Unbundling the Degree Effect in a Job Training Program for Disadvantaged Youth

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Abstract

Government-sponsored education and training programs have the goal to enhance participants' skills so as to become more employable, productive and dependable citizens and thus alleviate poverty and decrease public dependence. While most of the literature evaluating training programs concentrates on estimating their total average treatment effect, these programs offer a variety of services to participants. Estimating the effect of these components is of importance for the design and the evaluation of labor market programs. In this paper, we employ a recent nonparametric approach to estimate bounds on the "mechanism average treatment effect" to evaluate the causal effect of attaining a high school diploma, General Education Development or vocational certificate within a training program for disadvantaged youth 16-24 (Job Corps) relative to other services offered, on two labor outcomes: employment probability and weekly earnings. We provide these estimates for different demographic groups by race, ethnicity, gender, and two age-risk groups (youth and young adults). Our analysis depicts a positive impact of a degree attainment within the training program on employment probability and weekly earnings for the majority of its participants which in general accounts for $55 - 63$ percent of the effect of the program. The heterogeneity of the key demographic subgroups is documented in the relative importance of a degree attainment and of the other services provided in Job Corps.

1 Introduction

Over the last decades, more and more countries have expressed a rising concern on the widening gap between the skills of their workforce and those of their counterparts in other industrialized countries and United States is not an exception. While undertaking significant measures to reconstruct labor market policies in order to initiate welfare reforms and continue economic expansion, U.S. Government has to cope with persistent unemployment and declines in real income particularly for the less skilled individuals. In an competitive world, education has been characterized as the key.

U.S. for decades has employed Active Labor Market Programs, ALMP, so as to improve the functioning of the labor market by exposing workers with limited skills to employment services, labor market training and subsidized employment (Ashenfelter, 1977; Calmfors, 1994; LaLonde, 1995; Friedlander et al., 1997). In class-instruction and vocational training offered by government-sponsored labor market training programs have been considered the heart of ALMPs. The hope is that enrollment in those programs will enhance participants' skills (such as academic, vocational, and social skills) so as to become more productive and employable citizens and thus increase their future earnings as well as the time spend employed and reduce their social welfare dependence.

Most of the studies evaluating ALMP concentrate on estimating their total average treatment effects (ATE)[1] but in practice most of these programs are a bundle of different services provided to their participants. In this study, we analyze one of the largest U.S. government-sponsored education and training program for disadvantaged youth, namely Job Corps (JC), with respect to its causal effect of attaining a degree relative to other services offered in the program (such as health services, counseling, social skills training and job placement assistance), on the participants' future labor outcomes: weekly earnings and employment probability.

The analysis over this age group is of particular interest, as the sooner those individuals are able to experience higher employment rates and increased earnings the higher will be the returns over their working cycle. To our knowledge few studies conducted in the U.S. concentrate on evaluating training programs aiming at youth and most of those studies have reported discouraging impacts (Orr et al., 1996; Heckman et al., 1999; LaLonde, 2003) but contrary to those studies, JC has been reported to have positive effects for the majority of its participants (Mallar et al., 1982; Schochet et al., 2001). In addition, little has been determined over the heterogeneity of the different racial, ethnic and gender groups those programs attract.

In the mid 1990's, a nation-wide study was conducted in order to evaluate the effectiveness of JC, namely the National Job Corps Study (NJCS), with the asset of the study being the random assignment of eligible applicants into a treatment and control group[2]. NJCS showed statistically significant positive effects of the program with respect

[1] Mallar, 1982; Card and Sulliman,1988; Cave and Doolitle,1991; Heckman et al., 1999; Schochet et al., 2001.

[2] Treated eligible applicants could enroll in the program whereas control eligible applicants were denied

to the outcomes of our interest and in this paper we employ data from this study to ask the question: How much of this estimated ATE is causally explained by the attainment of a credential within the program relative to other services offered for key demographic subgroups by race, ethnicity, gender and two age-risk groups.

The focus of our analysis is on labor market outcomes at quarter 12 after randomization took place, which denotes the end of the embargo period that excluded control members from attending the training program. From the initial data set, we restrict our sample to account for individuals with no missing values with respect to the outcomes of interest (weekly earnings and employment probability), the treatment selection indicator and the mechanism we employ (attainment of a high school diploma, GED or vocational certificate). In our analysis, we have also accounted for sampling weights since the demographic groups were sampled with different weighting rates thus generalizing our analysis to the intended NJCS study population.

We base our inference on a growing strand of literature which emphasizes ATE's decomposition into direct (net average treatment effects, $NATE$) and indirect effects (mechanism average treatment effects, $MATE$) through which the treatment affects the outcome of interest (Cai et al., 2008; Sjölander, 2009; Flores and Flores-Lagunes, 2010a). We use a nonparametric approach [3] and we refrain from point-identification which is typically employed in studies estimating $ATEs$, by deriving bounds for the "mechanism average treatment effect" (attainment of a GED certificate, high school diploma or vocational degree within the training program). We rely on the recent work on partial identification of $MATE$, which rests on a set of weak monotonicity assumptions within or across certain-subpopulations, as presented in Flores and Flores-Lagunes (2010a), hereafter F-FL, within the principal stratification framework, as introduced by Frangakis and Rubin (2002).

Our results highlight the importance of the remedial education and vocational training

access for three consecutive years.

[3]Since the use of parametric evaluation models (e.g. Lalonde, 1986) has received criticism researchers have turned towards non parametric identification of treatment effects thus not relying on functional forms or distributional assumptions (Manski, 1990; Angrist and Imbens, 1991) but still the identification of ATE requires the use of other assumptions such as monotonicity (Manski, 1990; Heckman, 1990; Angrist and Imbens, 1991; Angrist and Pischke, 2010).

offered within the program. Indicatively for the overall population of our study, our estimates suggest that degree attainment has a positive effect on weekly earnings and employment probability which accounts for at most 63 and 55 percent of the estimated positive ATE on the aforementioned labor outcomes, respectively. Our examination of the role of degree attainment across different demographic groups by ethnicity, race and gender indicates a considerable heterogeneity in this estimated causal mechanism effect. Interestingly, when we analyze separately for the two age-risk groups, our estimates suggest that older participants are likely to benefit more from the remedial education and vocational training offered within the program which leads to a degree attainment, as the estimates for ATE and the upper bound of $MATE$ receive the higher values relative to the special-risk group and the overall study population.

In general, our analysis comes in accordance with the education literature suggesting positive effects of schooling and training with respect to individual's future labor outcomes (Card, 1995;1999). It also implies that the causal role of channels offered in the JC other than the degree attainment, such as health services, social skills training and job assistance are important as well in the determination of a person's future employment probability and weekly earnings. Further, our estimates also suggest that the relative importance of the degree obtainment and thus for the other possible mechanisms (services) through which the training program affects future labor market outcomes vary by the subgroups' average initial schooling level and previous labor market experience. All of these findings represent novel estimates that inform policy makers about the effectiveness of different components of the JC.

The remainder of the paper is organized as follows: In section 2, we present information with respect to the training program we examine and describe the data used in our empirical application which come from the NJCS. In Section 3, we describe the econometric framework upon which we are basing our inference as well as the mechanism we are using and the parameters of interest. Section 4, includes the estimates of our study with respect to the different demographic ethnic, racial, gender and age risk groups. Section 5 is dedicated to discussion of our findings.

2 Context of the Study

2.1 Job Corps

Job Corps is a training-program aiming at disadvantaged youth between sixteen and twenty-four years old, established by the Economic Opportunity Act of 1964, operating under the provisions of the Workforce Investment Act of 1998 and administered by the Department of Labor through a national office and nine regional offices. Every year, JC accepts about $60,000$ new participants in its 120 centers located across the U.S.A. with an average $\$14,000$ cost per participant.

Applicants must meet the following criteria in order to be considered eligible for JC: (1) be of age 16 to 24; (2) have registered with the selective service board if aged 18 or older; (3) have parental consent; (4) be a legal U.S. resident; (5) be economically disadvantaged;[4] (6) need additional education, training or job skills; (7) live in a disruptive environment; (8) have a clean health history; (9) be free of serious behavioral problems; (10) have an adequate child care plan and (11) possess the capability and aspirations to benefit from JC.

Job Corps services are delivered in three stages: outreach and admissions (OA), center operations (CO), and placement. Outreach and Admissions are situated in disadvantaged communities and recruit for JC mostly through schools, courts, employment services and welfare agencies. OA counselors are responsible for ensuring that applicants meet the eligibility criteria and informing them with respect to the program.

Center operations take place at 120 Job Corps centers nationwide in both rural and urban areas (110 at the time of the study). The majority of those centers are operated by private contractors and around one-quarter are operated by the U.S. Department of Agriculture and U.S. Department of Interior. CO involve vocational training, academic education, residential living,[5] health care and additional services including counseling,

[4]According to JC a youth is categorized as economically disadvantaged if her/his family is receiving public assistance or the family income is below the poverty level as defined by the Department of Health and Human Services (DHHS). Schochet et al. (2001).

[5]The majority of the Job Corps participants reside at the operating centers while in the program with only around 12 percent being nonresidential students.

social skills training, health education, and recreation.

JC provides an intensive education curriculum which includes academic classroom instruction and vocational skills training. Academic education emphasizes in remedial education (reading, math and writing skills) and in a General Education Development program of high school equivalency. Vocational training may vary by center but typically includes business and clerical, health, culinary arts and cosmetology, construction, and building and apartment maintenance. Average duration of the program is eight months and is characterized by an open-exit educational philosophy where instruction is individualized and self-paced. Typically, an individual is considered a graduate if she has completed 60 or more calendar days of enrollment and has completed the requirements of Career Technical Training (CTT), or earned a High School Diploma (HSD) or its equivalent GED or who completes both, while enrolled in Job Corps.

Lastly, placement agencies help participants find jobs in training related occupations by providing assistance with resume writing and interviewing as well as services for job placement and referral. Usually placement activities are performed by state employment offices, private contractors and sometimes by the operational centers. Moreover, placement agencies are responsible with the task of distributing the stipend students receive after leaving JC.

2.2 National Job Corps Study

In 1993 the National Job Corps Study, funded by the U.S. Department of Labor and conducted by Mathematica Policy Research, Inc. (MPR) was designed to address the effectiveness of the program. NJCS is the first nationally representative experimental evaluation of a government-sponsored education and training program for disadvantaged youth (Schochet et al., 2008) relative to previous evaluations of similar programs conducted at selected areas (LaLonde, 1995). Sample intake occurred between November 1994 and February 1996 and applications were reviewed for eligibility by JC's outreach and admissions agencies according to specific criteria.[6]

[6]Groups excluded from the study: (i) youths who previously participated in JC; (ii) people who applied to one of seven small, special JC programs whose eligibility criteria or services differed from those in the regular JC program; (iii) for cost reasons, applicants from four OA agencies in Alaska,

The asset of the study was the random assignment of the total eligible pool of applicants ($N = 80,883$), into a control group ($N = 5,977$) and a treatment group ($N = 9,409$); the remaining youth were randomly assigned to a program non research group (Schochet et al., 2001). Individuals assigned to the treatment group were eligible to enroll in JC while individuals assigned to the control group were denied access to the program for three years (they were eligible though to apply to other training or educational programs). At the time the study was conducted, MPR randomly assigned youths in treatment and control group and notified the OA counselors. OA agencies assigned individuals to a center within a month's period and the individuals who enrolled in the centers did so within one to four weeks after assignment.

Randomization occurred after the youths were determined as eligible to participate in the training program and not after they enrolled in the operation centers thus the treatment group includes both youths that enrolled in the training program (about 73%) and those that did not enroll but were admitted. Non-compliance with the treatment assignment was observed also for the control group. In fact around 1.4% of individuals assigned to the control group did participate in the program prior to the end of the three-year embargo period.[7] Following randomization, a baseline interview was conducted for both groups and follow-up interviews took place at three subsequent time periods: 12, 30 and 48-months.[8]

The NJCS is based on a differences-in-means estimator accounting for non-compliance: individuals in the control group that enrolled prior the end of the embargo period and individuals admitted in the JC but never enrolled (Schochet et al.,2001). The study was reported not to have an effect on the program operations, which suggests that NJCS evaluated the training program as it would have normally operated had no study being conducted at that time. Moreover, no evidence has been documented suggesting that

Hawaii, Puerto Rico, and the Virgin Islands that recruit about 3% of JC participants. Source: Schochet et al., 2001; Schochet et al.,2008.

[7]About 30% of crossovers occured before random assignment and 70% after random assignment and is attributed to staff errors, Schochet et al. (2001); Schochet et al.,(2008).

[8]The response rates were fairly high and similar for the two program groups. Specifically, the response rate was 95% to the baseline interview and 90%,79% and 80% to the 12,30 and 48-month follow-up intreviews, respectively. Source: Schochet et al., 2001.

the study had an adverse effect on the behavior and the labor outcomes of individuals assigned to the control group, as many control agents participated in other education and training programs or were employed shortly after being rejected (Schochet et al.,2008).

Schochet et al. (2001), documented statistically significant positive effects of JC at the beginning of the third year (quarter 12) which persisted through the end of the 48-month follow up period (quarter 16)[9]. Specifically, they reported that JC generated positive earning impacts around \$24.5 and \$25.2, on weekly earnings 12 quarters and 16 quarters after randomization respectively and around 4.4% and 3.3%, on employment probability for quarters 12 and 16 respectively. These effects represent the average effects for the individuals that comply with their treatment and control assignment, indicating the effects of JC relative to other education and training programs.

The study also reported impacts of the program on the earnings and employment rate for different key subgroups. Positive earnings impacts were found for groups of participants at special risk for poor outcomes (such as very young students, females with children and youths arrested for minor criminal offenses) and also for groups at lower risk (older participants with a high school credential). Moreover, earning gains were similar for both sexes, whites and African Americans, and for students residing in JC centers and nonresidential designees. Contrary to those positive effects, NJCS reported no earning gains for Hispanic students and for participants 18 and 19 years old (Schochet et al., 2001; Schochet et al., 2008).

Apart from the labor outcomes (employment rates and earnings) the study focused on analysisng the impact of the training program on education (high school diploma and GED) and training outcomes (vocational degree). According to Schochet et al. (2001), JC serves primaly youths with no high school credential and it is reported that around 80% of the participants do not have a high school diploma or GED credential prior entering the program. Emphasizing on remedial education and vocational training, NJCS reported notable differences between the program control and treatment groups with respect to their participation in further education and the number of certificates awarded.

Nearly 93% of the treatment group engaged in education or training compared to

[9]Prior to the end of the embargo period labor outcomes for the control group were larger than those of the treatment group and that is attributed to the participation of the latter to the training program.

72% of the control group. As mentioned earlier, embargo from JC did not imply embargo from other training or educational programs. From the 72% of the control group which sought training, 37% participated in GED programs, 32% attended high school and 29% enrolled in vocational or technical schools. On average, JC participants received 998 hours of education which corresponds to roughly one school year versus 853 hours of schooling for the control group, which is equivalent to roughly three-quarters of an academic year. Moreover, the participants in the program received around three times more vocational training than the members of the control group.

JC had also an effect on the number of certificates its participants obtained in the 48-month period. Around 46% of the treatment group participants without a high school credential obtained a degree within the completion of the program in contrast to only 27% of the control group members. In addition, 45% of the JC treatment group participants reported receiving a vocational degree compared to around 15% of the control group participants.

