# A Study of the Impact of *Project Lead The Way* on Achievement Outcomes in Iowa

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## Abstract

Iowa has implemented the secondary engineering curriculum *Project Lead The Way* (PLTW) in an effort to create a more seamless transition for students from secondary school into science, technology, engineering, and mathematics post-secondary programs. PLTW has been implemented in all fifty states; however, there has been sparse research to-date that has rigorously measured the impact of PLTW on mathematics and science achievement. We used Iowa's statewide longitudinal data system to follow multiple cohorts of PLTW participants and nonparticipants from 8th grade into secondary education. We derived a comparable treatment and control group by matching students based on their propensity to enter PLTW, permitting a stronger interpretation of the program's impact than prior studies. The findings indicate PLTW participants are more likely to be white, male, and perform in the upper quartile in mathematics and science prior to PLTW enrollment. Further, we found statistically significant evidence that PLTW increases mathematics or science scores on the Iowa Test of Educational Development by 5 points after controlling for selection bias. The 5 point increase in mathematics score corresponds to roughly a half of a grade level. The effect size ($f^2$) for mathematics was 0.15 and 0.05 for science—a moderate and small effect size, respectively. Further studies will also need to properly account for pre-existing ability in mathematics and science when determining achievement outcomes to ensure results are not being driven by pre-existing ability. This study has implications for researchers, practitioners, and policy makers regarding the comprehensive evaluation design and the critical role that PLTW can play to increase the participation, both generally and within non-traditional groups, in postsecondary STEM education in the U.S.

## Introduction

In 2005 Iowa implemented the PLTW curriculum to create a seamless transition for students from secondary school into STEM majors at two- and four-year postsecondary institutions.[1] Since then, enrollment has grown to over 2,000 students and it is currently offered in 101 of 260 Iowa school districts. The increase in Iowa's enrollment coincided with growth of PLTW nationwide (e.g., see Ref 2-4).

The program is a sequence of year-long courses designed to teach engineering and problem solving concepts to high school students. The curriculum is divided into two strata[5]—foundation courses (Introduction to Engineering Design and Principles of Engineering) and specialization courses (Aerospace Engineering; Biotechnical Engineering; Civil Engineering and Architecture; Computer Integrated Manufacturing; and Digital Electronics). The sequence of courses ends with a capstone course (Engineering Design and Development) which requires students to take their own idea from design through development. In addition, Gateway to Technology is offered in middle school in selected school districts.

The PLTW curriculum is optional in Iowa school districts as it is in most states. Each course is one full Carnegie unit (e.g., full year) and is offered to anyone between ninth and twelfth grade. The curriculum requires students to enroll in mathematics and science as pre- or co-requisite courses in conjunction with the PLTW curriculum. PLTW is open to any student who meets the minimum requirements, but Misko[6] and other PLTW administrators have noted the program is generally targeted toward the top 80% of a school's population. In addition, PLTW courses can qualify students for high school and college credit. Students are also encouraged to enroll in college preparatory mathematics, biology, chemistry, and physics courses.

The foundation courses provide an overview of engineering and introduce students to various engineering aspects, such as design, and manufacturing processes. These courses involve students learning 3-D computer modeling, designing and reverse engineering objects, applying the fundamentals of physics, and using electronics and computer programs to build robotic machines. Specialization courses allow students to explore a specific engineering discipline in more detail.

The PLTW courses offer projects which would seem engaging for a variety of students. For example, one segment of the curriculum requires students to design and build a small mechanical robot that sorts marbles made from various materials (such as metal, wood, and glass) into bins to mimic sorting of recyclable materials. The marbles are sorted based on their opacity, which is determined by shining a light on the marble and determining the amount of ohms received by a sensor on the other side. Students utilize software to adjust the sensitivity of the sensor, which is crucial for performance.

PLTW's curriculum contains detailed daily lesson plans and is disseminated through rigorous professional development courses. All PLTW teachers must attend a two week summer training institute for each course to be taught (cf. Ref 5). The summer training involves a university professor and experienced PLTW teacher (master teacher) for both theory and application with a heavy emphasis on the pedagogical approach of project based learning. In Iowa, most of the training originates from engineering departments at The University of Iowa or Iowa State University. Eventual teachers learn the same software, theory, and applications that their students will use.

## Literature Review

Several studies have attempted to explore the impact of PLTW on various educational outcomes,[7-9] a serious limitation of these studies is the lack of control for pre-existing ability. However, some researchers have begun to address this issue. A research brief by the Southern Regional Education Board (SREB) matched PLTW participants with career and technical education students with similar demographics and fields of study. SREB found that PLTW students who enrolled in two or more PLTW courses did significantly better in mathematics and science on the High Schools that Work (HSTW) assessment than career/technical students in comparable fields.[8] Differences between PLTW students and similar career/technical students were also found for subsequent course-taking behavior, with PLTW students more likely to complete the four years of mathematics and science.[10] However, this may not have been an appropriate control group since the PLTW courses can all result in college credit while many career/technical courses do hot provide college credit and may attract different students. In addition, SREB's study was limited to matching on students' race and gender and did not consider prior grades or academic performance.

