The 5 Billion Dollar McCleary Act:
Do Changes in Expenditure Improve Student Outcomes?

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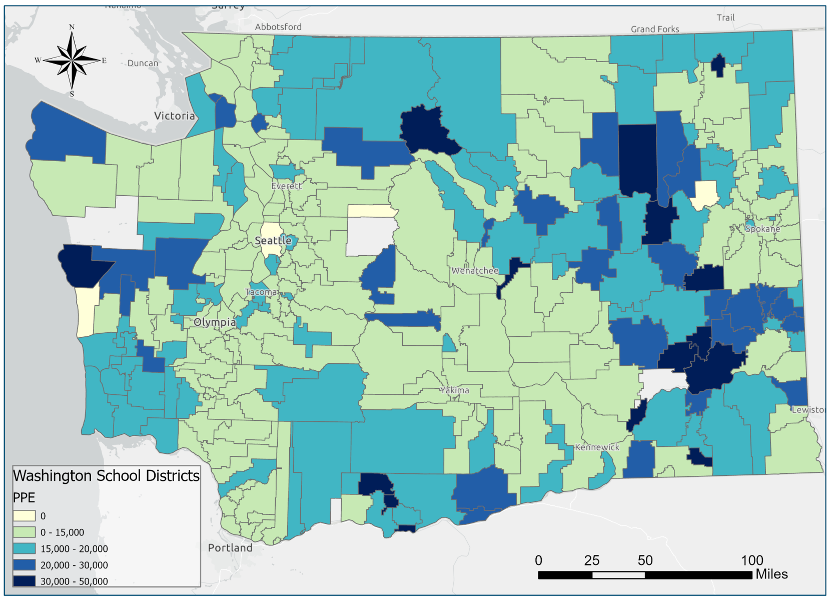
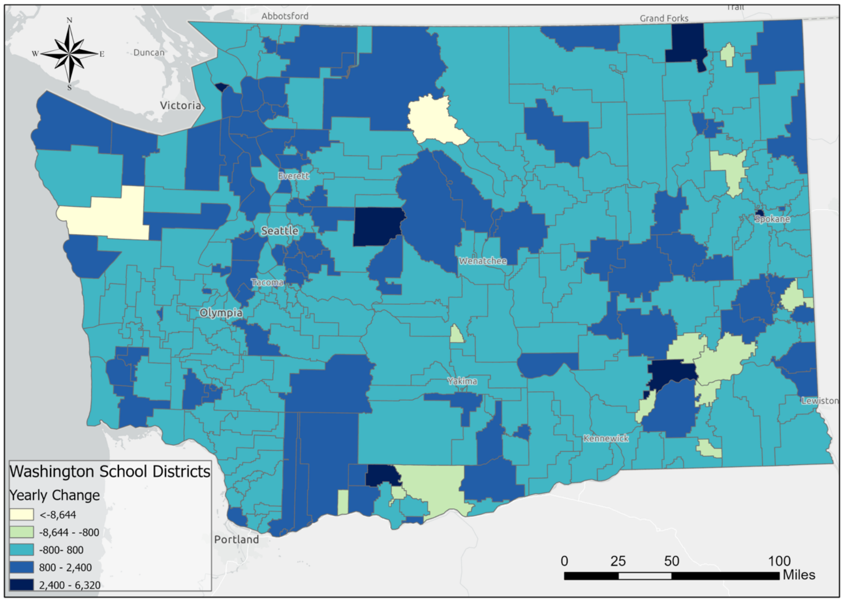
2017-18 Per Pupil Expenditure in 2021 dollars.



OLS Estimated Real Slope of Expenditure 2017-2022



*All map values are in September 2021 dollars.

Abstract:

In this study, I infer how changes in per pupil expenditure impact student outcomes. From 2017-2022, Washington schools received an average of 20% more real funding per student. The aim of the spending was to create a more adequate and equal K-12 school system. As a result, this funding hit different schools at different times in different quantities. We can utilize this natural experiment to look at how school funding changed student outcomes. To study this, I built a fixed effects model, with log(per pupil expenditure) as an independent variable, and student outcomes as the dependent variable. Using longitudinal data from 2017-2022 on students, schools, and county-level crime, I have not found a statistically significant causal relationship between per pupil expenditure (PPE) and student outcomes. However, this relationship is sensitive to functional forms. When regressions are not weighted by enrollment, PPE reduces crime rates. When the regression includes more interactions, PPE improves attendance rates. The lack of robustness indicates that the mechanisms for improving student outcomes may change contextually. In other words, this model is constrained because it oversimplifies the inputs for improving student outcomes.