2.3 Data and Descriptive Statistics

We obtain our data from the NJCS and we focus our analysis on quarter 12 after randomization, which corresponds to the time period that the embargo from the training program for the control group ended. As we have already mentioned, the purpose of our study is to estimate the causal effect of attaining a degree within JC on the future labor outcomes. For that reason we constructed a binary "mechanism" variable which corresponds to whether an individual attained a high school, GED or vocational certificate. For the analysis that follows our **study** sample consists of individuals with no missing values on key baseline variables − such as age −(we lose $n = 5587$ observations), with no missing values on the outcomes of interest (we lose $n = 307$ observations) and lastly with no missing values on the degree attainment indicator (we lose $n = 1472$ observations). In the end, our study's overall sample consists of 8020 individuals with $N_T = 5,045$ people assigned to the treatment and $N_C = 2,975$ people assigned to the control group, respectively.

Decomposing our overall sample into ethnic and race subgroups we have that whites account for 24% with 1253 (712) being at the treatment (control) group, African Americans account for 50% of the sample with 2564 (1507) being in the treatment (control) group and Hispanics represent 18% of the sample where 871 (551) of them were assigned to the treatment (control) group respectively. With respect to gender we have 42% of the population being females where 2296 (1105) belong to the treatment (control) group and the rest being males where 2749 (1870) were assigned to the treatment (control) group respectively. Importantly, in our youth-group we observe the majority of our sample 78%, 3886 treated and 2409 control individuals.

Sampling into control and treatment groups differed for some population subgroups for both programmatic and research reasons mainly with respect to the sample design, the survey design and interview nonresponse and the selection of states to the Unemployment Insurance sample and nonresponse to the records release form (Schochet et al.,2003). For example, they report incidences where OA agencies experienced difficulties in recruiting females for residential slots thus, sampling rates to the control group were set lower for females in areas from which high concentrations of residential students come. Controlling for design weights, the impact estimates can be generalized to the intended study population.[10] All the descriptive statistics presented below have been computed by controlling for the design weights used in the NJC study.

In the following subsection, based on the public release data of NJCS, we provide descriptive statistics for the NJCS data set, our sample decompositions and also comment on differences with respect to educational attainment prior entering the program. In addition, we provide estimates with respect to labor market outcomes 12 and 16 quarters after randomization as well as estimates for the attainment of a high school diploma, GED or vocational degree.

$Description\ of\ summary\ statistics_{sample15386}$ (baseline interview):

Table A: Individuals in the two program groups (treatment and control) do not vary significantly with respect to their characteristics with the exception of the guilt indicator. Their average age is around 18 to 19 years old, not married (around 94%), they do not

[10] According to the documentation for NJCS: applicants in the 48 contiguous states and the District of Columbia who applied to Job Corps during the 13-month period between November 17, 1994, and December 16, 1995, and who were determined to be eligible for the program.

have a child (only around 18% have a child) and are not considered head of the household (89%). Around 46% reside in metropolitan statistical areas and around 32% in primary metropolitan statistical areas. The majority of the eligible participants do not have a high school diploma or GED at the baseline interview (less than 25% does) or a vocational degree (around 2%), whereas those considering English as their first language account for (86%) and a percentage of around $13-14$ has being convicted for minor offenses. Prior to application to the program, most of the eligible applicants were unemployed (around 58%) and those that were employed received on average roughly $110 per week.

What is important with respect to our research is that the majority of the individuals in both groups do not have a secondary education credential (high school diploma or GED) when applying to the training program. That is anticipated, as JC attracts people without a high school diploma or GED and one of the eligibility criterion is the need for further education and vocational training. Schochet et al. (2001), have commented on the extensive education participants of the program receive relative to other remedial education programs that people in the control group may attend. According to that, we expect people attending the program to have a higher probability of receiving an education credential by exiting the program and that is depicted in our data as 65 out of 100 in the treatment relative to 44 out of 100 in the control group obtained a vocational, high school or GED certificate.

By decomposing our sample by demographic groups with respect to ethnicity and race (Table B) we are able to identify the heterogeneity of the individuals belonging to those groups. Hispanic eligible applicants are more likely to be married, live in primary metropolitan statistical areas and not have English are the first language. White applicants are more likely to be males, have a higher percentage of employment and higher weekly earnings but at the same time is the group that has the highest unemployment rate and are the less likely to reside in a primary metropolitan statistical area. Black participants are more likely to be head of the household and have a child and with respect to labor outcomes they are the ones that face the lowest percentage of employment and the lower weekly earnings.

Control and treatment groups vary with respect to some baseline characteristics in the ethnic and racial groups. For the white subgroup, the difference between control and treatment group with respect to having a child and baseweek earnings is significant at the 5% level whereas the two groups differ at the 10% level with respect to residing in a primary metropolitan statistical area and the guilt indicator. Hispanics, do depict a significant difference at the 5% level with respect to whether they reside in a (primary) metropolitan statistical area and at the 1% level with respect to unemployment indicator.

Furthermore, statistically significant at the 1% level is the difference between the number of high school, GED or vocational degrees awarded to the treatment relative to the control group. For whites: 71(49) out of 100 for treatment (control) group, for blacks: 62(42) out of a 100 for the treatment (control) group and lastly for Hispanics: 65(44) out of 100 for treatment (control) group respectivelly. The Hispanics is the only group that does not have a significant difference with respect to the employment probability and weekly earnings outcome for quarter 12 and quarter 16 after randomization. That can be indicative of the program not having an impact on the future labor market outcomes for that key subgroup. Whites and black participants do seem to benefit by participating in the program as the impacts are significant in the 3rd and 4th year after randomization.

When it comes to gender classification (Table C): Females are more likely to be married, be head of the household, have a child and an education credential and/or a vocational degree prior applying for entering the program. On the other hand, male eligible participants have a higher likelihood to be found guilty of a minor offense and are more likely to be employed and receive higher weekly earnings. The women participants are reported to have a significant difference (5%) with respect to whether they had a secondary education credential or equivalent prior applying to the JC. Both genders have significant positive gains 12 and 16 quarters after randomization with respect to labor outcomes and consistent with the previous comment, treatment and control groups differ at a 1% level when it comes to the attainment of an educational credential when applying to JC.

We take our analysis one step further by differentiating between two age /education level categories: special-risk and low-risk of having poor labor outcomes. In the special-risk group which we will refer to as the youth group, we have accounted for eligible participants less than 20 years old. The second group we investigate is the one of low-risk for poor outcomes which we will refer to as young adults, consists of participants 20 to

24 years old.

Many of the differences across those two risk groups are actually expected (Tables D through I). Older students report higher employment rates and weekly earnings though at the same time they face higher unemployment rates. They also are more likely to be married and have children when applied for admission to JC. Younger applicants are less likely to have a high school, GED or vocational credential prior entering the training program but they are characterized by higher rates of criminal behavior. Those facts suggest that younger applicants are more liable to difficult economic conditions and are harder to serve than older individuals.

The data depict a significant positive impact of participating in the training program for both age-risk subgroups with respect to their labor outcomes (mean weekly earnings and mean employment probability) 12 and 16 quarters after randomization. In addition in the study period, 63(43) out of 100 people in the treatment(control) in the youth group and 72(48) out of 100 people in the young adults group obtained an education or a vocational degree, with those differences being significant at the 1% level.

By further decomposing the two age-risk groups into ethnic and race subgroups we observe that for the youth, white participants differ significantly at the 5% level from the control individuals with respect to previous weekly earnings; black at the 10% level with respect to the primary metropolitan statistical area indicator and Hispanics at the 10% level with respect to the metropolitan statistical area indicator. Black participants show significant differences with respect to future labor outcomes for quarters 12 and 16 after randomization. Estimates depict only a 5% difference in earnings at quarter 16 for white participants but again Hispanics participants do not experience a significant impact. With respect to the degree attainment indicator, control and treatment groups for all racial, ethnic and gender groups differ at the 1% level. Further, at this age-risk group, men are the ones that experience a significant positive impact for the weekly earnings at quarter 12 after randomization whereas for women, even though there is reported a positive impact it is actually insignificant.

For the young adults key subgroup we have that whites in the treatment group differ from the control in the female, child, PMSA and language indicator; blacks differ at the guilt and Hispanics at the age, PMSA and unemployment indicator. Females differ with respect to the guilt and degree attainment indicator prior applying to JC and men with respect to the child and marriage indicator. All treatment subgroups have a significant positive difference when it comes to the certificates earned indicator and also positive and significant impacts are reported for the whites, black and the two gender groups for the earnings outcomes in quarters 12 and 16 after randomization. Hispanics are reported to have a negative and significant at the 10% level difference in the mean weekly earnings outcome at quarter 12 after randomization but the negative difference is insignificant with respect to the other labor outcomes.

Concluding this section we would like to address the issue of non-compliance with respect to the treatment assignment. Because of non-compliance with the treatment assignment, 27% of the people assigned in the treatment group did not participate in the program whereas 1.4% assigned in the control group did participate in the program, thus the ATE should be interpreted as average "intent-to-treat"' effects, (ITT). For simplicity, we will refer to this effect as the ATE of the program on the outcome and to the treatment assignment as participation in JC.

3 Econometrics Framework and Parameters of interest

We want to identify and estimate the effect of participation in JC, T (treatment), on the participants' labor outcomes, Y (employment probability and weekly earnings) that works through the exposition to remedial education and vocational training that led to the attainment of a high school diploma, GED or vocational certificate by the completion of the training program , S (referred to as the degree attainment indicator, mechanism or channel). We have a random sample of size n originating from a large population. For each unit $i \in n$, we assign a treatment indicator $T_i \in \{0,1\}$ where $T_i = 0$ represents that the individual i is assigned to the control group thus denied access to the training program and $T_i = 1$ is assigned to the treatment group, hence being able to enroll in JC.

Since the degree attainment is affected by participation in the program, we denote its potential values as $S_i(\tau)$ where $\tau \in \{0,1\}$, so the value $S_i(1)$ is indicative of the potential value of the degree indicator for an individual i participating in the training program otherwise the potential value of the degree indicator would be $S_i(0)$. We also define a binary degree attainment indicator, thus $\{S_i(1), S_i(0)\}$ can take values $\{s_1 = \{0,1\}, s_0 = \{0,1\}\}$ We define the "composite" potential outcome $Y_i(\tau, m)$ where τ corresponds to one of the treatment values ($\tau \in \{0,1\}$) and m refers to one of the potential values of the mechanism variable ($m \in \{S_i(1), S_i(0)\}$).

For every individual we observe the vector (T_i, S_i, Y_i) with the potential outcome value given by $Y_i \equiv T_i Y_i(1) + (1 - T_i) Y_i(0)$ and the potential degree attainment indicator value given by $S_i = T_i S_i(1) + (1 - T_i) S_i(0)$. Under that format we define the following potential outcomes:

$Y_i(1, S_i(1)) \equiv Y_i(1)$ represents the potential outcome individual i would receive if were exposed to the treatment and the mechanism variable was not blocked. It refers to the potential outcomes' value (weekly earnings, employment probability) of a person assigned to participate in JC ($T = 1$) with the potential value of either a high school diploma, a vocational degree or a GED certificate within the program given by $\{s_1 = \{0,1\}\}$.

$Y_i(0, S_i(0)) \equiv Y_i(0)$ represents the potential outcome individual i would receive if were not exposed to the treatment and the mechanism variable was blocked at $S_i(0)$. It will be indicative of the potential outcome's value (either weekly earnings or employment probability) of an individual denied enrollment in JC ($T = 0$) with a degree attainment potential value of $s_0 \in \{0,1\}$.

$Y_i(0, S_i(1))$ represents the potential outcome individual i would receive if were not exposed to the treatment but received a value of the post-treatment variable equal to $S_i(1)$. This potential outcome would refer to individuals that were denied access to the program but the value of the mechanism is held to what would have been observed had they been assigned to participate in JC (i.e. s_1).

$Y_i(1, S_i(0))$ represents the potential outcome individual i would receive if were exposed to the treatment and the channel variable was blocked at the value $S_i(0)$. This potential outcome would refer to an individual assigned to enroll in JC but the value of the mechanism is held to what would have been observed had they not been assigned to participate in JC (i.e. s_0).

Following the program evaluation literature, for each individual we define the average treatment effect which is given by $ATE_i = E[Y_i(1) - Y_i(0)]$. We proceed by making the following assumptions:[11] first, that for a specific unit the assignment to a treatment arm is not affected by another unit's treatment assignment, i.e. neither $Y_i(1)$ nor $Y_i(0)$ is affected by what treatment assignment any other individual received. Second, for a specific individual, assignment to a treatment status is not affected by the method used to assign that treatment status to another individual. In our context, if individual i was assigned to the treatment group the potential outcome would be of the form $Y_i(1, S_i(\cdot))$ and likewise for individual j the potential outcome would be of the form $Y_j(1, S_i(\cdot))$.[12]

Taking the above into consideration we decompose the population average treatment effect $ATE = E[Y(1) - Y(0)]$ using the potential outcome $Y(1, S(0))$ that includes the effect of T on Y which is not affected by the mechanism S (Robins and Greenland,1992; Pearl, 2001):

$$ATE = E[Y(1) - Y(1, S(0))] + E[Y(1, S(0)) - Y(0)]. \tag{3.1}$$

We define the (causal) net average treatment effect, $NATE$ as

$$NATE = E[Y(1, S(0)) - Y(0)] \tag{3.2}$$

and the (causal) mechanism average treatment effect, $MATE$ as

$$MATE = E[Y(1) - Y(1, S(0))]. \tag{3.3}$$

$NATE$ captures the effect of the treatment on the outcome when the mechanism is held constant at a level $S(0)$. Intuitively, it could be considered as the difference between a potential outcome $Y(1, S(0))$ in which the individual is assigned to a treatment equivalent to the original one but the effect of the treatment on the mechanism is blocked by holding $S = S(0)$. Then, the net treatment effect for individual i is the difference between the outcome of this alternative treatment, Y (1, S(0)), and Y(0) from the original control treatment.

In our context, $NATE$ would capture the difference of the effect of the training program through its various services but the remedial education and vocational training

[11] Those assumptions are widely used in the literature and are known under the term stable unit treatment value assumptions (SUTVA), Rubin (1980).

[12] For simplification we will not use a subscript in what follows.

component that led to the attainment of a degree, on the participants' labor outcomes. When all the effect of the treatment on the outcome works through the mechanism, $NATE = 0$ whereas $NATE = ATE$ when none of the effect works through the mechanism either because T does not affect S (participating in JC does not affect whether you attain a high school, GED or vocational degree) or S does not affect Y (attainment of a degree does not affect labor outcomes).

$MATE$ captures the effect of a change in the mechanism S on the outcome Y which is due to the treatment T. All the ways a treatment may affect an outcome are held constant since $Y(1, S(0))$ captures that effect. For example, in the experimental setting we are examining, all the services that are provided in JC apart from the degree effect are captured by $Y(1, S(0))$. When all the effect of the treatment on the outcome works through the mechanism, then $MATE = ATE$.

$MATE = 0$ in two cases: (i) when $S(1) = S(0) = s$, that is S has the same value for all the cases, thus participation in JC (treatment) does not affect the degree attainment indicator and (ii) when the mechanism does not affect the outcome, thus $\{S(0), S(1)\}$ is independent of $\{Y(1), Y(0)\}$, meaning whether you acquired a degree certicate or not either from participating in JC or not your future earnings or employment probability remains unaffected.[13]

The strand of literature that focuses on point identification and estimation of net and mechanism average treatment effects relies on typically strong assumptions that may not hold in several economic applications. Most common are the unconfoundedness assumptions requiring the treatment and the mechanism to be random or exogenous conditional on covariates, functional or distributional forms for the outcomes with a bounded support , or constant treatment effects assumptions (Robins and Greenland, 1992; Petersen et al.,2006; Flores and Flores-Lagunes, 2009; Lechner and Melly, 2010; Imai et al., 2010).