In a follow-up to an earlier study, Tran & Nathan[11,12] collected transcript data from a school district in Wisconsin which was heavily represented by racial minorities as well as a high proportion of students eligible for free or reduced lunch prices. Their study matched PLTW participants with nonparticipants using results of prior achievement scores in mathematics and science, gender, and free and reduced lunch eligibility. Tran & Nathan measured relative change of mathematics and science scores between the state-mandated tests, a part of the No Child Left Behind requirements between 8th and 10th grade. They found that PLTW had no measurable impact on science scores while PLTW participants actually scored lower in mathematics compared to similar students.

It is important to note that there were some limitations in the Tran and Nathan study, such as the short time frame between the two standardized assessments. The structure of the study only permitted students to realistically enroll in a single class, although a very small number enrolled in two courses. Additionally, the paper's focus was on a single school district with a limited sample size. The study also investigated the integration of math in the PLTW curriculum. In a curriculum review, Prevost et al.[13] and Nathan et al.[14] found some, but minimal alignment between PLTW curriculum and standards set by the National Council of Teachers of Mathematics. This is not surprising as the PLTW curriculum was not intended as a math curriculum, but a STEM curriculum that may use math as a tool.

Thus, while there have been studies of PLTW, there is a need for evaluations to be conducted on a large, state-wide level such as the current research. Iowa provides a unique opportunity to assess the outcomes of PLTW. About 33% of the schools in Iowa participate in the PLTW program. However, Iowa also has a K-12 database that is not available in most states. To help address the current lack of study of PLTW, we have initiated a study using the Iowa K-12 database (maintained by the Iowa Department of Education) combined with data from community colleges to assess the impact of PLTW courses on high school students.

## Methodology

### *Research Questions*

The following research questions guided this evaluation at this early stage:

- RQ1: What are the socio-demographic, academic, and cognitive characteristics of PLTW students and what characteristics are associated with PLTW participation?
- RQ 2: Do PLTW students take more math and science courses than non-PLTW students?
- RQ3: Is the cognitive improvement for PLTW students greater than that for non-PLTW students?

### *Data*

The Iowa Department of Education maintains a longitudinal data set that tracks students through high school into college and the workforce. Since 2005, each student has been assigned a unique student identifier, which is retained as they progress through high school, including if they transfer to any other secondary institution within Iowa. Figure 1 shows the path of students from middle school through the workforce. Our focus in this paper is the short-term impact on high school achievement tests, so the main source of data will be limited to the secondary school data set.

Iowa's administrative records also contain socio-demographic data, achievement scores in the area of mathematics, science, and reading, institutional-level factors, and course enrollment information. Socio-demographic information includes the student's race/ethnicity, gender, eligibility for free and reduced lunch (an underreported proxy for economic status[15]), and whether the student is homeless. The data set contains scores from the Iowa Test of Basic Skills (ITBS) for 8th grade and Iowa Test of Educational Development (ITED) for 11th grade, including scores by subject exam (reading, science, and mathematics). It also contains information on whether students have a special need, indicated by a Section 504 disability or individual education plan (IEP). Finally, the school district is recorded, which we can use to control for institutional-level factors.

We limited our analysis to all students enrolled in school districts offering PLTW, which yielded over 35,000 students. Since the focus of this paper is the relative growth in test scores between the 8th grade ITBS and 11th grade ITED, the timeframe of the data means we had to limit our data to the class of 2009 and the class of 2010. Further, students were only included if their records were available in 8th and 11th grade. Consequently, the sample size included 26,030 students.

PLTW participants were identified through course records. All PLTW programs are assigned a program number using the Classification of Instructional Programs (CIP), which indicates a list of PLTW courses offered at each school district. Students were considered a PLTW participant if they enrolled in at least one PLTW course in either 9th or 10th grade. For the purposes of this study, nonparticipants are students who did not enroll in a PLTW course in 9th or 10th grade, but were enrolled in a school district that offered the program.

Table 1 shows the descriptive statistics from the PLTW dataset for the 2009 and 2010 cohorts. Total enrollment was 1,321 students, compared to 24,709 students in the control group. The data strongly suggests the presence of selection bias. Participants were disproportionally white males compared to nonparticipants. Eighty-five percent of the PLTW participants were male and 91 percent of the participants were white. By contrast, 49% of non-participants were male 80% were white. The proportion of females entering PLTW (20%), however, is approximately the same amount of females entering mechanical and electrical engineering programs nationwide.[9]

Further, the economic status proxies indicated PLTW participants were less likely to come from low-income families. Sixteen percent of participants were eligible for free or reduced lunch, compared to 32 % of the control group. PLTW participants were also twice as likely to be identified as a part of a gifted & talented program (21%) and were seven times less likely to have an IEP (2%).

