The Impact of ACT Kaplan Online Prep Live on ACT Score Gains

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Quasi-experimental methods were used to examine the impact of the ACT® Kaplan® Online Prep Live (OPL) program on official ACT® test score gains. Using propensity score matching based on hypothesized criteria for self-selection into OPL, we identified a matched sample of 1,800 ACT test takers. Using multiple regression, we explored whether enrollment in OPL affects ACT score gains for OPL registrants relative to non-OPL registrants. The study found that OPL registrants had a higher retest gain score on the English, math, and science subject tests and the Composite relative to non-OPL registrants. OPL enrollment improved the ACT Composite score even more for low-income students. Some interesting subgroup differences in gain scores on the ACT subject tests and ACT Composite were also observed.

Objective

In this initial study, we examined the impact of the ACT Kaplan Online Prep Live (OPL) program on score gains among high school students who took the ACT more than once. OPL is a research-based, instructor-led online teaching community focused on core academic content as well as non-cognitive content designed to improve learning and ultimately students' success. The core of the community includes live-instruction as well as activities facilitated by trained instructors.

We investigated official ACT score gains resulting from enrolling in the OPL program between ACT administrations. We used propensity score matching techniques to identify a group of similar students who took the ACT during multiple administrations but who did not participate in the OPL program. This study addresses the following research questions:

1. **How does enrollment in OPL affect score gains among students who retake the ACT?**
2. **Does the effect of enrollment in OPL on score gains differ for students in gender, family income, and racial minority membership subgroups?**

Perspective

Students make use of many test preparation resources in an attempt to gain a competitive edge in the college admissions process. As a result of the importance of these exams in the admissions process, a multibillion dollar industry has emerged that is designed to help students prepare to do their best on these exams (Barnes Reports 2017). This industry is supported by the notion that test-preparation programs result in significant score gains and a postsecondary competitive edge (MacGowen 1999; McDonough 1997). Students therefore participate in these test preparation programs in an attempt to improve their scores and thus their chances for college admission and scholarship opportunities.

Although most high school students aspire to achieve some form of postsecondary education, research shows that a significant percentage of students are unprepared to make a successful transition to college and career after completing high school (ACT 2015). This percentage is even greater for underserved learners who often have fewer opportunities to take rigorous courses or be exposed to high-quality instruction. Research shows that low-income and minority students tend to underperform on certain ACT subject tests relative to higher-income and/or White students (ACT 2015; McNeish, Radunzel, and Sanchez 2015; Sanchez 2013). There are also concerns about equity of access to high-quality test preparation for underserved learners. For example, Buchmann, Condron, and Roscigno (2010) discuss "shadow education," which includes various forms of instruction beyond the scope of traditional formal education. These types of extra-educational activities can be quite costly. With this reality in mind, the ACT Kaplan Online Prep Live (OPL) program is offered free of charge for 12 months to all students who register for the ACT with a fee waiver.[1]

Methods

Participants

This study used OPL enrollment and ACT test data from the 2015-2016 and 2016-2017 academic years. The sample included 1,771 OPL registrants and 623,172 non-OPL registrants. Propensity score methods were used to identify a matched analytical sample of 1,800 students; 900 students in both the treatment and control groups. This reduction was a result of a combination of both the requirement for students to have no missing data on relevant study variables as well as the propensity score matching algorithm used. It is possible that non-OPL students have used other test preparation books or programs; this information was not available.

Variables

Fourteen student characteristics were considered in this study. The variables considered as well as the demographic characteristics of this sample are shown in Table 1. These characteristics were included because of the relationship they are believed to have with participating in test preparation as well as their impact on ACT scores.

Student background variables. We considered self-reported gender, race/ethnicity, family income, parental education, coursework taken, school type, and declaring a need for help in school. All variables were provided during registration for the ACT. Percentages for the unmatched and matched samples are provided in Table 1. The matched sample is compared in the balancing evaluation section below.

Prior and post ACT test scores. One proximal determination of efficacy for an ACT test preparation program is official ACT scores; this study examined growth in scores from a prior to a subsequent official ACT test administration. For students who participated in OPL, a prior ACT test administration was identified that was closest to the purchase of the OPL product but no longer than one year prior to purchase.[2] A post-OPL-enrollment ACT test administration was then identified that was closest to the end of the active license period and either within or no more than six months beyond the active license period for OPL. For the control group, students had to have taken the ACT during the 2015-2016 or 2016-2017 academic years at least twice, had to take a prior ACT test anytime during high school, and a second ACT test anytime during the 2016-2017 academic year.[3]

Prior academic measures such as test scores and HSGPA as well as coursework taken were important to consider in this study because students with low academic performance may be motivated to seek aid to perform better, while students with higher academic performance may be looking for ways to increase their scores for a competitive edge in college admissions to selective institutions and/or merit-based scholarships.

Learning and motivation proxy variables. We needed to account for the single largest alternative explanation of growth in test scores– learning due to school instruction –by using proxy variables. In order to account for school learning, we included the number of instructional months elapsed during the retesting window in our model. Additionally, to account for possible differential motivation and opportunity to learn, we included the number of months between their prior test administration and their high school graduation. Advanced coursework was included as a proxy for motivation as students taking advanced coursework may represent more motivated students that have had greater exposure to test content. Finally, a public school indicator was included to try to account for possible differences in the availability of school test preparation opportunities.

