International Journal of
Online and Distance Learning
(IJODL)

School-based Learning Community Impact on Future Earnings

Mouhamadou F. Ndiaye Ph.D

International Journal of Online and Distance Learning
ISSN 2520-4033 (online)
Vol.6, Issue 1. No.1, pp 1 - 13, 2026

www.iprjb.org

School-based Learning Community Impact on Future Earnings

Mouhamadou F. Ndiaye Ph.D
Assistant Professor Economic &Finance, Eastern Connecticut State University

Article History

Received 18th January 2026

Received in Revised Form 20th February 2026

Accepted 25th March 2026

How to cite in APA format:

Ndiaye, M. (2026). School-based Learning Community Impact on Future Earnings. *International Journal of Online and Distance Learning*, *6*(1), 1–13. https://doi.org/10.47604/ijodl.3692

Abstract

Purpose: Achieving higher future wages post-college remains a challenge. The decision to pursue higher education for occupational aspirations can be influenced by lifelong earnings expectations. The League of Innovative Schools (LIS) was created in 2011 by professionals in the New England region in the United States of America to promote school-based learning communities.

Methodology: The research adopted desktop literature review. Previous research has indicated that the LIS outperforms in science, reading, and has higher graduation rates than traditional schools. Furthermore, previous studies suggested that individuals who enroll in a US college with an average Standardized test score of 100 points higher will see a 3 to 7 percent increase in their lifetime earnings. The present study evaluates the impact of the school-based Professional Learning Community on US Standardized test scores and lifetime earnings change by using a propensity score matching and an inverse weighting method.

Findings: The findings provide strong evidence that high school educators at state and regional forums who collaborate and share innovative practices will improve overall school performance and boost standardized test scores of participating schools. Despite the absence of causality in our study, we found a positive correlation between the school-based community learning program and future earnings, giving convincing evidence to school districts and state education policymakers concerning future funding decisions regarding the school-based professional learning community.

Unique Contribution to Theory, Practice and Policy: Additionally, our conclusions provide Private Operators and Donors to School-based Professional Learning Communities with evaluation information on the effectiveness of their program, (1) facilitate the use of an econometric model framework by economists and researchers for similar studies, (2) initiate discussions with states and counties to examine the success of school-based professional learning communities in boosting overall exam scores, (3) lastly, it suggests a future in-depth examination of the differences between the old and new standardized exam formats, which could impact test variability.

Keywords: *School-based Learning Communities, Lifetime Earnings, Standardized Test Score, Propensity Score Matching (PSM), Inverse Weighting Method (IPW)*

JEL Codes: *A2, J24, A21, C2*

International Journal of Online and Distance Learning
ISSN 2520-4033 (online)
Vol.6, Issue 1. No.1, pp 1 - 13, 2026

www.iprjb.org

INTRODUCTION

Government officials and private education consortia are constantly introducing innovative learning programs. High schools are targeted to improve overall achievement and increase students' chances of securing better colleges and increasing their potential lifetime earnings. However, achieving higher future wages post-graduation remains a challenge.

Lifetime earnings expectations can influence individuals' decisions about higher education, especially when it comes to occupational aspirations (Carnevale et al., 2013; Smith & Powell, 1990). In addition, obtaining a college degree and access to education are key factors in achieving upward mobility, which is a key pathway to higher earnings. Therefore, schools that can improve student learning and SAT scores will likely offer more opportunities for graduates to attend college. Higher college going rates could lead to high future earnings.

The League of Innovative Schools (LIS) was established in 2011 as a network for professional learning in the region. The LIS was included in the New England Secondary School Consortium organized by a non-profit entity. Secondary schools in New England had the opportunity to join the LIS. The LIS was designed to promote school-based professional learning communities that engage in continuous school improvement. These school teams were also connected to each other within a larger regional network (e.g., state network). Member schools collaborated to enhance instruction and student achievement by sharing innovative practices with each other at state and regional forums. Additionally, previous research has shown that SAT scores are connected to one's lifetime earnings. Diette and Raghav (2014) predicts that those with low SAT math scores will receive lower grades in majors with higher earnings, based on their findings. Furthermore, Kane (1998) suggested that those who attend college with an average SAT score of 100 points higher will boost their lifetime earnings by 3% to 7%. As a result, this paper analyzed the potential consequences of LIS membership on students' SAT scores and their potential lifetime earnings. The research was conducted without random selection of participating schools because the LIS is voluntary thus, to minimize the influence of selection bias, we use a propensity score matching (PSM) and an inverse weighting (IPW) method based on Rosenbaum and Rubin (1983) and Horvitz and Thompson (1952). Despite the average SAT lower than the 100 points threshold of Kane's (1998) estimation to impact future lifetime earnings in our final results, we found strong evidence indicating an increase in the SAT scores of schools that participated in the program relevant to future education policies improvement.