Finally, we found PLTW participants had higher achievement in mathematics and science than non-PLTW participants prior to entering in the program. Eighth grade mathematics scores show mean mathematics scores were in the 80th percentile, compared to the 60th percentile for nonparticipants. Science scores show a similar pattern. The mean participant score was the 84th percentile compared to the 64th percentile for nonparticipants.

*Analysis*

Since enrollment in PLTW is not random, we must be control for pre-existing achievement not attributable to the program. Data shown in Table 1 demonstrates that PLTW participants already exhibit higher mathematics and science scores prior to enrolling into PLTW. Thus, a simple comparison between expected values (e.g., mean differences) between the treated and control group is highly biased.

It is important to note that there are two levels of selection bias: for school districts and for students. Most noticeably, school districts that offer PLTW have a larger number of students, and are more likely to be in an urban setting. The average size of a PLTW district in 2007 was 1,830 students compared to the 339 students for non-PLTW districts. While it is possible to control for selection bias with observed variables, such as size, we also know that PLTW districts were also selected on non-observables, such as relationships between PLTW program officers and administrators and the willingness of administrators to pursue "innovative" programs. In order to limit bias from school district-level selection bias, the control group consists only of students from districts offering PLTW, but who did not enroll in any PLTW courses.

In addition to school district selection bias, we have already highlighted data which suggest selection bias at the student level. We can determine if there is any selection bias by estimating the likelihood of entering PLTW while conditioning on data prior to enrollment. We use socio-demographic and testing data from 8th grade—the year prior to any PLTW enrollment—to calculate the conditional probability of enrolling in PLTW in 9th or 10th grade given the observed covariates (p. 296, Ref 16)

$$\rho(\mathrm{X}) = E(\tau = 1|\mathrm{X}) = \varphi(\alpha_i + \tilde{\beta}\mathrm{X} + \epsilon_i) \qquad (1)$$

where ρ(X) is the propensity score, τ indicates treatment (enrolling in PLTW = 1), X is a matrix of historical socio-demographics (gender, race, free/reduced lunch, and homeless status) and testing data (reading, mathematics, and science) from 8th grade—a year prior to PLTW entry—and ϕ(•) is the logit function.[i]

*Matching*

With selection bias, the distribution for the outcome of interest (Y, Y') is unequal across the treatment variable (τ'). Specifically, Table 1 shows the outcome of interest (11th grade test scores) are much higher for participants, but participants are also more likely to be male, white, high-achievers in mathematics and science, are more likely to be in gifted and talented programs, and are less likely to be eligible for free or reduced lunch. Rosenbaum and Rubin[18,19] prove that the distribution of outcomes can be balanced using propensity scores. Namely, students with similar propensity scores, ρ(X), are matched while unmatched students are discarded from the data. We can estimate the impact of PLTW on student outcomes by comparing the expected values of the treatment and control group once the propensity of PLTW entry, ρ(X), is estimated.

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[i] This leaves the question if participation was determined by an unobserved variable. This cannot be answered with the data and is a weakness of propensity score analysis and we must rely on the stable unit treatment value assumption (SUTVA), which ignores any unobserved covariate that affects the probability of treatment. Some of this concern is mitigated since unobserved covariates are likely correlated with observed variable, thereby limiting the reliance on SUTVA.[17]

We chose to use genetic algorithms to find the minimal distance between treatment and control units. Genetic algorithms are based on the principles of population biology which use selection, recombination, and mutation of estimates to derive optimal solutions.[20,21] These algorithms are computationally more efficient than other algorithms to find solutions to optimization problems. In this case, we used genetic algorithms from Ho, Imai, King, & Stuart[22] to minimize the distance (difference) between the treatment and control group. The distance between these two groups are defined by the generalized Mahalanobis distance measure.[23] The genetic algorithms search to find an optimal mix of students and weights to minimize the difference in characteristics between these two groups. Once an optimal solution is derived, the matched students and corresponding regression weights are used in the subsequent analysis. In this study we matched one participant to two nonparticipants with genetic algorithms. We will refer to this as the one-to-two matching genetic algorithm.

**Results**

Table 2 shows the results of the propensity score estimates. Males, gifted and talented, and ITBS scores on mathematics and science were positively correlated with entry into PLTW, while free lunch eligibility and individualized education plans (IEP) were negatively correlated with PLTW participation.

Table 3 shows the descriptive statistics for the matched data set using a genetic algorithm with a maximum ratio of two control students for every treatment case. PLTW participants comprise approximately 38% of the sample, which was almost mostly white (90%) and male (85%). Average test scores are much higher for the matched data set than the full sample (see Table 1). The average 8th grade mathematics score was 284 points and science was 289 points. The demographic profile of the balanced data set now mirrors the typical profile of a PLTW participant demonstrated in Table 1.

