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Energy Efficiency Measures in Oregon Instructional School Facilities Implemented Under SB 1149, and Improved Student Performance

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Abstract—**Energy generation, transmission, and distribution, requires a costly infrastructure to meet increasing demand. The success of energy efficiency measures (EEM's) are largely based on cumulative energy and cost savings. This research attempts to add improved student learning to the list of benefits when implementing EEM's in instructional school facilities. Our literature review of current research demonstrates that maximizing natural daylight in the design of school buildings reduces energy consumption, as well as improves student performance [1]. Additionally, EEM's can benefit student performance through direct and indirect environmental improvements that enhance usability, productivity, and comfort [2]. Through statistical analysis of data collected by the Oregon Department of Energy and the Oregon Department of Education, student mathematics assessment passing rates, before and after EEM implementations, are compared and analyzed using a panel analysis methodology and a simple pooled regression. The result of our research finds a positive significant correlation between EEM's and improved student performance. An average increase in mathematics assessment passing rates of 0.3808% after EEM implementation, provides a basis for further analysis. Finally, this research aims to promote energy conservation projects in instructional school facilities, by identifying improved student learning in addition to already established cost-savings, and environmental benefits.**

I. Summary Background

Energy conservation in residential, commercial, and industrial sectors are supported by local governments through the development and implementation of strategies and subsidies that improve energy efficiency. Oregon's Senate Bill, SB 1149, passed by legislature and implemented in March of 2002, restructures the electricity market by providing residential, commercial, and industrial customers of Portland General Electric (PGE) and Pacific Power, a portfolio of energy options. Additionally, SB 1149 created a 3% public purpose charge for energy efficiency, development of renewable energy generation, and low-income energy assistance. Of the total public purpose charge, 10% of the collected public funds are designated for energy efficiency programs in public K-12 schools within the utilities' service territories. To qualify under SB 1149, eligible school facilities must be a public K-12 instructional school facility, and operate within the service territories of either utility [3]. Currently, throughout the State of Oregon, 16 school districts, representing 815 K-12 instructional school facilities, are eligible to use public funds for energy efficiency improvement measures [4]. Of these eligible schools, 453 fall under PGE's territory, with the remaining 362 falling under Pacific Power [5]. Furthermore, since 2002, over 300 K-12 instructional school facilities have participated in the SB 1149 Schools Program, and have served over 250,000 students [6].

II. Introduction

Although previous research and conservation projects demonstrate that energy efficiency measures reduce energy consumption and provide energy cost savings, little research identifies improved student learning as an externality of conservation in public schools. Our research attempts to determine a correlation between improved student performance after energy efficiency measures (EEM) are implemented in public instructional school facilities. Using a simple pooled regression of available data from the Oregon Department of Education and the Oregon Department of Energy, our study compares student passing rates in standardized tests within each school before and after implementing EEM's to determine the effect, if any, on improved student performance.

The scope of our research is limited to public elementary and middle schools in Oregon that are eligible for EEM implementation since 2002 under SB 1149, with an overall student population of greater than 150 students. Additionally, the EEM's and subsequent schools that we consider in our analysis are limited to the following three categories: lighting, heating, ventilation, and air conditioning (HVAC), and building envelope. Our assumptions and scope are further defined in the data and methodology section. The objective of our research is to provide compelling evidence that demonstrates a correlation between implemented EEM's and improved student performance. Through our statistical analysis, we hope to provide a sound methodology that can be used as a model for other conservation projects in public schools. Additionally, we hope to provide a basis for further research to identify the EEM or combination of EEM's that provide the greatest impact on improved student performance – further promoting conservation projects in public schools.