Analysis

Propensity Score Model

Propensity score matching is a widely used quasi-experimental methodology for constructing a counter-factual in causal inference research (D'Agostino 1998; Rosenbaum and Rubin 1983; Rosenbaum and Rubin 1985). This methodology involves the calculation of a single metric, the propensity score, which simplifies the matching process by only requiring that the matching be based on this metric rather than on numerous individual characteristics. Employing this methodology to obtain a balanced sample allowed us to make causal statements about student enrollment in OPL and performance on the ACT.

Logistic regression was used to predict enrollment in OPL given students' other characteristics. The conditional probabilities obtained from this model were the propensity scores. Using stepwise selection, as well as the forced inclusion of certain characteristics to help with group balancing, nine characteristics were retained in the propensity score model (Table 2 and Table 3).

To run the match process and produce a matched sample, we used the SAS software macro "OneToManyMTCH" (Parsons 2004). This macro uses a greedy, nearest-neighbor, matching algorithm to identify a matched sample. We used one-to-one matching between the treatment and control groups.

The matched samples were compared on the student characteristics. The standardized mean group differences were below the recommended cutoff of 10% for most variables, with all below 12% (Table 4). For continuous variables, the distributions prior to and post matching were also visually compared. The distributions for the probability of participation in OPL (i.e. the propensity scores; Figure 1), log of instructional months elapsed (Figure 2), prior ACT Composite score (ACTC) (Figure 3), months to graduation (Figure 4), and HSGPA (Figure 5) show that the post-matching distributions for each variable were similar.

Research Questions

Question 1: How does enrollment in OPL affect score gains among students who retake the ACT?

We first tested for a global effect of OPL enrollment on ACT score gains for students who retested. We estimated a linear regression model using the SAS software GLIMMIX procedure. We considered inclusion of the same student characteristics used in the propensity score model. Five models were estimated, one for each ACT subject test and ACT Composite (ACTC) score. Prior ACTC score was not included as an independent variable because of its relationship with gain scores. All variables in this model were grand-mean centered.

Question 2: Does the effect of enrollment in OPL on score gains differ for students in gender, family income, and racial minority membership subgroups?

In order to explore the differences in the effect of program enrollment for subgroups, we included interaction terms between treatment condition and subgroup membership indicators for minority, income, and gender subgroups to the models in research question 1 that identified a significant effect for OPL enrollment. As recommended by the *Standards for Educational and Psychological Testing*, we examine subgroup differences in the impact of preparation and the implications to score validity and interpretation (American Educational Research Association, American Psychological Association, and National Council on Measurement in Education, 2014). All variables in this model were grand-mean centered. To examine group differences, model estimates were used to obtain marginal means for each subgroup.

Results

Research Question 1.

We found that enrollment in OPL had a statistically significant positive effect on ACTC gain scores for retested students ($p < 0.0001$). Even after accounting for the other variables in the model, students who participated in OPL increased their gain score by 0.5366 scale score (Table 5).[4, 5] When we consider that it has been shown that nine months of instruction, one academic year, is associated with an average score gain of 1.64 (Camera and Allen 2017), we see that enrollment in OPL resulted in 33% of the gain typically seen in an entire year of classroom instruction. When we then look at the average per-month gain in ACTC score, by months of instruction, this corresponds to the observed mean growth after about 2.4 months of attending school.[6]

We also found that enrollment in OPL had a statistically significant positive effect on ACT English (ACTE; Table 6), math (ACTM; Table 7), and science (ACTS; Table 8) gain scores. Students who participated in OPL had an average score gain above non-participants of about 0.91, 0.51, and 0.39, respectively. Enrollment in OPL was not found to have a significant effect on ACT reading gain scores (Table 9). This analysis reveals that OPL has a large impact on ACT English gain scores, moderate impact on ACT math gain scores, and smaller impact on ACT science gain scores. These score gains correspond to the average gain observed for the national population after approximately 3.3 months, 2.6 months, and about 1.9 months of attending school, respectively.

Research Question 2.

Interactions between treatment condition and family income, gender, and minority membership were evaluated by running three separate models for each ACT subject and ACT Composite score from research question 1 that identified a significant effect for OPL enrollment. For the ACTC analyses, the only model with a significant interaction was between treatment and family income (Table 10). The increase in gain score for OPL enrollment was greatest for low-income students followed by middle and finally high-income students (Table 11). In particular, among students in the control group, high-income students had higher gain scores than low-income students. However, among students in the treatment group, there were not significant differences in gain scores among income groups. As a result, low-income students who participated in OPL had a gain score that was almost 1 scale score point higher than that of low-income non-participants.

For the subject tests analyses, a significant interaction between OPL enrollment and race/ethnicity was found on the reading test (Table 12). Minority OPL participants had a higher ACTR gain score than White students (Table 13). Minority students who participated in OPL had an average gain score that was 0.828 scale score points higher than that of minority non-participants. (Table 13). The interaction between treatment and income approached significance for the science subject test ($p = 0.0556$; Table 14). Similar to the ACT Composite results, the typical increase in gain score associated with OPL enrollment was significantly different from zero among low-income students (Table 15). For low-income students, those who participated in OPL had a gain score that was almost 1 scale score point higher than that of non-participants.