*Test Scores*

Table 4 shows the subsequent estimate of PLTW's impact on mathematics scores. The DID estimator (Δ) shows participants had a relative gain of 5.2 points ($p = 0.01$) on the national scale score. Table 5 shows the estimated impact of PLTW on science scores to also be 5.2 points ($p = 0.02$) on the national scale score. The point-estimates show PLTW participants gained an average of 36 points ($T + \Delta$) compared to a 30.8 point gain for non-participants (T). While holding other variables constant, a PLTW participant scored in the 91st percentile in mathematics compared to the 81st percentile for similar nonparticipants by the 11th grade.[ii]

[ii] The percentiles are based on national percentile rank. The percentiles are translated from the raw scores by summing the intercept (α), PLTW participant (τ), ITED ($T$), and interaction term (Δ) coefficients. Thus, these percentiles are being computed for white, female students who are not eligible for free or reduced lunch, nor homeless, nor a member of any special population.

The gap in science scores is less pronounced. The mean science percentile for a participant is the 83rd percentile compared to the 80th percentile for the control group.

Additional covariates portray other important information that is not directly attributable to PLTW. Demographic covariates show African-American and Hispanic students' score significantly lower than white students on the 8th grade ITBS. Asian students, meanwhile, score equivalently to white students in both mathematics and science. Males score around 3 points higher than females in mathematics, but both genders had statistically equivalent ITBS scores on the science subtest.

Economic status also impacts test scores with students eligible for free or reduced lunch scoring lower on both subtests. Homeless students had mixed results, scoring lower on the science exam, but having equivalent mathematics scores to non-homeless students. Special populations also had statistically different test performance; students with an IEP or Section 504 plan scored lower on both subtests, the former with a large disparity in scores. Gifted and talented students scored significantly higher on mathematics and science exams.

*Effect Size*

The results show PLTW leads to a 5.2 increase for mathematics and science scores. Statistical significance indicates that the estimates from the impact are unlikely a statistically anomaly of a program that provides no or even negative impact. The evidence from the 2009 and 2010 cohorts suggest PLTW participation leads to an average increase of 5 points in math and science scores.

However, these results do not yet show the relative effect size—whether they are small or large. Literature on this topic provides several options (cf. Ref 24). The most straightforward calculation of effect size is Cohen's d: $\Delta/\sigma_\Delta$. That is, the estimated impact of PLTW divided by the standard deviation. Using the results from the data matched using genetic algorithms (one-to-two) shows the estimated effect size is 0.16 for mathematics and 0.14 for science. Typically, effect sizes below 0.2 are considered "small" impacts.

The calculation of the effect size, however, is more complicated in this case. Effect sizes from results that employ regression are sometimes expressed from Cohen's $f^2$:

$$f^2 = \frac{R^2_{X,\Delta,\tau} - R^2_X}{1 - R^2_{X,\Delta,\tau}} \qquad (2)$$

where $R^2_{X,\Delta,\tau}$ denotes the pseudo $R^2$ for the regression model which includes socio-demographics (X), the interaction term ($\Delta$), and PLTW participation ($\tau$). The recommended thresholds for $f^2$ are slightly different than d. A small effect is around 0.02, a moderate effect is approximately 0.15, and large effect is 0.35. Using McFadden's adjusted $R^2$ formula, we determined the approximate effect size was 0.15 for mathematics and 0.05 for science. Thus, the impact on mathematics scores could be considered a "moderate" effect while the impact on science seems relatively "small."

**Conclusions**

There are several points of interest based on these results. First, PLTW in Iowa tends to attract white males and students who have higher achievement in mathematics and science in junior high. The percentages of women who enter PLTW are approximately the same percentage that enters mechanical and electrical engineering programs.[9] Overall, the selection bias was rather significant, with participants scoring between 0.72 and 0.9 standard deviations higher on mathematics and science scores prior to entering PLTW. We strongly suggest that future research on PLTW needs to reflect selection bias in their analysis of the program.

We controlled for selection bias using propensity score matching that predicted entry into the program based on demographics, economic status, and whether the student was a part of a special population. We used a differences-in-differences growth model to measure the relative growth of students between 8th and 11th grade. We found that PLTW increase both mathematics and science scores by 5.2 points.

It is not immediately clear if 5.2 points is a large, modest, or small increase. A measure of effect size—Cohen's $f^2$—showed the impact was approximately 0.15 for mathematics and 0.05 for science—a moderate and small impact, respectively. Our results show a stronger impact than similar studies utilizing matching. Using the intercept and participation coefficients, we found this roughly equates PLTW students performing in the 91st percentile in mathematics while non-participants scored in the 81st percentile. PLTW participants scored in the 83rd percentile in science achievement compared to the 80th percentile for similar non-participants.