Introduction:

This study utilizes an exogenous shock to education spending. In 2012, the United States supreme court ruled in favor of McCleary in McCleary v. State of Washington. The Supreme Court mandated that Washington State was failing to uphold its constitutional duties to provide ample funding for basic education. It took 9 years to improve education spending, during which the State of Washington was fined $100,000 a day. In 2018, the Washington legislature was able to draw enough money to meet the expected 5 billion dollars a year increase in K-12 education spending (Barlet 2018).

Washington State has over 1 million K-12 students. This is almost twice the entire population of Wyoming, and these students represent about 1/7 of all of Washington's residents. How education funding should be spent is not always immediately clear. Before the McCleary act, local school districts were responsible for raising additional money by passing local levies. This raised issues of inequality in school funding, as only some schools were able to raise enough money to adequately meet the students' needs. In the 2017-18 school year, between federal, state, and local income streams, the average school in Washington used about $15,400 a year pr. student, in 2021 dollars. From 2017-2022, the average school's spending pr student increased by about 3,000 real dollars or 20%. These statistics include private schools, preschools, and education spending in juvenile dentition centers.

Studying the economics of education is important because it helps us understand how investments in education can impact individuals, communities, and the entire economy. By describing how educational investments have played out in the past five years, Washington administrators can more accurately weigh costs and benefits. Good data science can help inform education spending, for the sake of Washington's students. This study is but one example of how access to public data can be a powerful tool for accountability.

Literature Review:

Marie Canony's 2011 paper "The Role of Schools in the Production of Achievement" developed the framework for student inputs used in this paper. Canony argued that education is an essential part of the production function for skills. Understanding what drives educational success is important for understanding labor markets. In her study, Canony investigated how inputs impact an individual student's outcomes. Canony used a family's savings for post-secondary education as a control for unobserved ability to learn. In other words, Canony used family wealth as a method to control different access to funds. The study's conclusion was that a school's skills, such as its effectiveness and productivity, are what contributes most to student outcomes. In a fixed effects model, these unchanging characteristics will not be visible. Canony also found that school inputs like spending and teachers can only sometimes improve outcomes. Additionally, Canony found that schools are an important equalizer. For example, K-12 education can mitigate the differences that black and white students encounter in the labor market. An important aspect of Canony's data was that she could observe inputs from 8th grade to 12th grade. Canony found that if inputs are only altered in 12th grade, the effects will be insignificant. If the effects are felt both in 8th grade and in 12th grade, they will be much stronger.

Marie Canony's 2011 models were partially inspired by Eric Hanushek's 1986 paper "The Economics of Schooling: Production and Efficiency in Public Schools." Hanushek argues that it is hard to make a good school system. The educational process has been extensively researched, but the policy prescriptions from this research are ambiguous. Using econometric methods to study school inputs and outputs is difficult because, in part, it is hard to quantify student outcomes. Many researchers reject econometric studies of school inputs and outputs because they believe that neither can be adequately quantified. Standardized test scores may or may not have any link with future outcomes. If standardized tests can't predict future outcomes, then it is a poor metric of student success.

Hanushek, like Canony, found that a student's outcome is a function of the cumulative inputs of their family, their peers, their school, and their teachers. My study neglects to measure cumulative inputs, and thus may be unable to capture patterns in PPE and student outcomes. Hanushek also found that spending on teachers makes up about 2/3 of school expenditures. In his analysis of 142 studies, he found no causal relationship between expenditure and student outcomes. When differences in family background are controlled for, the spending on students outside of spending on teachers has no effect on student outcomes. Like my study, he found that studies in the discipline of education are commonly plagued by poor data quality.

K–12 CLASS SIZE REDUCTIONS AND STUDENT OUTCOMES: A REVIEW OF THE EVIDENCE AND BENEFIT–COST ANALYSIS by the Washington State Institute for Public Policy was a 2013 meta-analysis contracted by the Washington State Legislature. The analysis, done by Aos and Pennucci, informed Washington administrators. The study approximates the costs and benefits of decreasing the student: teacher ratio by 1. The researchers used studies from other states and high-income countries. They found that small class sizes are important, especially at younger ages. Small classes can significantly improve student outcomes, including non-cognitive outcomes. They also estimated that reducing the student teacher ratio by one would cost $160 to $196 2011 dollars per student ($216 to $264 2022 dollars). Note that if the findings hold true for this study, decreasing the student teacher ratio by one would result in a 1.4% to 1.7% increase in per pupil expenditure.

