</td>
</tr>
<tr>
<td>$\pi_1$</td>
<td>0.512</td>
<td></td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>1.587</td>
<td>0.022</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>0.297</td>
<td>0.013</td>
</tr>
<tr>
<td>$\pi_2$</td>
<td>0.436</td>
<td></td>
</tr>
<tr>
<td>$\mu_3$</td>
<td>1.780</td>
<td>0.017</td>
</tr>
<tr>
<td>$\sigma_3$</td>
<td>0.045</td>
<td>0.011</td>
</tr>
<tr>
<td>$\pi_3$</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>$\beta_{\text{max}}$</td>
<td>0.789</td>
<td>0.019</td>
</tr>
<tr>
<td>$\beta_{\text{min}}$</td>
<td>0.737</td>
<td>0.019</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.5031</td>
<td>0.060</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.5000</td>
<td></td>
</tr>
</tbody>
</table>

With the parameter estimates we can calculate the average probability of begin matched conditional on age and race. These forecasts are given in Table 5. We see that white teenagers above the age of sixteen have a similar chance of matching with a firm at 82%. The corresponding figure for sixteen year old whites is 73.4%. In contrast, the range for black teenagers is 71% chance of matching for sixteen and seventeen year olds to 78% and 81% for eighteen and nineteen year olds respectively. The match rates for eighteen and nineteen year
Table 4: Estimates of Targeting

<table>
<thead>
<tr>
<th>Race</th>
<th>Age</th>
<th>Signal 1</th>
<th>Signal 2</th>
<th>Signal 3</th>
<th>Signal 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>0.156</td>
<td>0.200</td>
<td>0.268</td>
<td>0.376</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>0.952</td>
<td>0.031</td>
<td>0.011</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>18</td>
<td>0.999</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>19</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.999</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.999</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>18</td>
<td>0.364</td>
<td>0.268</td>
<td>0.206</td>
<td>0.163</td>
</tr>
<tr>
<td>19</td>
<td>0.621</td>
<td>0.210</td>
<td>0.106</td>
<td>0.064</td>
<td></td>
</tr>
</tbody>
</table>

old blacks are higher as they are somewhat pooled with the older whites.

Table 5 also shows the average probability that a match is successful, that is, has a surplus value at least at the level of the minimum wage, conditional on age and race. Here we see large differences across age and to some extent across race as well. Nineteen year old blacks are then primarily unemployed due to not matching with a firm. Compared with nineteen year old blacks, Seventeen year old whites are more likely to be unemployed due to lower surplus values once a match has been obtained.

Table 5: Predicted Match Probabilities by Age and Race

<table>
<thead>
<tr>
<th></th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whites</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pr(Match)</td>
<td>0.734</td>
<td>0.821</td>
<td>0.826</td>
<td>0.823</td>
</tr>
<tr>
<td>Pr(Success</td>
<td>Match)</td>
<td>0.926</td>
<td>0.939</td>
<td>0.953</td>
</tr>
<tr>
<td>Blacks</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pr(Match)</td>
<td>0.706</td>
<td>0.708</td>
<td>0.779</td>
<td>0.808</td>
</tr>
<tr>
<td>Pr(Success</td>
<td>Match)</td>
<td>0.904</td>
<td>0.922</td>
<td>0.939</td>
</tr>
</tbody>
</table>
The parameter estimates of the wage generating process and the zero profit condition are then used in the search decisions to form the probability of obtaining a successful match as well as the expected wage conditional on a successful match. These estimates are reported in Table 6. Search costs are significant and the estimate of the variance on preferences is small suggesting that labor market conditions are important in determining job search.

Reservation values for sixteen year olds are substantially higher than for those older. Blacks have higher reservation values and lower search costs. This seems unlikely and may result from us not being precise in the definition of labor markets as a more finer definition then the state may be needed. while those coming from a single parent families have lower reservation wages. Those from single parent households have lower reservation wages and higher costs while the opposite is true for those who have parents with higher parental education.

