Education Advocate Program (EAP) and Educational Outcomes in Washington State

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About the ERDC

The research presented here uses data from the Education Research and Data Center, located in the Washington Office of Financial Management. ERDC works with partner agencies to conduct powerful analyses of learning that can help inform the decision-making of Washington legislators, parents, and education providers. ERDC's data system is a statewide longitudinal data system that includes de-identified data about people's preschool, educational and workforce experiences.

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Executive Summary

The Washington State Education Advocate Program (EAP) is a statewide educational assistance program to re-engage youth coming out of detention and juvenile rehabilitation administrative centers with school. Most importantly, the program's primary aim is to prevent high-risk youth from re-entering the juvenile justice system. The present study investigates the impact of EAP on high school and postsecondary outcomes in the state. Our sample population is youth involved in the juvenile justice system referred to the Education Advocate Program (EAP) in Washington State public schools while enrolled in the 9th to 12th grade during the 2010-2019 academic years. In the current study, we estimated the association between EAP and high school and postsecondary outcomes using propensity score matching (PSM) and inverse-probability weighting regression adjustment (IPWRA).

Here are key takeaways from this study:

Descriptive analyses of the report found:

1. 59% of EAP students achieved regular school attendance in the sample.
2. 70% of EAP students attained no full-day unexcused school absences in the sample.
3. About 11% of EAP participants received high school diplomas, while 31% of EAP participants dropped out of high school.

Further statistical analysis in this report found:

4. Participation in EAP is significantly associated with gender (male), offense types, student economic status, and school mobility.
5. EAP students had a lower probability of dropping out of high school than the comparison group.
6. Participation in EAP decreased full-day unexcused absences and increased regular attendance.

Our research affirmed the association between EAP participation and school attendance, as well as the association with the high school dropout rate. However, this result needs to be interpreted with caution. The present study employed data from the JRA transition facility only, resulting in limited treatments.

Introduction

The Washington State Education Advocate Program (EAP) is a juvenile-justice school-community program aimed at helping student with re-entry. It began statewide in February 2006 (Burley, 2012 & 2011). The Washington Office of Superintendent of Public Instruction (OSPI) works with the nine regional Educational Service Districts (ESD), giving them funding under the federal Title I Neglected-Delinquent grant to provide advocate positions for the program. The EAP helps identify vocational and employment opportunities or re-engages youth with schools, especially the high-risk population coming out of detention centers and juvenile rehabilitation administrative (JRA) facilities. EAP helps justice-involved students overcome barriers to return successfully to school and facilitates school coordination activities for those re-engaging in school. Program goals include reducing the high school dropout rates and reducing the juvenile crime rate in Washington state. Eligibility is for youth involved in the juvenile justice system between 5 and 21 years of age, meeting specific criteria. First, they are considered moderate to high risk of reoffending. Second, they are school-based youth at risk of dropping out of school or showing signs of disengagement from school (Schutte & Maike, 2009).

The EAP services offered include school dropout prevention/intervention and re-engagement services. The dropout prevention/intervention assists youth at risk of dropping out of school, while the re-engagement program helps those who have dropped out to re-engage in school. There is also a work support program that provides career planning and connects youth to skill certificate programs and workforce development agencies within the community. Additionally, transition services support justice-involved youth to transition from institutional settings to their homes, school systems, and communities or pursue General Education Development (GED) options. EAP advocates are usually housed in the school, community, detention centers, and JRA facilities.

The program uses a case management model aimed at providing one-on-one support services to youth exiting county detention centers and JRA facilities. The EAP case management model identifies three tiers of services distinguished by the student's risk of reoffending, level of support, student's intensity and needs to develop appropriate individualized goals (Schutte & Maike, 2009). The case management services include assessing student risk, needs, strengths, as well as counseling, coaching, and group support to help youth acquire improved coping skills, develop healthy relationships, and succeed in school. Other services include providing homework assistance, developing and monitoring individualized student success plans, linking students and parents to schools and community services, monitoring behavioral cues, school attendance, grades, and probation compliance. The case management may continue voluntarily until the youth is 21 years of age or no longer on probation.

The present study aims to investigate the impact of the EAP in Washington on high school and postsecondary outcomes by addressing the following research questions:

- Does EAP participation affect school attendance?
- Does EAP participation affect high school graduation and reduce the likelihood of dropping out?
- Does EAP participation affect postsecondary enrollment and postsecondary degree attainment?