Scholarly Significance

This study examined the effects of enrolling in the ACT Kaplan Online Prep Live program. The OPL program focuses on core academic content as well as noncognitive content designed to improve learning and ultimately students' success. This study demonstrates that enrolling in OPL had a positive effect on gain scores. This was seen for the ACT English, math, and science subject tests as well as for ACT Composite. No significant effect was found for enrolling in OPL on ACT reading scores. We also found some interesting differences in the impact on gain scores for subgroups, as reported in the results section, where minority and low-income students experienced comparatively higher gains. Each of these findings provides causal support for the efficacy of participating in the OPL program.

These finding are practically important because while the potential engagement with test preparation lasts several weeks, the associated gains are aligned to the gains of multiple months of school attendance. This first study on OPL enrollment shows promising results. Future studies will focus on patterns of usage, yielding further insights into how best to help students prepare for the ACT.

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Notes

1. To qualify for an ACT fee waiver, a students must meet certain criteria. For example, they must be currently enrolled in the 11th or 12th grade; be a US citizen or testing in the US, US territories, or Puerto Rico; and must meet one or more indicators of economic need listed on the ACT Fee Waiver form. For the full criteria for eligibility, see https://www.act.org/content/dam/act/unsecured/documents/FeeWaiver.pdf.
2. This prior ACT test was used to measure growth relative to prior performance. This prior may not have been the first time a student has taken the ACT.
3. The two tests may or may not have been in the same academic year.
4. In the current model, we chose to retain all predictors from the propensity score model in the final regression model. An alternative methodological choice for model building would be to eliminate nonsignificant predictors despite inclusion in the propensity score model. If we eliminated all nonsignificant predictors, the estimate of ACTC gain was 0.5302. If we further removed all predictors included in the propensity score model, the estimate of ACTC gain was 0.5278. Similar results were found for each subject test with the difference never exceeding 0.027.
5. In the propensity score matching literature, there is some debate about whether there is a need to account for the shared variance that results from matched pairs. To check for the effect of this shared variance, cluster robust standard errors that accounted for the paired clusters was implemented in a separate model. Accounting for the shared variance did not have a major impact on estimates of the impact of program participation. For example, the estimates of the effect of OPL participation between unaccounted for and accounted for shared variance were 0.5336 and 0.5365, respectively, a difference of 0.0029. For the subject tests, the maximum difference was 0.0015; the ACT scale ranges from 1 to 36.
6. Camera and Allen (2017) estimated the typical month-to-month gain associated with schooling for the ACT Composite, English, math, reading, and science score to be 0.227, 0.277, 0.199, 0.228, and 0.200 respectively.

Tables and Figures

Table 1. Propensity Score Model Sample Characteristics

	Pre-Match (N=1,347,051)		Post-Match (N=1,800)	
	Control	Treatment	Control	Treatment
Family Income				
Low-income	11.71%	23.66%	31.67%	31.56%
Middle-Income	28.80%	25.97%	35.56%	34.33%
High-Income	29.53%	23.72%	32.78%	34.11%
Missing Income	29.96%	26.65%	0.00%	0.00%
Gender				
Female	58.02%	56.13%	50.56%	55.22%
Male	41.98%	43.87%	49.44%	44.78%
Minority				
White	62.41%	45.51%	54.11%	55.22%
Minority	20.28%	31.51%	45.89%	44.78%
Missing	17.31%	22.98%	0.00%	0.00%
Parental Education				
Missing	17.16%	15.08%	1.67%	3.11%
Less than a BA	24.81%	30.66%	38.00%	37.22%
At least a BA	58.03%	54.26%	60.33%	59.67%
English Coursework				
Less than 4 years	3.24%	2.43%	3.22%	1.44%
4 years	96.76%	97.57%	96.78%	98.56%
Math Coursework				
Less than Algebra II	11.48%	12.37%	17.78%	14.00%
Beyond Algebra II	88.52%	87.63%	82.22%	86.00%
Science Coursework				
Less than Chemistry	27.44%	25.80%	28.78%	28.11%
Beyond Chemistry	72.56%	74.20%	71.22%	71.89%
Taken any AP coursework				
Yes	64.5%	66.4%	68.11%	72.56%
No	35.5%	33.6%	31.89%	27.44%
Attended Public School				
Yes	74.46%	80.465	86.89%	86.78%
No	20.19%	13.78%	13.11%	13.22%
Missing	5.35%	5.76%	0%	0%
Declared Need for Help				
Yes	60.12%	64.71%	75.89%	76.33%
No	39.88%	35.29%	24.11%	23.67%
HSGPA (Mean)	3.58	3.58	3.46	3.52
Mean Prior ACT Composite score (Standard Deviation)	22.57 (4.77)	22.16 (4.65)	21.20 (4.51)	21.65 (4.43)
Log of the number of months elapsed between retesting (Mean)	1.67	1.41	1.45	1.43
Number of months to graduation for prior test date (Mean)	14.42	14.57	14.69	14.41

Note: Low-income is less than $36,000, middle income is $36,000 to $100,000, and high-income is over $100,000. Variables that were not retained in the propensity score model may show greater similarity in the pre-match sample than the post-match sample.

