# The Impact of Career Academies on STEM Coursetaking: Moving to the Next Level

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**Abstract**
Propensity score (PS) methods provide viable strategies for reducing selection bias in non-experimental (observational) studies. An NSF funded project previously used propensity score analysis to examine the impact of special educational programs on advanced mathematics course enrollment (Rodriguez de Gil et al., 2012). Results indicated that students who enrolled in career academies were almost twice as likely to enroll in a Calculus course. Encouraged by the findings from the previous study, we are currently using PS and discrete-time survival analyses to investigate rigorous high school STEM/ICT coursetaking for students in a southern state who identified an interest in STEM or ICT careers as part of their 8th grade electronic Personal Education Planners (ePEPs) and the persistence of STEM coursetaking through high school. Comparison of rigorous STEM coursetaking trends and persistence with national data (High School Longitudinal Study: HSLS:09) will be made. This study reports on correlates of 8th and 9th grade coursetaking and procedures used to identify the initial STEM cohort from the HSLS09 national dataset.

**Key Words:** Propensity scores, observational studies, ITEST ePEP, HSLS:09

## 1. Introduction

This study is derived from an ongoing grant funded by the National Science Foundation (NSF #113950) which examines STEM persistence in a cohort of Florida 8th grade students who intended to follow a STEM course of study during high school. Propensity score methods were used to create equivalent groups in the Florida cohort which consisted of Career Academy STEM and non-Career academy STEM high school students. Discrete-time survival analysis (Singer & Willet, 1993) will be used to evaluate persistence in STEM coursetaking from grades 9-11.

A third component of the grant was to compare persistence trends in the Florida cohorts to national data from the 2009 High School Longitudinal Survey (HSLS:09) including follow-up datasets in 2011 and 2013. This paper provides a detailed description of the methods used in the propensity score process to create equivalent groups in the HSLS:09 dataset.

## 2. Methods

### 2.1 Data Sources

Longitudinal survey data from the High School Longitudinal Survey (HSLS:09), a nationally representative study of 9th graders in 2009 and follow-up data in 2011 were obtained from the Institute of Education Sciences (IES), National Center for Educational Statistics (NCES). The secure data contained surveys of students, school administrators, school counselors, and parents.

### *2.1.1 Sample*

The baseline survey sample consisted of 25,210 students from 944 schools selected from 7 regional areas in the United States. The baseline study sample consisted of students ($n$ = 16,790) enrolled in regular, charter, or magnet high schools ($n$ = 870).

### *2.1.2 Identification of STEM Cohort*

STEM students at baseline were identified by enrollment in rigorous (see Burkham & Lee, 2003) $8^{th}$ grade math courses with a grade of C or better and intent to enroll in rigorous $9^{th}$ grade math courses or enrollment in rigorous $8^{th}$ grade science courses with a grade of C or better and intent to enroll in rigorous $9^{th}$ grade science courses (Table 1).

STEM persistence for the first follow-up (2011) was defined by enrollment in either rigorous math or science courses (Table 2.). In addition to enrollment in rigorous math or science courses, a student must have participated in the baseline survey and be attending a high school at the time of the follow-up survey.

## 2.2 Propensity Score Method

### *2.2.1 Selection of Covariates*

We selected variables to predict the propensity to be STEM that were related to rigorous STEM coursetaking and persistence in STEM coursetaking during high school. Selected from the student, school, and parent surveys, .the covariates included students' demographic and home/school background such as gender, race, home language, the discussion of career or job plans with an adult, and extra-curricular STEM interests, e.g., math or science club. School-related covariates included STEM courses offered on-site and off-site, school locale, participation in public school choice, offer of tutoring/remedial services, percentage of free-reduced lunch, student ethnic groups, and number of certified math/science teachers. Parent covariates included ethnicity, composite SES, participation in students' school, language spoken in the home and child's disability. In total, 227 covariates were selected for the propensity score estimation with 156 binary and 71 continuous variables. (See Supplemental Data).