Since the parameters of a probit are difficult to interpret, in Table 7 we forecast how the probability of searching changes as we vary either labor market conditions or the demographics of searchers. Theses simulations take all other characteristics as given and vary the values of the relevant variables.

Changing expected wages leads to a labor supply elasticity of 1.03. Since higher expected wages will also lead to higher probabilities of finding a match, the total response to better labor market conditions would be even higher. This number is significantly lower than Ahn, Arcidiacono, and Wessel’s (2005) estimate for white male teenagers suggesting that the exclusion restriction, prime age male unemployment rate, works better for whites than for blacks. It may be that more detailed geographic is needed in forming the exclusion restriction.

Of particular interest are how difference in preferences and labor market conditions for blacks and whites drive the differences in search behavior. Recall that blacks are substantially less likely to search than whites. The estimates show that this difference is split between differences in preferences and differences in labor market conditions, with differences in preferences the larger of the two effects. Moving everyone’s preferences from those of blacks to those of
Table 6: Parameter Estimates of the Utility Function

<table>
<thead>
<tr>
<th></th>
<th>Reservation Values</th>
<th>Search Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1/\sigma_s)</td>
<td>0.748</td>
<td>(0.416)</td>
</tr>
<tr>
<td>Black</td>
<td>0.456</td>
<td>-0.575</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.294)</td>
</tr>
<tr>
<td>Household Head Unemployed</td>
<td>0.015</td>
<td>0.126</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.274)</td>
</tr>
<tr>
<td>Household Head Other†</td>
<td>0.103</td>
<td>0.547</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.260)</td>
</tr>
<tr>
<td>Household Head Some College</td>
<td>-0.010</td>
<td>-0.268</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.201)</td>
</tr>
<tr>
<td>Household Head College</td>
<td>0.222</td>
<td>-0.622</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.392)</td>
</tr>
<tr>
<td>Household Head Post-College</td>
<td>0.285</td>
<td>-0.420</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.366)</td>
</tr>
<tr>
<td>Single Parent</td>
<td>-0.147</td>
<td>0.529</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.294)</td>
</tr>
<tr>
<td>Age=17</td>
<td>-0.374</td>
<td>0.516</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.253)</td>
</tr>
<tr>
<td>Age=18</td>
<td>-0.275</td>
<td>-0.134</td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.415)</td>
</tr>
<tr>
<td>Age=19</td>
<td>-0.258</td>
<td>-0.981</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.425)</td>
</tr>
</tbody>
</table>

whites increases labor participation by a little under 36%. Changing expected wages and the probability of matching from those blacks face to the labor market conditions whites face increases labor force participation by a little over
Table 7: Changes in the Probability of Searching

<table>
<thead>
<tr>
<th>Percent Change in Probability of Searching</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% change in Expected Wage</td>
</tr>
<tr>
<td>Black Preferences to White Preferences</td>
</tr>
<tr>
<td>Black Labor Market to White Labor Market</td>
</tr>
</tbody>
</table>

7 Policy Simulations

We focus our policy simulations on changing the degree to which firms can target on the basis of race and age. We treat the economy as all individuals and assume they face the state-specific labor market from quarter one of 1995. Given the demographics and the parameter estimates, we first calculate the equilibrium with targeting. This is accomplished by starting out with an initial guess as to the probabilities each worker will search. Given these probabilities, we calculate expected wages and the probability of matching. Given these expected wages and match probabilities, we then update the search probabilities and continue updating until convergence. The response to the changes in policy is calculated in a similar manner. We consider two policy changes, no targeting on race and no targeting on either race or age. We assume that the parameters of the zero profit condition are the same as with targeting except that now firms can no longer target according to the policy change.