Table 2. Student Characteristics Considered and Retained in the Propensity Score Model

Retained in Propensity Score Model	Student Characteristic
✓	Prior ACT Composite score
✓	HSGPA
✓	Square of HSGPA
✓	Gender (Female)
✓	Interaction between HSGPA and Gender (Female)
✓	Square of prior ACT Composite score
✓	Log of the number of instructional months
✓	Square of Log of the number of instructional months
	Indicator for taking any AP coursework
	Declaring a need for help with deciding educational and occupational plans, improving mathematical skills, improving reading speed and comprehension, improving study skills, or expressing ideas in writing.
✓	Number of months to graduation from prior test date
✓	Square of number of months to graduation from prior test date
✓	Family Income(<$36,000, $36,000-$100,000, and > $100,000)
✓	Minority membership (African American, Hispanic, American Indian, or Native Hawaiian)
	One parent has at least a Bachelor's degree
	Taken 4 years of English
✓	Taken math coursework beyond Algebra II
	Taken science coursework beyond Chemistry
✓	Attended a public school

Note: The logarithmic transformation of the number of instructional months elapsed during retesting window was used because this term aided in matching.

Table 3. Parameter Estimates for the Logistic Propensity Model

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-9.9602	1.2931	59.5632	<.0001
Prior ACT Composite	0.2665	0.0689	14.9637	0.0001
HSGPA	-0.2242	0.7383	0.0922	0.7614
HSGPA*HSGPA	0.0284	0.1139	0.0623	0.8029
Gender (Female)	-0.1739	0.2542	0.4678	0.494
HSGPA*Gender (Female)	0.0067	0.0717	0.0088	0.9255
Square of prior ACT Composite	-0.0057	0.0015	13.8305	0.0002
Log of instructional months	0.7074	0.2018	12.2836	0.0005
Square of log of instructional months	-0.6090	0.0714	72.7728	<.0001
Months to graduation	0.1535	0.0227	45.7435	<.0001
Square of months to graduation	-0.0021	0.0006	12.0238	0.0005
Low-Income	-0.4108	0.0487	75.4627	<.0001
Middle-Income	-0.0256	0.0426	0.3623	0.5472
Minority	0.4148	0.0392	111.8994	<.0001
Coursework beyond Algebra II	-0.1714	0.0507	11.4071	0.0007
Attend public school	0.1475	0.0509	8.4039	0.0037

Table 4. Mean Comparison of Matched Sample

Variable Description	Pre-Match Treatment Mean	Pre-Match Control Mean	Pre-Match Difference	Pre-Match Standardized Difference (%)	Post-Match Treatment Mean	Post-Match Control Mean	Post-Match Difference	Post-Match Standardized Difference (%)
Prior ACT Composite	22.1581	22.5701	-0.412	-8.74	21.6544	21.2011	0.4533	10.13
HSGPA	3.5787	3.5754	0.0032	0.71	3.5161	3.4598	0.0564	11.53
Log of Instructional Months Between two tests	1.4107	1.6739	-0.2631	-41.07	1.4319	1.4487	-0.0168	-2.67
Months to Graduation	14.5731	14.422	0.1511	2.48	14.4122	14.6856	-0.2733	-4.20
Gender (Female)	0.5613	0.5803	-0.019	-3.84	0.5522	0.5056	0.0467	9.35
Low-Income	0.3226	0.1673	0.1553	36.71	0.3156	0.3167	-0.0011	-0.24
Middle-Income	0.3541	0.4112	-0.0571	-11.77	0.3433	0.3556	-0.0122	-2.56
High-Income	0.3233	0.4215	-0.0982	-20.41	0.3411	0.3278	0.0133	2.82
Coursework beyond Algebra II	0.8763	0.8852	-0.0089	-2.75	0.8600	0.8222	0.0378	10.34
Attend Public School	0.8538	0.7867	0.0671	17.55	0.8678	0.8689	-0.0011	-0.33
Minority	0.4091	0.2453	0.1638	35.45	0.4478	0.4589	-0.0111	-2.23
Parents have at least a Bachelor's degree	0.6390	0.7005	-0.0615	-13.11	0.6158	0.6136	0.0023	0.47
Took four years of English	0.9757	0.9676	0.0081	4.89	0.9856	0.9678	0.0178	11.79
Coursework beyond Chemistry	0.742	0.7256	0.0163	3.70	0.7189	0.7122	0.0067	1.48
Attended Public school	0.8538	0.7867	0.0671	17.55	0.8678	0.8689	-0.0011	-0.33
Taken any AP courses	0.664	0.6450	0.0191	4.01	0.7256	0.6811	0.0444	9.74
Self-reported Need for help	0.6471	0.6012	0.0459	9.49	0.7633	0.7589	0.0044	1.04

Note: All variables listed were considered for inclusion in the propensity score matching, but not all were retained. See Table 2 for a list of retained variables.