Data Description:

The data used in this study is longitudinal data at the school level, for the five school years between September 2017 and June 2022. A summary of all variables can be found in Table 1. Unfortunately, clean data on schools in Washington is somewhat scarce. The data used in this study was compiled from 16 different datasets. Some of these datasets have only been downloaded a handful of times. Various holes in each dataset, as well as inconsistencies in how school data has been recorded, has resulted in many missing observations. Some variables, like test scores, only describe four years. Other variables, like crime data, are only available at a county-level aggregation. However, I try to mitigate the inconsistencies in the data by using sound statistical procedures. The short length of time analyzed is another limitation of this study, and a reason to run more studies in the future. The Washington Office of Superintendent Public Instruction (OSPI) began consistently publishing data in 2017. With more years of data, one could better find the effect though the noise (Canony 2011). Heavy suppression of student scores, poverty rates, graduation rates, and attendance rates are important for the privacy of the students, but also inconvenient to the study.

The student outcome variables used in this study include attendance, graduation rates, standardized test scores, and arrest statistics for people 17 and younger. Attendance rates were gathered from the OSPI's Comprehensive Education Data and Research Systems (CEDARS) database. Each school's attendance rate reflects the percentage of students who average two or fewer absences per month, divided by the number of students enrolled for at least 90 days. Attendance is suppressed when there are less than 10 students. Attendance is also suppressed when attendance rates are so high that one could extrapolate that there are fewer than 10 students not in regular attendance. Assuming a linear relationship, this suppression should not bias our results. However, if we cannot observe attendance rates fluctuate, we cannot produce statistically significant estimates of how attendance fluctuates with PPE (per pupil expenditure). Models which weigh the schools based on their enrollment are less affected, as bigger schools are less suppressed.

Graduation rates were likewise gathered from the CEDERS database. Data on graduation only pertains to high schools. I chose to only include the percentage of students who graduated in 4 years. Alternative schools and tribal schools are inconsistently observed. Students who got an AA degree at a college instead of finishing high school are also not necessarily counted as graduating. Graduation rates are understandably sensitive, and data suppression once again affects small schools the most. Assuming a linear relationship, this suppression should once again not bias our results, only cost us confidence.

Standardized tests were measured by the percentage of students who passed their English-language-arts (ELA) and their mathematics exams. Each school's percentage of math or ELA tests passed is a running three-year average. This is inconvenient to our study, but important for the privacy of the test takers. The standardized tests were either the Smarter Balanced Tests, or WA-AIM tests, which are taken by both elementary students and highschoolers. The metric used in this study, percentage passed, represents the number of students who met the standardized test standards, divided by the number of students who took the test. There is little incentive for students, especially those not in high school, to take this test seriously, unless pressure is applied by parents, or self-inflicted. Standardized tests were not administered in the 2020-21 school year, so there are only four years available for analysis. Suppression and autocorrelation will once again bias our results. If 2/3 of all observations are mechanically paired with the observation before and after, the regression estimates will be inefficient. The state-wide pattern of test results indicates steady passing rates, a drop following quarantine, followed by slow improvements.

Crime rates were pulled from the Washington State Statistical Analysis Center. The Washington Statistical Analysis Center is a clearinghouse for Washington crime data. The county-level data describes the number of juvenile arrests and sentences (17 and younger) from 2018-2021. Temporally, crime data lines up awkwardly with school data. The 2018 data is paired with the 2017-18 school year, 2021 data paired with the 2020-21 school year. There is no data available for the 5^{th} year of this study. Data on the number of arrests reflects the sum of all reports filed to the Washington Association of Sheriffs and

Police Chiefs. The variables “car days” and “jail days” were calculated from different data, collected by the County Superior and District Court Clerks. The variable “car days” represents the minimum total number of days juveniles are sentenced to each year. It is calculated by multiplying the number of juveniles who were sentenced for an automotive crime multiplied by the average minimum sentence (in number of days) for vehicular crimes that year. The variable “jail days” represents the sum of the minimum number of days juveniles were sentenced to for the crimes of arson, hacking, theft, assault, public disturbance, and automotive crimes. There is no suppression in crime data, but the dataset is limited to the 39 counties observed over 4 years.

The central independent variable used in this study is per pupil expenditure (PPE). Per pupil expenditure is the amount of money spent on each student in one school year. This data was downloaded from the OSPI website, where administrative data from DATA.gov was merged with Comprehensive Education Data and Research Systems (CEDARS) data. By pulling data from three OSPI datasets, we could observe per pupil expenditure across five different years. This was done by determining what organizations were schools, aggregating their total expenditure, and then dividing by their total enrollment. The measurements were then converted into real September 2022 dollars. This was done using the Bureau of Labor Statistics CPI calculator. We assumed that all payments took place in September of that school year, because this is when the budget is assigned by the legislature.