Table 8 shows the changes in the probabilities of searching and matching for blacks and whites with the removal of targeting. The removal of targeting on race lowers the equilibrium values of $S$ for white teenagers. All blacks search more and have a greater probability in matching successfully. This effect is largest for seventeen year old blacks who were mainly pooled with sixteen year old blacks but are now pooled with all older workers.
The removal of targeting based on both race and age reduces both the probability of search and the employment rate for older whites but helps sixteen year old whites. Recall that that firms were able to partially screen out white sixteen year olds. Hence, white sixteen year olds actually see increases in the probability of searching and matching. This is not the case for white teenagers who are older than sixteen. These teenagers faces small drops in the probability of matching which in turn leads to small drops in the probability of searching. Note that these drops have a reenforcing dimension. As nineteen year old whites drop out of the labor market, the expected surplus from a match from the firm’s perspective falls. With falling expected surpluses, more teenagers will choose not to participate in the labor force.

The losses faced by white teenagers over sixteen are counterbalanced by the gains for black teenagers younger than nineteen. The younger black teenagers see their probability of matching increase by almost fifteen percent for sixteen and seventeen year olds and over three percent for eighteen year olds. Black nineteen year olds have reduced probabilities of search and lower matching rates. They are affected by two conflicting influences. They benefit from the removal of targeting on race but are hurt by the removal of targeting on age, with the latter being slightly stronger than the former.

8 Conclusion

Differences in labor market outcomes between blacks and whites are stark. Wage differences are small relative to differences in unemployment. In fact, nineteen year old blacks earn more than seventeen year old whites despite having higher unemployment rates. The effect of these unemployment rates is magnified by the resulting lower search rates for black teenagers.

We propose and structurally estimate a search model with endogenous labor demand and labor supply. Unemployment has two sources in the model. First, unemployment comes from workers not matching with firms. Second, those who do match may draw match values so low that firms are unwilling to pay these
Table 8: Changes in Labor Market Outcomes with the Removal of Targeting

<table>
<thead>
<tr>
<th></th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whites</td>
<td>-0.81%</td>
<td>-0.97%</td>
<td>-0.36%</td>
<td>-0.12%</td>
</tr>
<tr>
<td>Pr(Search) Blacks</td>
<td>2.57%</td>
<td>13.52%</td>
<td>1.63%</td>
<td>0.29%</td>
</tr>
<tr>
<td>No Targeting on Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whites</td>
<td>-1.44%</td>
<td>-1.62%</td>
<td>-1.53%</td>
<td>-1.55%</td>
</tr>
<tr>
<td>Pr(Emp</td>
<td>Search) Blacks</td>
<td>4.69%</td>
<td>18.11%</td>
<td>6.67%</td>
</tr>
<tr>
<td>Change in</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whites</td>
<td>4.91%</td>
<td>-2.96%</td>
<td>-1.30%</td>
<td>-0.43%</td>
</tr>
<tr>
<td>Pr(Search) Blacks</td>
<td>7.32%</td>
<td>11.47%</td>
<td>0.80%</td>
<td>-0.07%</td>
</tr>
<tr>
<td>No Targeting on Race or Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whites</td>
<td>8.31%</td>
<td>-4.42%</td>
<td>-4.95%</td>
<td>-4.95%</td>
</tr>
<tr>
<td>Pr(Emp</td>
<td>Search) Blacks</td>
<td>14.81%</td>
<td>14.78%</td>
<td>3.07%</td>
</tr>
</tbody>
</table>

workers the minimum wage. Firms are able to partially target their search and we find that firms find it easier to target their search on the basis of race than on the basis of age. The primary reason for unemployment among nineteen year old blacks then comes from the low probability of matching with a firm. In contrast, the main reason for unemployment among seventeen year old whites are match values below the minimum wage.

Removing firm targeting decreases the black-white unemployment gap. In response to the higher employment rates, more blacks search. However, pooling black and white workers leads to higher unemployment for older whites as blacks have on average lower surplus values. This has a reenforcing effect as whites respond to the higher unemployment rates by exiting the labor force.

Our model could easily be extended to examine targeting based on many other observable characteristics, such as gender, education, and age. Possible avenues for future work include relaxing the assumption that workers can not
influence the signal they emit or moving to a more dynamic model where the value of future search would influence the wage setting stage. Future extensions should include older individuals as well where the unemployment differences between blacks and whites are even more stark.

References