In the context of our empirical application, even in the simplified setting of random

[13]The above parameters have been introduced in slightly different names in the literature. $NATE$ and $MATE$ are also known as the (average) pure direct and indirect effects (Robins and Greenland, 1992; Robins, 2003) or as the (average) natural direct and indirect effect (Pearl, 2001). $MATE$ is also referred to as the average mediation effect (Imai et al., 2010).

assignment into treatment, we face limitations in point identifying the parameters as there is no random selection with respect to whether the individual will be exposed to remedial education and/or vocational training and thus earning a degree. As we have mentioned in a previous section, additional training occurs at the individual level so there is no specific norm that all participants have to follow once entering the training program. Moreover, the individual selects in which field to receive vocational training which implies that we do not have random assignment of the mechanism values. Thus units with different values of the mechanism are not comparable and the simple difference of potential outcomes does not yield a causal effect.

Due to the difficulty in point estimating net and mechanism average treatment effects a large literature concentrates in deriving non-parametric bounds. Kaufman et al. (2005) and Cai et al. (2008) derive non-parametric bounds for net average treatment effects (direct effects) under monotonicity and no-interaction assumptions. The latter paper extends Kaufman et al. (2005) by employing a linear programming technique in a randomized-binary setting (treatment T - intervention Z - outcome Y) in order to estimate the average controlled direct effect (ACDE) of a treatment on an outcome, in the presence of unmeasured confounders between an intermediate variable and the outcome. Sj$\ddot{o}$lander (2009), assuming a framework equivalent to the one introduced in Cai et al., extends their analysis by estimating bounds of the natural direct effect (NDE) under the premises: (a) randomization of X, (b) a set of monotonicity assumptions, and (c) no-interaction assumptions. Flores and Flores-Lagunes (2010a), use a binary setting for the treatment, the mechanism and the outcome and employ a non-parametric estimation technique to identify net and mechanism average treatment effects (NATE and MATE, respectively). They assume randomization of the treatment and introduce a set of weak assumptions, such as weak monotonicity of different potential outcomes within or across given sub-populations. They also allow for heterogeneous effects and they do not require an outcome with a bounded support.

In the subsequent section we estimate our bounds for the mechanism average treatment effect,$MATE$, by employing the results introduced by Flores and Flores-Lagunes (2010a).

3.1 Nonparametric Partial Identification of $MATE$

In order to evaluate and causally interpret $MATE$ with respect to JC, we employ the principal stratification setting introduced by Frangakis and Rubin (2002). In the context of our application where assuming a binary treatment T and degree attainment indicator S, we can conceptually partition individuals into groups where, within each group, all individuals have the same value vector of degree attainment indicator $\{S(0) = s_0, S(1) = s_1\}$ with $s_0, s_1 \in \{0, 1\}$.

We can define four principal strata: $\{S_i(0) = 0, S_i(1) = 0\}$, $\{S_i(0) = 0, S_i(1) = 1\}$, $\{S_i(0) = 1, S_i(1) = 0\}$, $\{S_i(0) = 1, S_i(1) = 1\}$. These strata define the following categories of individuals: the not affected at 0 ($n0$), the affected positively (ap), the affected negatively (an) and the not-affected at 1 ($n1$) respectively. For an individual in the stratum ($n0$), for example, the degree attainment indicator takes the value 0 irrespectively of the treatment assignment, so even if the individual participated in JC or not she did not receive a credential.

Affected positively are considered the agents that benefited from undertaking additional education and/or vocational training within the program and received a high school diploma, GED or vocational credential by the completion of the program whereas if being assigned to the control group would not receive any secondary education equivalent or vocational degree. The affected negatively strata consists of people that if able to attend JC would not receive a credential by the completion of the program whereas if assigned to the control group would receive a credential. Lastly, individuals in the not-affected at 1 strata are those that would always be able to acquire a degree whether they enrolled in JC or assigned to the control group.

Unfortunately, we are unable to observe directly the four possible principal strata but only treatment and degree attainment indicators for each individual and that leads to the observation of a mix of strata unless we impose some assumptions. To be more specific, for each individual we observe a value for the treatment variable (T_i) and a value for the mechanism variable (S_i^{obs}) but we cannot distinguish in which stratum an individual with $\{T_i = 1, S_i^{obs} = 0\}$ belongs to. The possible combinations of the treatment and the mechanism in the format of principal stratification are presented in the following table.

Table 1: Principal Strata

		T_i	
		0	1
S_i^{obs}	0	ap, $n0$	$an, n0$
	1	$n1, an$	$n1, ap$

3.1.1 Basic Assumptions and Bounds on $E[Y(0)|ap]$ and $E[Y(1)|ap]$

The approach we follow in this subsection is close to the one presented in Lee (2009). The two assumptions below have been used in several articles in the net and direct effect literature strand for deriving bounds on $NATE$ (Sjȯlander, 2009; Flores and Flores-Lagunes, 2009; Flores and Flores-Lagunes, 2010a), on other direct effects (Kaufman et al., 2005; Cai et al., 2008) and on deriving bounds on mechanism effects (Flores and Flores-Lagunes, 2010a).

Fist we assume that treatment is randomly assigned which implies that treatment received by each individual is independent of her potential values of the mechanism variable and her potential outcomes:

Assumption A 1 (*Random Treatment Assignment*)

$$Y(1), Y(0), Y(1, S(0)), S(1), S(0) \perp T$$

Assumption $A1$ allows point identification of $E[Y(1)]$, $E[Y(0)]$, $E[S(1)]$, and $E[S(0)]$ thus allowing for point identification of ATE but not of $MATE$ since we cannot point identify $E[Y(1, S(0))]$.

We proceed by employing an assumption used in several studies that deal with estimation and identification of average treatment effects (Imbens and Angrist, 1994; Cai et al., 2008; Sjölander, 2009; Lee, 2009; Lechner and Melly, 2010; Flores and Flores-Lagunes,2009; 2010a) at the individual-level which will allows us to identify certain principal strata, the monotonicity assumption.

Assumption A 2 (*Individual-Level Monotonicity of T on S*)

$$S_i(1) \geq S_i(0), \forall i$$

Assumption $A2$ implies that participating in JC (treatment effect) has a non-negative effect on obtaining a certificate at the individual-level. That would imply that there are no individuals who would obtain a certificate if they did not participate in JC and would not if they participate. Knowing that JC facilitates the attainment of a GED or/and vocational certificate, this assumption is plausible.

Referring to Table 1, we have that individuals in the ($n0$) would never obtain a degree whether they participate in JC or not, ($n1$) would always obtain a degree, and individuals in (ap) are likely to attain a degree if they participate in the training program (JC) but would not otherwise. By employing the monotonicity assumption, stratum (an) is ruled out and units belonging to strata ($n0$) and ($n1$) can be identified.

To be more specific, units belonging to the stratum ($n0$) are the ones that received treatment and are characterized by $(T_i, S_i^{obs}) = (1, 0)$ thus $E[Y(1)|n0] = E[Y|T = 1, S^{obs} = 0]$ and units belonging to the stratum ($n1$) are the ones that did not receive treatment and are characterized by $(T_i, S_i^{obs}) = (0, 1)$ thus $E[Y(0)|n1] = E[Y|T = 0, S^{obs} = 1]$. The individuals that belong to $\{T = 0, S^{obs} = 0\}$ ($\{T = 1, S^{obs} = 1\}$) are a mix of the strata (ap) and ($n0$) or ($n1$) respectively.

Using assumptions A1 and A2 we can point identify the proportions of each strata as π_{an}, π_{n0}, π_{ap} and π_{n1}. Specifically, $\pi_{an} = 0$, $\pi_{n0} = Pr(S_i = 0|T_i = 1) = p_{0|1}$, $\pi_{n1} = Pr(S_i = 1|T_i = 0) = p_{1|0}$, and $\pi_{ap} = Pr(S_i = 1|T_i = 1) - Pr(S_i = 1|T_i = 0) = Pr(S_i = 0|T_i = 0) - Pr(S_i = 0|T_i = 1)$ thus $\pi_{ap} = p_{1|1} - p_{1|0} = p_{0|0} - p_{0|1}$ and we employ them in depicting average outcomes for the mixed strata:

$$E[Y^{obs}|T = 0, S^{obs} = 0] = \frac{\pi_{n0}}{\pi_{n0} + \pi_{ap}} E[Y(0)|n0] + \frac{\pi_{ap}}{\pi_{n0} + \pi_{ap}} E[Y(0)|ap] \tag{3.4}$$

$$E[Y^{obs}|T = 1, S^{obs} = 1] = \frac{\pi_{n1}}{\pi_{n1} + \pi_{ap}} E[Y(1)|n1] + \frac{\pi_{ap}}{\pi_{n1} + \pi_{ap}} E[Y(1)|ap] \tag{3.5}$$

Therefore $E[Y(0)|n0]$ can be bounded from above by the expected value of Y for the $\frac{\pi_{n0}}{\pi_{n0}+\pi_{ap}}$ fraction of the largest values of Y for those in the observed group with $T = 0$ and

$S^{obs} = 0$. It can also be bounded from below by the expected value of Y for the $\frac{\pi_{n0}}{\pi_{n0}+\pi_{ap}}$ fraction of smallest values of Y for those in the same observed group.

Likewise, $E[Y(1)|n1]$ can be bounded from above by the expected value of Y for the $\frac{\pi_{n1}}{\pi_{n1}+\pi_{ap}}$ fraction of the largest values of Y for those in the observed group with $T = 1$ and $S^{obs} = 1$. It can also be bounded from below by the expected value of Y for the $\frac{\pi_{n1}}{\pi_{n1}+\pi_{ap}}$ fraction of smallest values of Y for those in the same observed group.

Using the above conditions we can define bounds for the $E[Y(0)|ap]$ and $E[Y(1)|ap]$ parameters. Let y_r^{ts} be the r-th quantile of Y conditional on $T = t$ and $S = s$ with $F.(\bullet)$ the conditional density on $T = t$ and $S = s$ then we have that:

Proposition 3.1 *(Flores and Flores-Lagunes, 2010a) If Assumptions A1 and A2 hold then,* $L^{0,ap} \leq E[Y(0)|ap] \leq U^{0,ap}$ *and* $L^{1,ap} \leq E[Y(1)|ap] \leq U^{1,ap}$ *where:*

$$\begin{aligned}
L^{n0} &= E[Y|T=1,S=0] - U^{0,n0} \\
U^{n0} &= E[Y|T=1,S=0] - L^{0,n0} \\
L^{0,n0} &= E[Y|T=0,S=0,Y \leq y^{00}_{(p_{0|1}/p_{0|0})}] \\
U^{0,n0} &= E[Y|T=0,S=0,Y \geq y^{00}_{1-(p_{0|1}/p_{0|0})}] \\
L^{n1} &= L^{1,n1} - E[Y|T=0,S=1] \\
U^{n1} &= U^{1,n1} - E[Y|T=0,S=1] \\
L^{1,n1} &= E[Y|T=1,S=1,Y \leq y^{11}_{(p_{1|0}/p_{1|1})}] \\
U^{1,n1} &= E[Y|T=1,S=1,Y \geq y^{11}_{1-(p_{1|0}/p_{1|1})}] \\
L^{0,ap} &= E[Y|T=0,S=0,Y \leq y^{00}_{1-(p_{0|1}/p_{0|0})}] \\
U^{0,ap} &= E[Y|T=0,S=0,Y \geq y^{00}_{(p_{0|1}/p_{0|0})}] \\
L^{1,ap} &= E[Y|T=1,S=1,Y \leq y^{11}_{1-(p_{1|0}/p_{1|1})}] \\
U^{1,ap} &= E[Y|T=1,S=1,Y \geq y^{11}_{(p_{1|0}/p_{1|1})}]
\end{aligned}$$

3.1.2 Weak Monotonicity of Potential Outcomes within Strata

As we have already seen, we define $MATE = E[Y(1) - Y(1, S(0))]$. Using the decomposition of the overall population in strata we can define locally $MATE$ for each stratum:

$$LMATE_k = E[Y(1)|k] - E[Y(1, S(0))|k], fork = (n0), (n1), (ap) \tag{3.6}$$

Note that the local mechanism average treatment effect for stratum $(n0)$ and $(n1)$ has a value equal to zero as the treatment does not affect the mechanism for the individuals in those populations ($LMATE_{n0} = 0$ and $LMATE_{n1} = 0$) thus we can define $LMATE$ only for the affected positively individuals. $MATE$ is given by: $MATE = \pi_{ap} LMATE_{ap}$

From equation (4.1) we have that the parameter $E[Y(1, S(0))]$ is not identified from the data but under assumptions $A1$ and $A2$ we can express that parameter through the various strata:

$$E[Y(1, S(0))] = \pi_{n0} E[Y(1)|n0] + \pi_{n1} E[Y(1)|n1] + \pi_{ap} E[Y(1, S(0))|ap]. \tag{3.7}$$

In order to partially identify $E[Y(1,S(0))|ap]$ we employ weak mean inequalities at the principal strata level. We consider assumptions analogous to the ones in Sjölander (2009) where he assumes that i) $Y_i(1,s) \geq Y_i(0,s)$ for all i and ii) $Y_i(t,1) \geq Y_i(t,0)$ for all i and t. These assumptions imply that net and mechanism treatment effects are non-negative for all individuals in the strata. For the $(n0)$ stratum where the mechanism takes the value $S^{obs} = 0$ we have that $Y(0) = Y(0,0)$ and $Y(1) = Y(1,S(0)) = Y(1,0)$, for the $(n1)$ stratum where the mechanism takes the value $S^{obs} = 1$ we have that $Y(0) = Y(0,1)$ and $Y(1) = Y(1,S(0)) = Y(1,1)$. Lastly for the (ap) stratum we will have that $Y(0) = Y(0,0)$, $Y(1) = Y(1,1)$ and $Y(1,S(0)) = Y(1,0)$.

We relax the assumptions in Sjölander (2009) by not requiring monotonicity at the individual level but within the strata. Specifically we assume the following: i) the mean value of the potential outcome of interest for a person, in the affected positively stratum, who participated in JC and attained a degree within the program, is expected to be larger or equal to the mean value of the potential outcome of interest for an individual in the same stratum, who participated in the training program but the mechanism took the value equal to the one had she not participated in the program and ii) the mean value of the potential outcome of interest for a person, in any stratum, who participated in JC but the mechanism took the value had she not participated in the program, is greater or equal to the mean value of the potential outcome for an individual who had not participated in the program. The above are formalized in the assumption below:

Assumption B 1 *(Weak Monotonicity of Mean Potential Outcomes Within Strata)*
1. $E[Y(1,S(1))|ap] \geq E[Y(1,S(0))|ap]$, 2. $E[Y(1,S(0))|k] \geq E[Y(0)|k]$, *for* $k = n0, n1, ap$

Assumption B provides a lower and an upper bound for $E[Y(1,S(0))|ap]$. Particularly, assumption $B1.$ implies that $LMATE_{ap} \geq 0$ thus $MATE \geq 0$ whereas combining assumptions $A2.$ and $B1.$ we can infer that attainment of a high school, GED or vocational degree has a non-negative impact on potential employment and earnings. Assumption $B2.$ provides a lower bound for $MATE$ equal with zero and implies that other mechanisms (such as job-assistance and social skills training) have a non-negative effect on labor outcomes. Since JC is a program that provides a bundle of services aiming at improving future labor outcomes, we believe that this assumption is likely to be satisfied.