Lifetime Earnings Scholarly Viewpoints

In the United States, lifetime earnings have important implications for retirement outcomes and social security benefits. Among the pioneers in the literature on the economic effect of college quality, Weisbrod and Karpoff (1968) explored the “Monetary Returns to College Education, Student Ability, and College Quality,” followed by Solmon and Wachtel’s (1975) study on “The Effect of School Quality on Achievement, Attainment Levels, and Lifetime Earnings” and Kane (1998) on “Racial and Ethnic Preferences in College Admissions.” Later, authors such as Brewer and Ehrenberg (1996), Dale and Krueger (2002), and Diette and Raghav (2014), added popular measures of college quality, including mean SAT scores of entering freshmen, and improved the ordinary least square (OLS) model[13] used in previous studies. It is noteworthy to mention other studies on college quality and earnings, such as Solmon and Wachtel (1975) who found that the quality of the higher education institution has a significant impact on lifetime earnings of those who attend. Moreover, Hoekstra (2009) reported that attending the most selective state university increased earnings by 20% higher for

International Journal of Online and Distance Learning
ISSN 2520-4033 (online)
Vol.6, Issue 1. No.1, pp 1 - 13, 2026

www.iprjb.org

white men. Kane's (1998) analysis established that "attending a college with a 100-point higher average SAT scores is associated with 3 to 7 percent higher earnings later in life".

Even though a large literature has examined earnings differences by educational attainment (Hout, 2012), or quality and characteristics of colleges attended, research on the accumulation of lifetime earnings and SAT improvement by target program remains limited because of the lack of adequate data (Cooke, 2003).

According to recent figures from the Bureau of Statistics (BLS) as of recent years, the median lifetime earnings for a Bachelor's degree holder is roughly $2.8 million, compared to $1.6 million for a high school graduate.

School-based Professional Learning Community: The League of Innovative School (LIS)

Background

Professional learning communities or PLCs for short serve to reduce professional isolation, promote collaboration among educators, and promote sharing of teachers' expertise and insights (Dufour, 2004). Professional learning communities are often also referred to as collaborative learning communities, communities of practice, or critical friends' groups. Regardless of what name is used, PLCs have become a common technique to organize professional development in schools. For Dufour (2004), who is considered a pioneer on the topic, a professional learning community is a method that develops collaborative learning among its participants.

Professional learning communities can create conditions for professional interactions among teachers (Brouwer et al., 2012), Although some evidence suggests that PLCs have a positive effect on student outcomes (Lomos et al., 2011), questions still remain as well as calls for more targeted research on effects (Hairon et al., 2017). Concerns have been raised about the methodological limitations of studies assessing the effects of PLCs (Doğan & Adams, 2018). Assessing the effects of such programs on student performance is difficult because many factors could play a fundamental role in the achievement outcome.

The League of Innovative Schools

The League of Innovative Schools (LIS) was created in 2011 and invited any New England secondary school to participate as members. The LIS has been a major feature of the New England Secondary School Consortium.[1] As of 2020, the LIS represented a hundred and ninety (190) schools in five different New England states.

The LIS is a regional professional learning community working towards improving knowledge and skills of the educators through professional dialogue, collaborative study, and exchange of expertise. The LIS aims to develop strong leadership and teaching to improve achievement and attainment among students. Member schools are encouraged to promote student-centered learning and engage in continuous school improvement. The LIS is intended to offer an environment conducive to collaboration, sustained school improvement, and the strong professional relationships necessary for improving student achievement. The LIS "spreads good ideas" through innovation and inspiration for participating teachers and promotes expertise and mutual learning among educators which is a key for professional fulfillment.

[1] The New England LIS is not to be confused with the federally supported Digital Promise League of Innovative Schools (https://digitalpromise.org/about/our-history/).

Practically, the LIS brings together school-based teams of educators to work on school improvement practices. These teams work regularly on their school improvement plans and also network with other teams within their state and across New England on common problems of practice. Five New England state departments of education also sponsor their own state-based LIS networks; they provide opportunities for their LIS members to tap into state agency resources and attend annual conferences.

METHODOLOGY

Identification

To study the effects of the LIS on student SAT scores, one can specify "SAT scores (SAT)" as a depending variable, "Science Proficient (SP)" and "Four Year Graduation Rate (4YGR)" as independent variables among others and run an ordinary least square regression method in the form: $SAT = \beta_1.LIS + \beta_2.SP + \beta_3.4YGR + \ldots\ldots + u$ to get the proper coefficient. However, our dataset lacks a measure for *innate ability*, which is positively correlated with SAT, SP and 4YGR, thus our regression coefficients results could overestimate the marginal effects, because of omitted variable bias. Furthermore, the SAT scores of schools from the treatment and comparison group could differ even in the absence of treatment leading to a 'self-selection bias.' Therefore, in the absence of randomization, the ordinary least square method (OLS) can be biased, and an instrumental variable (IV) method could fix the selection bias (Abadie, 2003; Heckman and Salvador, 2003; Yen et al., 2008). However, good instrumental variables are hard to find (Imbens & Woolridge, 2009). Furthermore, the IV method does not take into account the exogeneity assumptions, and violates the overlap assumption (Imbens, 2004).

Consequently, a *quasi-experimental method* such as propensity score matching (PSM) will allow to have a sample of the treated (schools that are part of the LIS) and the untreated group based on their propensity score. Then, we will apply three types of matching techniques (near neighbor, radius and Kernel) to estimate the treatment effect on the treated (ATT).