Study Population

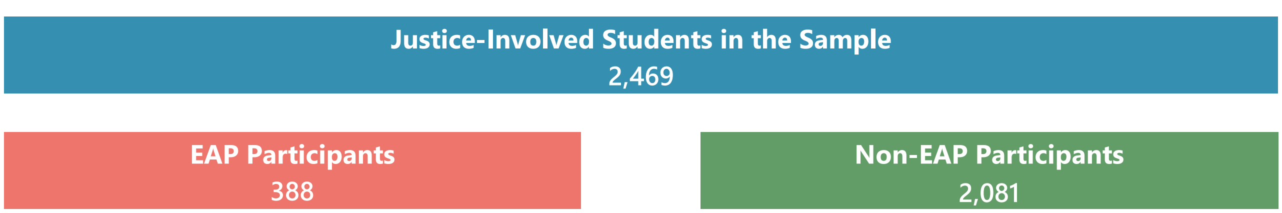
Data sources include the Comprehensive Education Data and Research System (CEDARS), provided by the Office of Superintendent of Public Institution (OSPI), and postsecondary education enrollment from Washington's Public Centralized Higher Education Enrollment System (PCHEES) and the State Board for Community and Technical College (SBCTC). The juvenile justice data used for the study was obtained from the Administrative Office of the Courts (AOC) database.

The sampling population includes the students involved in the juvenile justice system referred to Education Advocate Program (EAP) while enrolled in 9^{th} to 12^{th} grade in Washington state public schools during the 2010-2019 academic years. Because of data availability, our study focuses only on EAP students in the Juvenile Rehabilitation Administration (JRA) transition facility obtained from the Administrative Office of the Courts (AOC) database.

We merged the JRA-EAP data with the participant data from OSPI to identify the treatment and control groups used for the study. The treatment group is the high school students (enrolled during 2010-2019) involved in the juvenile justice system who participated in the EAP. The control group is high school students (enrolled during 2010-2019) who were referred to the EAP but did not participate in the program.

The final sample contains 2,469 observations, including 388 EAP participants and 2,081 non-EAP participants, covering the 2010-2019 academic year.

Figure 1: Sample Description



Analytical Approach

We employed propensity score matching (PSM) and inverse-propensity weighting regression analysis (IPWRA) to address the research questions given the quasi-experimental nature of the data due to the selection bias problem in the data. We provide the details regarding these methods in the appendix of this report. Allan et al. (2020) noted that PSM and IPWRA may not always lead to the same study conclusions since each method has technical differences in methodology and measurements. More specifically, we have 388 treatment (EAP) and 2081 control (Non-EAP) groups in the present study, which might pose a severe challenge in identifying enough treatment groups when using PSM only. Therefore, we will share findings from both analysis techniques in this report.

What we found

Descriptive Analysis

We first looked at the demographic and high school characteristics of EAP and Non-EAP participants. These results are available in Table A of the appendix. For this report, we have included specific outcomes relevant to our research questions, including attendance, high school graduation, postsecondary enrollment, and postsecondary achievement.

High School Outcomes. Table 1 provides the breakdown of high school outcomes for EAP and non-EAP participants. Attendance data was available for the 2013-2018 school years. The table shows that approximately 60% of both EAP and non-EAP participants achieved regular high school attendance[1] Across both groups, around 70% of students reported no full-day unexcused absences. About 11% of EAP participants received high school diplomas, compared to about 19% of non-EAP participants. About 31% of EAP participants dropped out of high school, compared to 23% of non-EAP participants. In addition, 2% of students in the non-EAP group received GED certificates. The sample size for EAP participants that received GED certificates is too small to report.

Postsecondary Enrollment and Achievement. Table 1 also provides the breakdown of postsecondary outcomes for EAP and non-EAP participants. The postsecondary enrollment shows that 5 out of 10 students in the EAP group and 4 out of 10 students in the non-EAP group were enrolled in various postsecondary programs. The analysis indicated that about 4% of EAP and 6% of non-EAP participants received postsecondary degrees.

[1] Regular attendance is defined as having, on average, less than two absences per month (OSPI).