The implications of the above assumptions with respect to bounds are presented in the proposition below:

Proposition 3.2 *(Flores and Flores-Lagunes, 2010a) If assumptions $A1, A2$ and B hold then,* $0 \leq LMATE_{ap} \leq (U^{1,ap} - L^{0,ap})$ *and* $0 \leq MATE \leq (E[Y|T=1] - E[Y|T=0] - max(L_1, L_2, L_3, L_4))$ *where:*

$$\begin{aligned} L_1 &= E[Y|T=1] - p_{0|1} min\{E[Y|T=1, S=0], U^{0,n0}\} \\ &- p_{1|0} E[Y|T=0, S=1] - (p_{1|1} - p_{1|0}) U^{1,ap} \\ L_2 &= p_{1|0} max\{E[Y|T=0, S=1], L^{1,n1}\} + p_{0|1} E[Y|T=1, S=0] \\ &+ (p_{1|1} - p_{1|0}) L^{0,ap} - E[Y|T=0] \\ L_3 &= E[Y|T=1] - E[Y|T=0] - (p_{1|1} - p_{1|0})(U^{1,ap} - L^{0,ap}) \\ L_4 &= p_{1|0} max\{0, L^{n1}\} + p_{0|1} max\{0, L^{n0}\} \end{aligned}$$

and the terms $U^{1,ap}, L^{0,ap}, U^{0,n0}$ *and* $U^{1,ap}$ *as defined in Proposition 3.1*

3.1.3 Weak Monotonicity of Mean Potential Outcomes Across Strata

In this subsection we consider the probability that mean potential outcomes vary weakly monotonically across strata, relaxing in that way assumption B that imposes a restriction with respect to the sign of the mean potential outcomes. With respect to our application, the mean potential outcome (earnings or employment) of individuals who receive a degree by participating in the program which would have not had they not participated in the program - (ap) stratum- is, in value, less (greater) than or equal to the corresponding mean potential outcome of individuals that always (never) receive a degree whether trained or not. Assumption C formalizes the notion that some strata have more favorable characteristics and thus better mean potential outcomes.

Assumption C 1 *(Weak Monotonicity of Mean Potential Outcomes Across Strata)* 1. $E[Y(1, S(0))|ap] \geq E[Y(1)|n0]$, 2. $E[Y(1)|n1] \geq E[Y(1, S(0))|ap]$, 3. $E[Y(0)|ap)] \geq E[Y(0)|n0]$, 4. $E[Y(0)|n1] \geq E[Y(0)|ap]$, 5. $E[Y(1)|ap] \geq E[Y(1)|n0]$ *and* 6. $E[Y(1)|n1] \geq E[Y(1)|ap]$

With respect of how assumption C affects the estimation of bounds for $E[Y(t,s)|ap]$ we have that: assumptions $C1$. and $C2$. provide an upper and a lower bound for $E[Y(1,S(0))|ap]$ respectively. Assumption $C4$. implies that an upper bound for $E[Y(0)|ap]$ is $E[Y(0)|n1] = E[Y|T=0,S=1]$ and when combined with **Proposition 3.1** it provides an upper bound for $E[Y(0)|ap] \leq min\{E[Y|T=0,S=0], U^{0,ap}\}$. Assumption $C3$. implies that a lower bound for $E[Y(0)|ap]$ is $E[Y(0)|n0]$ and when combines with **equation 3.5** provides a bound $E[Y(0)|ap] \geq E[Y|T=0,S=0]$ since $E[Y|T=0,S=0] \geq L^{0,ap}$. Assumption $C3$. implies that $E[Y(0)|n0] \leq E[Y|T=0,S=0]$ and combining assumption $C6$. with **equation 5.6** yields an upper bound for $E[Y(1)|ap] \leq E[Y|T=1,S=1]$. In the following proposition we present bounds under the set of assumptions $A1, A2$ and C:

Proposition 3.3 *(Flores and Flores-Lagunes, 2010a) If assumptions $A1, A2$ and C hold then we have, $\bar{L}_m^{ap} \leq LMATE_{ap} \leq \bar{U}_m^{ap}$ and $\bar{L}_m \leq MATE \leq \bar{U}_m$ where*

$$\begin{aligned}
\bar{L}^{ap} &= E[Y|T=1,S=0] - min\{U^{0,ap}, E[Y|T=0,S=1]\} \\
\bar{U}^{ap} &= U^{1,n1} - E[Y|T=0,S=0] \\
\bar{L}_m^{ap} &= max\{L^{1,ap}, E[Y|T=1,S=0]\} - U^{1,n1} \\
\bar{U}_m^{ap} &= E[Y|T=1,S=1] - E[Y|T=1,S=0] \\
\bar{L} &= E[Y|T=1] - E[Y|T=0] - (p_{1|1} - p_{1|0})\bar{U}_m^{ap} \\
\bar{U}^1 &= E[Y|T=1] - E[Y|T=0] + p_{1|1}(U^{1,n1} - E[Y|T=1,S=1]) \\
\bar{U}^2 &= E[Y|T=1] - E[Y|T=0] - (p_{1|1} - p_{1|0})\bar{L}_m^{ap} \\
\bar{L}_m &= E[Y|T=1] - E[Y|T=0] - min\{\bar{U}^1, \bar{U}^2\} \\
\bar{U}_m &= E[Y|T=1] - E[Y|T=0] - \bar{L}
\end{aligned}$$

Finally, combining all the assumptions we are able to derive a tighter set of bounds.

Proposition 3.4 *(Flores and Flores-Lagunes, 2010a) If assumptions* $A1, A2, B$ *and* C *hold then* $0 \leq LMATE_{ap} \leq \tilde{U}_m^{ap}$ *and* $) \leq MATE \leq \tilde{U}_m$ *where:*

$$
\begin{aligned}
\bar{L}^{n0} &= E[Y|T=1,S=0] - E[Y|T=0,S=0] \\
\bar{L}^{n1} &= E[Y|T=1,S=1] - E[Y|T=0,S=1] \\
\tilde{U}_m^{ap} &= E[Y|T=1,S=1] - max\{E[Y|T=1,S=0], E[Y|T=0,S=0]\} \\
\tilde{L}^{1} &= p_{1|0} max\{E[Y|T=1,S=1], E[Y|T=0,S=1]\} \\
&+ (p_{1|1} - p_{1|0}) max\{E[Y|T=1,S=0], E[Y|T=0,S=0]\} \\
&+ p_{0|1} E[Y|T=1,S=0] - E[Y|T=0] \\
\tilde{L}^{2} &= p_{1|0} max\{0, \bar{L}^{n1}\} + p_{0|1} max\{0, \bar{L}^{n0}\} + (p_{1|1} - p_{1|0}) max\{0, \bar{L}^{ap}\} \\
\tilde{U}_m &= E[Y|T=1] - E[Y|T=0] - max\{\tilde{L}^{1}, \tilde{L}^{2}\}
\end{aligned}
$$

Concluding this section, we note that the combination of the assumptions leads to some testable implications that can be used to falsify the assumptions. The group of assumptions $A1, A2$ and C yields the following testable implications: $E[Y|T=0,S=1] \geq E[Y|T=0,S=0]$ and $E[Y|T=1,S=1] \geq E[Y|T=1,S=0]$ which in the context of our application will imply that people receiving a secondary education credential (high school diploma, GED equivalent) or a vocational degree are expected to have better labor outcomes relative to people with no credential either they participate in the training program or not. Adding assumption B in the previous set of assumptions we can test whether $E[Y|T=1,S=1] \geq E[Y|T=0,S=0]$ which in our empirical analysis will imply that individuals that participated in the training program and received a certificate (either educational or vocational) perform better in the labor market (higher earnings and higher employment probability).

In the section that follows we present the results of our empirical application. We present estimated bounds for the mechanism effect, $MATE$, and also point estimates of the overall impact of the program with respect to the labor market outcomes of interest and the degree attainment. The values of the testable implications present a criterion that the assumption that we have imposed are valid.

4 Analysis

In this empirical application, by employing a non-parametric technique, we estimate bounds for the causal effect of degree attainment through which JC affects labor outcomes (weekly earnings and employment probability) relative to other services provided within the training program such as social skills training, health services and residential support. The period of interest in this application is the time that the embargo for the control group ended, quarter 12 after randomization. We provide bounds for several demographic specifications: ethnicity and race, gender and two age risk groups. In the analysis that follows we will analyze the bounds we obtain by accounting for all the possible assumptions (which are actually the tightest bounds) upon which we base our inference regarding the impact of attaining a degree on the participants' labor outcomes. Estimates for the bounds for different sets of assumptions are depicted in the Tables section. For the estimates depicted in our analysis we are in the process of obtaining standard errors, which is not a trivial task.

4.1 Analysis for the Overall Study Population

Before we start analyzing our results we demonstrate the estimated proportions of the individuals considered in our analysis specifically, not affected at 0, not affected at 1 and affected positively: $(n0), (n1), (ap)$. Referring to Table 2 for the overall sample we have that the estimated proportions of the strata $(n0), (n1), (ap)$ equal $0.345, 0.446$ and 0.209 respectively of the population, which depicts that around 79 percent of the population belong to the strata for which the treatment does not affect the mechanism variable. Our estimates depict that a respective percentage (around 79) of the population of each ethnic, racial and gender subgroup belongs to the strata for which the treatment does not affect the mechanism.

In simple words, the remedial education and/or vocational training component of the training program affects positively 21% of the people in each group (subgroup). Those individuals were able to acquire an educational and/or vocational certificate within the program something that they would not be able to achieve had they not participated in JC. Interesting observation is that the program affects positively the same portion of individuals in each demographic group and that the composition of the strata is almost the same for all the demographic specifications.

In the upper panel of Table 3 we present point estimates for the average treatment effect of the training program with respect to the labor outcomes on which we focus our analysis (weekly earnings for the quarter 12 and employment probability on that period) and with respect to the degree attainment. As our results suggest, JC had a positive effect on weekly earnings ($22.21) and employment probability (4.5%) for the overall population. Importantly, we observe a positive effect of JC on the attainment of a high school, GED or vocational degree which favors our hypothesis that the remedial education or vocational training component of the program that leads to the obtainment of the equivalent certificate has an important effect on future labor outcomes.

The last two panels in Table 3 depict the values for the testable implications for employment probability and weekly earnings. All of them are positive which adds to the validity of our assumption upon which we built the bounds for the mechanism and the net average treatment effect.

In the upper part of Tables 4 and 5 we present the estimated bounds for the overall population based on the different possible set of assumptions. Accounting for the following assumptions: randomization ($A1$), individual level monotonicity ($A2$), weak monotonicity within (B) and across strata (C) we observe that the lower bound for $MATE$ is zero which is a result of the restrictive B assumption. For the employment probability outcome, the upper bound of $MATE$ is 2.5% and for the weekly earnings outcome, we observe that $MATE$ has an upper value bound equal to $14.02. Under this set of assumptions the average effect of JC on weekly earnings (probability of employment) that is due to the attainment of a certificate is at most 55 (63) percent of the total ATE on these outcomes respectively.

Comparing to the study by F-FL (2010a), who provided point estimates for the ATE of the program as well bounds for the $MATE$ and $NATE$ we obtain slightly different estimates. Their results are based on the same population sample (program treatment and control group) but in their analysis they did not account for the design weights the different subpopulations in the program at the period of the study were selected. Their empirical application suggested a positive estimate for the ATE on obtaining a degree within the program equal to 0.21 and a positive estimate for the ATE on employment probability of 0.04, estimates that are really close to our estimations.

We do obtain though different estimates when we analyze the effect of the training program on weekly earnings and in consequence the causal effect of obtaining a degree within the program on that outcome. F-FL (2010a) reported an estimated value of the ATE on earnings equal to \$18.11 and an estimated upper bound for $MATE$ equal to \$11.26, thus attainment of a degree within the program accounts for at most 62% of the ATE on weekly earnings. In our analysis the estimated ATE on earnings is equal to \$22.28 and an estimated upper bound for MATE is equal to \$14.02, thus the attainment of a degree within the program accounts for at most 63% of the ATE on earnings. Accounting for sample and design weights will play an important role when we analyze key subgroups (such as female population).

Our estimates for the overall sample of our study, highlight the significance of the attainment of a certificate through the training program and come in accordance with the education literature suggesting positive returns of schooling and training with respect to labor outcomes (Card, 1995;1999). Our results also imply that the causal role of other components of the program net the degree attainment (e.g., health services,social skills training, job placement services, etc.) is important as well (the upper bound of the degree attainment does not equal the total impact ot JC on participants' labor outcomes).

JC aims at individuals who are in need of additional academic and/or vocational training thus the earning of a GED or vocational credential through the program is expected to have a positive causal effect on future earnings and employment probability but other services especially placement services play an important role as well for future labor outcomes. The analysis in the subsequent sections will help us properly evaluate the effects of earning a credential with respect to different demographic groups by race, ethnicity, gender and age groups, thus accounting for the heterogeneity of key subgroups.

4.1.1 Analysis by Ethnic, Racial, and Gender Classification

As we have already presented, JC has a positive effect on the future labor market outcomes of the average participant and on the attainment of a high school diploma, GED or vocational certificate. In table 3 we present the point estimates we obtain when decomposing our sample in ethnic, race and gender subgroups. With respect to the labor market outcomes we observe a positive effect for the white subgroup equal to 3.3 percent for the employment probability and equal to $22.8 for the weekly earnings. The African-Americans have shligtly larger effects 6.4 percent on employment probability and $29.16 on weekly earnings. In contrast with those two groups, for Hispanics our estimates suggest a negative effect of participating in the training program on future weekly earnings and employment probability. For the different ethnic and race groups in our analysis we observe a positive average treatment effect of the program on the obtainment of a degree.

In the analysis that follows we will abstract from analyzing negative impacts that were reported for the Hispanic population unless otherwise noted. As the study from Schochet et al. (2001) reported, JC did not increase the employment and earnings of Hispanic youths; the effects were negative but insignificant. They were unable though to provide a satisfactory explanation for those findings. In their justification, they ruled out differences in age, enrollment rates or length of participation time in the program. In addition they stated that language was not actually a negative factor, as they found similar impacts for Hispanic participants with first language English and for those without, and they also controlled for concentration of the Hispanics in certain centers or regions concluding that this was not a reason.

Some evidence with respect to the Hispanic population and their performance in the labor market are presented in Flores-Lagunes et al. (2010b). In their paper, they analyzed the sample of Hispanics that participated in NJCS and their finding suggest a strong relation between the local unemployment rates Hispanics face and their future earnings. Importantly, not only the performance of that group with respect to earnings is affected by the higher local unemployment rates they face, but they point that the differential effects are higher relative to whites. As they suggest, JC "shields" white graduates from adverse local labor market deficiencies but not Hispanics.

When we focus on analyzing gender groups we observe positive effects in the average treatment effect of JC on the labor market outcomes and on the degree attainment. Specifically for the female (male) participants we have a positive 5.8 (3.5) percent effect on employment probability and a positive $22 ($23.3) effect on weekly earnings. With respect to the effect of the program on attaining a high school, GED or vocational degree, participation in the training program has a larger positive effect equal to 22% for females relative to a (20%) effect for males participants

In Tables 4 and 5 we present the estimated bounds with respect to the different plausible sets of assumptions. Focusing on the estimated bounds when we account for all possible assumptions we have the following:

With respect to ethnic and race subgroups: The lower bound for $MATE$ is zero. Specifically for the white population, the upper bound of $MATE$ accounts for 0.019 ($12.31) on employment probability (weekly earnings) outcome. Under this set of assumptions the average effect of JC on weekly earnings (probability of employment) that is due to the attainment of a certificate is at most 57 (53) percent of the total ATE on these outcomes, respectively. For the black population, the upper bound of $MATE$ equals 0.031 (thus has at most an impact of 3.1%) for employment probability and equals $14.12 with respect to the weekly earnings inference. Overall for this population, $MATE$ accounts for at most 49% of the ATE on employment probability and 48% of the ATE on weekly earnings.