The enrollment at each school was derived from the OSPI’s Comprehensive Education Data and Research Systems (CEDARS). This is a metric of every registered K-12 student in the state of Washington. A student is registered as enrolled if they are attending a school on the first business day of October. Enrollment increases when the school size increase. This means that more kids are entering school than leaving. In modeling, changing enrollment may be an indication of what school districts are seeing immigration because of desirable nearby attributes, like a booming job market. It is also an indication that an individual school is experiencing self-selection bias. Because the school is doing well, parents who are invested in their kids’ education are putting their kids in particular schools. In either cases, including enrollment helps control for unobserved attributes of a school that do change over time.

Data on the number of teachers at every school was collected from The Teacher Quality Database. The database also has information on teacher experience, field, and number of teachers teaching in every field. The teacher-to student ratio used in this study is derived from the number of students enrolled, divided by the number of teachers in any given school. This means that teachers who are specifically teaching special education or running start programs are still included. Information on the number of teachers who have a mathematics or ELA specialization is also available through the Teacher Quality Database. There is some suppression of this variable, so schools with no math teachers (such as some elementary schools) are unobserved.

Student free and reduced priced lunch rates (FRPL) represent the percentage of students eligible for free and reduced priced lunches. Students receive FRPL if their family does not meet certain financial criteria. FRPL provides an unbiased and commonly used metric for the finances of parents in a school system.

Table 1:	List of variables used in analysis	
Variable:	Variable meaning:	Suppressed data?
attendance	% students with <2 absences/ month	yes
graduation	% students who graduate in 4 years	yes

mathpass	% of students in school who pass their grade's math exam	yes
engpass	% of students in school who pass their grade's English language arts exam	yes
crime	Number of arrests for given crime in county	
PPE	Per pupil expenditure	
log(*PPE*)	natural log scaled per pupil expenditure	
enrollment	number of students at a given school	
log(*enrollment*)	natural log scaled enrollment	
stud:teach	ratio of students/teachers at a school	
%FRPL	the percentage of students at a school who qualify for free or reduced priced lunch	yes
2018-19	The change in dependent variable intercept from 2017-16 schoolyear to 2018-19 schoolyear	
2019-20	The change in dependent variable intercept from 2017-16 schoolyear to 2019-20 schoolyear	
2020-21	The change in dependent variable intercept from 2017-16 schoolyear to 2020-21 schoolyear	
2021-22	The change in dependent variable intercept from 2017-16 schoolyear to 2021-22 schoolyear	
ME 2018-19	The marginal effect of log scaled PPE on outcome from 2017-18 to 2018-19	
ME 2019-20	The marginal effect of log scaled PPE on outcome from 2017-18 to 2019-20	
ME 2020-21	The marginal effect of log scaled PPE on outcome from 2017-18 to 2020-21	
ME 2021-22	The marginal effect of log scaled PPE on outcome from 2017-18 to 2021-22	

Note: crime statistics are aggregated at a county level. All county level statistics are an average of schools in the county.

In this study, I use four different analytical samples, depending on the student outcome in question. All summary statistics are calculated using averages weighted by enrollment. The first analytical sample is the broadest and is used to study the effect of per pupil expenditure (PPE) on attendance rates. Descriptive statistics can be found in Table 2. The observations available represent only 75% of the schools in Washington. Some schools are not represented because they only teach early daycare, or other programs that do not keep detailed data with the OSPI. Many of the schools are not represented due to data suppression. I have included all observations that are not suppressed. This means that there are observations from some private schools, some juvenile detention centers, some special ed programs, and some running start programs. One could make the argument that these schools all have fundamental differences, and it may be best to study them separately. However, due to the time constraints of this study, there was not enough time to go through the 12,500 observations and sort them. While these institutions make up a very small fraction of the students in Washington, they represent many of the outliers (observed in the min/max columns of the descriptive statistics). Models that weigh schools based on average enrollment are less influenced by these outliers.

Table 2:

Descriptive Statistics for Analytical Sample No. 1:
N= 1,677 weighted schools containing ave. 957,000 students, sampled 4.9 times

Variable	Mean	Std. dev.	Min	Max
attendance	80%	14%	6%	99%
totalppe	$15,964	$2,781	$3,661	$129,822
ln(ppe)	9.67	0.15	8.21	11.77
stud:teach	15.42	4.30	1.97	364.96
enrollment	808	507	3	2907
%FRPL	47%	24%	0%	100%

The data used to analyze the impact of PPE on test results is drawn from a smaller pool of observations. Table 3 describes the analytical sample. Fewer schools consistently report information on their Math and English teachers. Additionally, OSPI data does not distinguish between having 0 ELA teachers, and simply not logging data. Heavy suppression of testing data also narrows the number of observable schools. I have not selected to remove any observations that are not already removed by the OSPI. Note that mathpass has a slightly higher standard deviation than engpass. This is consistent with the literature (Canony 2011, Hanushek 1986), but the difference is not as stark as in other datasets.