III. Literature Review

This literature review has identified key research regarding physical learning environments in school classrooms, and our

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findings determine a primary focus on daylighting and HVAC. The direct effects of lighting in classrooms are logical to discern. Students achieve better test scores in well-lit environments as opposed to dimly-lit ones; making it easier for students to read their material naturally leads to better results [7]. What is not as readily apparent are the psychological and biological influence that lighting has on human beings. 6% of the population suffers from intense seasonal depression while 20% suffers from mild seasonal depression [8]. It has been proven that depression has a direct connection to poorer academic results [9]. Seasonal depression has been treated successfully by an increase in bright, white light in the person's environment [10].

As biological entities, humans have a circadian rhythm. This is evolution's way of telling us that when it is dark we should rest and when it is light we should be more active. When it is time to rest the human body produces melatonin to help with sleep. Natural lighting suppresses melatonin output in people who are studying at nighttime [11]. Students who study in natural lighting show less fatigue afterwards than those who study in traditionally illuminated environments [12]. Daylighting in schools has been found to have a positive impact on student test scores, student health, and absence rate. In one study, students who attended daylit schools tested 5%-14% better than students who attended non-daylit schools [13]. In another study "students in classrooms with the most daylighting were found to have 7%-18% higher scores than those in the least" [14]. The effects of lighting in schools are diverse and profound in their influence upon students.

Air is a fundamental requirement for human survival. We need air to breathe. It follows that the quality of the air should have a beneficial or detrimental impact on the person breathing it. Students breathe air from the same ventilation systems every day. Does the quality of this air affect their academic performance? Substandard indoor air quality (IAQ) has been proven to have an adverse effect on student performance. In the paper, "A preliminary study on the association between ventilation rates in classrooms and student performance," the authors R. J. Shaughnessy et al, study classroom carbon dioxide (CO_2) concentrations in 54 U.S. elementary schools. Using CO_2 concentrations as a proxy for the quality of the ventilation and air handling systems feeding the elementary schools, the study compares standardized test scores to CO_2 levels found in classrooms. As a result, this study finds a "significant association between classroom-level ventilation rate and test results in math" [15].

Asthma is a prevalent condition as 6-8% of American youth are diagnosed with the chronic lung disease [16]. "However, in asthma hot spots, for example, low income, urban, minority neighborhoods in Detroit, New York City, and other major cities, rates > 20% have been reported" [17]. Students with asthma have difficulty breathing and poor air quality worsens the symptoms. Even outside of students suffering from asthma, poor indoor environmental quality affects student performance. One study of 100 classrooms found that "87 had ventilation rates below the recommended guidelines" [18]. The same study found a linear association between the CO_2 rates present in the air and student performance. "For every unit (1 1/s per person) increase in the ventilation rate within that range, the proportion of students passing standardized test (i.e., scoring satisfactory or above) is expected to increase by 2.9% for math" [19]. HVAC systems are the source of a school's air. HVAC systems that output air of a poor quality are linked to adversely affect student test scores. Furthermore, optimal temperatures led to an increase in performance [20].

Based on the findings supported in previous research, this paper focuses on schools with EEM's that are related to lighting, HVAC and building envelope.

IV. Data

The Oregon Department of Education compiles annual school report cards which are based on each school's reported student passing rates in standardized tests for subjects such as reading/writing, mathematics, and science within the state. Of the available data, this analysis uses only math test passing rates in the statistical model, for reasons based on the consistency and unambiguity of testing methodology for mathematics.

There were many inconsistencies over the years among high schools with regards to reporting passing rates in standardized tests. Inconsistencies in reporting were also found for subjects such as science and reading/writing. During certain years, some schools did not report student assessments in science. Reading and writing were reported as two separate subjects for several years, and were reported as a single subject called English Language Arts (ELA) in other years – this was not the case for the subject of mathematics. As such, the analysis conducted in this paper focuses only on elementary and middle schools as part of the sample, and uses publicly accessible data on mathematics assessment passing rates from 2003-2016.