Table 5. Parameter Estimates for the ACT Composite Gain Score Linear Model

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.8468	0.1660	5.10	<.0001
Treatment Group	0.5366	0.0887	6.05	<.0001
HSGPA	0.4550	0.1535	2.96	0.0031
HSGPA*HSGPA	0.0728	0.1498	0.49	0.6269
Gender (Female)	0.2232	0.0898	2.49	0.013
HSGPA*Gender(Female)	-0.1674	0.1869	-0.90	0.3706
Log of instructional Months	0.5406	0.0829	6.52	<.0001
Square of log of instructional Months	0.1933	0.0987	1.96	0.0502
Months to graduation	0.0377	0.0092	4.08	<.0001
Square of months to graduation	-0.0017	0.0007	-2.29	0.0222
Low-income	0.0515	0.1234	0.42	0.6763
Middle-income	-0.1343	0.1115	-1.20	0.2288
Minority membership	0.0660	0.1001	0.66	0.5098
Coursework below Algebra II	0.0341	0.1251	0.27	0.7854
Public school	0.0596	0.1325	0.45	0.6528

Note: All variables are grand-mean centered.

Table 6. Parameter Estimates for the ACT English Gain Score Linear Model

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.4688	0.2674	5.49	<.0001
Treatment Group	0.9111	0.1430	6.37	<.0001
HSGPA	0.6143	0.2473	2.48	0.0131
HSGPA*HSGPA	0.1622	0.2413	0.67	0.5015
Gender (Female)	0.1101	0.1447	0.76	0.447
HSGPA*Gender(Female)	-0.1221	0.3011	-0.41	0.6851
Log of instructional Months	0.8785	0.1336	6.58	<.0001
Square of log of instructional Months	0.5039	0.1590	3.17	0.0015
Months to graduation	0.0376	0.0149	2.53	0.0115
Square of months to graduation	-0.0016	0.0012	-1.35	0.1772
Low-income	0.0474	0.1988	0.24	0.8115
Middle-income	-0.2865	0.1797	-1.59	0.111
Minority membership	0.0356	0.1613	0.22	0.8253
Coursework below Algebra II	-0.1894	0.2016	-0.94	0.3475
Public school	-0.2030	0.2135	-0.95	0.3417

Note: All Variables are grand-mean centered.

Table 7. Parameter Estimates for the ACT Math Gain Score Linear Model

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.3602	0.2169	1.66	0.097
Treatment Group	0.5132	0.1160	4.43	<.0001
HSGPA	0.3908	0.2006	1.95	0.0516
HSGPA*HSGPA	0.1413	0.1957	0.72	0.4706
Gender (Female)	0.2065	0.1174	1.76	0.0786
HSGPA*Gender(Female)	-0.2188	0.2442	-0.9	0.3705
Log of instructional Months	0.3671	0.1084	3.39	0.0007
Square of log of instructional Months	0.1594	0.1289	1.24	0.2164
Months to graduation	0.0230	0.0121	1.91	0.0564
Square of months to graduation	-0.0008	0.0010	-0.82	0.4127
Low-income	0.1350	0.1613	0.84	0.4028
Middle-income	0.1798	0.1458	1.23	0.2174
Minority membership	0.0718	0.1308	0.55	0.5832
Coursework below Algebra II	0.0347	0.1635	0.21	0.832
Public school	0.0395	0.1732	0.23	0.8196

Note: All Variables are grand-mean centered.

Table 8. Parameter Estimates for the ACT Science Gain Score Linear Model

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.6320	0.2823	2.24	0.0253
Treatment Group	0.3898	0.1509	2.58	0.0099
HSGPA	0.3979	0.2611	1.52	0.1277
HSGPA*HSGPA	-0.1841	0.2547	-0.72	0.47
Gender (Female)	0.1038	0.1528	0.68	0.4969
HSGPA*Gender(Female)	-0.0816	0.3179	-0.26	0.7975
Log of instructional Months	0.2934	0.1410	2.08	0.0376
Square of log of instructional Months	-0.1499	0.1678	-0.89	0.372
Months to graduation	0.0471	0.0157	3.00	0.0028
Square of months to graduation	-0.0024	0.0013	-1.9	0.0582
Low-income	0.2171	0.2099	1.03	0.3013
Middle-income	-0.1223	0.1897	-0.64	0.5192
Minority membership	0.2478	0.1703	1.46	0.1458
Coursework below Algebra II	0.1298	0.2128	0.61	0.5418
Public school	-0.3969	0.2254	-1.76	0.0784

Note: All Variables are grand-mean centered.

Table 9. Parameter Estimates for the ACT Reading Gain Score Linear Model

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.0172	0.3540	2.87	0.0041
Treatment Group	0.3556	0.1892	1.88	0.0604
HSGPA	0.3879	0.3274	1.18	0.2362
HSGPA*HSGPA	0.2278	0.3194	0.71	0.4759
Gender (Female)	0.3267	0.1915	1.71	0.0882
HSGPA*Gender(Female)	-0.3216	0.3986	-0.81	0.4198
Log of instructional Months	0.5213	0.1768	2.95	0.0032
Square of log of instructional Months	0.2380	0.2104	1.13	0.2583
Months to graduation	0.0442	0.0197	2.25	0.0249
Square of months to graduation	-0.0029	0.0016	-1.81	0.071
Low-income	-0.1354	0.2632	-0.51	0.607
Middle-income	-0.2943	0.2379	-1.24	0.2161
Minority membership	-0.2091	0.2135	-0.98	0.3275
Coursework below Algebra II	0.0831	0.2668	0.31	0.7556
Public school	0.8174	0.2826	2.89	0.0039

Note: All Variables are grand-mean centered.