Furthermore, we included an inverse probability weighting (IPW) technique used to control for selection on observables (Robins & Finkelstein, 2000; Robins, Hernan, & Brumback, 2000) as a robust check for the PSM model. According to Imbens (2004), IPW uses the inverse of the propensity score as weights when computing the average outcome variable (SAT scores).

Propensity Score Model (PSM)

The Propensity Score Matching (PSM) technique allows researchers to build counterfactuals using observational data by adjusting covariates between the treated and control units. PSM can lead to an unbiased causal effect results with observational data under strong ignorable assumptions (Rosenbaum & Rubin, 1983) and a common support. However, Heckman, Ichimura, and Todd (1997) proved that omitting important variables can increase bias in the estimations and only variables that correlate with the treatment and the outcome should be included.

Let's suppose in our binary treatment, the treatment indicator T_i equals one (1) if school *i* receives treatment (member of the LIS) and zero (0) otherwise. The potential outcome variable (SAT score) is defined as Y_i (T_i) for each school *i*, with *i* = 1, ..., *N* and *N* indicates the total number of schools. Therefore, the treatment effect for a school *i* is φ:

$$\boldsymbol{\varphi = Y_i(1) - Y_i(0)} \tag{1}$$

However, only one of the potential outcomes is observed for each school *i*. Consequently, estimating the individual treatment effect φ_{i} is impossible.

One achievable identification strategy tested by Rosenbaum and Rubin (1983) indicates that "if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on a balancing score b(X)". The propensity score (PS):

$$\boldsymbol{P(T = 1|X) = P(X)} \tag{2}$$

could be the probability for a school to participate in a treatment given its observed covariates X. Therefore, the independence assumption based on the propensity score (PS) can be written as follows:

$$\boldsymbol{Y(0), Y(1)\ \text{II}\ T|P(\mathbf{X}), \forall\ \mathbf{X}} \tag{3}$$

Another important requirement to build our model is the common support or overlap condition, which eliminates the perfect predictability of T given X:

$$\boldsymbol{0 < P(T = 1|X) < 1} \tag{4}$$

Supposing that we have met the independence condition and the common support assumption with an overlap between both units, the general PSM estimator for an average treatment effect on the treated ATT can be written as follows:

$$\boldsymbol{\theta = E_{P(X)|D=1}\{E[Y(1)|T = 1, P(X)] - E[Y(0)|T = 0, P(X)]\}} \tag{5}$$

We can proceed to a more detailed and formal description of these estimators and build up our matching method and our inversed probability weight (IPW) method. We begin with a combined analysis of the Radius and Nearest-Neighbor Matching then followed by the Kernel matching we will use in our model.

Nearest Neighbor (NN) and Radius Matching

Let T_0 be the set of j untreated schools and T_1 be the set of i treated schools, then let ${}^{T_1}_{i}Y$ and ${}^{T_0}_{j}Y$ be the observed outcomes of the treated and control units, respectively. We define μ(i) as the set of control school matched to the treated unit i with a propensity score of pi. We also denote ${}^{T_0}_{i}\psi$ the number of controls matched with observation i $\in T_1$ for the radius and nearest neighbor matching. We allocate weights $w_{ij} = \frac{1}{{}^{T_0}_{i}\psi}$ if j $\in$ μ(i) and $w_{ij} = 0$ otherwise, and set $w_j = \sum_i w_{ij}$ to derive the estimators $\emptyset_1$ for the NN and radius matching:

$$\boldsymbol{\emptyset_1 = \frac{1}{\psi^{T_1}} \sum_{i \in T_1} {}^{T_1}_{i}Y - \frac{1}{\psi^{T_1}} \sum_{j \in T_0} w_j\, {}^{T_0}_{j}Y} \tag{6}$$

$\psi^{T_1}$is the number of units in the treated group

Kernel Matching

To derive the Kernel matching estimator, we suppose δ_n is the bandwidth parameter and Ω(.) is a kernel function. Thus, the Kernel matching estimator is:

$$\emptyset_2 = \frac{1}{\psi^{T_1}} \sum_{i\in T_1} \left\{ {}^{T_1}_{i}Y - \frac{\sum_{j\in T_0} {}^{T_0}_{j}Y\Omega\left(\frac{p_j - p_i}{\delta_n}\right)}{\sum_{k\in T_0} \Omega\left(\frac{p_k - p_i}{\delta_n}\right)} \right\} \quad (7)$$

Inversed Probability Weight (IPW) Method

The propensity score generated in equation (5) will help create a new sample with a distribution of measured baseline covariates independent of the treatment assignment. For the LIS school (treated), inverse weights add to zero and $\frac{p(X)}{1-p(X)}$ for the control group.

We can define the weights according to Hirano and Imbens (2001) as follow:

$$w_i = T_i + (1 - T_i)\frac{p(X)}{1-p(X)} \quad (8)$$

5. Dataset and Sources

Research on the accumulation of lifetime earnings and SAT improvement by target program remains limited due to the lack of adequate data (Cooke 2003; Elder and Pavalko 1993). The State of Connecticut Department of Education data website (edsight.ct.gov) provided this paper's data source. A data portal that offers information about state districts and schools. Furthermore, it has publicly available school and district profiles and performance data, including graduation rates and academic test results. As a result, a panel dataset was created for two years (2016-2018) that included a treatment variable (LIS), an independent variable (SAT scores), and eight chosen covariates related to the independent variables.