### *2.2.2 Cleaning of Covariates*

Codes designating that a survey item was "skipped legitimately" (-7) were deleted for all covariates. Codes indicating that a survey item was a "non-response" or "not applicable" (-8) were recoded as 0. Missing items in the survey that were coded -9 were recoded as ".".

### *2.2.3 Multiple Imputation of Missing Data*

Variables in the dataset were evaluated for missing values. Observations with 50% or greater covariates missing were removed from the dataset, resulting in a reduction of sample size (Total $n$ = 11,460, STEM Cohort = 2,850, Non-STEM = 8,610). Multiple imputation was then performed using SAS PROC MI (SAS Institute, 2010) which created five datasets with imputed values for the variables with incomplete data.

***Table 1****. Criteria for STEM Cohort at Baseline.*

| Course | Level (Burkham & Lee, 2003) |
|---|---|
| **8th Grade*** | |
| Advanced or Honors Math 8 (not including Algebra) | 4 |
| Algebra I (including 1A & 1B) | 4 |
| Algebra II or Trigonometry | 5 |
| Geometry | 4 |
| Biology | 3 |
| Life Sciences | 3 |
| Pre-AP or Pre-IB Biology | 3 |
| Chemistry | 4 |
| Environmental Science | 2 |
| Physics | 4 |
| **and** | |
| **9th Grade** | |
| Geometry | 4 |
| Algebra II | 5 |
| Trigonometry | 6 |
| Statistics/Probability | 6 |
| Analytic Geometry | 6 |
| Advanced Math | 6 |
| Physics I | 4 |
| Chemistry I | 4 |
| Anatomy/Physiology | 3 |
| Advanced Biology | 3 |
| Advanced Chemistry | 6 |
| Advanced Physics | 6 |

** with grade of C or better*

### *2.2.4 Balance Diagnostics*

To assess common support (overlap) of the propensity score distribution between groups, box plots were examined before and after trimming. To assess balance between the groups on the selected covariates, we examined box plots and computed Cohen’s d (standardized mean difference) for each continuous variable. A standardized mean difference smaller in magnitude than 0.25 (Stuart, 2010) was used as our criterion for acceptable balance. Balance for dichotomous and discrete ordinal covariates was evaluated using odds ratios. Equivalent values of effect sizes for the odds ratio in comparison with Cohen’s d are shown in Table 3 (Chen et al., 2010).

**Table 2**. Criteria for STEM Persistence at Follow-up.

| Course | Level (Burkham & Lee, 2003) |
|---|---|
| Algebra III | 6 |
| Analytic Geometry | 6 |
| Trigonometry | 6 |
| Pre-calculus or Analysis and Functions | 7 |
| AP Calculus AB or BC | 8 |
| Other Calculus | 8 |
| AP Statistics | 8 |
| IB Mathematics, standard level | 8 |
| IB Mathematics, higher level | 8 |
| IB Biology | 6 |
| Anatomy or Physiology | 2 |
| Chemistry II | 6 |
| AP Chemistry | 6 |
| IB Chemistry | 6 |
| AP Environmental Science | 6 |
| IB Environmental Systems and Societies | 6 |
| Physics I | 4 |
| Physics II | 6 |
| AP Physics B or C | 6 |
| IB Physics | 6 |
| AP Computer Science | 6 |
| IB Design Technology | 6 |
| Engineering (general, robotics, aeronautical, mechanical, or electrical engineering) | 6 |

**Table 3.** Equivalent Effect Sizes for the Odds Ratio compared to Cohen's *d*.[1]

| | Cohen's *d* | | |
|---|---|---|---|
| | 0.2 | 0.5 | 0.8 |
| OR Equivalence | 1.68 | 3.47 | 6.71 |

[1] Based on a 0.10 prevalence rate for the outcome of interest, i.e., female, male, Asian, etc., in the non-exposed (non-STEM) group.