Table 3:

Descriptive Statistics for Analytical Sample No. 2:
N= 1,350 weighted schools containing ave. 836,000 students, observed 3.1 times

Variable	Mean	Std. dev.	Min	Max
mathpass	40%	19%	2%	95%
engpass	58%	18%	4%	97%
PPE	$15,511	$2,784	$991	$132,859
enrollment	977.9	567.7	8.0	2906.6
stud:teach	16.18	3.59	0.89	53.47
stud:math	113.7705	115.8708	2.241429	836.74
stud:eng	99.8	103.6	5.7	836.7
%FRPL	45%	23%	0%	100%

The third analytical sample in this study is used to measure the effect of PPE on graduation rates. This sample represents only the High schools in the state of Washington. Descriptive statistics on high schools only can be viewed in Table 4. Graduation rates are understandably sensitive and are also heavily suppressed. I have not elected to remove any observations that are not already removed by the OSPI. Attendance rates are lower in high schools, and enrollment is higher, meaning less suppression.

Table 4:

Descriptive Statistics for Analytical Sample No. 3:

N= 324 weighted schools, containing ave. 304,000 students observed 4.6 times

Variable	Mean	Std. dev.	Min	Max
% graduation	87%	11%	5%	99%
PPE	$15,399	$2,694	$5,243	$102,146
attendance	74%	14%	6%	99%
stud:teach	17.1	4.4	0.9	104.9
enrollment	1401	557	3	2907
% FRPL	42.63%	20.99%	0%	100%

Crime rate data is only visible at the county level, and thus the data had to be aggregated. The county-level descriptive statistics on education and juvenile crime can be viewed in Table 5. The suppression of data made the county level aggregation somewhat difficult, and results may be somewhat biased due to the unavoidable underestimation of attendance and FRPL. Enrollment rates and PPE, the two most important variables, should be robust and accurate at the county level. I have also included crime density measures, which describe the rate of arrests pr every 1000 registered high school students.

Table 5:

Descriptive Statistics for Analytical Sample No. 4:

N= 39 weighted counties, representing ave. 323,000 students

Variable	Mean	Std. dev.	Min	Max
arson	0.855	2.209	0.0	15
arson density	0.09	0.40	0.0	4.48
hacking	0.092	0.388	0.0	3
hacking density	0.01	0.03	0.0	0.25
assault	73.9	115.2	0.0	499
assault density	9.15	6.27	0.0	31
drugs	17.99342	32.40769	0.0	176
drugs density	2.89	3.87	0.0	23
theft	37.5	66.05266	0.0	424
theft density	4.73	5.16	0.0	34.04
destprop	18.6	27.4	0.0	136
destprop density	2.81	5.49	0.0	62.85
car days	47.3	107.3	0.0	749
car days density	10.0	28.8	0.0	263
jail days	2889	5315	0.0	35543
jail days density	423	451	0.0	3249
enrollment	8254	14912	107	83319

stud:teach	14.0874	3.179366	5.283125	19.935
attendance	69%	15%	0%	90%
PPE	$15,901	$2,315	$12,520	$26,665
% FRPL	50%	12%	26%	77%
% graduation	75%	24%	4%	98%

crime density refers to crime incidents pr. every 1000 high school students

Model and Analysis

The goal of this study is to measure the effect of per pupil expenditure (PPE) on student outcomes. To measure the average student's outcome instead of the average school's outcome, observations are weighted by enrollment. The simplest statistical method for inferring PPE changes with student outcomes is a log linear regression. Mathematically speaking, the value of β2 measures the correlation between log(PPE) values and student outcome variables. In short, β2 describes how a student outcomes change when per pupil expenditure increases by 100 percent.

$$StudentOutcome = \beta_0 + \beta_2 \log(PPE) + e$$

Omitted variables bias the results, predicably described by Thiel's Misspecification Theorem. Including other potential key variables improves the accuracy of the model. The value of β2 now represents how student outcomes change when per pupil expenditure increases by 100 percent, holding all other variables equal (*Ceteris paribus).* The model is now more interesting, because we can observe how student outcomes change when poverty rates change, attendance rates change, enrollment changes, or student teacher ratios change.

$$StudentOutcome = \beta_0 + \beta_1 \log(PPE) + \beta_2 \log(enrollment) + \beta_3 \frac{students}{teachers} + \beta_4 \%FRPL + e$$

There are potential caveats to this model. The issue of bias is of chief concern when using regression analysis to infer cause and effects. Omitted variables, selection bias, simultaneity, reverse causality, and measurement error can all bias the outcomes of the model. To measure how PPE changes student outcomes, I must mitigate the impact of these potential biases. I can utilize the longitudinal structure of the data to control the omitted variable of covid and online school. Similarly, I can utilize the longitudinal structure to control for unchanging characteristics within each school.