With respect to gender subgroups: For female participants the upper bound of the degree effect on employment probability is 3.4% and on weekly earnings $14.39. That suggests that the impact of a degree attainment within the training program has at most 58% (65%) of the total ATE on the labor outcomes (employment probability and weekly earnings, respectively). Finally for the male subgroup, our estimates depict a mechanism average treatment effect on the two outcomes at most 0.8% on employment probability and $10.99 on weekly earnings. Hence $MATE$ accounts at most for 20% (47%) of the total ATE on the labor outcomes, respectively.

Our results indicate that the average effect of the training program, on the labor outcomes we are interested in, that is due to the earning of a certificate is heterogeneous across the different demographic groups. With respect to the racial and ethnic classification, our estimates point that White participants benefit more from the academic and vocational training which aims at the completion of a schooling level sufficient to lead to a certificate prior exiting JC, relative to the other groups and that is depicted on the higher percentages of $MATE$ on the labor outcomes.

With respect to gender classification, we observe that a certificate attainment within the training program accounts for a higher percentage of the total average treatment effect of JC for female than male participants. This result is more notable for the employment probability outcome as the magnitude of the ATE for females is almost double that for males and the $MATE$ is four times up. That difference diminishes with respect to the weekly earnings outcome indicating that the female population benefits more from the mechanism effect when it comes to future employment chances. Our results come in accordance with previous studies that have evaluated the effectiveness of training programs with respect to labor market outcomes. Those studies have demonstrated that women, especially low-skilled, benefit more from second-opportunity programs such as government-sponsored job training programs (Bloom, Orr and Bell, 1997; Greenberg and Robins, 1997).

4.2 Analysis by Age-risk Classification

As we have mentioned in a previous section, only few studies in the training-program evaluation literature focus on estimating effects for youth and the majority of them concluded that programs serving youth are less likely to exhibit positive impacts relative to programs that target adults (Freidlander et al, 1997; Kluve, 2006). Our analysis in contrast with those studies depicts positive average treatment effects of the training program on future labor market outcomes and on the attainment of a degree through the program for youth and young adults. In the subsection below we present the results of our analysis for the overall population of age less than 20-years-old and also for the different ethnic, race and gender groups within this sample.

4.2.1 Analysis for the Special Risk Age Group (students less than 20 years-old)

Focusing on estimating possible effects of the training program for this group is of particular significance not only because it represents the largest portion of our sample, but because the individuals belonging in this group are likely more sensitive to unstable economic conditions (female with children, large portion of high school dropouts). In the special-risk group we observe the largest portion of the JC applicants 6295 out of 8020 for our sample where 2409 belong in the control and 3886 belong in the treatment group. The composition of the low-risk group is 519 people in the control and 1059 in the treatment group respectively.[14]

We start our analysis by providing estimates for the strata proportions we have for the special risk population (Table 6). In this age classification we do not have the same portion of the population for which the treatment does not affect the mechanism variable as it was the case with the overall population (as a reminder in the overall sample we have that 79% of the population belong in strata where participation in JC does not affect the attainment of a degree). For the population in the special-risk age group, around 20 percent of the population belongs in strata for which participation in JC does affect the obtainment of a high school diploma, GED or vocational certificate, the rest belong either to the $(n0)$ or $(n1)$ strata.

In the upper panel of Table 7 we present point estimates for the average treatment effect of the training program with respect to the labor outcomes on which we focus our analysis (weekly earnings for the quarter 12 and employment probability on that period) and with respect to the degree attainment. As our results suggest, JC had a positive effect on weekly earnings ($16.97) and on employment probability (3.5%) for the youth. We also observe a positive effect of JC on the attainment of a high school, GED or vocational degree equal to 20.1%. These estimates are smaller in value relative to our study population sample which comes in accordance with studies that report a smaller effect of training programs on youth participants (Heckman et al., 1999; LaLonde, 2003; Kluve,2006). The last sections in Table 7 depict the values for the testable implications for employment probability and weekly earnings. All of them are positive which adds some evidence in favor of our assumptions upon which we built the bounds for the mechanism effect.

The estimated bounds for the two labor market outcomes based on the possible set of assumptions are depicted in tables 8 and 9. Under the randomization $A1$, individual-level monotonicity $A2$ and weak monotonicity within B and across strata C assumptions we get the tighter possible bounds. Restricted by the weak monotonicity within strata assumption, the value of the lower bound for the degree effect is zero. For the employment probability outcome the upper bound of $MATE$ receives a value equal to 1.9% whereas for

[14]Note that with that classification we loose 147 individuals that were older than 24.

the weekly earnings outcome, the upper bound of $MATE$ takes a value equal to \$11.22. Under this set of assumptions the average effect of JC on weekly earnings (probability of employment) that is due to the attainment of a certificate is at most 66 (54) percent of the total ATE on these outcomes, respectively.

4.2.2 Analysis by Ethnic, Race and Gender Classification

Decomposing the population in ethnic and race groups we observe some differentiation to the proportion of people that belong in strata for which the treatment (participation in JC) does not affect the attainment of a degree (Table 6) . Specifically, less than 19% of white applicants, around 20% of black and 19% of Hispanics applicants belong to the affected positively stratum thus obtained a degree which would not otherwise. With respect to the gender classification, around 23% of women and around 17% of men participants belong to the affected positively stratum.

As we have already presented, JC has a positive effect on the younger students' future labor market outcomes and on the attainment of a high school diploma, GED or vocational certificate. In the upper panel of Table 7 we present the estimated average treatment effects of participating in the training program with respect to ethnic, racial and gender decomposition.

For the white students, we observe a positive effect of participating in JC equal to 1.6 percent on the employment probability and equal to \$13.46 on the weekly earnings outcome, respectively. The ATE of the program on the African-American students' labor market outcomes is 4.8 percent on the employment probability and \$19.37 on the weekly earnings outcomes,respectively.

Importantly, for the Hispanic participants we observe positive impacts of participating in the training program on both labor outcomes, though smaller in magnitude relative to the other racial subgroups. The ATE of the program on future employment probability takes a value equal to 0.9% and on the weekly earnings takes a value equal to \$8.48. As our estimates suggest, participation in JC has a positive impact on the degree attainment for the key ethnic and race groups we examine.

When we focus on analyzing gender groups we observe positive effects in the average treatment effect of JC on both labor market outcomes and on degree attainment.

Specifically for the female (male) participants we have a positive 4.2 (3) percent effect on employment probability and a positive \$13.36 (\$20.32) effect on weekly earnings. With respect to the effect of the program on attaining a degree, participation in the training program has a larger positive effect equal to 22% for women relative to a 17% effect for men.

In Tables 8 and 9 we present the estimated bounds with respect to the different plausible sets of assumptions. *Ethnic and racial subgroups*: Specifically under assumptions $A1, A2, B$ and C, for the white subgroup we have that $MATE$ has an effect of at most \$6.35 on weekly earnings and an effect of at most 0.7% on employment probability. Overall, under this set of assumptions the average effect of JC on weekly earnings (probability of employment) that is due to the attainment of a certificate is at most 47 (43) percent of the total ATE on these outcomes, respectively.

For the black population in this age group, $MATE$ has an upper bound equal to 0.027 thus accounting for at most 56% of the ATE on the employment probability outcome and an upper bound equal to \$11.59 on weekly earnings hence accounting for at most 59% of the ATE on the outcome. Lastly for Hispanics, our estimates suggest that the degree attainment within the program has a positive impact of at most \$3.93 on weekly earnings and implies that the mechanism average treatment effect accounts for at most 46% of the ATE on the outcome.

Gender subgroups: For the female subpopulation our estimates suggest that the mechanism average treatment effect on employment probability is at most 2.9% and on weekly earnings is at most \$10.48. Thus a degree attainment within the program accounts for at most 69% (78%) of the total ATE on the respective labor outcomes. Finally for the male subgroup, our estimates suggest a really small effect of the degree attainment on employment probability as the upper value is estimated at 0.01% whereas the impact of the degree attainment within JC on weekly earnings accounts for at most \$7.41 hence 36% of the ATE on the outcome.

The results for this age group indicate that the total average treatment effect of JC on the employment probability has a greater magnitude for the black subgroup, followed by the white and in the case of the Hispanics we observe a positive value. But with respect to the part of the ATE that $MATE$ accounts for we observe that African Americans benefit more as $MATE$ accounts for a higher portion for that group with respect to the employment probability outcome relative to the whites. Our estimates show that with respect to the weekly earnings we observe positive $ATEs$ for all ethnic and racial subgroups. Further, it is the first time we observe a positive mechanism average treatment effect for the Hispanics, though in magnitude has a lesser value relative to the other subgroups.

With respect to the gender classification, again we observe that the mechanism average treatment effect accounts for a higher percentage of the ATE for the female population relative to the male population. The percentages are so high in the case of the women for both labor outcomes pointing not only the significance of the attainment of a certificate through the program but the significance of education in combating unemployment spells, thus affecting future earnings and employment probability.

Positive effects with respect to weekly earnings for all ethnic, racial and gender groups we are examining add to the labor-education literature which highlights the relation between schooling level and future earnings. Overall the estimates we obtain for this specification are smaller in magnitude compared to the ones from the overall study population with the exception of the Hispanics where we observe for the first time positive effects of the training program.

4.2.3 Analysis for the Low Risk Age Group $(20-24)$

In this age-risk group we analyze individuals of age 20 to 24. In this group we encounter fewer participants which can be indicative that the training program attracts younger individuals in general. We defined this group as low-risk group for poor future labor outcomes as in this specification we have older thus more mature people, with a higher likelihood to have a credential prior applying to the program, and importantly with a higher probability of having previous working experience. Further, these individuals are more likely to be "family providers" (having a child, being married, being head of the household) thus we expect a higher commitment on their part in the services offered through the program and thus a higher chance of receiving positive effects through the treatment. We continue by analyzing the overall young adult population and then we proceed by analyzing the different racial, ethnic and gender groups.

We start our analysis by providing estimates for the strata proportions we have for the low risk population (Table 10). In this age classification we do not have the same portion of the population for which the treatment does not affect the mechanism variable as it was the case with the overall population (as a reminder in the overall sample we have that 79% of the population belong in strata where participation in JC does not affect the attainment of a degree). For the overall population in the age group 20-24, around 23 percent of the population belongs in strata for which participation in JC does affect the obtainment of a high school diploma, GED or vocational certificate, the rest belong either to the $(n0)$ or $(n1)$ strata.

In the upper section of Table 11 we present point estimates for the average treatment effect of the training program with respect to the labor outcomes on which we focus our analysis (weekly earnings for the quarter 12 and employment probability on that period) and with respect to the degree attainment. As our results suggest, JC had a positive effect on weekly earnings ($33.43) and employment probability (6.2%) for the overall population. We also observe a positive effect of JC on the attainment of a high school, GED or vocational degree equal to 23.9%. These estimates are larger in value relative to the overall population sample which could imply that indeed programs targeting older participants will have a better effect relative to the ones targeting youth (less than 20 years old). The last sections in Table 11 depict the values for the testable implications for employment probability and weekly earnings. All of them are positive which adds to the validity of our assumption upon which we built the bounds for the mechanism and the net average treatment effect.

The estimated bounds for the two market labor outcomes based on the possible set of assumptions are depicted in tables 12 and 13. As expected under the assumptions random assignment $A1$, individual level monotonicity $A2$, weak monotonicity within strata B and weak monotonicity across strata C we get tighter bounds. The lower bound for $MATE$ is zero and the upper bound of $MATE$ we obtain which depicts the maximum impact of a degree attainment on labor outcomes is 3.5% on the employment probability outcome and $18.84 on weekly earnings. Under this set of assumptions the average effect of JC on weekly earnings (probability of employment) that is due to the attainment of a certificate is at most 56 (56) percent of the total ATE on these outcomes, respectively.

4.2.4 Analysis by Ethnic, Race and Gender Classification

We provide the estimates we have for the various strata in our analysis in Table 10. As in the previous age classification we do not have the same portion of the population for which the treatment does not affect the mechanism variable in the various ethnic, race and gender subgroups. Specifically, around 32% of white participants, 20% of black and 26% of Hispanics are affected positively by the participation in the training program thus obtained a degree which would not otherwise. The gender classification depicts that men are the ones that would benefit the most from participation in the JC relative to women with respect to the obtainment of a degree which is the opposite with the special risk age group (youth less than 20 years old).

In Table 11 we present the estimates that we get the different ethnic, race and gender subgroups. With respect to the labor market outcomes we observe a positive effect for the white subgroup equal to 10.3 percent for the employment probability and equal to \$54.39 for the weekly earnings. In contrast with the previous specifications, African-Americans have smaller effects 9.1 percent on employment probability and \$53.9 on weekly earnings. In accordance with the overall population though, we observe negative ATE for Hispanics on future weekly earnings and on employment probability. For the different ethnic and race groups in our analysis we observe a positive average treatment effect of the program on the obtainment of a degree.

When we focus on analyzing gender groups we observe positive effects in the average treatment effect of JC on the labor market outcomes and on the degree attainment. Specifically for the female (male) participants we have a positive 9.5 (3.2) percent effect on employment probability and a positive \$43.73 (\$25.09) effect on weekly earnings. With respect to the effect of the program on attaining a high school, GED or vocational degree, participation in the training program has a larger positive effect equal to 16% for females relative to a (30%) effect for male participants. As we can observe in this risk specification the difference in the magnitude of the average treatment effects with respect to the two genders is noticeable especially on weekly earnings and degree obtainment.

The estimated bounds for the two market labor outcomes based on the possible set of assumptions are depicted in tables 12 and 13.

Ethnic and race subgroups: For the white population, the lower bound which is restrictively given by the within monotonicity assumption is zero and the upper bound for $MATE$ on employment probability is 0.064 and on weekly earnings is \$24.19. This suggests that a degree attainment within JC has a positive impact on weekly earnings (probability of employment) at most 44 (62) percent of the total ATE on these outcomes, respectively. For the black population, the upper bound of $MATE$ equals 0.040 with respect to the employment probability and \$19.44 with respect to weekly earnings. Overall for this population, $MATE$ accounts for at most 44% of the ATE on employment probability and 36% of the ATE on weekly earnings.

Gender Subgroups: For the female subpopulation our estimates suggest that $MATE$ has a positive effect on the employment probability labor outcome equal to 0.041 that accounts for at most 42% of the ATE on that outcome. Moreover, with respect to the weekly earnings outcome, $MATE$ has a value equal to \$16.46 which accounts for at most 37% of the ATE on weekly earnings. Last for the male subgroup, the mechanism average treatment effect on the two outcomes accounts for at most 2.4% (\$21.61) respectively. Hence the $MATE$ is approximately 75% (86%) of the total ATE on the respective labor outcomes.

Our estimates indicate a higher value of the ATE for the white population as well as for the percentage $MATE$ accounts for, with respect to both labor outcomes of interest relative to the African Americans participants. Even though the magnitude of the ATE is larger for the female group relative to the male for both outcomes, $MATE$ accounts for a higher percentage of the average treatment effect in the case of males. The low percentage of $MATE$ for the females may point that other services may have a higher impact on the labor outcomes of interest, such as employment services, health services, child care and counseling relative to the male participants of that age group.