There have been two major changes reflected in our data that affect our model – changes in assessment standards, and changes in cut scores. The first, is the change in assessment standards from the Oregon Assessment of Knowledge and Skills (OAKS) to the Common Core State Standards (CCSS). The transition from OAKS to CCSS began in the 2010-2011 school year, and was completed over time as the CCSS was phased-in across the state. Since the 2014-2015 school year, students no longer take the OAKS exam in mathematics and ELA. To complicate things further, the phase-in of new assessment standards did not occur in a uniform and controlled implementation. In an interview, Dr. Mark Freed, Mathematics Education Specialist with the Oregon Department of Education, stated that "the Oregon State Board can adopt content standards, but specific timelines are not necessarily explicit within our laws" [21]. Dr. Freed further explained that "2011-12 would have been the first full school year educators had the new standards. Some districts jumped in right away, some districts waited until the assessment changed, but most likely phased in implementation between 2011-2014. A majority of districts likely were fully implemented by the 2013-14 school year" [22]. Secondly, cut scores within standards have changed, most notably to prepare for the increased rigor of the CCSS. Table 1 below shows the increase in cut scores of the mathematics achievement standards for the OAKS assessment [23].

TABLE I. MATHEMATICS ACHIEVEMENT CUT SCORE INCREASE [24]

Grade	Adopted 2010-2011 Achievement Standards			Previous (2006 – 2010) Achievement Standards			Change from Previous to 2010-11 Achievement Standards		
	Nearly Meets	Meets	Exceeds	Nearly Meets	Meets	Exceeds	Nearly Meets	Meets	Exceeds
3	205	212	219	201	205	217	+4	+7	+2
4	212	219	227	208	212	225	+4	+7	+2
5	219	225	234	214	218	229	+5	+7	+5
6	222	227	237	216	221	232	+6	+6	+5
7	228	232	242	221	226	238	+7	+6	+4
8	230	234	245	225	230	241	+5	+4	+4
HS	232	236	251	231	236	246	+1	0	+5

Using available data through the *SB 1149 Schools Program*, the sample schools used in this research consist of all elementary and middle schools eligible for EEM's. Additionally, the Oregon Department of Energy supplied a comprehensive list of elementary and middle schools that have implemented EEM's under SB 1149. The requested EEM's fall under three general categories: lighting measures, HVAC measures, and building envelope measures. Table 2 below, shows specific measures for each general category, and the number of schools to implement each measure. Included in the data are the years in which the EEM's were installed at each school, as well as the type of EEM's that were implemented. The data was specific to only elementary and middle schools that were eligible for the SB 1149 program. Thus, the overall sample of schools used in this analysis is limited to all elementary and middle schools in Oregon that are eligible for EEM's under SB 1149.

TABLE II. EEM CATEGORIES [25]

General Category	# of Measures per General Category	Specific Measures in Each Category	# of Specific Measures
Lighting	289	Controls	38
		Fixture Modification	100
		Lamp Modification	146
		Other	5
Heating	194	Boiler Equipment	121
		Distribution System	38
		Maintenance	18
		Other	17
Cooling	5	Chiller / AC Equipment	3
		Distribution System	1
		Other	1
Ventilation / Distribution	38	Controls	6
		Distribution System	5
		Flow Issues	2
		Heat Recovery Options	3
		Other	22
Building Envelope	96	Insulation	38
		Doors	19
		Windows	37
		Other	2

V. METHODOLOGY

Using the available data described above, schools were categorized into "control" and "treatment" groups where the control group are schools that are eligible but never implemented EEMs and the treatment group are eligible schools that have implemented EEMs at any point between 2003-2016. Simple pooled regression (a form of panel analysis) was chosen to conduct our research. The regression investigates correlation between EEM implementation and student passing rates of standardized math tests within the sample of schools. Different statistical methods to determine causation are discussed in this paper's *future research* section.

In this analysis, the outcome of interest was set as the student passing rates in standardized mathematics tests and EEM Implementation was set as an explanatory variable. Since cut rates change every year, and testing standards are not implemented uniformly, a same year comparison approach (setting academic year as an explanatory variable) was used in an attempt to control for the differences between each academic year. The hypothesis in our model proposes that student passing rates in standardized math tests at each school is positively affected by EEM implementation.