Table 10. Parameter Estimates for the ACT Composite Gain Score Linear Model with Treatment by Family Income Interaction

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.8486	0.1657	5.12	<.0001
Treatment Group	0.5366	0.0886	6.06	<.0001
Treatment*Income Main effect				0.0166
Treatment Group*Low-income	0.5900	0.2192	2.69	0.0072
Treatment Group*Middle-income	0.1044	0.2139	0.49	0.6256
HSGPA	0.3703	0.1249	2.97	0.0031
HSGPA*HSGPA	0.0754	0.1495	0.5	0.614
Gender (Female)	0.2173	0.0897	2.42	0.0155
HSGPA*Gender(Female)	0.1708	0.1867	0.92	0.3603
Log of instructional Months	0.5451	0.0828	6.58	<.0001
Square of log of instructional Months	0.1848	0.0985	1.88	0.0609
Months to graduation	0.0379	0.0092	4.11	<.0001
Square of months to graduation	-0.0018	0.0007	-2.38	0.0174
Low-Income	0.0519	0.1232	0.42	0.6736
Middle-Income	-0.1319	0.1113	-1.18	0.2365
Minority membership	0.0717	0.1001	0.72	0.474
Coursework beyond Algebra II	0.0483	0.1250	0.39	0.6991
Public school	0.0569	0.1323	0.43	0.667

Note: All variables are grand-mean centered.

Table 11. Mean ACT Composite Gain Score for Participation in OPL by Family Income

Effect	Treatment	Control	Difference	Standard Error	Pr > |t|
Low-income	1.6499	0.7463	0.9036	0.1573	<.0001
Middle-income	1.5909	1.1728	0.4181	0.1496	0.0053
High-income	1.4068	1.0932	0.3136	0.1530	0.0404

Table 12. Mean ACT Reading Gain Score for Participation in OPL with Treatment by Minority Membership Interaction

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.9919	0.3538	2.8	0.0051
Treatment Group	0.3533	0.1890	1.87	0.0618
Treatment Group*Minority Interaction	0.8684	0.3797	2.29	0.0223
HSGPA	0.2491	0.2665	0.93	0.3501
HSGPA*HSGPA	0.2347	0.3191	0.74	0.4621
Gender (Female)	0.3126	0.1914	1.63	0.1027
HSGPA*Gender(Female)	0.3387	0.3982	0.85	0.3951
Log of instructional Months	0.5407	0.1768	3.06	0.0023
Square of log of instructional Months	0.2256	0.2103	1.07	0.2835
Months to graduation	0.0425	0.0197	2.16	0.0309
Square of months to graduation	-0.0029	0.0016	-1.84	0.0658
Low-Income	-0.1082	0.2632	-0.41	0.6811
Middle-Income	-0.2557	0.2382	-1.07	0.2832
Minority	-0.2183	0.2133	-1.02	0.3062
Coursework beyond Algebra II	0.0875	0.2665	0.33	0.7426
Public school	0.8252	0.2823	2.92	0.0035

Note: All variables are grand-mean centered.

Table 13. Mean ACT Reading Gain Score for Participation in OPL by Minority Status

Effect	Treatment	Control	Difference	Standard Error	Pr > |t|
White	1.3215	1.3619	-0.0404	0.2563	0.875
Minority	1.974	1.146	0.828	0.2800	0.0031

Table 14. Parameter Estimates for the ACT Science Gain Score Linear Model with Treatment by Family Income Interaction

Effect	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.6349	0.2820	2.25	0.0245
Treatment Group	0.3898	0.1508	2.59	0.0098
Treatment*Income Main Effect				0.0556
Treatment Group*Low-income	0.8213	0.3731	2.20	0.0278
Treatment Group*Middle-income	0.0923	0.3641	0.25	0.7998
HSGPA	0.3506	0.2126	1.65	0.0992
HSGPA*HSGPA	-0.1806	0.2545	-0.71	0.478
Gender (Female)	0.0953	0.1526	0.62	0.5324
HSGPA*Gender(Female)	0.0845	0.3178	0.27	0.7903
Log of instructional Months	0.2995	0.1409	2.13	0.0337
Square of log of instructional Months	-0.1621	0.1677	-0.97	0.334
Months to graduation	0.0474	0.0157	3.02	0.0026
Square of months to graduation	-0.0025	0.0013	-1.98	0.0483
Low-Income	0.2182	0.2097	1.04	0.2982
Middle-Income	-0.1185	0.1895	-0.63	0.532
Minority membership	0.2543	0.1704	1.49	0.1358
Coursework beyond Algebra II	0.1508	0.2128	0.71	0.4785
Public school	-0.4007	0.2251	-1.78	0.0753

Note: All variables are grand-mean centered.