Comparing young adults with younger students and our study population, our analysis reports higher estimates for the ATE on both labor outcomes of interest and higher estimated values for the upper bounds of the degree attainment effect on both weekly earnings and employment probability. That can be attributed to a couple of reasons:
i) From the baseline interview we can infer that younger participants are in a disadvantage regarding their previous education (fewer having a secondary education credential while

applying to the program) and have less previous working experience which affects their future labor outcomes; ii) Older applicants are considered more mature and dependable thus they are expected to try to benefit more from the components of the training program especially in the case where they are head of the household and parents. The summary statistics provide evidence that older students have a higher probability of having a child and also being married and being head of the household; iii) it may imply that services offered through the training program and importantly for the in-class education and vocational training that led to the attainment of a certificate are better suited for older participants.

5 Discussion of Results and Conclusion

In this article we employed a non-parametric approach to estimate bounds on the "mechanism average treatment effect" so as to evaluate the causal effect of obtaining a high school diploma, GED certificate or vocational degree within a training program for disadvantaged youth (JC) on future labor outcomes relative to other services provided through the program. In our analysis, we provided estimates for our study population as well as for various demographic groups by race, ethnicity, gender and for two age risk groups.

Focusing on the two main estimates of our study, namely the average treatment effect of participating in the training program with respect to labor market outcomes (weekly earnings and employment probability), and the impact of a degree attainment within the program on those outcomes relative to other components of the training program (upper bound of a degree attainment effect), we present the following figures. Those figures summarize the main results of our analysis with respect to employment probability and weekly earnings respectively for all possible sample decompositions at quarter 12 after randomization.

The upper part in Figure 1 depicts our results for the employment probability outcome whereas in the lower part we depict our results for the weekly earnings outcome. Our analysis suggests a positive impact of the training program on the two labor outcomes for Whites and Blacks with a highest value of the total impact of participating in the training program for the later subgroup. The upper bounds for $MATE$, which actually present the maximum proportion the attainment of a degree (the upper bound) accounts of the ATE on employment probability, are also positive and as indicated by our estimates the group that obtains the greatest value is the Whites relative to the other ethnic and racial subgroups.

Analyzing separately by gender, our estimates depict that both genders are benefited from participating in the training program (positive $ATEs$) with the women population having a higher impact on the employment probability outcome relative to men. The degree attainment effect has also a positive impact on the two labor outcomes, with $MATE$ accounting for a higher percentage of the ATE on employment probability and weekly earnings for women relative to men.

Figure 2 depicts the results for our study sample and our two age-risk subgroups: youth and young adults. The estimates suggest that participation in the JC has a positive impact on the two labor outcomes for the specifications we are examining and importantly, $MATE$ accounts for a high percentage of the ATE on the respective outcomes. The impact of the program for youth is smaller relative to the overall study population and the young adults subgroup which may suggest that the services provided in the program tackle better the needs of older participants. When we analyze the impact of a degree attainment (upper bound of $MATE$) as a percentage of the ATE on the respective outcomes, we depict that a degree attainment accounts for a higher percentage for the youth subgroup relative to young adults. That suggests that older participants may benefit more from other services net the degree attainment (such as councelling, health services and job search assistance).

In the figures that follow, we depict our estimates with respect to the different demographic decompositions of the youth and young adults subgroups by ethnicity, race and gender.

We demonstrate our estimates for the youth population in Figure 3, where the upper part of the figure is indicative of our results for the employment probability outcome and the lower part of the figure for the weekly earnings outcome. Similar to the results for our study population, Blacks is the subgroup for which we observe a higher total impact of the training program but in this case for that subgroup, a degree attainment accounts for a higher percentage of the ATE on the respective labor outcomes relative to the other ethnicities and races. For this age group is the first time that our analysis depicts a positive impact of JC on the Hispanics and furthermore we obtain a positive impact of a degree attainment on the weekly earnings outcome.

Analyzing by gender, we observe that women are benefiting more from participating in JC with respect to the employment probability outcome relative to the weekly earnings one (higher value of ATE on the respective outcomes). Importantly, our estimates suggest that women are the ones that face a higher positive impact of attaining a degree within the program relative to men on the respective outcomes. In addition, for female eligible participants $MATE$ accounts for at most 69% and 78% of the ATE on employment probability and weekly earnings highlighting the importance of attainning a degree for females at that age group within JC.

Lastly, in Figure 4 we depict the estimates of our analysis with respect to the young adults subgroup when we analyze separately for ethnicity, race, and gender. Though from Figure 2 we have pointed that JC has a higher impact for its older students our estimates depict the heterogeneity of those students when we account for ethnicity, race, and gender. White students are the ones that are benefited more from the program (ATE) and from a degree ($MATE$) relative to Black students. Notice that for Hispanics our estimates suggest a non-positive impact of participating in the program.

As we have already mentioned, the total impact of the training program on both labor outcomes of interest is higher for the older students relative to the younger ones. Contrary though to the inference for the gender decomposition of the youth subgroup, when we analyze young adult women we observe that a degree attainment accounts at most for a smaller percentage of the ATE relative to other services offered in the training program. Still though that percentage is higher for the employment probability outcome than for the weekly earnings outcome which may imply that young adult women even though they acknowledge the significance of earning a degree on their future earnings, they seem to benefit more from other services provided through the program (such as job search assistance, councelling, child care). In addition, females in this age group are more likely to have a degree prior applying to the training program and thus the portion of the applicants that will benefit from the remedial education and the vocational training is smaller relative to women in the youth age-group (that is also depicted in the proportion of the (ap) stratum).

For concluding remarks, our analysis suggests that Job Corps has a positive effect for the majority of its participants and particularly through the remedial education and/or vocational training that may lead to the award of a degree, relative to the other services it offers, on the students' future labor outcomes. These results add to the training-program evaluation literature (Heckman et al., 1999; Schochet et al., 2001,2008; Kluve, 2006) by providing evidence in favor of the in-classroom instruction training programs offer. Especially in the case of Job Corps, which addresses disadvantaged youth of age 16 to 24 with the majority of them being high school dropouts, the self-paced and individualized attributes of the program provide an environment in which participants can enhance their skills thus recoup their "training" costs through higher employment probability and increased weekly earnings.

In addition, our inference can be related to the education literature (Becker,G.S., 1967; Griliches,Z. 1977 and Card,D. 1995,1999) suggesting positive returns of schooling and training with respect to individuals' future earnings and employment opportunities. As we have mentioned, Job Corps offers a tentative education curriculum with the average participant receiving education equivalent to a year of schooling relative to (3/4) for the control group. That suggests that Job Corps engage its participants in investing in human capital hence becoming more employable citizens and enjoy higher employment rates and earnings.

Interestingly, the individuals who benefit more from participating in the program and from its remedial education and/or vocational component that leads to the obtainment of a degree are young adults (magnitudes of ATE and $MATE$) relative to younger participants. For the younger participants though we observe that the degree attainment accounts for a higher percentage of the ATE on the labor market outcomes. Younger participants are more likely not to have a credential prior applying to the training program but at the same time they have spent less time away from a schooling environment. So the remedial education and vocational training offered in an individualized and self-paced setting is more likely to benefit those participants relative to the other services provided through the program and thus account for a higher percentage of the overall impact of the program.

Finally, our analysis suggests that the causal role of mechanisms other than degree attainment (such as health services, councelling, child care and social skills training) has a non-negative impact on the participants' future labor outcomes. The heterogeneity is particularly depicted in our estimates for the young adults which are more likely to have a credential and previous working experience prior applying to the training program and also are more likely to be providers in the family (being married, have a child, being head of the household). That may raise a concern that the services offered through the program are better suited for young adults rather than youth which comes in accordance with previous studies pointing that training programs have positive effects only for the older participants (Cave and Doolittle, 1991; Couch, 1992; Orr et al., 1994).

Table A: Summary Statistics (overall sample)

Baseline Interview:			
Covariates	Control	Treatment	*difference*
Age	18.789	18.841	0.052
	0.035	*0.028*	
Female	0.450	0.445	-0.005
	0.008	*0.007*	
Has child	0.189	0.187	-0.002
	0.006	*0.005*	
Married	0.064	0.058	-0.005
	0.004	*0.003*	
Head of Hh	0.119	0.111	-0.008
	0.005	*0.004*	
MSA	0.452	0.461	0.008
	0.008	*0.007*	
PMSA	0.312	0.319	0.007
	0.008	*0.006*	
English	0.862	0.867	0.005
	0.006	*0.004*	
Guilt	0.131	0.143	0.011*
	0.006	*0.005*	
Hs_GED	0.250	0.239	-0.011
	0.007	*0.006*	
Base_voc	0.018	0.020	0.002
	0.002	*0.002*	
emp	0.200	0.209	0.009
	0.007	*0.005*	
unemp	0.581	0.585	0.003
	0.008	*0.006*	
Baseweek	108.384	110.288	1.904
	1.844	*1.479*	
Earnings History:			
Earnq 12	176.480	193.693	17.213***
	3.282	*2.770*	
Earnq 16	195.995	214.108	18.112***
	3.241	*2.737*	
Employment Probability History:			
Workq 12	0.631	0.662	0.031**
	0.008	*0.006*	
Workq 16	0.689	0.712	0.023**
	0.008	*0.006*	
Sample	**3677**	**5815**	
Certificates earned			
	0.447	0.657	0.210***
	0.009	*0.007*	
Sample	**2975**	**5045**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)
The estimates account for design weights
Numbers in *Italic* are standard errors

Table B: Summary Statistics for racial/ethnic groups (overall sample)

Baseline Interview:		**White**			**Black**			**Hispanic**	
Covariates	Control	Treatment	*difference*	Control	Treatment	*difference*	Control	Treatment	*difference*
Age	18.838	18.825	-0.013	18.694	18.812	0.117*	18.866	18.820	-0.046
	0.070	*0.055*		*0.049*	*0.041*		*0.082*	*0.069*	
Female	0.380	0.365	-0.015	0.482	0.476	-0.01	0.468	0.499	0.031
	0.016	*0.012*		*0.012*	*0.009*		*0.020*	*0.016*	
Has child	0.124	0.096	-0.028**	0.228	0.241	0.012	0.202	0.191	-0.011
	0.011	*0.008*		*0.010*	*0.008*		*0.016*	*0.012*	
Married	0.079	0.077	-0.002	0.039	0.033	-0.006	0.093	0.095	0.002
	0.009	*0.007*		*0.005*	*0.003*		*0.011*	*0.009*	
Head of Hh	0.113	0.093	-0.020	0.126	0.125	-0.001	0.118	0.108	-0.010
	0.010	*0.008*		*0.008*	*0.006*		*0.013*	*0.010*	
MSA	0.485	0.469	-0.016	0.474	0.468	-0.007	0.408	0.465	0.057**
	0.016	*0.013*		*0.012*	*0.009*		*0.019*	*0.016*	
PMSA	0.143	0.169	0.026*	0.347	0.369	0.023	0.473	0.416	-0.056**
	0.011	*0.010*		*0.011*	*0.009*		*0.020*	*0.016*	
English	0.989	0.987	-0.002	0.983	0.974	-0.009	0.453	0.475	0.023
	0.003	*0.003*		*0.003*	*0.003*		*0.020*	*0.016*	
Guilt	0.177	0.203	0.026*	0.111	0.122	0.011	0.108	0.108	0.000
	0.012	*0.010*		*0.007*	*0.006*		*0.012*	*0.010*	
Hs_GED	0.307	0.289	-0.019	0.219	0.213	-0.006	0.233	0.232	0.000
	0.015	*0.012*		*0.010*	*0.008*		*0.017*	*0.013*	
Base_voc	0.021	0.023	0.001	0.017	0.018	0.001	0.024	0.026	0.002
	0.005	*0.004*		*0.003*	*0.002*		*0.006*	*0.005*	
emp	0.256	0.276	0.020	0.166	0.180	0.013	0.207	0.183	-0.025
	0.014	*0.012*		*0.009*	*0.007*		*0.016*	*0.012*	
unemp	0.610	0.607	-0.002	0.583	0.572	-0.011	0.559	0.601	0.042*
	0.016	*0.013*		*0.012*	*0.009*		*0.019*	*0.016*	
Baseweek	126.613	137.054	10.441**	97.086	97.952	0.867	111.206	104.318	-6.888
	3.654	*3.129*		*2.515*	*1.944*		*4.342*	*3.521*	
Earnings History:									
Earnq 12	218.538	239.778	21.240**	145.049	167.914	22.865***	195.317	191.802	-3.515
	6.512	*6.052*		*4.333*	*3.514*		*8.357*	*6.829*	
Earnq 16	231.045	265.399	34.354***	167.419	189.376	21.957***	222.041	206.664	-15.377
	6.554	*5.725*		*4.332*	*3.630*		*8.206*	*6.551*	
Employment Probability History:									
Workq 12	0.723	0.735	0.012	0.572	0.623	0.050***	0.659	0.654	-0.006
	0.014	*0.011*		*0.012*	*0.009*		*0.019*	*0.015*	
Workq 16	0.770	0.798	0.028*	0.636	0.671	0.0348**	0.721	0.700	-0.021
	0.014	*0.010*		*0.011*	*0.009*		*0.018*	*0.015*	
Sample	**953**	**1503**		**1811**	**2911**		**994**	**1646**	
Certificates earned:									
	0.498	0.712	0.214***	0.420	0.628	0.208***	0.448	0.653	0.205***
	0.019	0.013		0.013	0.010		0.021	0.016	
Sample	**712**	**1253**		**1507**	**2564**		**551**	**871**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)
The estimates account for design weights
Numbers in *Italic* are standard errors

Table C: Summary Statistics by gender (overall sample)

Baseline Interview:	Female			Male		
Covariates	Control	Treatment	difference	Control	Treatment	*difference*
Age	18.912	18.993	0.081	18.689	18.720	0.031
	0.057	*0.042*		*0.044*	*0.038*	
Female						
Has child	0.293	0.294	0.000	0.103	0.101	-0.002
	0.012	*0.009*		*0.006*	*0.005*	
Married	0.078	0.077	0.000	0.052	0.043	-0.009
	0.007	*0.005*		*0.005*	*0.004*	
Head of Hh	0.156	0.160	0.003	0.089	0.071	-0.017**
	0.010	*0.007*		*0.006*	*0.005*	
MSA	0.465	0.488	0.023	0.442	0.439	-0.004
	0.013	*0.010*		*0.010*	*0.009*	
PMSA	0.330	0.333	0.003	0.296	0.307	0.011
	0.012	*0.009*		*0.010*	*0.008*	
English	0.864	0.863	-0.001	0.860	0.869	0.009
	0.009	*0.007*		*0.007*	*0.006*	
Guilt	0.074	0.085	0.011	0.177	0.189	0.012
	0.007	*0.005*		*0.008*	*0.007*	
Hs_GED	0.310	0.281	-0.029**	0.202	0.206	0.004
	0.012	*0.009*		*0.008*	*0.007*	
Base_voc	0.020	0.022	0.002	0.017	0.019	0.001
	0.004	*0.003*		*0.003*	*0.002*	
emp	0.200	0.197	-0.003	0.201	0.219	0.018
	0.011	*0.008*		*0.008*	*0.007*	
unemp	0.566	0.580	0.014	0.594	0.589	-0.005
	0.013	*0.010*		*0.010*	*0.009*	
Baseweek	94.923	95.010	0.087	119.403	122.552	3.149
	2.684	*1.945*		*2.499*	*2.149*	
Earnings History:						
Earnq 12	143.987	157.913	13.925**	203.077	222.416	19.338***
	4.677	*3.470*		*4.469*	*4.106*	
Earnq 16	160.802	176.218	15.416**	224.803	244.524	19.721***
	4.517	*3.448*		*4.453*	*4.034*	
Employment Probability History:						
Workq 12	0.593	0.632	0.039**	0.662	0.686	0.024*
	0.013	*0.009*		*0.010*	*0.008*	
Workq 16	0.659	0.690	0.031**	0.714	0.730	0.016
	0.013	*0.009*		*0.010*	*0.008*	
Sample				**2244**	**3117**	
Certificates earned:						
	0.467	0.687	0.220***	0.431	0.633	0.202***
	0.015	0.010		0.011	0.009	
Sample	**1105**	**2296**		**1870**	**2749**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)