A summary of the dataset is provided in Table 1.

Table 1: Summary Statistics for Variables, Sources and Period

	Variables	**Years**	**Sources**
Dependent	Connecticut	**2016-2018**	Connecticut State
Treatment	School	**2016-2018**	(Dept. Education)
Covariates	Day SAT	**2016-2018**	Connecticut State
	League of	**2016-2018**	(Dept. Education)
	Innovative School	**2016-2018**	Connecticut State
	Black	**2016-2018**	(Dept. Education)
	Educators	**2016-2018**	Connecticut State
	Certified Teacher	**2016-2018**	(Dept. Education)
	(General	**2016-2018**	Connecticut State
	Education)	**2016-2018**	(Dept. Education)
	Chronic	**2016-2018**	Connecticut State
	Absenteeism		(Dept. Education)
	Four-Year		Connecticut State
	Graduation Rate		(Dept. Education)
	Free Lunch		Connecticut State
	Program		(Dept. Education)
	Non-White pupil		Connecticut State
	Pupil -Teacher		(Dept. Education)
	Ratio		Connecticut State
	Science		(Dept. Education)
	Proficient		Connecticut State
	White		(Dept. Education)
	Educators		

RESULTS

Preliminaries

Prior to implementing PSM and IPW, the paper thoroughly examined the descriptive statistics in Table 2 and performed a T-test to determine the similarity between the treated (LIS schools) and the control group every year.

Table 2: Descriptive Statistics

INDICATORS				Dependent	Treatment	Covariates								
				Connecticut School Day SAT	League of Innovative School	Black Educators	Certified Teacher (General Education)	Chronic Absenteeism	Four-Year Graduation Rate	Free Lunch Program	Non-White pupil	Pupil - Teacher Ratio	Science Proficient	White Educators
CONTROL GROUP	2015	(n=168)	*Mean*	979.056	0.000	6.280	23.661	13.456	89.744	0.334	0.353	12.839	0.450	87.957
	2016	(n=173)		984.044	0.000	6.941	22.787	12.803	90.500	0.324	0.387	13.765	0.423	85.837
	2017	(n=170)		984.423	0.000	7.334	21.567	12.325	90.377	0.389	0.399	14.544	0.472	87.204
	2018	(n=175)		970.217	0.000	7.528	23.879	13.883	90.970	0.416	0.427	13.990	0.512	86.799
	2015	(n=168)	*Std. Dev.*	122.294		7.435	16.789	12.221	11.478	0.287	0.281	1.846	0.211	12.667
	2016	(n=173)		128.862		6.544	14.546	13.784	12.655	0.243	0.277	1.987	0.198	13.332
	2017	(n=170)		117.054		7.078	15.675	13.788	11.998	0.265	0.245	1.990	0.243	13.040
	2018	(n=175)		116.012		7.221	16.545	16.269	13.122	0.293	0.299	1.867	0.209	13.745
	2015	(n=168)	*Min*	960.081	0.000	4.978	22.313	11.178	87.853	0.242	0.261	12.233	0.337	85.948
	2016	(n=173)		963.987	0.000	5.613	23.554	10.210	88.616	0.265	0.298	12.432	0.319	83.171
	2017	(n=170)		966.318	0.000	5.930	21.987	9.800	88.561	0.275	0.300	12.123	0.419	85.236
	2018	(n=175)		951.928	0.000	6.056	23.965	10.794	89.093	0.288	0.324	12.879	0.468	84.695
	2015	(n=168)	*Max*	998.030	0.000	7.583	25.009	15.734	91.635	0.427	0.445	13.446	0.563	89.966
	2016	(n=173)		1004.100	0.000	8.268	26.766	15.395	92.384	0.587	0.433	13.787	0.489	88.503
	2017	(n=170)		1002.528	0.000	8.737	24.776	14.849	92.192	0.443	0.457	14.998	0.507	89.173
	2018	(n=175)		988.505	0.000	9.000	26.097	16.971	92.848	0.511	0.512	14.007	0.523	88.904
TREATED	2015	(n=26)	*Mean*	998.833	1.000	4.654	19.342	9.500	88.133	0.345	0.408	12.452	0.522	90.800
	2016	(n=29)		996.053	1.000	3.900	18.098	7.307	87.311	0.435	0.412	13.089	0.543	89.705
	2017	(n=32)		999.000	1.000	3.719	20.564	8.400	91.676	0.412	0.405	14.880	0.577	89.847
	2018	(n=38)		987.050	1.000	3.569	21.774	9.388	91.845	0.523	0.543	13.211	0.598	90.895
	2015	(n=26)	*Std. Dev.*	89.454		3.675	13.020	8.405	13.296	0.222	0.289	2.223	0.232	8.556
	2016	(n=29)		95.176		2.087	12.008	5.279	12.767	0.324	0.212	2.776	0.243	8.665
	2017	(n=32)		79.933		3.876	13.877	3.869	14.087	0.231	0.243	3.675	0.104	7.867
	2018	(n=38)		90.799		2.332	14.009	6.425	13.007	0.335	0..233	2.990	0.246	8.454
	2015	(n=26)	*Min*	954.349	1.000	2.281	16.260	3.488	81.521	0.234	0.264	11.347	0.445	86.545
	2016	(n=29)		950.179	1.000	1.746	17.897	4.383	81.214	0.311	0.342	12.012	0.456	85.698
	2017	(n=32)		957.902	1.000	1.449	19.897	6.166	87.214	0.195	0.388	12.065	0.478	85.057
	2018	(n=38)		944.555	1.000	1.260	20.675	5.964	88.825	0.345	0.456	13.055	0.491	86.628
	2015	(n=26)	*Max*	1043.318	1.000	7.026	22.424	15.512	94.746	0.456	0.552	13.558	0.598	95.055
	2016	(n=29)		1041.926	1.000	6.054	21.665	10.230	93.407	0.546	0.644	14.101	0.602	93.713
	2017	(n=32)		1040.098	1.000	5.988	22.342	10.634	96.139	0.512	0.677	15.066	0.618	94.637
	2018	(n=38)		1029.545	1.000	5.877	23.006	12.811	94.865	0.659	0.607	14.996	0.621	95.162
P-Values	2015	(n=26)	*Ha: diff != 0*	0.506		0.433	0.035	0.319	0.532	0.213	0.142	0.512	0.292	0.544
	2016	(n=29)		0.069		0.312	0.652	0.130	0.536	0.631	0.514	0.540	0.054	0.534
	2017	(n=32)		0.617		0.441	0.315	0.293	0.107	0.101	0.042	0.411	0.276	0.122
	2018	(n=38)		0.053		0.323	0.278	0.278	0.354	0.241	0.523	0.652	0.175	0.034