Table 1: High school and postsecondary outcomes for EAP and Non-EAP participants

	EAP (*n* = 388)		**Non-EAP (*n* = 2081)**	
Outcomes	*n*	*%*	*n*	*%*
Regular attendance[1]	229	59.2%	1233	60.1%
Full day unexcused school absences				
No absences	274	70.7%	1396	67.1%
1- 10 absences	38	9.8%	241	11.6%
11-20 absences	22	5.6%	124	5.9%
21 & above absences	54	13.9%	320	14.7%
High School Diploma received	41	10.5%	386	18.6%
High School Dropout	122	31.4%	470	22.6%
GED certificate	*	*	44	2.1%
Postsecondary enrollment[#]	201	51.8%	923	44.4%
Postsecondary degree achievement[#]	17	4.4%	120	5.8%

Notes: [1] Attendance and absence data is available from OSPI CEDARS data from 2013 to 2018 school years. # includes only Washington public two-year and four-year colleges and universities; * implies data not reported because n<10

Determinants of EAP Participation[2]

Demographic and severity of offense: Table 2 provides the probit regression model estimates of factors associated with EAP participation.

The analysis suggests several findings. First, the probability of involvement in EAP increases among male students compared to female students. Second, we do not find strong evidence suggesting racial/ethnic differences play a role in predicting EAP participation in the study. Finally, the table also shows that the probability of participating in EAP increased among students involved in drug violations and felony property compared to those engaged in public order taken as reference.

Free and Reduced-Price Lunch. Eligibility for free and reduced-price lunch (FRPL) programs can be reflective of economic status. FRPL has often been considered an indicator of children living in poverty (Wang & Fawzi 2020; Gassman-Pines & Bellows, 2018). Table 2 shows that the probability of FRPL eligibility in EAP increased significantly among the recipients of FRPL compared to non-FRPL. This finding implies that students from families living below the poverty line are more likely to be referred to EAP than students from families living above the poverty line.[3]

Student Mobility[4]. Student mobility is also a significant driver of EAP participation in the sample. Students with higher school mobility are more likely to be in EAP. Student mobility may be due to placement change, lack of service, family economic situation, or disciplinary actions, as Gertseva and McCurley (2018) noted.

[2] Not all juvenile delinquents transitioning from County Detention/JRA facilities can be served intensively through EAP. The EA establishes eligibility criteria and assess risk factors based upon individual youth's needs. The eligibility criteria and target population may vary between programs because of the unique demographics of each local facility, priority of need, resources available, and limiting duplication of effort (Schutte & Maike, 2009). However, the information about program selection criteria is not available from datasets employed in the present study. The treatment predictor variables used here might be considered as proxy to true program determinants.

[3] As shown in Table A of the appendix more than 90% of the students in both groups were eligible for FRPL which can be considered evidence of low income in the study.

[4] Student mobility refers to students changing schools during a school year.

Table 2: Determinants of EAP participation

Variables	Coefficient	Stand. Error
Gender (male)	0.5545***	0.1364
Race		
Asian	2.4407***	0.3221
African American	0.3481	0.3107
Multiple Races	0	
Native Hawaiian	0.2320	0.5685
Not provided	0.7359	0.6395
Hispanic	0.1052	0.3105
White	0.2745	0.2889
Offense Type		
Drug law violations	1.1503***	0.2206
Misdemeanor Property	0.1712	0.2774
Misdemeanor Person	0.2347	0.2657
Felony Property	0.4491***	0.1937
Felony Person	-0.0154	0.1873
Student Characteristics/Program Participation		
Free Reduced Priced Lunch (FRPL) status	0.6579*	0.3672
Special Education status	1.0355	1.1405
English Language Learners (ELL) status	0.2167	0.1935
Homelessness status	-0.1578	0.1163
Disability status	-0.9103	1.1398
Migrant status	0.2994	0.2616
Leaner Assistance Program (LAP) status	-0.1314	0.1239
School mobility	0.0460***	0.0139
504 Plan	-0.0036	0.2058
School Year dummies included	Yes	Yes
Constant	-3.2346***	0.4695
Number of obs. 2349		
Prob > chi^2 : 0.000		
Pseudo R^2: 0.6578		

Notes: Reference groups are American Indian/Alaskan Native among race/ethnicity and public order among offense type. Military parent status is available only from 2017 and forward.
***, **, and * denote significance at the 1%, 5%, and 10% respectively.