The estimates account for design weights

Numbers in *Italic* are standard errors

Table D: Summary Statistics (youth sample)

Baseline Interview:			
Covariates	Control	Treatment	*difference*
Age	17.747	17.759	0.012
	0.022	*0.018*	
Female	0.434	0.433	0.000
	0.010	*0.008*	
Has child	0.123	0.129	0.007
	0.006	*0.005*	
Married	0.041	0.039	-0.003
	0.004	*0.003*	
Head of Hh	0.069	0.064	-0.005
	0.005	*0.004*	
MSA	0.455	0.457	0.002
	0.010	*0.008*	
PMSA	0.306	0.314	0.009
	0.009	*0.007*	
English	0.876	0.882	0.006
	0.006	*0.005*	
Guilt	0.138	0.147	0.009
	0.007	*0.005*	
Hs_GED	0.147	0.138	-0.009
	0.007	*0.005*	
Base_voc	0.007	0.008	0.001
	0.002	*0.001*	
emp	0.187	0.199	0.013
	0.007	*0.006*	
unemp	0.553	0.554	0.000
	0.010	*0.008*	
Baseweek	95.334	97.813	2.480
	2.024	*1.648*	
Earnings History:			
Earnq 12	166.778	178.822	12.043**
	3.758	*3.199*	
Earnq 16	190.157	200.158	10.001**
	3.757	*3.133*	
Employment Probability History:			
Workq 12	0.611	0.633	0.023*
	0.009	*0.007*	
Workq 16	0.681	0.693	0.012
	0.009	*0.007*	
Sample	**2712**	**4209**	
Certificates earned			
	0.437	0.638	0.201***
	0.010	*0.008*	
Sample	**2409**	**3886**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)
The estimates account for design weights
Numbers in *Italic* are standard errors

Table E: Summary Statistics for racial/ethnic groups (youth sample)

Baseline Interview:	**White**			**Black**			**Hispanic**		
Covariates	Control	Treatment	*difference*	Control	Treatment	*difference*	Control	Treatment	*difference*
Age	17.730	17.786	0.056	17.712	17.730	0.018	17.848	17.744	-0.104
	0.043	*0.035*		*0.031*	*0.025*		*0.054*	*0.043*	
Female	0.360	0.364	0.004	0.462	0.457	-0.005	0.448	0.481	0.033
	0.018	*0.015*		*0.013*	*0.011*		*0.023*	*0.019*	
Has child	0.065	0.055	-0.010	0.151	0.170	0.019	0.148	0.136	-0.012
	0.009	*0.007*		*0.010*	*0.008*		*0.016*	*0.013*	
Married	0.047	0.053	0.006	0.024	0.018	-0.006	0.083	0.070	-0.013
	0.008	*0.007*		*0.004*	*0.003*		*0.013*	*0.009*	
Head of Hh	0.069	0.053	-0.015	0.070	0.069	-0.001	0.074	0.079	0.005
	0.010	*0.007*		*0.007*	*0.005*		*0.012*	*0.010*	
MSA	0.478	0.471	-0.007	0.476	0.459	-0.017	0.406	0.456	0.050*
	0.019	*0.015*		*0.014*	*0.011*		*0.022*	*0.018*	
PMSA	0.138	0.150	0.013	0.344	0.372	0.028*	0.464	0.422	-0.042
	0.013	*0.011*		*0.013*	*0.011*		*0.023*	*0.018*	
English	0.986	0.991	0.005	0.991	0.980	-0.01	0.469	0.508	0.04
	0.005	*0.003*		*0.003*	*0.003*		*0.023*	*0.019*	
Guilt	0.185	0.206	0.022	0.120	0.122	0.003	0.116	0.128	0.013
	0.015	*0.012*		*0.009*	*0.007*		*0.015*	*0.012*	
Hs_GED	0.179	0.172	-0.007	0.132	0.119	-0.013	0.137	0.135	-0.002
	0.015	*0.011*		*0.009*	*0.007*		*0.016*	*0.013*	
Base_voc	0.005	0.010	0.005	0.007	0.006	-0.001	0.013	0.011	-0.001
	0.003	*0.003*		*0.002*	*0.002*		*0.005*	*0.004*	
emp	0.250	0.267	0.016	0.155	0.175	0.020	0.179	0.166	-0.013
	0.016	*0.013*		*0.010*	*0.008*		*0.018*	*0.014*	
unemp	0.587	0.588	0.001	0.546	0.527	-0.019	0.548	0.575	0.027
	0.019	*0.015*		*0.013*	*0.011*		*0.023*	*0.018*	
Baseweek	112.231	124.193	11.962**	84.922	84.936	0.014	99.413	93.228	-6.185
	4.135	*3.528*		*2.710*	*2.136*		*4.903*	*3.892*	
Earnings History:									
Earnq 12	217.784	225.816	8.032	135.363	149.249	13.885**	180.513	188.029	7.516
	7.643	*6.720*		*4.930*	*4.021*		*9.607*	*8.167*	
Earnq 16	231.213	254.736	23.523**	161.498	171.963	10.465*	214.663	201.320	-13.343
	7.810	*6.574*		*4.907*	*4.103*		*9.602*	*7.529*	
Employment Probability History:									
Workq 12	0.727	0.722	-0.006	0.546	0.582	0.035**	0.631	0.642	0.011
	0.017	*0.014*		*0.013*	*0.011*		*0.022*	*0.018*	
Workq 16	0.767	0.788	0.021	0.630	0.643	0.013	0.704	0.695	-0.008
	0.016	*0.012*		*0.013*	*0.010*		*0.021*	*0.017*	
Sample	**692**	**1096**		**1365**	**2119**		**480**	**727**	
Certificates earned									
	0.512	0.700	0.188***	0.400	0.604	0.203***	0.440	0.634	0.194***
	0.021	0.015		0.014	0.011		0.024	0.019	
Sample	**594**	**990**		**1227**	**1973**		**433**	**672**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)

The estimates account for design weights

Numbers in *Italic* are standard errors

Table F: Summary Statistics by gender (youth sample)

Baseline Interview:	**Female**			**Male**		
Covariates	Control	Treatment	difference	Control	Treatment	*difference*
Age	17.778	17.851	0.073*	17.723	17.689	-0.034
	0.036	*0.027*		*0.028*	*0.024*	
Female						
Has child	0.204	0.214	0.009	0.060	0.065	0.005
	0.013	*0.009*		*0.006*	*0.005*	
Married	0.059	0.054	-0.005	0.028	0.027	-0.001
	0.007	*0.005*		*0.004*	*0.003*	
Head of Hh	0.077	0.086	0.009	0.063	0.048	-0.015**
	0.008	*0.006*		*0.006*	*0.004*	
MSA	0.465	0.487	0.022	0.448	0.434	-0.014
	0.016	*0.012*		*0.012*	*0.010*	
PMSA	0.328	0.326	-0.001	0.289	0.305	0.016
	0.015	*0.011*		*0.011*	*0.010*	
English	0.880	0.876	-0.004	0.872	0.886	0.014
	0.010	*0.008*		*0.008*	*0.007*	
Guilt	0.087	0.089	0.002	0.177	0.192	0.015
	0.009	*0.007*		*0.009*	*0.008*	
Hs_GED	0.194	0.178	-0.016	0.111	0.108	-0.003
	0.012	*0.009*		*0.008*	*0.006*	
Base_voc	0.008	0.011	0.003	0.006	0.006	0.000
	0.003	*0.002*		*0.002*	*0.002*	
emp	0.187	0.193	0.007	0.187	0.204	0.017
	0.012	*0.009*		*0.009*	*0.008*	
unemp	0.536	0.546	0.010	0.567	0.560	-0.007
	0.016	*0.011*		*0.012*	*0.010*	
Baseweek	83.826	86.269	2.443	104.148	106.648	2.499
	2.992	*2.228*		*2.712*	*2.352*	
Earnings History:						
Earnq 12	134.513	140.700	6.187	191.493	207.993	16.501**
	5.506	*4.021*		*5.015*	*4.673*	
Earnq 16	154.144	163.991	9.847	217.742	227.834	10.093
	5.213	*3.947*		*5.132*	*4.577*	
Employment Probability History:						
Workq 12	0.569	0.597	0.028	0.643	0.661	0.018
	0.016	*0.011*		*0.012*	*0.010*	
Workq 16	0.654	0.678	0.024	0.701	0.703	0.003
	0.015	*0.011*		*0.011*	*0.009*	
Sample	**1007**	**1882**		**1705**	**2327**	
Certificates earned:						
	0.442	0.676	0.234***	0.432	0.609	0.177***
	0.017	0.011		0.013	0.010	
Sample	**863**	**1701**		**1546**	**2185**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)
The estimates account for design weights
Numbers in *Italic* are standard errors

Table G: Summary Statistics (young adults sample)

Baseline Interview:			
Covariates	Control	Treatment	*difference*
Age	21.484	21.577	0.094**
	0.037	*0.029*	
Female	0.501	0.478	-0.022
	0.017	*0.013*	
Has child	0.364	0.327	-0.037*
	0.016	*0.012*	
Married	0.123	0.110	-0.013
	0.011	*0.008*	
Head of Hh	0.255	0.228	-0.028
	0.015	*0.011*	
MSA	0.446	0.471	0.025
	0.017	*0.013*	
PMSA	0.321	0.327	0.007
	0.016	*0.012*	
English	0.820	0.827	0.007
	0.013	*0.010*	
Guilt	0.110	0.127	0.017
	0.011	*0.009*	
Hs_GED	0.537	0.513	-0.023
	0.017	*0.013*	
Base_voc	0.044	0.050	0.006
	0.007	*0.006*	
emp	0.239	0.231	-0.008
	0.014	*0.011*	
unemp	0.657	0.672	0.015
	0.016	*0.012*	
Baseweek	145.268	143.240	-2.028
	4.069	*3.130*	
Earnings History:			
Earnq 12	203.891	232.049	28.158***
	6.922	*5.594*	
Earnq 16	212.020	252.089	40.069***
	6.682	*5.746*	
Employment Probability History:			
Workq 12	0.690	0.735	0.044**
	0.016	*0.012*	
Workq 16	0.713	0.764	0.051**
	0.015	*0.011*	
Sample	**1468**	**2353**	
Certificates earned			
	0.484	0.723	0.239***
	0.022	*0.014*	
Sample	**519**	**1059**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)
The estimates account for design weights
Numbers in *Italic* stand for standard errors

Table H: Summary Statistics for racial/ethnic groups (young adults sample)

Baseline Interview:

	White			Black			Hispanic		
Covariates	Control	Treatment	*difference*	Control	Treatment	*difference*	Control	Treatment	*difference*
Age	21.468	21.493	0.025	21.520	21.645	0.125*	21.401	21.589	0.188*
	0.073	*0.057*		*0.055*	*0.042*		*0.085*	*0.070*	
Female	0.440	0.370	-0.069*	0.539	0.535	-0.004	0.537	0.543	0.01
	0.032	*0.025*		*0.025*	*0.019*		*0.040*	*0.032*	
Has child	0.258	0.197	-0.061*	0.458	0.422	-0.037	0.354	0.338	-0.016
	0.028	*0.021*		*0.025*	*0.018*		*0.038*	*0.031*	
Married	0.157	0.147	-0.010	0.086	0.077	-0.009	0.107	0.161	0.054
	0.024	*0.018*		*0.014*	*0.010*		*0.025*	*0.024*	
Head of Hh	0.222	0.194	-0.028	0.299	0.276	-0.023	0.240	0.184	-0.056
	0.027	*0.020*		*0.023*	*0.017*		*0.034*	*0.025*	
MSA	0.504	0.463	-0.041	0.468	0.495	0.027	0.418	0.492	0.074
	0.032	*0.026*		*0.025*	*0.019*		*0.040*	*0.032*	
PMSA	0.144	0.211	0.068**	0.350	0.359	0.009	0.490	0.400	-0.09*
	0.023	*0.021*		*0.024*	*0.018*		*0.040*	*0.032*	
English	0.996	0.976	-0.020**	0.952	0.957	0.004	0.401	0.385	-0.016
	0.004	*0.008*		*0.011*	*0.008*		*0.039*	*0.032*	
Guilt	0.153	0.196	0.043	0.085	0.116	0.031*	0.090	0.050	-0.040
	0.023	*0.021*		*0.014*	*0.012*		*0.023*	*0.014*	
Hs_GED	0.630	0.610	-0.020	0.490	0.478	-0.012	0.474	0.498	0.024
	0.031	*0.025*		*0.025*	*0.019*		*0.040*	*0.032*	
Base_voc	0.067	0.057	-0.010	0.040	0.045	0.006	0.036	0.070	0.034
	0.016	*0.012*		*0.010*	*0.008*		*0.015*	*0.017*	
emp	0.269	0.285	0.016	0.204	0.191	-0.013	0.275	0.226	-0.049
	0.029	*0.023*		*0.020*	*0.015*		*0.036*	*0.027*	
unemp	0.673	0.676	0.003	0.689	0.699	0.010	0.594	0.675	0.08*
	0.030	*0.024*		*0.023*	*0.017*		*0.039*	*0.030*	
Baseweek	166.791	168.829	2.038	133.914	134.517	0.603	143.113	135.385	-7.728
	7.423	*6.389*		*5.832*	*4.209*		*9.081*	*7.957*	
Earnings History:									
Earnq 12	218.679	275.131	56.452**	179.505	219.764	40.259***	229.405	194.350	-35.055*
	13.009	*13.140*		*9.435*	*7.188*		*16.931*	*13.044*	
Earnq 16	232.228	296.678	64.450***	186.882	239.462	52.580***	234.699	213.594	-21.105
	12.838	*11.929*		*9.564*	*7.819*		*16.152*	*13.849*	
Employment Probability History:									
Workq 12	0.707	0.765	0.058	0.665	0.737	0.072**	0.741	0.671	-0.070
	0.030	*0.022*		*0.023*	*0.016*		*0.035*	*0.031*	
Workq 16	0.777	0.830	0.053*	0.657	0.748	0.091***	0.763	0.703	-0.061
	0.027	*0.019*		*0.023*	*0.016*		*0.034*	*0.030*	
Sample	**238**	**374**		**410**	**722**		**156**	**238**	
Certificates earned:									
	0.421	0.759	0.338***	0.509	0.715	0.206***	0.455	0.719	0.264***
	0.047	0.028		0.031	0.019		0.049	0.034	
Sample	**110**	**241**		**257**	**540**		**106**	**176**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)

The estimates account for design weights

Numbers in *Italic* stand for standard errors

Table I: Summary Statistics by gender (young adults sample)

Baseline Interview:

Covariates	Female Control	Female Treatment	difference	Male Control	Male Treatment	*difference*
Age	21.490	21.609	0.118*	21.477	21.549	0.07
	0.057	*0.041*		*0.049*	*0.042*	
Female						
Has child	0.503	0.478	-0.025	0.225	0.188	-0.04
	0.025	*0.018*		*0.019*	*0.015*	
Married	0.126	0.135	0.008	0.120	0.088	-0.032*
	0.017	*0.013*		*0.015*	*0.011*	
Head of Hh	0.343	0.330	-0.012	0.167	0.133	-0.034*
	0.024	*0.017*		*0.017*	*0.013*	
MSA	0.457	0.483	0.025	0.434	0.460	0.026
	0.025	*0.018*		*0.022*	*0.019*	
PMSA	0.334	0.356	0.022	0.307	0.301	-0.007
	0.024	*0.018*		*0.021*	*0.017*	
English	0.816	0.835	0.019	0.823	0.819	-0.005
	0.020	*0.014*		*0.017*	*0.014*	
Guilt	0.044	0.077	0.033**	0.177	0.174	-0.003
	0.010	*0.010*		*0.017*	*0.014*	
Hs_GED	0.590	0.533	-0.056*	0.483	0.495	0.012
	0.025	*0.018*		*0.023*	*0.019*	
Base_voc	0.041	0.046	0.006	0.047	0.053	0.006
	0.010	*0.008*		*0.010*	*0.008*	
emp	0.231	0.202	-0.029	0.248	0.257	0.009
	0.021	*0.015*		*0.019*	*0.016*	
unemp	0.638	0.666	0.028	0.677	0.679	0.001
	0.024	*0.017*		*0.021*	*0.017*	
Baseweek	122.928	114.940	-7.988	167.688	169.201	1.514
	5.629	*3.898*		*5.684*	*4.675*	
Earnings History:						
Earnq 12	168.262	198.497	30.234**	239.645	262.829	23.184*
	9.182	*6.884*		*10.006*	*8.625*	
Earnq 16	177.109	205.330	28.221**	247.055	294.984	47.930***
	9.203	*7.184*		*9.391*	*8.632*	
Employment Probability History:						
Workq 12	0.656	0.713	0.057**	0.724	0.754	0.030
	0.024	*0.017*		*0.020*	*0.016*	
Workq 16	0.672	0.714	0.042	0.753	0.809	0.056**
	0.024	*0.017*		*0.019*	*0.015*	
Sample	**393**	**745**		**492**	**723**	
Certificates earned:						
	0.549	0.718	0.169***	0.424	0.727	0.303***
	0.034	0.019		0.029	0.020	
Sample	**220**	**761**		**299**	**518**	

significant at the 1% (***), at the 5% (**) and at the 10% (*)

The estimates account for design weights

Numbers in *Italic* stand for standard errors

Table 2: Strata Proportions for Subpopulations Overall Sample

Strata proportions	Sample	White	Black	Hispanic	Female	Male
π_{ap}	0.209	0.212	0.207	0.209	0.212	0.200
π_{n1}	0.446	0.500	0.421	0.441	0.472	0.431
π_{n0}	0.345	0.288	0.372	0.350	0.316	0.369

Table 3: Point Estimates for Study Population

Parameters	**Estimates**					
	Sample	White	Black	Hispanic	Female	Male
(Total) Average Treatment Effects						
ATE on employment	0.045	0.033	0.064	-0.006	0.058	0.035
ATE on earnings	22.218	22.840	29.157	-0.279	22.030	23.308
ATE on obtainment of degree	0.21	0.214	0.208	0.205	0.220	0.202
Testable Implications for employment						
E[Y|T=0,S=1]-E[Y|T=0,S=0]	0.097	0.088	0.092	0.058	0.164	0.051
E[Y|T=1,S=1]-E[Y|T=1,S=0]	0.153	0.133	0.150	0.129	0.156	0.158
E[Y|T=1,S=1]-E[Y|T=0,S=0]	0.141	0.115	0.158	0.065	0.184	0.115
Testable Implications for earnings						
E[Y|T=0,S=1]-E[Y|T=0,S=0]	50.819	45.581	51.556	31.463	66.123	43.272
E[Y|T=1,S=1]-E[Y|T=1,S=0]	70.738	73.198	67.976	39.902	65.435	81.553
E[Y|T=1,S=1]-E[Y|T=0,S=0]	69.205	66.651	76.109	27.660	73.403	71.893

Table 4: Estimated Bounds of Degree Attainment on Employment Probability

	Assumptions A1,A2 and B		Assumptions A1,A2 and C		Assumptions A1,A2,B and C	
Subgroups	LB	UB	LB	UB	LB	UB
Sample	0	0.045	-0.094	0.032	0	0.025
White	0	0.033	-0.077	0.028	0	0.019
Black	0	0.064	-0.099	0.031	0	0.031
Hispanic	0	-0.006	-0.094	0.027	0	-0.009
Female	0	0.058	-0.096	0.033	0	0.034
Male	0	0.035	-0.085	0.031	0	0.008

Table 5: Estimated Bounds of Degree Attainment on Weekly Earnings

	Assumptions A1,A2 and B		Assumptions A1,A2 and C		Assumptions A1,A2,B and C	
Subgroups	LB	UB	LB	UB	LB	UB
Sample	0	22.22	-35.51	14.79	0	14.02
White	0	22.84	-37.87	15.51	0	12.31
Black	0	29.16	-33.21	14.06	0	14.12
Hispanic	0	-0.28	-28.36	8.33	0	-0.28
Female	0	22.030	-30.370	13.861	0	14.387
Male	0	23.308	-39.085	16.334	0	10.987

Table 6: Strata Proportions for Youth

Strata proportions	Sample	White	Black	Hispanic	Female	Male
π_{ap}	0.201	0.188	0.202	0.197	0.232	0.176
π_{n1}	0.435	0.512	0.401	0.434	0.442	0.431
π_{n0}	0.364	0.300	0.397	0.369	0.326	0.393

Table 7: Point estimates for Youth

Parameters	Estimates					
	Sample	White	Black	Hispanic	Female	Male
(Total) Average Treatment Effects						
ATE on employment	0.035	0.016	0.048	0.009	0.042	0.030
ATE on earnings	16.97	13.46	19.37	8.48	13.36	20.32
ATE on obtainment of degree	0.201	0.188	0.203	0.194	0.223	0.176
Testable Implications for employment						
E[Y|T=0,S=1]-E[Y|T=0,S=0]	0.086	0.073	0.079	0.023	0.152	0.039
E[Y|T=1,S=1]-E[Y|T=1,S=0]	0.140	0.123	0.133	0.102	0.126	0.159
E[Y|T=1,S=1]-E[Y|T=0,S=0]	0.123	0.090	0.132	0.057	0.150	0.109
Testable Implications for earnings						
E[Y|T=0,S=1]-E[Y|T=0,S=0]	47.665	44.561	47.948	15.273	62.468	38.036
E[Y|T=1,S=1]-E[Y|T=1,S=0]	63.775	73.957	57.062	28.848	52.969	79.788
E[Y|T=1,S=1]-E[Y|T=0,S=0]	60.877	58.442	61.191	25.760	58.141	67.956

Table 8: Estimated Bounds of Degree Attainment on Employment Probability - Youth

	Assumptions A1,A2 and B		Assumptions A1,A2 and C		Assumptions A1,A2,B and C	
Subgroups	LB	UB	LB	UB	LB	UB
Sample	0	0.035	-0.091	0.028	0	0.019
White	0	0.016	-0.068	0.023	0	0.007
Black	0	0.048	-0.091	0.027	0	0.027
Hispanic	0	0.009	-0.079	0.019	0	-0.004
Female	0	0.042	-0.105	0.029	0	0.029
Male	0	0.030	-0.076	0.028	0	0.0001

Table 9: Estimated Bounds of Degree Attainment on Weekly Earnings-Youth

	Assumptions A1,A2 and B		Assumptions A1,A2 and C		Assumptions A1,A2,B and C	
Subgroups	LB	UB	LB	UB	LB	UB
Sample	0	16.97	-31.41	12.81	0	11.22
White	0	13.46	-31.22	13.91	0	6.35
Black	0	19.37	-28.95	11.53	0	11.59
Hispanic	0	8.48	-23.26	5.67	0	3.93
Female	0	13.36	-31.08	12.27	0	10.48
Male	0	20.32	-31.24	13.99	0	7.41

Table 10: Strata Proportions for Young adults

Strata proportions	Sample	White	Black	Hispanic	Female	Male
π_{ap}	0.232	0.323	0.203	0.267	0.143	0.299
π_{n1}	0.485	0.436	0.506	0.443	0.568	0.425
π_{n0}	0.283	0.241	0.291	0.290	0.289	0.276

Table 11: Point Estimates for Young adults

Parameters	**Estimates**					
	Sample	White	Black	Hispanic	Female	Male
(Total) Average Treatment Effects						
ATE on employment	0.062	0.103	0.091	-0.076	0.096	0.032
ATE on earnings	33.434	54.391	53.9	-29.20	43.736	25.099
ATE on obtainment of degree	0.239	0.338	0.206	0.263	0.169	0.303
Testable Implications for employment						
E[Y|T=0,S=1]-E[Y|T=0,S=0]	0.118	0.115	0.118	0.148	0.180	0.092
E[Y|T=1,S=1]-E[Y|T=1,S=0]	0.195	0.194	0.191	0.238	0.249	0.144
E[Y|T=1,S=1]-E[Y|T=0,S=0]	0.174	0.198	0.206	0.058	0.265	0.110
Testable Implications for earnings						
E[Y|T=0,S=1]-E[Y|T=0,S=0]	55.328	47.760	58.449	79.145	67.193	67.078
E[Y|T=1,S=1]-E[Y|T=1,S=0]	90.948	72.780	93.917	80.425	101.280	79.681
E[Y|T=1,S=1]-E[Y|T=0,S=0]	85.382	92.055	110.432	29.431	109.192	75.284

Table 12: Estimated Bounds of Degree Attainment on Employment Probability - Young adults

	Assumptions A1,A2 and B		Assumptions A1,A2 and C		Assumptions A1,A2,B and C	
Subgroups	LB	UB	LB	UB	LB	UB
$Sample_{2024}$	0	0.062	-0.097	0.045	0	0.035
White	0	0.103	-0.125	0.062	0	0.064
Black	0	0.091	-0.084	0.039	0	0.040
Hispanic	0	-0.076	-0.142	0.063	0	-0.076
Female	0	0.081	-0.063	0.036	0	0.041
Male	0	0.032	-0.108	0.043	0	0.024

Table 13: Estimated Bounds of Degree Attainment on Weekly Earnings-Young adults

	Assumptions A1,A2 and B		Assumptions A1,A2 and C		Assumptions A1,A2,B and C	
Subgroups	LB	UB	LB	UB	LB	UB
$Sample_{2024}$	0	33.43	-45.89	21.11	0	18.84
White	0	54.39	-72.95	23.51	0	24.19
Black	0	53.89	-37.25	19.11	0	19.44
Hispanic	0	-29.19	-52.55	21.46	0	-29.19
Female	0	43.74	-22.34	14.53	0	16.46
Male	0	25.10	-68.66	23.84	0	21.61

Figure 1: Study Population

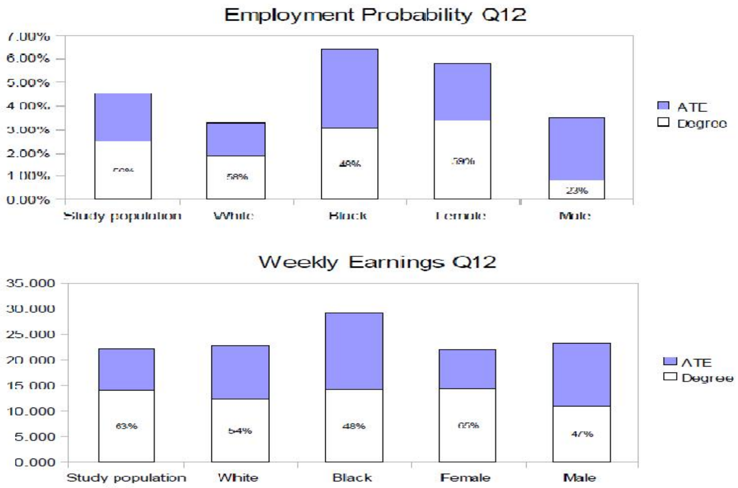


Figure 2: Study Population-Youth-Young Adults

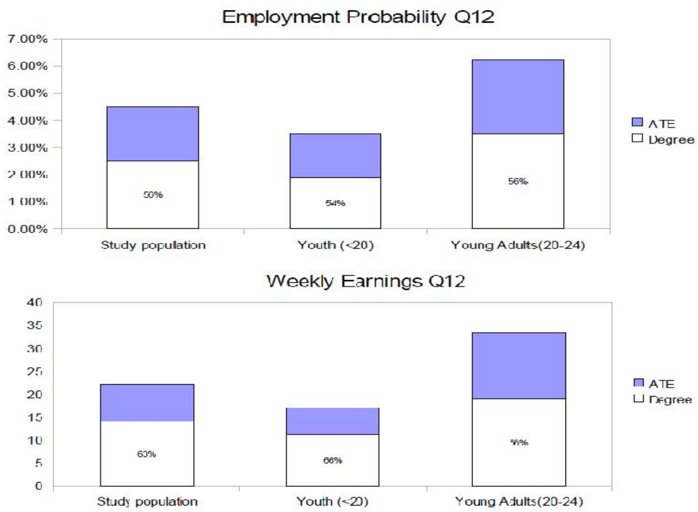


Figure 3: Youth Population

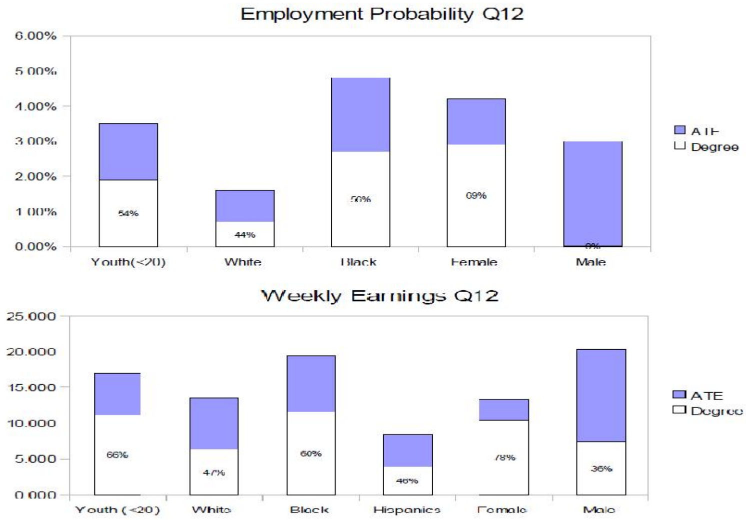
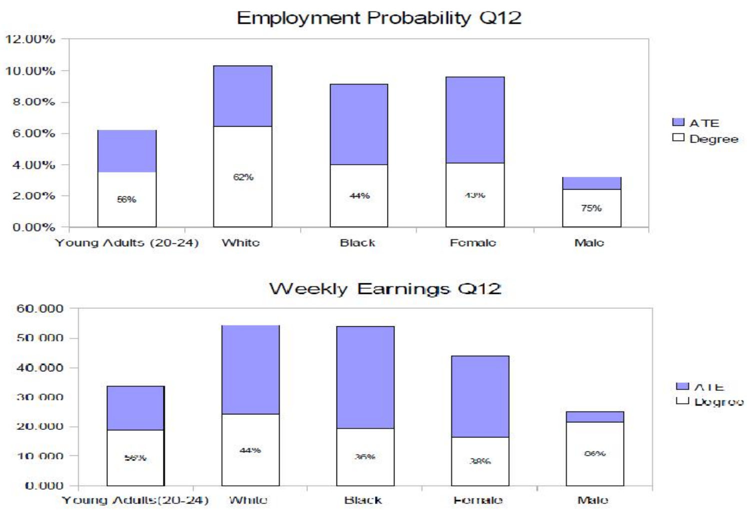


Figure 4: Young Adults Population



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