Preferred Equations:

In my preferred equations, I will be using a fixed effects regression. This improved technique allows me to consider each individual school's unique characteristics. These characteristics could be the leadership of the school, the local culture, and the self-selection of students into certain schools. By measuring the changes within each school over time, the fixed effect regression measures how schools deviate from their own mean, when certain variables are at play (like more funding). Constant, unobserved characteristics are no longer a cause of bias. The equational form of a fixed effects regression is as follows:

$$StudentOutcome_{it} = \alpha_i + \delta_t + \beta_1 \log(PPE)_{it} + \beta_2 \log(enrollment)_{it} + \beta_3 \frac{students}{teachers_{it}} + \beta_4 \%FRPL_{it} + e$$

The effect of Covid on students was a time shock affecting all student's outcomes. For the integrity of the model, it is important to account for years where "going to school" was fundamentally different due to quarantine. Because the pandemic had a strong correlation with funding, I do not want these fixed time shocks to bias the results downward. To mitigate the Covid time shock, I included a dummy variable for each year. These dummy variables allow me to control for the unique change in student outcomes due to exogenous shocks each year. By incorporating these dummy variables, I can accurately assess the impact of other independent variables on the outcome of interest while appropriately accounting for the disruptions caused by the pandemic. Accounting for time shocks changes the functional of the form to the following:

$$StudentOutcome_{it} = \alpha_i + \delta_t + \beta_1 \log(PPE)_{it} + \beta_2 \log(enrollment)_{it} + \beta_3 \frac{students}{teachers_{it}} + \beta_4 \%FRPL_{it} + FE_{2017-18_t} + FE_{2018-19_t} + FE_{2019-20_t} + FE_{2020-21_t} + FE_{2021-22_t} + e$$

In some cases, it may be appropriate to add additional variables. I analyze how changes in the student: math teacher ratio changes standardized test results. When identifying causes of changes in crime rates, I use changes in PPE, percent FRPL, student to teacher ratios, and enrollment.

Bias

Despite my best efforts to mitigate bias, it impacts this causality study. The most important potential caveat to this model is reverse causality. Assuming that administrators are working to make a fairer school system, they may give more resources to struggling schools. Thus, a school with low test scores may receive more funding. This reverse causality biases regression outputs downward, as the model is actually measuring how funding chases poor performance.

The pandemic changed what we are assuming to be fixed over time. For example, as students have to study from home instead of at school, their environment changes. The effect of the pandemic may be much worse in high FRPL schools. If %FRPL is correlated with a drop in student outcomes during the pandemic, then the coefficient %FRPL may be overestimated during a normal year and underestimated during the pandemic.

Explanation of Results:

My Data analysis found that more per pupil expenditure (PPE) does not immediately improve student outcomes. Under some conditions, there may be a relationship between PPE and student outcomes. Reverse causality may make it impossible to know how PPE affects test scores. All results are held to a standard of 95% significance.

Attendance Rates

I did not find a statistically significant relationship between expenditure on students and attendance rates. Instead, more teachers and more enrollments improve attendance rates. One more student in every classroom reduces attendance rates by .0005, or .05%. However, the relationship between per pupil expenditure and attendance rates is not so simple. One needs to spend more money in order to hire more teachers, more experienced teachers, or more educated teachers. By including the student teacher ratio, we are measuring how PPE (per pupil expenditure) affects attendance, after holding student:teacher ratios constant. The answer is that it does not. However, the effect of student: teacher ratios is significant, after holding PPE constant. When PPE is not included in the functional form, and not held constant, the relationship is even greater.

The model predicts that a 1% increase in enrollment results in a .049% increase in attendance rates. This relationship is likely because of selection bias. Enrollment in a particular school increase over time when students move to said school. Because parents who are very invested in their kids' education are more likely to enroll their children in a school that is doing well, the students that are showing up to said school are likely have better attendance rates. I am no sociologist, but I am assuming that parents who have the time to fuss over which school their child attends, also have the energy to fuss over their child's attendance rate.