Association between EAP and High School and Postsecondary Outcomes[5]

Propensity Score Matching (PSM)

Table 3 displays the analysis of the data using Propensity Score Matching (PSM). Before we discuss the results, it is important to mention that we conducted post-estimation diagnostic tests such as balanced covariates for the estimated PSM to check the consistency and robustness of the matching, as presented in Table B. As a result, the table shows that the distribution of the relevant variables in the control and treatment groups is balanced. And this is evident by the insignificant differences in the variables after matching. In addition, low pseudo-R^2 and a significant reduction in the mean standardized bias indicate successful balancing of the distribution of covariates between participants and non-participants groups. Finally, as a procedural issue, we allow a sufficient overlap between the control (non-EAP) and treatment (EAP) groups in the process of matching. Because of this, we impose common support to improve the matching while using different matching algorithms, including nearest neighbor, kernel, and radius caliper of 0.05, as shown in Table 3.

Attendance. The results presented in Table 3 based on PSM estimates show that EAP has no association with regular attendance. Also, participation in the program significantly decreases full-day unexcused absences in Table 3 except for the nearest neighbor.

High School Completion. The PSM analysis suggests that the probability of receiving a high school diploma decreases significantly among EAP participants. Our results also show no association between EAP participation and high school dropout, as presented in Table 3. We could not carry out the impact of EAP on GED due to the sample size.

Postsecondary Outcomes. Finally, Table 3 shows a lack of empirical evidence that participation in EAP is associated with postsecondary enrollment and degree achievement in the study.

[5] Except for student absences, all other outcome variables are binary (1/0) in Tables 3 and 4. Other than school full-day unexcused absences which was estimated using linear regression, we estimated the remaining outcomes using a probit regression model.

Table 3: PSM estimate of the impact of EAP on High school and postsecondary outcomes

Outcomes	Matching Algorithm Used		
	Nearest neighbor-NN	**Kernel**	**Caliper**
	Average Treatment Effect for Treated		
Regular attendance	0.0000	0.0163	0.0159
	[0.0782]	[0.0565]	[0.0563]
Full day unexcused absences	-1.2023	-4,9254***	-4.9856***
	[2.9774]	[2.0529]	[2.0563]
High School Graduation	-0.0952	-0.1020***	-0.1067***
	[0.0520]	[0.0311]	[0.0308]
High School Dropout	0.0476	0.0892	0.0143
	[0.0661]	[0.0495]	[0.0494]
Postsecondary enrollment	0.08333	0.0395	0.0484
	[0.07915]	[0.0572]	[0.0569]
Postsecondary degrees	0.0238	0.0063	0.0050
	[0.0339]	[0.0271]	[0.0270]

Note: Figure in parentheses is the standard error; ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Inverse-Propensity Weighting Regression Analysis (IPWRA)

Table 4 displays the analysis of the data using Inverse-Propensity Weighting Regression Analysis (IPWRA). We believe IPWRA provides a more robust estimate due to data limitations in this study.

IPWRA can compensate for the imbalance in the study groups, especially when using PSM (see Halpern, 2014). In sum, IPWRA explores total observation, while PSM is based on a matched sample- a subset of the study population, which might not produce robust results given the data limitation in the study. Another concern is a possible misspecification problem in PSM, which is not evident in IPWRA (Woodridge, 2007). However, IPWRA could still suffer from small sample size where some weights are extreme (Austin & Stuart, 2015).

Attendance. While the PSM analysis suggested no affect, IPWRA estimates suggest that participation in EAP increased regular attendance. Table 4 also shows that EAP significantly reduced full-day unexcused absences. The implication is that participation in the EAP increases regular attendance and lowers full-day unexcused absences.

High School Completion. In contrast to the PSM analysis, no evidence in Table 4 supports the finding that EAP participants were less likely to earn a high school diploma. Whereas the PSM analysis showed no impact on the likelihood of dropping out, the IPWRA analysis suggests that the probability of dropping out of high school decreases significantly among EAP participants. Again, we could not carry out the impact of EAP on GED due to the sample size.

Postsecondary Outcomes. In contrast to the findings in Table 3, we find that participation in EAP increases the probability of earning a postsecondary degree. However, there is a lack of evidence to show an impact for postsecondary enrollment.