Table 15. Mean ACT Science Gain Score for Participation in OPL by Family Income

Effect	Treatment	Control	Difference	Standard Error	Pr > |t|
Low-income	1.0078	0.0886	0.9192	0.2677	0.0006
Middle-income	0.9800	0.7898	0.1902	0.2547	0.4553
High-income	0.8154	0.7175	0.0979	0.2604	0.707

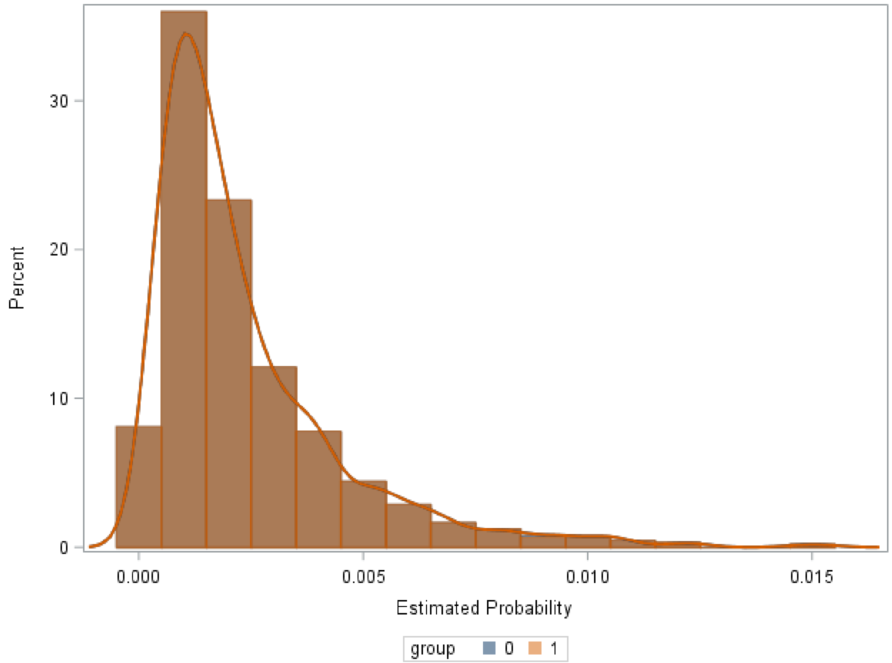

Figure 1. Distribution of probability of participating in OPL for treatment (1) and control (0) groups

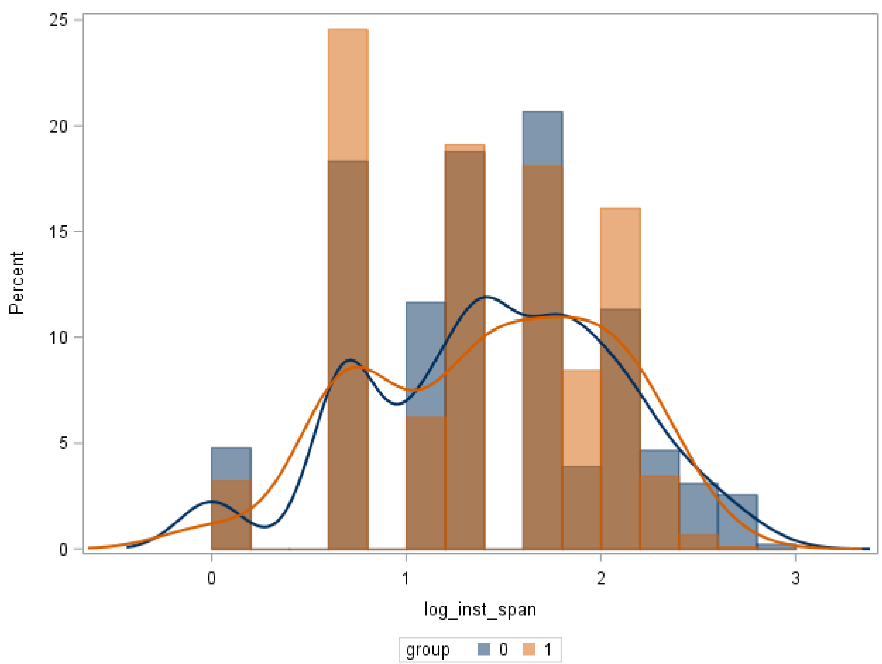

Figure 2. Distribution of the log of instructional months elapsed between tests for treatment (1) and control (0) groups