The model's general form is shown in (1) below, where y is our outcome of interest, α is a constant term, x_n are the explanatory variables (with n number of variables), β_n is the coefficient for the explanatory variables and μ is the random unobserved errors. In this case, there were two explanatory variables.

$$y_{it} = \alpha + \beta_1 x_{1it} + \ldots + \beta_n x_{n\,it} + \mu_{it} \quad (1)$$

EEM Implementation as an explanatory variable was assigned the categorical values of either N (for "no" implementation) or Y (for "yes" they had EEM Implementation at some point between 2003-2016) to separate the control group from the treatment group.

The distribution of passing rates over time was plotted for the entire sample of schools. Additionally, a comparison of passing rate distribution between our control (N) and treatment group (Y) for each academic year was also plotted. If the proposed hypothesis is true, then the median for the treatment group would be greater than the control group after EEMs were first implemented in schools, and the coefficient β should be a positive value.

VI. RESULTS

The following figures shows the distribution of student passing rates in math tests within our sample of schools starting from the 2003-2004 academic year (denoted as 2004) until in the 2015-2016 academic year (denoted as 2016). Fig.1 illustrates the combined distribution of student passing rates for the entire sample of schools (both the control and treatment groups) within each academic year as a box plot. The lines

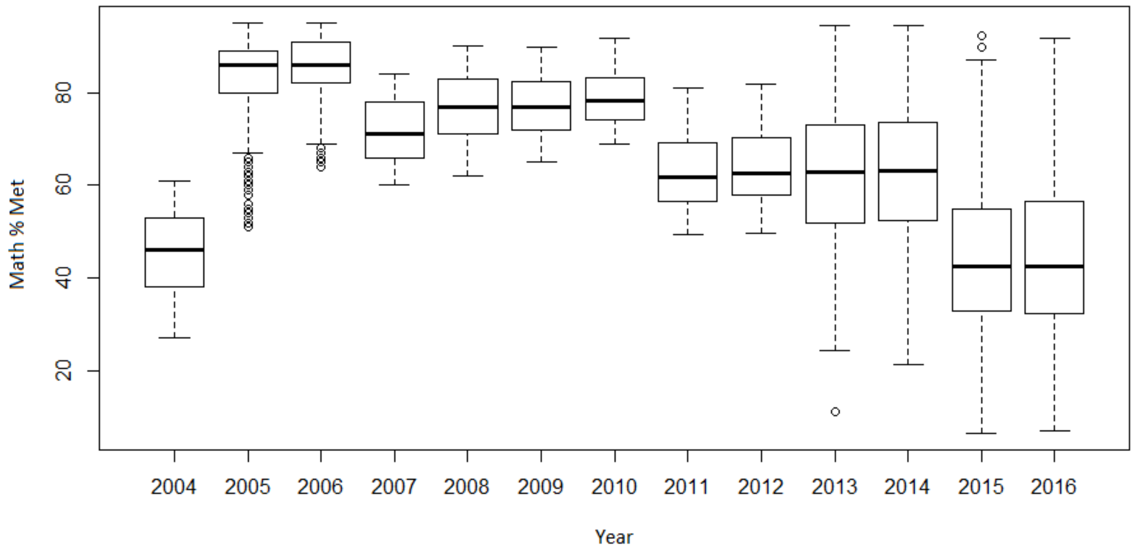

Fig. 1. Box Plot of Passing Rates for Math Testing by Year (Source Data: *Oregon Dept. of Education Aggregated Report Card Data*)