A plot of the mean outcome variable (SAT scores) comparison during [2016-2018] was generated to visually examine any differences (Figure 1). The analysis shows a higher mean SAT scores for the LIS school.

International Journal of Online and Distance Learning
ISSN 2520-4033 (online)
Vol.6, Issue 1. No.1, pp 1 - 13, 2026

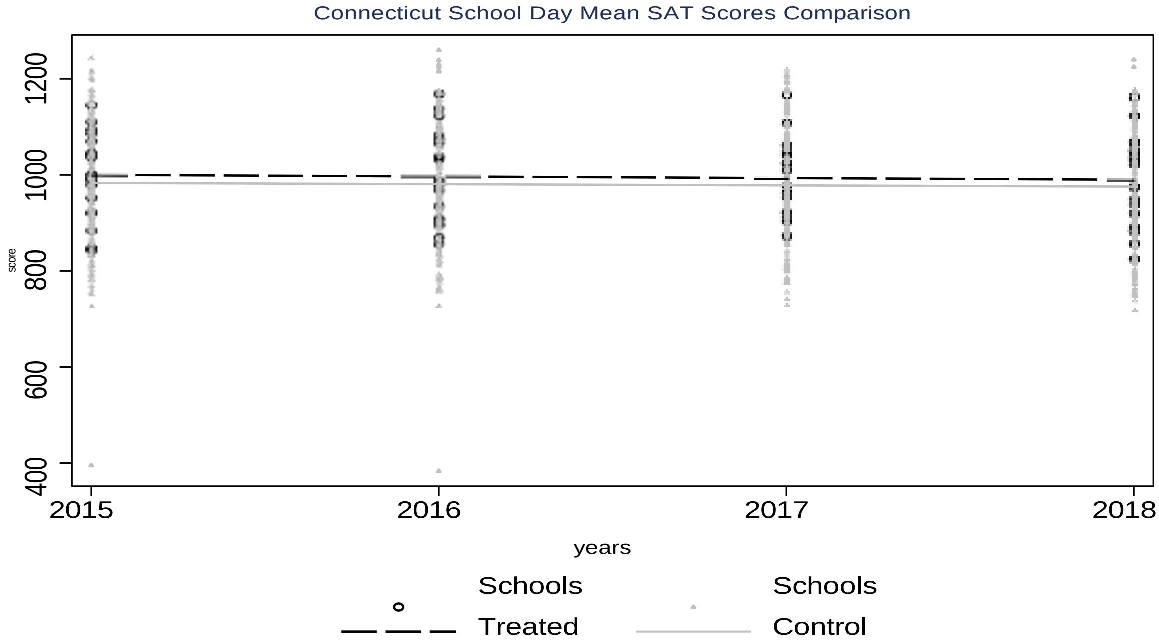

Figure 1: Mean Plot Comparison

Furthermore, the study included a visual depiction of all matching samples. A visual inspection of the distribution of estimated propensity scores for participating and non-participating schools (Figures 2, 3, and 4) confirmed the prerequisite common support condition.