### 2.3 Propensity Score Model

*2.3.1. Normalized Survey Weight*
A normalized survey weight was included as a predictor for the propensity to be STEM. It was calculated by multiplying the student survey weight included in the baseline dataset by the quotient of sample size over the sum of weights (Equation 1).

$$\text{Normalized Student Weight} = \text{Student Survey Weight} * (\text{sample N/sum of weights})$$

**Eq. 1**. Normalized Survey Weight

*2.3.2. Propensity Score Estimation*
Logistic regression was used to estimate the propensity to be STEM for each imputation. The propensity to be stem was predicted by the 227 covariates and the normalized student weight (DuGoff et al., 2014). The linear estimate XBETA was used as the propensity score (Figure 1).

```
proc logistic data= hsls.PS_estimation descending;
   title'HSLS STEM Cohort Propensity Model';
   by _imputation_;
   class  STEM_cohort ;
   model STEM_cohort = (227 covariates)norm_STUwt/
   lackfit  outroc = hsls.STEMcohort_r;
   output out= hsls.STEMcohort_p XBETA=STEMcohort_xb
   STDXBETA=STEMcohort_sdxb PREDICTED=STEMcohort_pred ;
run;
```

**Figure 1:** SAS code for Propensity Score Estimation

### 2.4 Propensity Score Conditioning

*2.4.1 Normalized Longitudinal Weights*
In preparation for propensity score conditioning, normalized longitudinal weights were calculated for each imputation using the student longitudinal weight provided in the follow-up dataset (Figure 2).

```
*Obtain normalized weights for each imputation;
data hsls.norm_mergeF1;
 set hsls.merge_f1;
 norm1_STUwt= W2W1STU* (9712/2219884);
 norm2_STUwt= W2W1STU* (9754/2232661);
 norm3_STUwt= W2W1STU* (9737/2227020);
 norm4_STUwt= W2W1STU* (9731/2223010);
 norm5_STUwt= W2W1STU* (9772/2235690);
 title 'Normalized Longitudinal Weights by Imputation';
 run;
```

**Figure 2:** SAS Code for Normalized Longitudinal Weights in Propensity score Conditioning

*2.4.2 Conditioning using PS-ANCOVA*
Propensity scores for each imputation were conditioned using PS ANCOVA (Austin, 2011; Lanehart et al., 2012; Shadish & Steiner, 2010). The model, stem persistence predicted by stem cohort group and the linear propensity score, was weighted by the normalized longitudinal weight (Figure 3). The balanced repeated replication weights, or BRR weights, from the baseline survey were used as replicate weights. Balanced repeated replication weights were used in the survey to construct replicate variance estimates for the student data (Ingels et al., 2011).

```
proc surveylogistic data= hsls.norm_mergeF1 varmethod= BRR;
where _imputation_ =1;
class STEM_cohort /desc;
weight norm1_STUwt;
repweights W1STUDENT001-W1STUDENT200;
model stem_persist(event='1') = STEM_cohort STEMcohort_xb ;
title 'Conditioning Model for Imputation 1';
run;
```

**Figure 3**: SAS Code for Conditioning by PS-ANCOVA

## 3. Results

### 3.1 Propensity Score Comparisons
Common support or areas of overlap for the propensity score distribution were evaluated and areas of non-overlap were trimmed (Figures 4 and 5). In Figure 4, the STEM students (1) with the highest propensity to be STEM and the non-STEM students (0) with the lowest propensity to be STEM were trimmed. Sample sizes for each imputation are shown in Table 4.