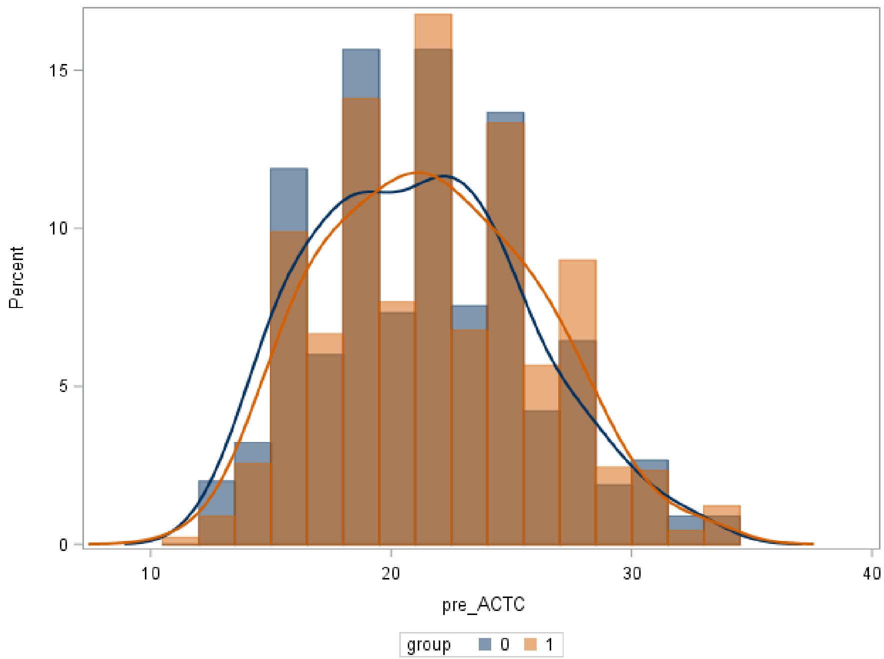

Figure 3. Distribution of Prior ACT Composite score for treatment (1) and control (0) groups

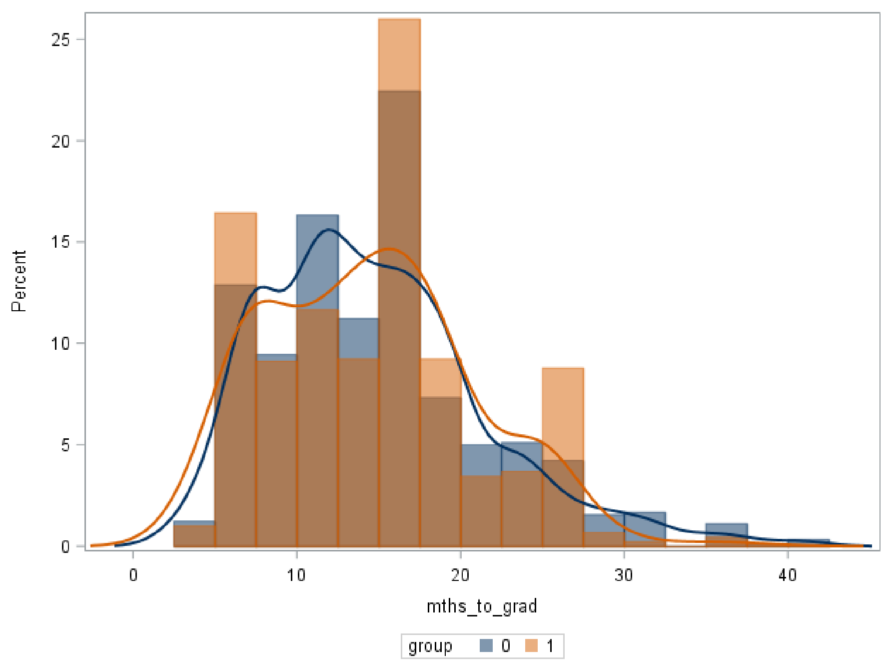

Figure 4. Distribution of months to graduation from prior ACT test for treatment (1) and control (0) groups

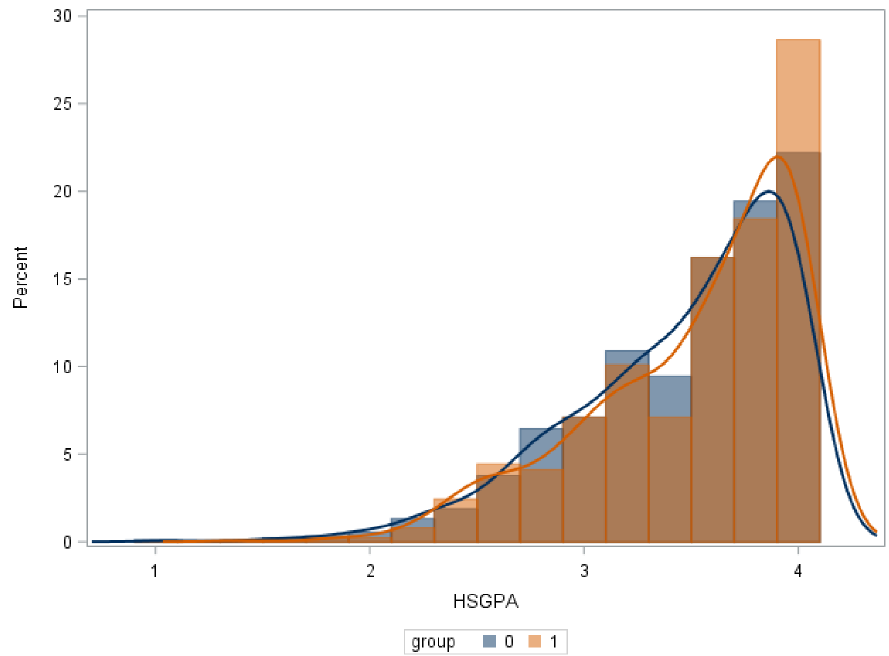

Figure 5. Distribution of HSGPA for treatment (1) and control (0) groups

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