Figure 2: Matching Schools Sample Density Comparison (2016)

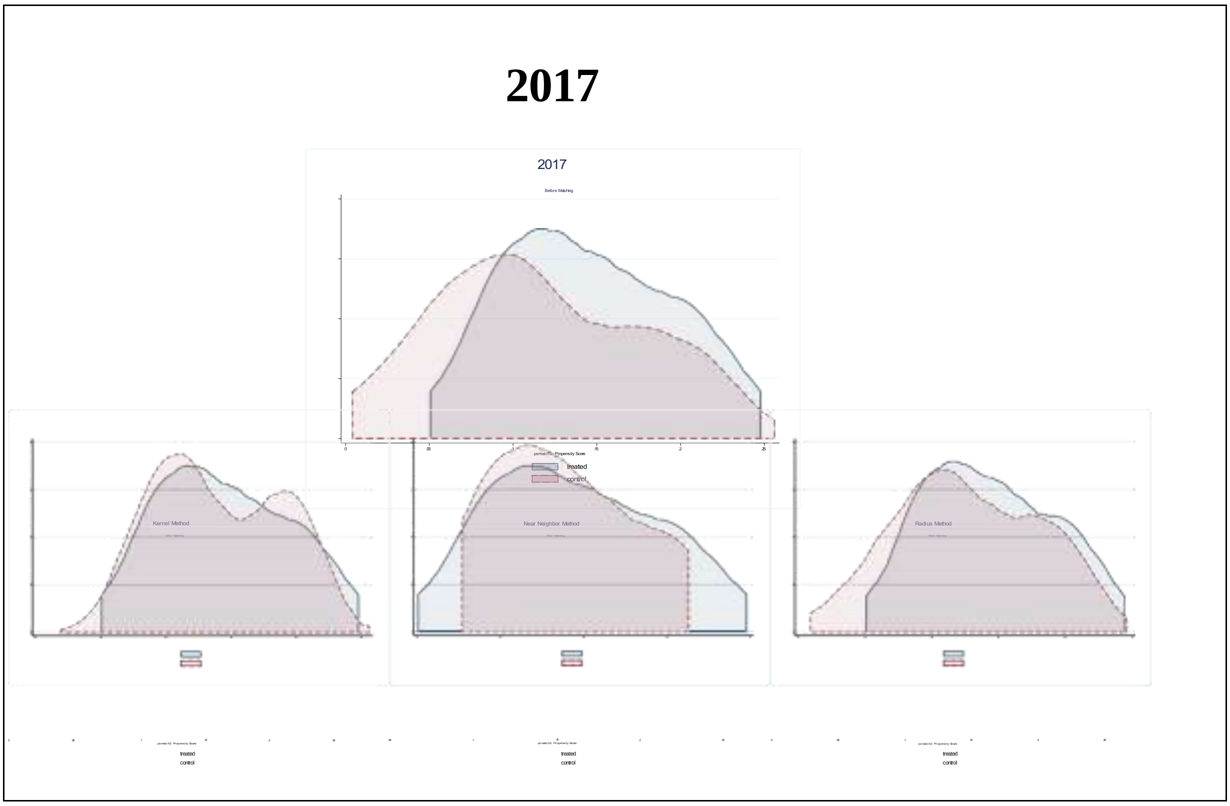

Figure 3: Matching Schools Sample Density Comparison (2017)