Table 5:

Estimated effects of PPE on Attendance Rates
1677 schools observed 5 times

Variable	Coefficient	Std. dev.	P value
ln(*PPE*)	-0.0232	0.0161	0.148
stud:teach	-0.0005	0.0002	0.006
ln(*enrollment*)	0.0493	0.0138	0.000
%FRPL	0.0001	0.0003	0.578
constant yr 2017-18	0.7232	0.2086	0.001
2018-19	0.0036	0.0018	0.052
2019-20	0.0699	0.0024	0.000
2020-21	-0.0307	0.0046	0.000
2021-22	-0.1630	0.0041	0.000

R Squared Within = .62

Test Scores:

I found that more per pupil expenditure does not improve the number of students meeting testing standards. The results suffer from autocorrelation, as test scores are a three-year average. The results can be viewed in Table 6. According to the literature, the results also likely suffer from reverse causality (Canony). This reverse causality would bias results downward, if the school system is giving more money to suffering schools. The model finds no significant patterns in PPE and percentage of students passing math exams. However, the model does find that PPE often increases when ELA test passing rates are decreasing. A 1% increase in PPE follows a .035% decrease in three-year average test passing rates. The pattern of reverse causality may be larger in ELA tests because ELA skills are necessary to learn other disciplines, such as mathematics. A 1% increase in ELA passing rates is correlated with a .64% increase in math passing rates. Administrators may give priority funding to an effort to improve ELA scores.

The number of students in an ELA classroom impacts both math test and ELA test passage rates. It appears that the number of students in a math classroom does not impact the percentage of students who pass either exam. An extra student for every ELA certified teacher results in .004% fewer students passing their ELA exam. For math exams, there is the opposite effect. An extra student for every ELA certified teacher result .007% more students passing their mathematics exam. This inverse relationship may be because ELA certified teachers are simply worse at teaching mathematics. In this case, More ELA teachers in a K-5th grade environment may result in better ELA scores, but worse math scores. Mathematics certified teachers may not be as attracted to K-5th grade teaching environments, and so their bias does not impact student outcomes. Alternatively, the inverse relationship could be because of the budget constraint faced by schools. When a school increases the number of ELA teachers, they may have to sacrifice other resources, hurting student's mathematics test scores. More post hoc analysis is required to parse out these different possibilities.

Table 6: Effect of Per Pupil Expenditure on Test Scores

Estimated Effects of PPE on Math Test Scores

1,350 schools observed 3.1 times

Variable	Coefficient	Std. dev.	P value
ln(*PPE*)	1.614	1.878	0.390
engpass	0.640	0.052	0.000
ln(*enrollment*)	7.55	1.50	0.000
stud:math	-0.00231	0.00340	0.497
stud:eng	0.00728	0.00234	0.002
%FRPL	0.0653	0.0352	0.064
constant yr 2017-18	-63.8	22.7	0.005
2018-19	-0.568	0.468	0.225
2019-20	*Quarintine, No Testing*		
2020-21	-6.35	1.12	0.000
2021-22	-5.74	0.69	0.000

Within Rsquare = .60

Estimated Effects of PPE on ELA Test Scores

1,350 schools observed 3.1 times

Variable	Coefficient	Std. dev.	P value
ln(*PPE*)	-3.519	1.649	0.033
mathpass	0.429	0.035	0.000
ln(*enrollment*)	-4.10	1.32	0.002
stud:math	0.000247	0.002889	0.932
stud:eng	-0.00435	0.00221	0.049
%FRPL	-0.127	0.035	0.000
constant yr 2017-18	111	21	0.000
2018-19	0.438	0.326	0.179
2019-20	*Quarintine, No Testing*		
2020-21	-7.53	0.77	0.000
2021-22	-3.28	0.61	0.000

Within Rsquare = .58

Graduation Rates:

The only variable linked to graduation is attendance rates. This robust conclusion can be viewed in Table 7. Every 1% increase in attendance rates improved graduation rates by .068%. On the ground expertise could best explain this relationship. In my inexperienced opinion, graduation is an outcome that takes 12 years of building to achieve. I would understand if graduation rates do not fluctuate rapidly from small contemporary changes in spending or class size. However, if a student is not consistently showing up to school, it may be because graduation is not in their cards, and thus they have no incentive for good attendance. In this case attendance and graduation are merely correlated. Other socio-economic variables drive both attendance rate and graduation rates.

Commented [al1]: this is a bit vague and informal. Can you more clearly state what you mean?