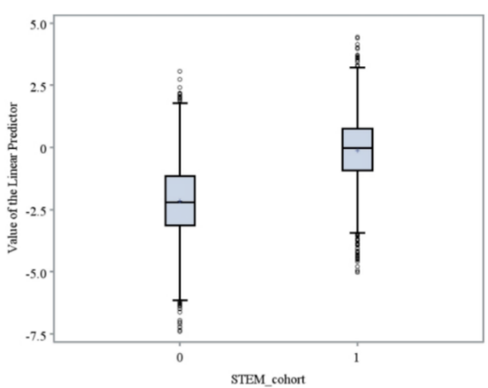


**Figure 4**: Propensity score distribution before trimming

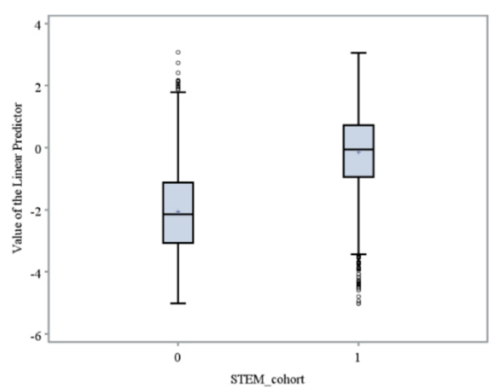


**Figure 5**:.Propensity score distribution after trimming

**Table 4.** Sample Sizes after Trimming

| | Untrimmed | | | Trimmed* | | |
|---|---|---|---|---|---|---|
| Imputation | Total | STEM | Non-STEM | Total | STEM | Non-STEM |
| 1 | 11460 | 2850 | 8610 | 11251 | 2830 | 8429 |
| 2 | 11460 | 2850 | 8610 | 11282 | 2830 | 8452 |
| 3 | 11460 | 2850 | 8610 | 11329 | 2832 | 8497 |
| 4 | 11460 | 2850 | 8610 | 11271 | 2831 | 8440 |
| 5 | 11460 | 2850 | 8610 | 11369 | 2829 | 8540 |

*Normalized weighted frequencies

In imputations 1, 2, and 4, a greater percentage of non-STEM students were trimmed compared to STEM students (Table 5).

**Table 5.** Percent Sample Lost to Trimming

| | Loss to Trimming | | | | | |
|---|---|---|---|---|---|---|
| | **Total** | | **STEM** | | **Non-STEM** | |
| Imputation | n | % | n | % | n | % |
| 1 | 209 | 0.02 | 20 | 0.01 | 181 | 0.02 |
| 2 | 178 | 0.02 | 20 | 0.01 | 158 | 0.02 |
| 3 | 131 | 0.01 | 18 | 0.01 | 113 | 0.01 |
| 4 | 189 | 0.02 | 19 | 0.01 | 170 | 0.02 |
| 5 | 91 | 0.01 | 21 | 0.01 | 70 | 0.01 |

### 3.2 Balance of Covariates

A partial listing of covariate balance for binary variables is shown in the Supplemental Data. The balance statistics were obtained by fitting logistic models for binary covariates and general linear models for continuous covariates to assess treatment group differences in the covariates after conditioning on the PS. Analogous models provided balance statistics before conditioning on the PS (standardized mean difference for continuous covariates and logistic regression for binary covariates).

The binary balance estimates after conditioning were within the OR effect size range for the majority of predictors, i.e., $\leq 1.68 \sim$ Cohen's $d$ of 0.25. Only three covariates, math competition (1.86), offsite Algebra II (1.71), and 9th grader enrolled in any Honors course (3.81) failed to meet the criteria for balance after conditioning. For the continuous covariates, all standardized mean differences were less than 0.25 in absolute value.

### 3.3. Estimates of Treatment Effects

*3.3.1 STEM Persistence*

At the end of 10th grade (HSLS:09 First Year follow-up), 75% of STEM students had persisted in STEM coursetaking compared to 33.6% of non-STEM students (Table 6). The

**Table 6**. Percentage of STEM Persistence in STEM and non-STEM students

| Group | Sample Size (weighted frequencies) | | | % STEM Persist |
|---|---|---|---|---|
| | Baseline | F1 Follow-up | STEM_Persist | |
| Non_STEM | 8,420 | 7,185 | 2,825 | 33.6% |
| STEM | 2,832 | 2,532 | 2,124 | 75.0% |
| Total | 11,252 | 9,717 | 4,949 | |

gender and ethnic distributions for STEM persistence after the first follow-up are shown in. Table 7. The attrition in STEM persistence between males and females was slightly higher for males, 25.6% vs. 23.0%, respectively (Table 8). Pacific Islander (92%), Asian (83%), and White (79%) students had greater persistence in STEM coursetaking while Black (43%) and Hispanic (35%) students experienced the greatest attrition in STEM coursetaking at first follow-up.