Table 4: IPWRA estimate of the association between EAP and high school and postsecondary outcomes

Outcomes	**Average Treatment Effect for Treated**	**Std. Error**
Regular attendance	0.3884***	0.0431
Full day unexcused absences	-58.0024*	25.3919
High School Graduation	-0.3044	0.1910
High School Dropout	-0.2452***	0.0264
Postsecondary enrollment	-0.1668	0.1089
Postsecondary degree achievement	0.0313***	0.0106

Note: ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Despite the mixed results and lack of empirical support for the effects of EAP on some of the selected outcomes across the tables, we believe our preferred IPWRA estimates presented in Table 4 provide valuable insights into the policy relevance of the EAP in Washington State. For instance, the participation in EAP is significantly associated with regular attendance and postsecondary degree attainment, and EAP participants are less likely to drop out or absent from school in the state. However, these results need to be interpreted with caution because of the lack of data covering students from other EAP locations such as detention transition centers and school-community-based high and middle school dropout prevention centers.

Conclusion

The study examined the association between the Washington state Education Advocate Program (EAP) and high school and postsecondary outcomes. The study examined outcomes of students involved in the juvenile justice system referred to Education Advocate Program (EAP) while enrolled in 9th to 12th grade in Washington state public schools during the 2010-2020 academic years. We employed propensity score matching (PSM) and inverse probability weighting regression adjustment (IPWRA) for the empirical analysis to address selection bias in the data.

The estimated binary model predicting program participation status showed gender (male), offense type, student economic status, and school mobility are significant factors associated with involvement in EAP. For the association between the program participation and educational outcomes, both PSM and IPWRA analysis produced mixed results. Nevertheless, our preferred estimates based on IPWRA showed that EAP students had fewer absences and achieved more regular attendance than non-EAP students. We also found that students participating in the program had a lower probability of dropping out of high school and a higher likelihood of receiving a postsecondary school degree. However, we find no evidence to support that EAP participation associate with postsecondary enrollment or high school diploma attainment.

A major limitation of this study comes from data availability. First, the present study does not include data covering students from other EAP locations such as detention centers and school-community. The present study employed data from the JRA transition facility only, resulting in limited treatments. The future challenge is to consider comprehensive data of EAP participants covering JRA transition facilities, detention transition centers, and school-community involved in dropout prevention and re-engagement services in the state. It is also vital to examine the impact of EAP on recidivism outcomes. Unfortunately, we could not address this in the present study due to a lack of data on recidivism rate or re-arrest data to compute this. Hence, future work can address this with the extended data to understand the program's effectiveness in reducing recidivism in Washington state.

Second, small sample size covering about ten years of data makes it challenging to evaluate program effectiveness for EAP program, considering the variation in changes of program availability, implementation, and participant composition over time using limited administrative data might provide a high-level picture of the disparity in educational outcomes between EAP participants and non-EAP students. To what extent does EAP impact those outcomes still requires further research to dive into with more data about EAP availability, placement, and detail time sequence between EAP participation and outcome measures. With more complete data, the heterogeneity of EAP impact could be identified and to better inform policymaking and program development.

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Appendix

Methodology

The administrative data used in the study represent a typical quasi-experimental design since the selection of the students into the EAP is non-random, which creates a selection bias problem. Therefore, to minimize the selection bias problem associated with data of this nature, the study employed propensity score matching (PSM) and inverse-probability weighting regression analysis (IPWRA). The PSM matches the treatment (i.e., EAP) and control (i.e., Non-EAP) units with the same propensity score to eliminate selection bias in the data. And the PSM achieves this by identifying individuals in the control group with similar characteristics as those in the treatment group using estimated propensity scores.

According to Austin and Stuart (2017), complete matching on the propensity score exists when the treated and control subject has a similar value of the propensity score. The propensity score is estimated using the probit model based on the specification below:[6]

$$EAP_i = \partial_0 + \sum_{j=1}^{J} \alpha_j X_i + \omega_i \qquad 1$$

Where EAP is a dummy variable which equals 1 for EAP participant and 0 otherwise throughout 2010 to 2019; X_i is the vector of students characteristics which include gender, race/ethnicity, high school characteristics such as free and reduced-price lunch (RFPL), homelessness, disability, learner assistance program (LAP), the severity of offense involvement, dummies representing school years, etc.; α_j is the parameter to be estimated and ω_i is the error term.