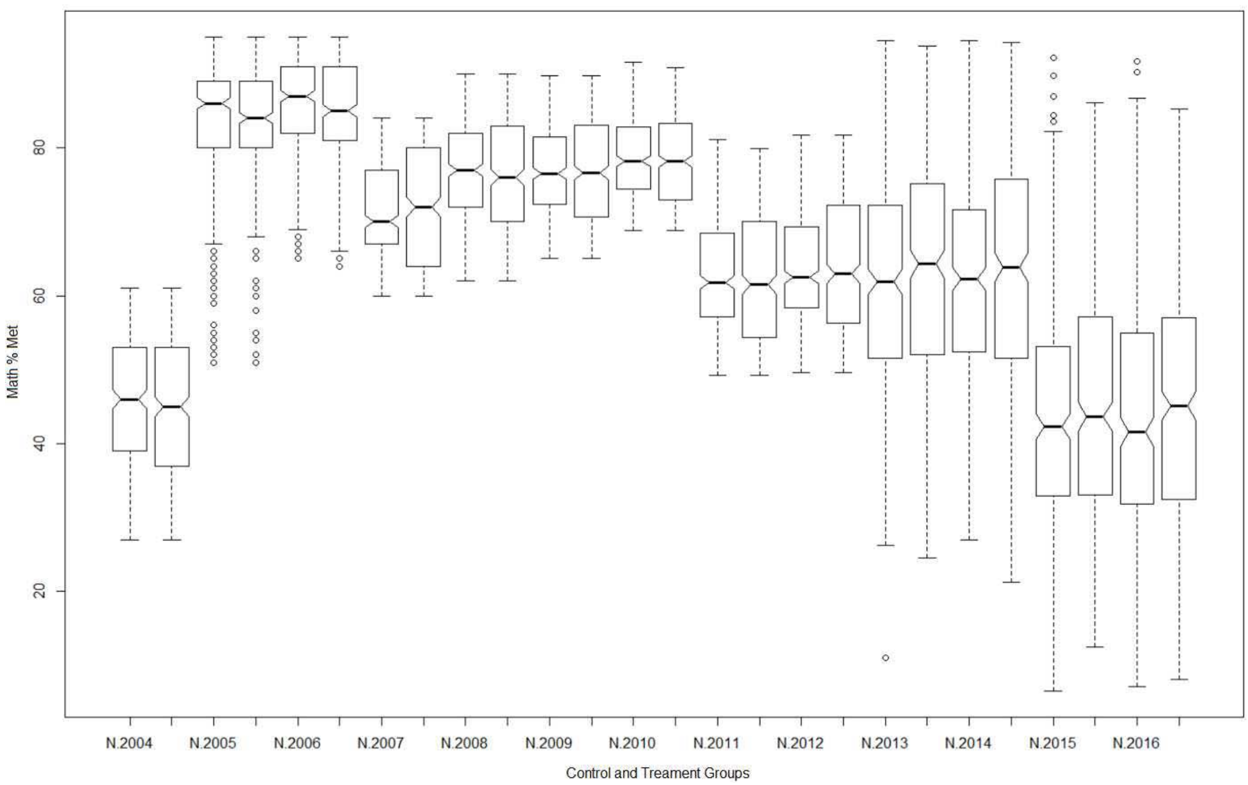

Fig. 2. Notched Box Plot of N and Y Passing Rates for Math Testing by Year (Source Data: *Oregon Dept. of Education Aggregated Report Card Data*)

represent the median passing rates for the entire sample of schools during each academic year.

As expected, due to changes in testing standards and cut scores, during certain years, there were drastic increases or decreases in the median passing rate compared to the previous academic year – specifically, the 2004-2005 academic year, 2006-2007 academic year, 2010-2011 academic year, and the 2014-2015 academic year.

Certain academic years had more difficult standardized tests compared to other years which led to lower passing rates in general. The variance of passing rates from 2013-2016 may be attributed to changes in assessment standards and cut scores. The new CCSS standards, which were to be implemented across the state by 2014-2015, had a voluntary phase-in period from 2011 to 2014. Schools joined the new standards in a staggered manner, resulting in a wider variance of passing rate results. Secondly, and specifically pertaining to the mathematics achievement standards, cut scores became increasingly higher in preparation for the increased difficulty of the new statewide standards [26]. The increase in cut scores of the mathematics achievement standards for the OAKS assessment is shown in Table 1.