Our findings contradict Tran & Nathan[12] who found PLTW had insufficient or adverse integration for science and mathematics, respectively. However, our findings support the conclusions of Tran & Nathan[11] who showed positive impacts on mathematics with weaker impact on science. Our statistical significance was higher, which likely related to the greater statistical power from the larger sample.

We also conducted some analysis that included additional mathematics and science courses (e.g., algebra 2, chemistry). PLTW students were much more likely to enroll in higher level mathematics and science courses, which support the findings from Bottom & Uhn.[10] It is possible, but we cannot conclusively determine, that PLTW's pre- and co-requisites lead students to enrolling in more mathematics and science courses in high school. It is also possible that

PLTW's program encourage students to enroll in additional coursework due to other factors, such as self-efficacy or student engagement.

Notwithstanding the reason, it is clear that these additional mathematics and science courses play an important role in the growth of test scores. Including these courses led to a substantial reduction in the estimated impact of PLTW. The pseudo $R^2$ suggests the additional courses simply supplant the variation explained by PLTW. These results strongly suggest that researchers need to also consider the role of other mathematics and science course, especially whether PLTW leads to increased enrollment in mathematics and science.

*Assessment Instrument*

The current policy environment has emphasized growth and measurable gains in core subjects within standardized testing. Nevertheless, the use of statewide standardized exams may be inappropriate for the evaluation of a problem-based learning (PBL) curriculum.[11,12,25,26] In studies already cited, PBL students perform at par or below on assessments which emphasize recollection and utilize multiple choice responses, but perform moderately better on assessments measuring applied skill.

To this extent, these results from the ITBS and ITED cannot be extrapolated to performance on the PISA or TIMSS. The literature has usually referenced performance on the latter tests to measure the international placing of U.S. students in mathematics and science. In particular, the PISA may be better-suited for a PLTW evaluation since it is intended to measure the applicability of mathematics and science knowledge to real-world problems.

*Limitations*

We have conducted a statewide evaluation of PLTW's impact on test scores. There are a few limitations that we would like to address in future research and evaluation. Namely, this study uses administrative data, which is distinct from transcript data as it only captures course enrollment, not completion. We may overestimate the enrollment in PLTW or other courses by not being able to remove students who dropped a course. Likewise, we also do not have access to student grades or grade point averages.

This study does not provide any controls for individual classrooms or teachers since the data was not available. There are multiple ways to view this issue and its impact. Within the context of a multi-level model, we essentially ignored another level where we observe students within a classroom that is within a school district. The effects of PLTW within the classroom may be positively correlated and vary within the school district. The variance of effects within the classroom can be influenced by teachers and their qualifications. Earlier, we noted the varying proportions of teachers with advanced degrees in each school district. Also, we noted the challenges in which PLTW can either be taught by teachers licensed in mathematics, science, or industrial technology. We are uncertain if teacher qualifications or licensures have a differential impact on student performance.

*Future Directions*

Test scores are relevant to the literature given the current policy environment's emphasis on measureable gains on standardized tests. Yet, gains on standardized tests are not the only goals of the program. Future iterations of this research will explore other outcomes that should be considered, such as college attendance, choice of majors, and college completion. The authors are currently using Iowa's SLDS to follow outcomes for the treatment and control group beyond high school, which will enable research of PLTW's long-term outcomes.

Future research is also needed on PLTW's impact on problem solving through testing instruments that are oriented toward evaluating problem-solving and critical thinking. Prior research on PBL has shown little success of students on fact-based exams, but it is possible PLTW improves critical thinking and problem solving abilities.[11,12,25,26]

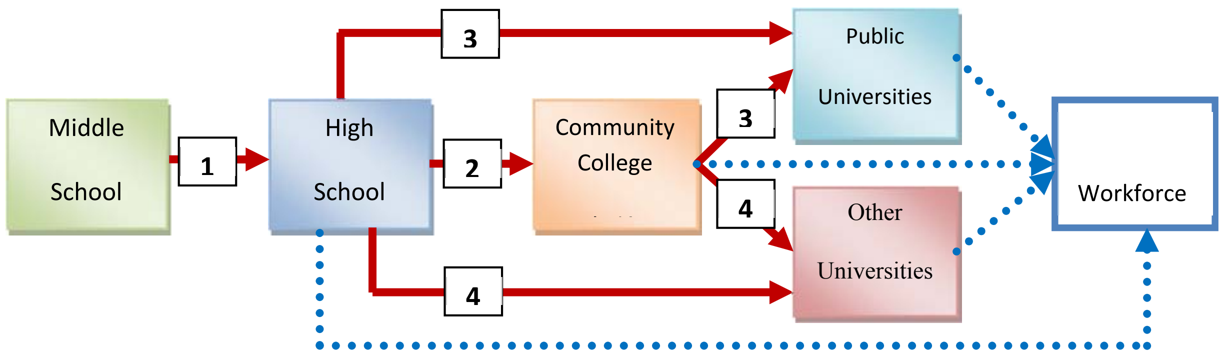
The results of this study also suggest a strong relationship between PLTW and enrollment in other mathematics and science courses. These other mathematics and science courses play an even larger role in mathematics and science achievement scores than PLTW. Future research is needed to explore this relationship and whether PLTW increases enrollment in these areas through the co- and pre-requisites, increased self-efficacy, increased student engagement, or other mechanisms.