Subsequently, we used different algorithms to obtain optimal pair matching with replacement, including nearest neighbor (NN), adius caliper, and kernel in the study. We also ensure common support for all matched observations to improve matching. The empirical model used to estimate the impact of EAP on high school and postsecondary outcomes for the matched sample is therefore specify below:

$$y_i = \emptyset_0 + \beta\, EAP_i + \tau_i \qquad 2$$

Where y_i is the high school and postsecondary outcomes, while EAP is as earlier defined; $\emptyset_0$ is the intercept, while β is the parameter to be estimated, which represents the impact of EAP on the potential outcomes.; τ_i is the error term.

The probability of receiving treatment (propensity score) is defined by Rosenbaum and Rubin (1983) as

[6] The description of variables used to generate the propensity scores in the present studyis presented in Table A of the appendix.

$$p(X) = \Pr(EAP = 1|X) = F\{h(X)\} = E(EAP|X) \quad 3$$

Where EAP and X are as defined earlier and $F\{.\}$ is a cumulative distribution function.

Given the data generating process of the outcome variables used in the present study, we estimated equation 2 using a linear regression model for student absence as an outcome. In contrast, all other outcomes (high school diploma, dropout, and postsecondary enrollment and achievement) were estimated using a probit regression model.

We also employed inverse-probability weighting regression adjustment (IPWRA) since PSM may be biased because of the misspecification problem (Woodridge 2007; Robins et al., 2007). Similar to PSM, this approach also uses propensity scores. The difference between PSM and IPWRA is how propensity scores control differences in the characteristics of EAP participants receiving the treatments to achieve the identification process. With IPWRA, estimated propensity scores are taken as a weight to reduce or eliminate the effects of confounding in the data (Guo and Fraser, 2015). This approach offers protection against misspecification of the model even if the regression model is incorrectly specified, which is why it is called the doubly robust method (Woodridge, 2007). Furthermore, in contrast to PSM based on the matched sample, IPWRA keeps all eligible observations. Guo and Fraser (2015) noted that propensity weighting is particularly appropriate when PSM could result in match failure that would decrease the same size and result in statistical power below desirable levels.

The empirical model used to estimate the impact of EAP on high school and postsecondary outcomes with IPWRA is specified below:

$$y_i = \emptyset_0 + \beta\, EAP_i + \sum_{j=1}^{J} \alpha_j Z_i + \tau_i \text{ (weight (w) is inverse of propensity scores)} \quad 4$$

Where y_i is the high school and postsecondary outcomes; EAP is as earlier defined; Z_i is the vector of students characteristics with the potential to influence y_i; $\emptyset_0$ is the intercept, while β is the parameter to be estimated which is equivalent to the average treatment on the treated (ATT)- the measure of the impact of EAP on the potential outcomes.; τ_i is the error term. Similar to PSM, the propensity scores are estimated using Equation 1.

Following the work of Hirano and Imbens (2001), inverse weights equal to 1 for EAP participants and $\frac{\hat{p}(X)}{1-\hat{p}(X)}$ for the non-EAP participants, while weights in Equation 3 can be defined in combined form as

$$w_i = EAP_i + (1 - EAP_i)\frac{\hat{p}(X)}{1-\hat{p}(X)} \quad 5$$

Where $\hat{p}$ are the estimated propensity scores, while EAP is as defined above.

Besides the fact that the Equation is based on the matched sample, another significant difference between Equations 2 and 4 is that the latter includes possible confounding variables and the treatment indicator, thus minimizing the misspecification problem in the model.

The estimated impact in present study is based on the average treatment effect on treated (ATT) computed for each of Equation 2 and 4 using the expression below:

$ATT = E\{E[Y_1|\ EAP = 1, P(x)] - E[Y_0|\ EAP = 0, P(x)]|EAP = 1\}$[7] 6

Where X and EAP as earlier defined; Y_1 and Y_0 represent the high school and postsecondary outcomes for EAP and non EAP, respectively; $P(X)$ is the estimated propensity score (PS)

[7] ATT is the average effect of treatment for those who receive the treatment, which in this case is EAP.