The notched box plot of Fig. 2 compares the median passing rate of the control group (which is the left side box plot denoted with N) to the treatment group (which is the right side box plot) for each academic year. If a school implemented any EEM *at any point* between 2010-2016, they were designated as Y for the entire period thus the plot illustrates the distribution of the passing rates for the same number schools in each category (N/Y).

The earliest implementation of EEM’s in the treatment group took place in 2010. Before the 2010-2011 academic year, the treatment group overall performed worse on standardized testing than the control group. After the 2010-2011 academic year, when the EEM’s began to be implemented, student performance in the EEM schools are better overall than non-EEM schools. This visual representation of the data supports the hypothesis and lends credence to future research.

The graph in Fig. 3 below looks at schools from 2010-2016 divided into two groups (EEM and Non-EEM schools) and their associated median passing rates. Unlike the previous graph, Fig. 3 includes the year that a school implements EEM’s. A school would exit the non-EEM group and enter the EEM group the year of completion of an EEM. The difference between the passing rates of the two groups provides a visual confirmation of the connection between EEM’s and passing rates.

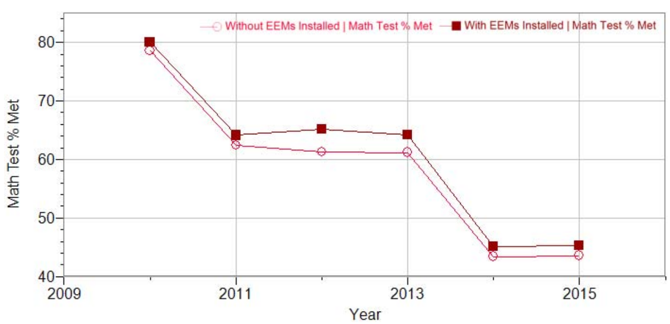

Fig. 3. Time Series Plot of Passing Rates for Math Testing by Year (Source Data: *Oregon Dept. of Education Aggregated Report Card Data*)

VII. Conclusion

The notched box plot and the simple median time-series highlight a relationship between EEM's and student passing rates in standardized math tests. In order to establish correlation, the results of the simple pooled regression should be analyzed to verify the proposed hypothesis. Table 3 shows the results of the regression analysis.

Where,

B, is the base value of coefficients

CI, is the range with standard error

P, is the P-value with a lower limit of < 0.001 (The actual p-value of our analysis is 2.2×10^{-16})

The R^2 and adjusted R values of the regression model provide details regarding the amount of variables explained in the analysis. The R^2 value is the percentage of the Math Pass Rate (outcome of interest) that the explanatory variables accounts for. Thus an R^2 value of 0.595 states that 59.5% of the Math Pass Rate is explained by our equation, leaving 40.5 % unexplained. The adjusted R accounts for whether or not an influx of variables is inflating the R^2 value. Since the adjusted R value is nearly identical, our data is not being manipulated by extraneous variables.

The p-value represents the chances that the independent variable (EEM’s) doesn’t affect the results. In other words, with a p-value less than 0.001 the chances that EEM’s have no effect on passing rates is negligible, indicating significant correlation between improved student performance and EEM implementation. It is interesting to note that 2015-2016, the years with the most variance of data points, also have the highest p-scores.