**Bibliography**


1. Maguire, K. (2006). *Statewide system to foster the intregration of academics into Career and Technical Education through Project Lead The Way* (Ph.D. Capstone). Iowa State University, Ames, IA.
2. Brandt, D. (2009, January). Feeding the need for industry: Zulma Toro-Ramos targets grade-school students for pre-engineering program. *Industrial Engineer*.
3. Cech, S. J. (2007, September 26). Engineering a Blueprint for Success. *Education Week*.
4. Spellman, K. (2007, February 1). Opportunities Come at the Strangest Times. *Techniques*.
5. Taylor, K. D., Foster, G. N., & Ratcliff, M. M. (2006). Project Lead The Way - Raising the Technical Literacy of High School Graduates. *Proceedings of ICEE 2006* (p. R3D-19 - R3D-21). Presented at the 9th International Conference on Engineering Education, San Juan, PR.

6. Misko, T. (2011). The “E” in STEM: Clarifying What Engineering Education Means for K-12 + The Opportunity Equation. Retrieved September 26, 2011, from http://opportunityequation.org/school-and-system-design/e-stem-clarifying-what-engineering#thor-misko
7. Blais, R. R., & Adelson, G. I. (1998). Project Lead the Way(SM) Models a Program for Changing Technology Education. *Tech Directions*, *58*(4), 40-43.
8. Bottoms, G., & Anthony, K. (2005). *Project Lead the Way: A Pre-engineering Cirriculum That Works* (Research Brief). Atlanta, GA: Southern Regional Education Board.
9. Walcerz, D. (2007). *Report on the Third Year of Implementation of the TrueOutcomes Assessment System for Project Lead The Way*. TrueOutcomes.
10. Bottoms, G., & Uhn, J. (2007). *Project Lead The Way Works: A New Type of Career and Technical Program* (Research Brief). Atlanta, GA: Southern Regional Education Board.
11. Tran, N., & Nathan, M. J. (2010a). An investigation of the relationship between pre-college engineering studies and student achievement in science and mathematics. *Journal of Engineering Education*, *99*(2), 1–15.
12. Tran, N., & Nathan, M. J. (2010b). The effects of pre-engineering studies on mathematics and science achievements for high school students. *International Journal of Engineering Education (Special Issue on Applications of Engineering Education Research)*, *26*(5), 1049-1060.
13. Prevost, A., Nathan, Mitchell J., Stein, B., Tran, Natalie, & Phelps, A. (2009). Integration of Mathematics in Pre-college Engineering: The search for explicit connections. Presented at the American Society for Engineering Education Annual Conference 2009, Austin, TX.
14. Nathan, Mitchell J., Tran, Natalie, Phelps, A., & Prevost, A. (2008). The Structure of High School Academic and Pre-Engineering Curricula: Mathematics. Presented at the American Society for Engineering Education 2007, Honollulu, Hawaii.
15. Harwell, M., & LeBeau, B. (2010). Student Eligibility for a Free Lunch as an SES Measure in Education Research. *Educational Researcher*, *39*(2), 120-131.
16. Rosenbaum, P. R. (2002). *Observational studies*. Springer.
17. Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*(1), 1-21.
18. Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55.
19. Rosenbaum, P. R., & Rubin, D. B. (1984). Reducing Bias in Observational Studies Using Subclassification on the Propensity Score. *Journal of the American Statistical Association*, *79*(387), 516-524.
20. Duffy, J. (2006). Agent Based Modeling and Human Subject Experiments. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of computational economics: Agent-based computational economics* (pp. 949-1012). Elsevier.
21. Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*. Ann Arbor: University of Michigan Press.
22. Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. *Journal of Statistical Software*, *42*(8).
23. Diamond, A., & Sekhon, J. S. (2010). Genetic Matching for Estimating Causal Effects: A General Matching Method for Achieving Balance in Observational Studies. *Working Paper*.
24. Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Routledge Academic.
25. Brophy, S., Klein, S., Portsmore, M., & Rogers, C. (2008). Advancing Engineering Education in P-12 Classrooms. *Journal of Engineering Education*, *97*(3), 369-387.
26. Hmelo, C. E., Gotterer, G. S., & Bransford, J. D. (1997). A Theory-Driven Approach to Assessing the Cognitive Effects of PBL. *Instructional Science*, *25*, 387-408.