Table 7:

Estimated Effects of PPE on Graduation Rates
441 schools observed 5 times

Variable	Coefficient	Std. dev.	P value
ln(*PPE*)	0.003	0.024	0.902
attendance	0.068	0.023	0.003
stud:teach	-0.001	0.001	0.153
ln(*enrollment*)	0.047	0.030	0.115
% FRPL	-0.001	0.000	0.286
constant yr 2017-18	0.453	0.340	0.184
2018-19	0.011	0.004	0.010
2019-20	0.033	0.006	0.000
2020-21	0.002	0.003	0.504
2021-22	0.028	0.010	0.004

Within Rsq. = 0.0713

Crime:

I did not find a relationship between PPE and juvenile arrest rates. This is robust for most crimes, including theft arrests, assault arrests, drug related arrests, days spent in jail, and days spent in jail for vehicular crimes. In the case of Destruction of Property, there is a significant positive relationship between PPE and destruction of property arrent rates. A 1% increase in PPE correlates with 2.1 more property damage arrests in each county, p=.056. This bias may be due to the simultaneity of equations. Notice that destruction of property is the only arrest type that is also positively tied with enrollment. It may be that destruction of property arrests are determined by both the amount of property damage committed, as well as the enforcement level for property damage. Enrollment increasing may be an indication that a county is becoming more favorable to live in, and thus experiencing immigration. The boom may improve police budget. Additionally, new arrivals to a county may be more suspectable to property crimes, or more likely to report property crimes. More post hoc analysis is required.

These findings are not robust to changing functional forms. When counties are unweighted by county enrollment, then there is a significant negative relationship between PPE and theft, assault, and drug arrests. A 1% increase in PPE results in about 8 fewer theft arrests, 1.2 fewer assault arrests, and .5 fewer drug arrests in every county. This change in patterns indicates that PPE in less populated counties must have a stronger relationship with 17 and under arrests.

Student to teacher ratios are positively correlated with the number of drug arrests. It may be that students with less one on one time with teachers are more likely to commit and get caught doing drug-related crimes.

Table 8: Estimated effect of PPE on juvenile crime arrests rates
39 counties observed 3.9 times

	Theft:		**Assault:**		**Drugs:**		**Destruction of Property:**	
	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
ln(*PPE*)	-516	0.390	409	0.441	278	0.103	211	0.056
stud:teach	-6.89	0.741	35.1	0.127	14.5	0.037	9.01	0.105
ln(*enrollment*)	7.38	0.887	104	0.163	10.5	0.767	33.3	0.092
% FRPL	5.20	0.346	2.32	0.516	-2.24	0.146	0.213	0.768
constant yr 2017-18	4939	0.414	-5323	0.355	-2833	0.133	-2440	0.049
2018-19	27.6	0.571	-11.0	0.818	-24.4	0.088	-12.3	0.109
2019-20	-43.0	0.282	-127	0.062	-75.2	0.001	-29.9	0.040
2020-21	-93.3	0.014	-176	0.025	-96.9	0.000	-53.2	0.001
Within Rsq:	Rsq 0.62		Rsq .68		Rsq .68		Rsq .57	

Commented [al2]: Make sure each table is referred to and discussed in the text.

Table 9: Estimated Effect of PPE on Juvenile Days Spent in Jail

	Days in Jail:		**Days in Jail for Vehicle Crimes:**	
	Coefficient	P value	Coefficient	P value
ln(*PPE*)	-15,395.94	0.572	-1534.231	0.127
stud:teach	61.3863	0.95	-19.32532	0.528
ln(*enrollment*)	1941.542	0.686	-65.69466	0.602
% FRPL	96.19756	0.732	19.57233	0.142
constant yr 2017-18	137616.5	0.642	15037.31	0.134
2018-19	-3415.792	0.11	-14.86299	0.747
2019-20	-2534.659	0.361	78.19741	0.386
2020-21	-3897.06	0.246	13.74277	0.852
	R sq .43		R sq .39	

Table 10:

Estimated Effects of PPE on Assault
38 counties observed 4 times

Variable	Coefficient	**Std. dev.**	P value
ln(*PPE*)	-121.672	**46.10259**	0.012
ln(*enrollment*)	9.551805	**18.14783**	0.602
% FRPL	2.411454	**0.8874622**	0.01
constant yr 2017-18	1062.776	**508.3613**	0.043
2018-19	13.12062	**6.55867**	0.053
2019-20	-25.64858	**8.651067**	0.005
2020-21	-25.96599	**11.44448**	0.029

R square within = .26

Conclusion:
My study analyzes how school inputs, such as spending, and teachers improve student outcomes in the State of Washington. I found that changing expenditure pr. student does not significantly improve any student outcomes. This is not to say that the 5 billion extra dollars Washington State is spending pr. year is going to waste. I found that improved student to teacher ratios can improve student attendance rates, ELA test passing rates, and arrests for drugs related crimes. I also found that results are sensitive to the functional form, indicating that the mechanisms by which student learn may be more complicated. I recommend that future studies account for the cumulative impacts of improved spending, instead of contemporary impacts. I implore future economists to take advantage of the longer run data that will be available in the years to come. With more observations, It may be easier to find a clear signal through the noise. Lasso and Ridge regression techniques may also be powerful tools for finding the most predictive elements of the model.

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