**Table 7**. Percentage of STEM Persistence by Gender and Ethnicity at First Year Follow-up

| | Baseline ($n$=2832) | | STEM Persist ($n$=2124) | |
|---|---|---|---|---|
| Covariate | N* | % | N** | %*** |
| Male | 1355 | 47.9% | 1009 | 35.6% |
| Female | 1477 | 51.1% | 1114 | 39.3% |
| White | 1689 | 59.6% | 1333 | 47.1% |
| Hispanic | 592 | 20.9% | 385 | 13.6% |
| Black | 119 | 4.9% | 79 | 2.8% |
| Asian | 205 | 7.2% | 169 | 6.0% |
| American Indian[2] | 7 | 0.2% | 7 | 0.2% |
| Pacific Islander | 13 | 0.5% | 13 | 0.5% |

* Baseline $n$ calculated using normalized weight

** STEM Persist $n$ calculated using longitudinal normalized weight

***STEM Persist % calculated using baseline $n$=2832

[2] Actual frequencies for American Indians and Pacific Islanders were > 3 at both timepoints.

**Table 8**. Percentage of Attrition in STEM Persistence by Gender and Ethnicity at First Year Follow-up.

| Covariate | % Persist | % Attrition |
|---|---|---|
| Covariate | | |
| Male | 74.4% | 25.6% |
| Female | 77.0% | 23.0% |
| White | 79.0% | 21.0% |
| Hispanic | 65.0% | 35.0% |
| Black | 56.9% | 43.1% |
| Asian | 82.9% | 17.1% |
| American Indian | No change | No change |
| Pacific Islander | 91.8% | 8.2% |

### *3.3.2 Odds of STEM Persistence*

The results of conditioning on the propensity score indicated that STEM students, on the average, were 4.9 times more likely to persist in STEM coursetaking than non-STEM students (Table 9).

**Table 9**. Odds of STEM Persistence for STEM Cohort

| Imputation | Odds Ratio | Lower CI | Upper CI |
|---|---|---|---|
| 1 | 4.93 | 3.75 | 6.49 |
| 2 | 4.87 | 3.68 | 6.45 |
| 3 | 4.83 | 3.65 | 6.39 |
| 4 | 4.74 | 3.59 | 6.25 |
| 5 | 4.96 | 3.78 | 6.49 |
| Overall | 4.86 | 3.69 | 6.41 |

## 4. Discussion

This study demonstrates that propensity score matching in observational studies is a robust method for eliminating selection bias. The general steps involved in propensity score analysis include covariate selection, propensity score estimation, trimming, balance of covariates before and after trimming, and conditioning on the propensity score. The evaluation of missingness in covariates selected to predict the propensity score and subsequent multiple imputation of the missing data is recommended. A recent simulation study indicated that imputation of missing covariates before estimation of the propensity scores resulted in less bias (Rodriguez de Gil, 2014). In the extant propensity score literature, balance on covariates is considered a necessary condition for unbiased results. However, Montgomery et al. (2014), found that increased balance provided improved treatment estimates in naïve conditioning models only, e.g. matching without calipers, ignoring covariates. Although many issues remain to be examined in the field of propensity score analysis, the propensity score method is a useful tool for creating equivalent groups in observational studies.

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## 5. Supplemental Data[3]

**Supplemental Table 1.** Student Covariates

| Covariate | Balance (Odds Ratio) | |
|---|---|---|
| | Before Conditioning | After Conditioning |
| Gender | 0.92 | 0.98 |
| Hispanic | 1.56 | 0.89 |
| White | 1.01 | 0.98 |
| Black | 2.34 | 0.81 |
| Pacific Islander | 1.04 | 0.99 |
| American Indian | 1.79 | 0.86 |
| Asian | 0.36 | 1.36 |
| Math Club | 0.29 | 1.47 |
| Math Competition | 0.18 | 1.86 |
| Math Camp | 0.45 | 1.28 |
| Math Tutor | 0.82 | 1.04 |
| Science Club | 0.41 | 1.27 |
| Science Competition | 0.28 | 1.47 |
| Science Camp | 0.29 | 1.53 |
| Science Tutor | 0.71 | 1.09 |
| No Math/Science Activity | 2.47 | 0.80 |
| Discussed Adult Careers/Jobs with Mother | 0.50 | 1.23 |
| Discussed Adult Careers/Jobs with Father | 0.49 | 1.22 |
| Discussed Adult Careers/Jobs with Friend | 0.65 | 1.12 |
| Discussed Adult Careers/Jobs with Teacher | 0.75 | 1.08 |
| Discussed Adult Careers/Jobs with Counselor | 0.87 | 1.03 |
| No Discussion of Adult Careers/Jobs | 1.93 | 0.86 |