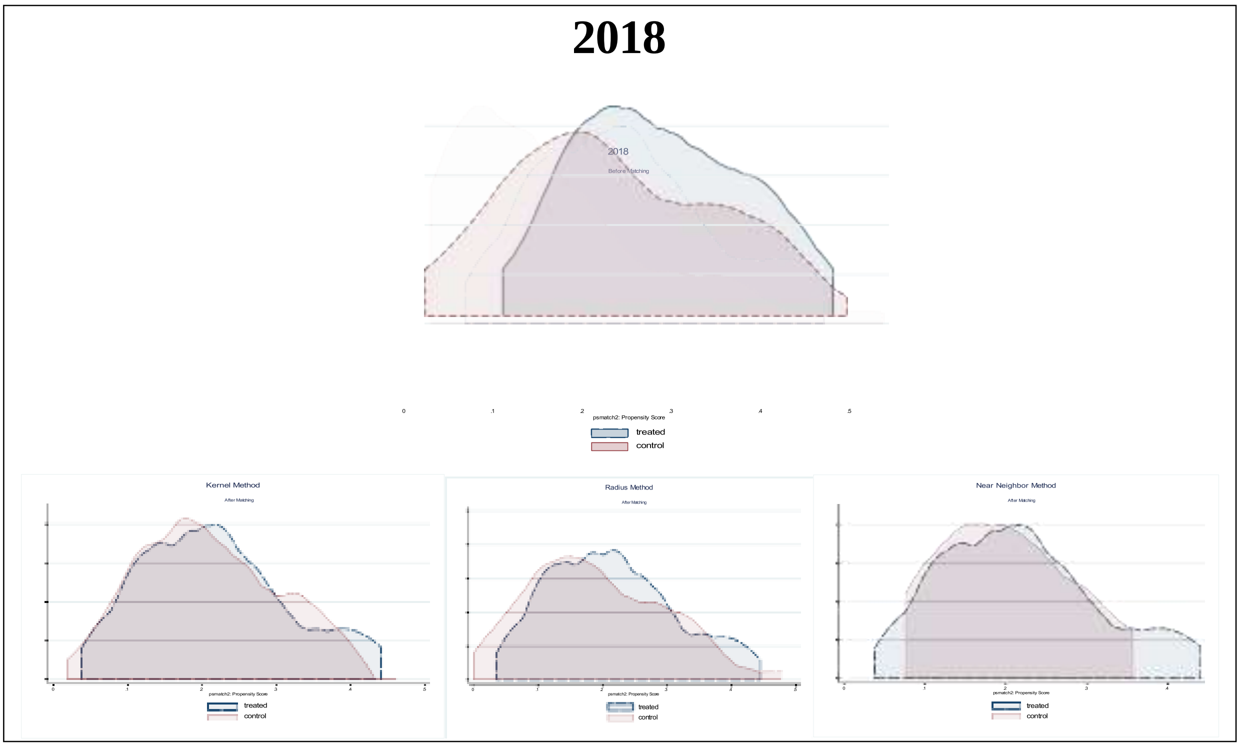

Figure 4: Matching Schools Sample Density Comparison (2018)

Propensity Score Matching (PSM) Results

Once the study established the balance on the propensity scores and covariates, a comparison between the three matching methods (NN matching, Kernel, Radius) was performed in Table 3. The results show a difference between the SAT scores from the participating school and the non-participant LIS for each year. The differences found within the matched sample suggest an average treatment effect of 6 points for 2016 and 2017 and 4 points for 2018 in the matched group. Furthermore, to alleviate selection bias in the results, the inverse probability weight was estimated each year and a new treatment effect generated for the sample. It is worth noting a higher variance caused by a few schools with larger weights that in the estimation. The IPW results suggested an average increase of 10 points in 2016, 8 points for 2017 and finally 5 points for 2018. Overall, an increase among the standard test scores for each year with both models (PSM et IPW).

Table 3: Propensity Score Matching and Inversed Probability Weight Results

VAR		Connecticut School Day SAT			
		Nn Matching	**Radius Matching**	**Kernel Matching**	**IPW**
2015		984.440	984.210	984.197	
2016		988.320	988.411	987.666	
	TREATED				
2017		998.120	998.110	998.833	
2018		996.780	994.243	996.442	
2015		979.411	980.322	987.699	
2016		984.645	981.541	982.320	
	CONTROL				
2017		996.767	991.865	994.670	
2018		993.232	992.980	993.087	
2015		5.029	3.888	2.354	11.739
2016		3.675	6.870	5.346	9.438
	ATT				
2017		1.353	6.245	4.163	7.661
2018		3.548	1.263	3.355	4.798
2015		2.580**	1.964**	2.53***	1.300
2016		2.441**	1.982**	2.87***	1.823*
	T-STAT				
2017		1.854*	2.904***	0.140	0.756
2018		2.994***	1.990**	2.34***	2.971***

Note: (1) ***, **, * denote statistical significance at the 1%, 5% and 10%
(2) T-values are calculated using bootstrap with 1000 repetitions.

Discussion

The paper's findings of a 4-to-10-point increase in SAT scores per year are significant and provide strong evidence for collaboration and the sharing of innovative practices among high school educators at state and regional forums to foster overall school performance, boost SAT scores. However, it's important to note the difference between the old and new SAT tests. For example, an old score of 2400 would be equivalent to 1600 score in the new format. Despite Kane's (1998) findings that a 100-point higher average on the old SAT can result in a 3 to 7 percent increase in lifetime earnings, our study, who uses the new SAT score excluded causality but suggested a positive correlation between the school-based community learning program and future earnings. Our method:

- Offers evidence to school, district, and state education policymakers to inform funding decisions related to school-based professional learning community.
- Provides private operators and donors to School-based Professional Learning Community with evaluation information on the effectiveness of their program.
- Allows economists and researchers an econometric model framework for similar studies.
- Engages states and counties to explore the success of school-based professional learning communities to improve overall exams scores.
- Suggests a future in-depth look at the differences between the old and new standardized exam formats, which could have an impact on test variance.

Conclusion

To improve overall achievement, the US education system and private education consortium have implemented a variety of programs for high schools. Those innovative learning methods could improve SAT scores, which could facilitate access to higher-ranked schools and potentially improve future lifetime earnings. In the New England region, the education authorities implemented the League of Innovative School (LIS), which is a voluntary, innovative school-based professional learning community. The LIS objective was to enhance the knowledge and skills of educators by engaging in professional dialogue, collaborative study, and exchanging expertise thus enhance overall reading, science scores and graduation rates. Consequently, this paper examined the impact of such a program (LIS) on the SAT scores of participating schools to assess potential increases in lifetime earnings. Especially, when previous findings suggested that a 100-point higher average SAT is associated with 3 to 7 percent higher earnings later in life (Kane 1998, p. 221-237).

The results of the study indicated a positive impact of the LIS program and an average increase of 7 points in SAT scores for participants. Thus, strong evidence for collaboration and the sharing of innovative practices. Especially among high school educators at state and regional forums to improve overall school performance and boost test score. Moreover our study excluded causality but suggested a positive correlation between the school-based community learning program and future earnings.