**Figure 1: Iowa Statewide Longitudinal Dataset: Tracking Project Lead The Way Students**




Note: The transition shown in [1] is tracked by Iowa's secondary data system (Project EASIER); the transition into community colleges [2] is from Iowa's community college data system (MIS), we obtain the transition into public universities, [3] through partnership with the State Board of Regents; and the transition into other higher education institutions [4] is from the National Student Clearinghouse.

**Table 1: Descriptive statistics of Project Lead The Way data set: 2009 & 2010 Cohorts**

| | Nonparticipants | | PLTW | |
|---|---|---|---|---|
| | (N = 24,709) | | (N = 1,321) | |
| | Mean | Standard | Mean | Standard |
| *Demographics* | | | | |
| Male | 0.49 | 0.50 | 0.85 | 0.36 |
| American Indian | 0.01 | 0.09 | 0.00 | 0.06 |
| Asian | 0.03 | 0.16 | 0.03 | 0.17 |
| Black | 0.09 | 0.29 | 0.03 | 0.16 |
| Hispanic | 0.07 | 0.26 | 0.03 | 0.17 |
| White | 0.80 | 0.40 | 0.91 | 0.29 |
| *Economic Status Proxy* | | | | |
| Free Lunch | 0.24 | 0.43 | 0.11 | 0.31 |
| Reduced Lunch | 0.07 | 0.25 | 0.05 | 0.21 |
| Homeless | 0.01 | 0.09 | 0.01 | 0.08 |
| *Special Populations* | | | | |
| Section 504 | 0.01 | 0.10 | 0.01 | 0.09 |
| Gifted & Talented | 0.10 | 0.29 | 0.21 | 0.41 |
| IEP | 0.15 | 0.36 | 0.02 | 0.13 |
| *Testing - 11th Grade ITED* | | | | |
| Reading - Standard Score | 285.75 | 43.84 | 307.29 | 35.44 |
| Reading - Percentile Rank | 59.38 | 26.77 | 73.19 | 20.63 |
| Mathematics - Standard Score | 286.43 | 41.55 | 319.42 | 28.89 |
| Mathematics - Percentile Rank | 60.89 | 28.63 | 83.27 | 18.27 |
| Science - National Standard Score | 294.70 | 44.21 | 323.90 | 34.95 |
| Science - Percentile Rank | 64.55 | 27.04 | 81.74 | 18.82 |
| *Testing - 8th Grade ITBS* | | | | |
| Reading - Standard Score | 254.56 | 41.13 | 274.68 | 29.33 |
| Reading - Percentile Rank | 57.63 | 27.57 | 72.23 | 20.42 |
| Mathematics - Standard Score | 257.45 | 37.47 | 282.95 | 25.41 |
| Mathematics - Percentile Rank | 59.57 | 27.70 | 79.52 | 18.18 |
| Science - National Standard Score | 263.88 | 36.22 | 285.17 | 27.92 |
| Science - Percentile Rank | 62.19 | 24.95 | 77.21 | 17.22 |

Note: Data represents pooled 2009 and 2010 cohorts. Testing data reflects national standard score and percentile ranks. Control group includes students from districts with PLTW, but who did not enroll in any of those courses.

**Table 2: Propensity Score Coefficients**

| | Coefficient | z-statistic |
|---|---|---|
| Intercept | -1654.0 | -19.57 |
| *ITBS, 8th Grade* | | |
| Reading | 0.0 | -1.86 |
| Mathematics | 0.0 | 8.69 |
| Science | 0.0 | 4.90 |
| *Demographics* | | |
| Black | -0.6 | -1.45 |
| Asian | 0.0 | -0.11 |
| Hispanic | -0.3 | -0.71 |
| Male | 1.8 | 21.72 |
| *Economic Status Proxy* | | |
| Free Lunch | -0.2 | -2.47 |
| Reduced Lunch | 0.0 | -0.14 |
| Homeless | -0.4 | -0.69 |
| *Special Populations* | | |
| IEP | -1.0 | -5.77 |
| Section 504 | -0.5 | -1.42 |
| Gifted & Talented | 0.3 | 4.28 |

Note: Estimates are for enrollment into PLTW courses in either 9th or 10th grade. Data includes controls for students in either the 2009 or 2010 cohorts.