TABLE III. Pooled Regression Results [27,28]

	Math		
	B	*CI*	*p*
(Intercept)	45.51	44.63 – 46.39	**<.001**
Year			
2005	36.86	35.68 – 38.04	**<.001**
2006	38.96	37.79 – 40.14	**<.001**
2007	26.16	24.98 – 27.34	**<.001**
2008	31.07	29.90 – 32.25	**<.001**
2009	31.33	30.16 – 32.51	**<.001**
2010	33.13	31.96 – 34.30	**<.001**
2011	17.15	15.98 – 18.32	**<.001**
2012	18.34	17.17 – 19.51	**<.001**
2013	16.75	15.58 – 17.92	**<.001**
2014	16.72	15.55 – 17.89	**<.001**
2015	-1.42	-2.58 – -0.25	**.017**
2016	-1.25	-2.42 – -0.08	**.036**
ImplementedEEM	0.38	-0.07 – 0.83	.100
Observations		9559	
R^2 / adj. R^2		.595 / .594	

The Implemented EEMY value (or the coefficient β in the model) is positive, indicating an increase in math scores for the treatment group as a result of having installed EEM's. The value of 0.3808 tells us that EEM's in schools raise math passing rate by 0.3808% for each individual school with an EEM per year. If a school has implemented an EEM(s) then that school's passing rate will improve by 0.3808% a year. The simple pooled regression has determined that there is a positive and significant correlation between EEM's and math passing rate.

A 0.3808% increase in math scores across the board isn't a fundamental shift in how we view EEM's in relation to student achievement and 59.5% of the observed outcome is accounted by the explanatory variables. Previous foundational studies along with the differences in medians in both the notched box-plot and time series indicate that the percentage could rise with continued research.

VIII. Future Research

Using a simple pooled regression, this study identifies a positive correlation between EEM's and improved student performance, but does not determine causality. This correlation serves as a basis for further analysis which can include a variety of statistical approaches. Passing rates are available by grade level, and future research can include an analysis of grade-level test scores for each school, as well as a more comprehensive study using difference-in-differences or a different quasi-experimental approach in order to determine causation. Potential future research can include multiple factors that may influence student test scores in our analysis. There are several school, family, and peer factors that affect a students' academic performance. Environmental factors, such as school size, neighborhood and student-teacher relationships may also affect student learning. Additional significant factors include a student's family background, socioeconomic status, and parental involvement [29]. Incorporating these factors as multiple predictor variables could improve the linear regression model. However, to isolate the effects of EEM's on improved student performance, a statistical matching of data or coarsened exact matching, should be utilized to address the bias from these variables. This would be an important step to inferring causality through a difference-in-differences approach.

Enlarging the scope to include SB 1149 eligible high schools, as well as non-SB 1149 K-12 schools, could be included in future research. A primary focus of this study was to develop a useful model and approach to determine the effects of EEM's on student learning, reflected in improved mathematics assessment passing rates. This same model can be applied to broader scope of schools. Additionally, using the mathematics assessment passing rates as a metric for improved student performance has its limitations in presenting a complete picture of student performance increases. For example, improved test scores that are below the cut-score are not reflected in the model for either control or treatment groups. This is a problem of scale and resolution, and constrains our model to only observing a magnitude increase in student performance that results in an increase of passing rates. Raw test score data, rather than passing rates, has the capability of showing improved student learning in an incremental scale. Future research using raw mathematics assessment scores would provide better detail of the scope of effects on student performance. The authors of this paper did not find raw test score data for any school under SB 1149, and do not know if this data is available for future research.

Finally, the effect on improved student performance analyzed in this research, is based on the aggregate of three categories of EEM's: lighting, HVAC, and building envelope. Future research isolating the effect of specific EEM's on improved student performance would provide insight into the effectiveness of specific measures, providing a basis for an impact analysis and decision model. This could further promote energy conservation and efficiency with regards to specific technologies and measures, by identifying improved student performance as a positive externality. The challenge with identifying the effect of a single measure, is the cooperative and codependent nature of energy conservation. For example, in the Oregon Department of Energy data, *building envelope* includes windows, doors, insulation, and other measures that may support HVAC efficiency. Additionally, windows providing daylight, may have an effect on lighting measures.

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