REFERENCES

1. A Student's Dilemma: Is There a Traoff- off Between a Higher Salary or Higher GPA. (2014). *Working Papers*.
2. Brewer, D., Eide, E., & Ehrenberg, R. (1996). *Does it pay to attend an elite private college? Cross cohort evidence on the effects of college quality on earnings*. Cambridge, MA: National Bureau of Economic Research.
3. Brewer, D. J., Eide, E. R., & Ehrenberg, R. G. (1999). Does it pay to attend an elite private college? Cross-cohort evidence on the effects of college type on earnings. *The Journal of Human Resources*, *34*(1), 104.
4. Brouwer, P., Brekelmans, M., Nieuwenhuis, L., & Simons, P. R. J. (2012). Community development in the school workplace. *International Journal of School Management*, *26*, 403–418.
5. Carnevale, A. P., & Smith, N. (2013). Workplace basics: the skills employees need and employers want. *Human Resource Development International*, *16*(5), 491–501.
6. Cobb, C. (2018). The League of Innovative Schools: Understanding Participation, Implementation of Student-Centered Teaching and Learning, and School Outcomes. Manuscript submitted
7. Cooke, T. J., & Boyle, P. (2011). The migration of high school graduates to college. *Educational Evaluation and Policy Analysis*, *33*(2), 202–213.
8. Dale, S. B., & Krueger, A. B. (2002). Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables. *The Quarterly Journal of Economics*, *117*(4), 1491–1527.
9. Doğan, S., & Adams, A. (2018). Effect of professional learning communities on teachers and students: reporting updated results and raising questions about research design. *School Effectiveness and School Improvement*, *29*(4), 634-659.
10. DuFour, R., DuFour, R., Eaker, R., & Karhanek, G. (2004). *Whatever it takes: How professional learning communities respond when kids don't learn*. Bloomington, IN: National Education Service.
11. Elcullada Encarnacion, R., Tourism and Hospitality Department, Oman Tourism College, Galang, A. A., Hallar, B. J., Department of Computer Science, Mariano Marcos State University, & BSIT Department, Mariano Marcos State University. (2021). The impact and effectiveness of E-learning on teaching and learning. *International Journal of Computing Sciences Research*, *5*(1), 383–397.
12. Hairon, S., Goh, J. W. P., Chua, C. S. K., & Wang, L. (2017). A research agenda for professionallearning communities: Moving forward. *Professional Development in Education*, *43*(1), 72–86.
13. Hoekstra, M. (2009). The effect of attending the flagship state university on earnings: A discontinuity-based approach. *The Review of Economics and Statistics*, *91*(4), 717–724.
14. Horvitz, D. G., & Thompson, D. J. (n.d.). A Generalization of Sampling Without Replacement From a Finite Universe Author(s. *Source: Journal of the American Statistical A.*
15. Hout, M. (2012). Social and economic returns to college education in the United States. *Annual Review of Sociology*, *38*(1), 379–400.
16. Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, *47*(1), 5–86.

17. Lomos, C., Hofman, R. H., & Bosker, R. J. (2011). Professional communities and student achievement–A meta-analysis. *School Effectiveness and School Improvement*, *22*(2), 121–148.
18. *Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme James J*. (n.d.). Heckman, Hidehiko Ichimura and Petra E. Todd.
19. Matching, U. (n.d.). *Instrumental Variables and Control Functions to Estimate Economic Choice Models James J*. Heckman & Salvador Navarro-Lozano.
20. Kane, T. J.(1998). Racial and Ethnic Preferences in College Admissions. *The Ohio Law Journal* Vol 59:971.
21. Oh, S.-Y., & Cho, I.-S. (2015). The employment determination factors of vocational highschool graduates: Group comparison among the employed, college students, and the undecided. *Journal of Adolescent Welfare*, *17*(4), 49–70.
22. Pavalko, E. K., Elder, G. H., Jr, & Clipp, E. C. (1993). Worklives and longevity: insights from a life course perspective. *Journal of Health and Social Behavior*, *34*(4), 363–380.
23. ResearchGate. (n.d.). Retrieved November 27, 2020, from Researchgate.net website: https://www.researchgate.net/deref/http%3A%2F%2Fdx.doi.org%2F10.1146%2Fannurev.soc.012809.102503
24. Rosenbaum, & Rubin. (1983). *central role of the propensity score in observational studies for causal effects PAUL R*.
25. Solmon, L. C. (1985). Quality of education and economic growth. *Economics of Education Review*, *4*(4), 273–290.
26. Solmon, L. C., & Wachtel, P. (1975). The effects on income of type of college attended. *Sociology of Education*, *48*(1), 75.
27. Vlachopoulos, P., Jan, S. K., & Buckton, R. (2020). A case for team-based learning as an effective collaborative learning methodology in higher education. *College Teaching*, 1–9.
28. Weisbrod, B. A., & Karpoff, P. (1968). Monetary returns to college education, student ability, and college quality. *The Review of Economics and Statistics*, *50*(4), 491.