**Table 3: Descriptive statistics of matched data set: Genetic matching one-to-two**

| Variable | Weighted Mean | Weighted Standard Deviation |
|---|---|---|
| PLTW Participant | 0.38 | 0.49 |
| *Demographics* | | |
| White | 0.90 | 0.30 |
| Black | 0.03 | 0.17 |
| Asian | 0.04 | 0.18 |
| Hispanic | 0.03 | 0.17 |
| American Indian | 0.00 | 0.06 |
| Male | 0.85 | 0.36 |
| *Economic Status Proxy* | | |
| Free Lunch | 0.11 | 0.31 |
| Reduced Lunch | 0.04 | 0.21 |
| Homeless Status | 0.00 | 0.06 |
| *Special Populations* | | |
| IEP | 0.02 | 0.14 |
| Section 504 | 0.01 | 0.09 |
| Gifted Talented | 0.23 | 0.42 |
| *11th Grade scores* | | |
| Reading | 306.28 | 37.31 |
| Mathematics | 315.06 | 31.14 |
| Science | 320.28 | 36.43 |
| *8th Grade Scores* | | |
| Reading | 277.48 | 30.72 |
| Mathematics | 283.72 | 26.66 |
| Science | 288.92 | 29.88 |

Note: Descriptive data for the treatment and control group after matching using propensity score matching using genetic algorithms with one treatment matched up to two nontreatment cases. The weighted means and standard deviations are based on the weights assigned from the matching algorithm.

**Table 4: Iowa Project Lead The Way's impact (fixed effects) on mathematics scores, 8th to 11th grade**

| | Genetic One-to-Two | |
|---|---|---|
| | Estimate | t-statistic |
| Intercept (α) | 272.5 | 150.87 |
| PLTW Participant ($\tau$) | 2.8 | 1.51 |
| ITED (Junior-year test) ($T$) | 30.8 | 21.40 |
| PLTW Participant x ITED (Δ) | 5.2 | 2.40 |
| *Additional Testing Controls:* | | |
| Midyear | 4.0 | 2.21 |
| Spring | 5.8 | 2.28 |
| *Demographics:* | | |
| African-American | -14.1 | -5.58 |
| Asian/Pacific Islander | 0.0 | -0.01 |
| Hispanic | -14.9 | -5.94 |
| American Indian | 15.1 | 1.94 |
| Male | 3.4 | 3.18 |
| *Economic Status Proxy* | | |
| Free Lunch Eligible | -8.0 | -6.01 |
| Reduced Lunch Eligible | -4.1 | -2.38 |
| Homeless | 3.4 | 0.40 |
| *Special Populations* | | |
| IEP | -31.6 | -13.73 |
| Section 504 Plan | -6.6 | -1.28 |
| Gifted and Talented | 26.2 | 26.08 |
| | | |
| Number of Observations | 4075 | |
| School Districts | 76 | |
| Intra-class Correlation (within | | |
| | | |
| AIC | 37739 | |
| BIC | 37941 | |
| LogLikelihood | -18837 | |
| McFadden's R-squared | 6.1% | |

Note: Estimates are for the national standardized test score, mathematics, between 8th grade Iowa Test of Basic Skills (ITBS) and 11th grade Iowa Test of Educational Development (ITED). Estimates are shown as national scale scores. Estimates are for the class of 2009 and 2010 cohorts.

**Table 5: Iowa Project Lead The Way's impact (fixed effects) on science scores, 8th to 11th grade**

| | Genetic One-to-Two | |
|---|---|---|
| | Estimate | t-statistic |
| Intercept ($\alpha$) | 279.8 | 139.19 |
| PLTW Participant ($\tau$) | -0.8 | -0.36 |
| ITED (Junior-year test) ($T$) | 32.1 | 20.67 |
| PLTW Participant x ITED ($\Delta$) | 5.2 | 2.02 |
| *Additional Testing Controls:* | | |
| Midyear | 2.3 | 1.16 |
| Spring | 3.5 | 1.24 |
| *Demographics:* | | |
| African-American | -13.4 | -4.61 |
| Asian/Pacific Islander | -0.4 | -0.14 |
| Hispanic | -17.1 | -5.93 |
| American Indian | -10.8 | -0.83 |
| Male | 0.2 | 0.15 |
| *Economic Status Proxy* | | |
| Free Lunch Eligible | -11.7 | -7.59 |
| Reduced Lunch Eligible | -7.6 | -3.74 |
| Homeless | -15.6 | -1.64 |
| *Special Populations* | | |
| IEP | -31.7 | -12.00 |
| Section 504 Plan | -8.6 | -1.51 |
| Gifted and Talented | 30.2 | 25.56 |
| | | |
| Number of Observations | 4071 | |
| School Districts | 76 | |
| Intra-class Correlation (within | | |
| | | |
| AIC | 29283 | |
| BIC | 39485 | |
| LogLikelihood | -19610 | |
| McFadden's R-squared | 4.7% | |

Note: Estimates are for the national standardized test score, mathematics, between 8th grade Iowa Test of Basic Skills (ITBS) and 11th grade Iowa Test of Educational Development (ITED). Estimates are shown as national scale scores. Estimates are for the class of 2009 and 2010 cohorts.