[3] Supplemental data includes only binary covariates selected from the student, school (math & science courses offered), and parent surveys. For a listing of school demographic and continuous covariate balances, please contact the author at rlanehar@usf.edu.

**Supplemental Table 2.** On Site and Off Site Math Course Covariates

| Covariate | Balance (Odds Ratio) | |
|---|---|---|
| | Before Conditioning | After Conditioning |
| *Offered Onsite* | | |
| PreAlgebra | 1.13 | 0.99 |
| Remedial Math | 1.05 | 0.99 |
| Integrated Mathematics 1 | 1.38 | 0.91 |
| Integrated Mathematics 2 | 1.29 | 0.94 |
| Algebra 1, Part 1 & 2 | 1.07 | 1.01 |
| Algebra 1 | 0.53 | 1.18 |
| Algebra 2 | 0.57 | 1.13 |
| Geometry | 0.45 | 1.22 |
| Trigonometry | 0.93 | 1.04 |
| Algebra 3 | 0.96 | 1.00 |
| Analytical Geometry | 0.86 | 1.05 |
| Calculus | 0.90 | 1.03 |
| Calculus AP (AB) | 0.64 | 1.12 |
| Calculus AP (BC) | 0.55 | 1.17 |
| Calculus IB | 0.75 | 1.06 |
| Computer Science | 0.73 | 1.09 |
| Computer Science AP (A) | 0.58 | 1.15 |
| Computer Science AP (AB) | 0.50 | 1.24 |
| Statistics | 0.86 | 1.06 |
| Statistics AP | 0.64 | 1.11 |
| | | |
| *Offered Offsite* | | |
| PreAlgebra | 0.94 | 1.05 |
| Remedial Math | 1.17 | 0.97 |
| Integrated Mathematics 1 | 0.77 | 1.02 |
| Integrated Mathematics 2 | 0.87 | 1.01 |
| Algebra 1, Part 1 & 2 | 0.97 | 0.96 |
| Algebra 1 | 2.09 | 0.95 |
| Algebra 2 | 3.57 | 1.71 |
| Geometry | | |
| Trigonometry | 0.98 | 0.98 |
| Algebra 3 | 1.27 | 0.99 |
| Analytical Geometry | 1.25 | 0.92 |
| Calculus | 1.09 | 0.94 |
| Calculus AP (AB) | 1.58 | 0.91 |
| Calculus AP (BC) | 1.09 | 1,01 |
| Calculus IB | 0.90 | 1.03 |
| Computer Science | 0.94 | 1.02 |
| Computer Science AP (A) | 0.83 | 1.04 |
| Computer Science AP (AB) | 1.03 | 1.04 |
| Statistics | 1.15 | 0.96 |
| Statistics AP | 1.03 | 0.98 |
| No Math Courses Offered Off-Site | 0.98 | 1.03 |