Table A: Demographics and high school characteristics of EAP and Non-EAP participants

Variables	EAP (n=388)		Non-EAP (n=2081)	
	Frequency	*Percentage*	*Frequency*	*Percentage*
Gender				
Male	316	81.44	219	10.52
Female	72	18.56	1862	89.48
Races/ethnicity				
American Indian	N/A	N/A	92	4.42
Asian American	308	79.38	29	1.39
African American	14	3.61	294	14.13
Multiple Races	-	-	120	5.77
Native Hawaiian	N/A	N/A	24	1.15
Not Provided	N/A	N/A	N/A	N/A
Hispanic/Latino	16	4.12	486	23.40
White	45	11.60	1027	49.35
Type of offense				
Public order	N/A	N/A	280	13.46
Drug law violations	311	80.15	86	4.13
Misdemeanor Property	N/A	N/A	97	4.66
Misdemeanor Person	N/A	N/A	106	5.09
Felony Property	29	7.47	366	17.59
Felony Person	29	7.47	1146	55.07
Free Reduced Priced Lunch (FRPL) status				
Yes	383	98.91	1945	93.46
No	N/A	N/A	136	6.54
Special Education status				
Yes	156	40.21	790	37.96
No	232	59.79	1291	62.04
English Language Learners (ELL) status				
Yes	37	9.54	167	8.02
No	351	90.46	1914	91.98
Homelessness status				
Yes	106	27.32	525	25.23
No	282	72.68	1556	74.77

Variables	*Frequency*	*Percentage*	*Frequency*	*Percentage*
Disability status				
Yes	156	40.21	804	38.64
No	232	59.79	1277	61.36
Migrant status				
Yes	20	5.15	68	3.27
No	368	94.85	2013	96.73
Leaner Assistance Program (LAP) status				
Yes	100	25.77	502	24.12
No	288	74.23	1579	75.88
School mobility				
1-5 moves	131	33.93	934	44.88
6-10 moves	175	44.99	879	42.24
11-15 moves	71	18.25	229	11.01
>15 moves	11	2.83	39	1.87
504 Plan status				
Yes	33	8.51	151	7.26
No	355	91.49	1930	92.74

Note: N/A implies not reported because n<10

Table B: Covariant balancing and matching quality test

Variables	Before matching			After matching		
	EAP	*Non-EAP*	*P-value*	*EAP*	*Non-EAP*	*P-value*
Gender (male)	0.8144	0.1005	0.000	0.1429	0.1476	0.932
Asian	0.7938	0.0148	0.000	0.0476	0.0524	0.889
African American	0.0361	0.1499	0.000	0.1667	0.1609	0.921
Multiple Races	0	0		0	0	
Native Hawaiian	0.0026	0.0122	0.090	0.0119	0.0120	0.090
Not provided	0.0026	0.0041	0.662	0.0119	0.0061	0.695
Hispanic	0.0412	0.2483	0.000	0.1928	0.2209	0.627
White	0.1159	0.5237	0.000	0.5357	0.5080	0.721
Drug law violations	0.8016	0.0418	0.000	0.0833	0.0775	0.890
Misdemeanor Property	0.0129	0.0469	0.002	0.0595	0.0531	0.857
Misdemeanor Person	0.0155	0.0520	0.002	0.0714	0.0601	0.769
Felony Property	0.0747	0.1759	0.000	0.3452	0.2676	0.278
Felony Person	0.0747	0.5507	0.000	0.3452	0.4312	0.256
Free Reduced Priced Lunch (FRPL) status	0.9871	0.9368	0.000	0.9881	0.9623	0.285
Special Education status	0.4021	0.3784	0.381	0.4524	0.4213	0.687
English Language Learners (ELL) status	0.0954	0.0841	0.472	0.1191	0.1103	0.860
Homelessness status	0.2732	0.2545	0.441	0.2976	0.2562	0.551
Disability status	0.4021	0.3850	0.529	0.4524	0.4243	0.717
Migrant status	0.0516	0.0346	0.110	0.0476	0.0407	0.829
Leaner Assistance Program (LAP) status	0.2577	0.2417	0.502	0.1905	0.2191	0.648
School mobility	7.6366	6.465	0.000	8.4405	7.3360	0.060
504 Plan status status	0.0851	0.0739	0.450	0.0476	0.0677	0.580
Pseudo R^2	0.651			0.029		
Pro>Chi2	0.000			0.999		
Mean Bias	57.2			8.3		
Median Bias	20.3			6.4		