**Supplemental Table 3.** On Site and Off Site Science Course Covariates

| Covariate | Balance (Odds Ratio) | |
|---|---|---|
| | Before Conditioning | After Conditioning |
| *Offered On-Site* | | |
| General Science | 0.97 | 1.02 |
| Physical Science | 1.41 | 0.92 |
| Earth Science | 0.85 | 1.05 |
| Environmental Science | 0.97 | 1.01 |
| Principles of Technology | 1.09 | 0.99 |
| Biology 1 | 0.71 | 0.99 |
| Life Science | 0.88 | 1.03 |
| Chemistry 1 | 0.89 | 0.83 |
| Physics 1 | 0.64 | 1.16 |
| Integrated Science 1 | 0.91 | 1.06 |
| Integrated Science 2 | 0.82 | 1.07 |
| Anatomy | 1.13 | 0.98 |
| Environmental Science AP | 0.67 | 1.08 |
| Advanced Biology | 0.67 | 1.08 |
| Advanced Chemistry | 0.65 | 1.09 |
| Advanced Physics | 0.61 | 1.13 |
| Other Biological Science | 0.84 | 1.05 |
| Other Physical Science | 0.71 | 1.08 |
| Other Earth/Environmental Science | 0.85 | 1.05 |
| *Offered Off-Site* | | |
| General Science | 1.09 | 0.99 |
| Physical Science | 0.73 | 1.04 |
| Earth Science | 0.89 | 1.00 |
| Environmental Science | 0.92 | 0.99 |
| Principles of Technology | 0.83 | 1.01 |
| Biology 1 | 1.82 | 1.18 |
| Life Science | 0.98 | 1.01 |
| Chemistry 1 | 1.12 | 1.22 |
| Physics 1 | 1.56 | 0.98 |
| Integrated Science 1 | 1.22 | 1.01 |
| Integrated Science 2 | 1.02 | 0.99 |
| Anatomy | 0.75 | 1.12 |
| Environmental Science AP | 1.03 | 0.94 |
| Advanced Biology | 1.27 | 0.91 |
| Advanced Chemistry | 1.28 | 0.93 |
| Advanced Physics | 1.10 | 0.94 |
| Other Biological Science | 0.77 | 1.06 |
| Other Physical Science | 0.96 | 1.03 |
| Other Earth/Environmental Science | 0.98 | 0.98 |
| No Science Courses Offered Off-Site | 1.11 | 0.99 |

**Supplemental Table 4. Parent Covariates**

| Covariate | Balance (Odds Ratio) | |
|---|---|---|
| | Before Conditioning | After Conditioning |
| *Parent Information* | | |
| 9th grader has sibling who attends/attended his/her HS in last 5 years | 1.04 | 1.01 |
| Parent 1 is Hispanic/Latino/Latina | 1.52 | 0.93 |
| Parent 1 is White | 1.12 | 1.10 |
| Parent 1 is Black/African American | 2.54 | 0.83 |
| Parent 1 is Asian | 0.32 | 1.43 |
| Parent 1 is Native Hawaiian/Pacific Islander | 1.12 | 0.96 |
| Parent 1 is American Indian/Alaska Native | 1.67 | 0.88 |
| Parent 2 is Hispanic/Latino/Latina | 1.45 | 0.96 |
| Parent 2 is White | 0.83 | 1.10 |
| Parent 2 is Black/African American | 1.85 | 0.87 |
| Parent 2 is Asian | 0.34 | 1.38 |
| Parent 2 is Native Hawaiian/Pacific Islander | 1.38 | 1.08 |
| Parent 2 is American Indian or Alaska Native | 1.53 | 0.94 |
| Whether student was born in the U.S. | 0.56 | 1.09 |
| Language other than English is regularly spoken in home | 0.78 | 1.02 |
| Ninth grader has repeated a grade | 4.65 | 0.76 |
| Doctor/school has told parent 9th grader has learning disability | 4.59 | 0.78 |
| Doctor/school has told parent 9th grader has developmental delay | 4.55 | 0.74 |
| Doctor/school has told parent 9th grader has hearing/vision problem | 1.70 | 0.86 |
| Doctor/school has told parent 9th grader has bone/joint/muscle problem | 1.36 | 0.89 |
| Doctor/school has told parent 9th grader has ADD or ADHD | 3.15 | 0.78 |
| Ninth grader has skipped a grade | 0.80 | 1.01 |
| Whether 9th grader is currently enrolled in honors course | 0.14 | 3.83 |
| Attended a general school meeting since start of 2009-10 school year | 0.54 | 1.16 |
| Attended a PTO meeting since start of 2009-10 school year | 0.87 | 0.99 |