Public School Expenditures and Suspensions*

An Exploratory Analysis of How Expenditures Affect the Rate of In-School Suspensions

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Abstract

For decades, not only have exclusionary punishment practices forcibly removed children from educational opportunities and fueled the school-to-prison pipeline they have also indirectly negatively affected students who attend high-suspension rate schools. A broad range of studies have documented the suspension inequality that largely affects students of colour, students with discibilities, LGBTQ+ students and students from socioeconomically disadvantaged neighbourhoods. In this study, I attempt to add to the current literature by exploring if any association between school expenditures and suspension rates exists. Although there is some relationship discovered, it is not the best fit model and therefore, causality cannot be found. In the later half of the paper, I discuss how causality can be found with the right study and a discussion on the necessary steps to lower suspension rates for the benefit of all students and staff.

*Code and data are available at: https://github.com/rachaellam/edu-suspension-analysis.git.

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1 Introduction

1.1 Disciplinary Inequality

Zero tolerance policies that began as a mechanism to lower crime rates percolated into school policies and practices. In 1994, the Gun Free Schools Act compelled states who received federal funding to pass a state law that required local educational agencies to expel any student that was discovered to have brought a weapon to school. Although this act was intended to reduce violent crimes, it instead allowed schools to increase the use of out of school suspensions (OOS) for non-violent offenses such as “vulgar language, dress code violations, tardiness, or generic insubordination” (Baker-Smith 2018).

The negative consequences of these exclusionary practices, such as OOS and in school suspensions (ISS), have been well documented in numerous studies. Students who encounter disciplinary action are more likely to have lower academic achievements and higher involvement in the criminal justice system (Baker-Smith 2018). One study found that instances of delinquency or crime only occurred after an OOS, validating the existence of the school-to-prison pipeline. Additionally, while ISS are seen as a less punitive form of punishment, students who received ISS had lower GPAs and higher dropout rates (Jabbari and Johnson Jr 2019). These negative repercussions do not only affect students who directly receive disciplinary sentences but also indirectly impact students who attend high-suspension rate schools (Hinze-Pifer and Sartain 2018). Suspensions can lead to an increase in fear of crime and teacher attrition (Hinze-Pifer and Sartain 2018), which can all negatively affect the performance of students and staff.

Although OOS and ISS lead to a substantial number of disadvantageous impacts for all students, they disproportionately affect students of colour. Racial disparities in exclusionary punishments begin as early as preschool where black students experience more severe and frequent punishments (Skiba, Mediratta, and Rausch 2016). Black students are 3.5 times more likely to receive OOS than white students (Skiba, Mediratta, and Rausch 2016) and in one randomized experiment, results indicated that teachers were more likely to punish a student who committed a second offense if they were black (Baker-Smith 2018). This disciplinary inequality affects all students of colour, as Indigenous and Lantinx students share similar experiences. Race, gender, sexual orientation and disability all increase a student’s chance of being subject to exclusionary practices (Skiba, Mediratta, and Rausch 2016).

1.2 Outline

Socioeconomic circumstances also play a crucial role in determining OOS and ISS rates. It was found that schools with a larger percentage of students from low socioeconomic backgrounds were associated with high rates of school suspensions (Lee et al. 2011). Additionally, schools with majority white students had more financial resources than schools with majority of students of colour (Lee et al. 2011). Due to this significant function of wealth in disciplinary measures, it is necessary to further explore this relationship. In this paper, I used data from the Civil Rights Data Collection (CRDC) for the 2015-2016 school year to investigate the connection between suspension rates and school expenditures on personnel and nonpersonnel and to gain a better understanding of how resources influence punishment. After a discussion of the data and the model used, I find that, while there is an association between teacher salary and non-personnel expenditures and ISS rates, there is no association between non-personnel expenditures and number of days missed due to OOS. Unfortunately, causality cannot be found with the available data, but I will discuss what can be done to address causality with the appropriate data. Finally, I will end with a discussion on what can be done to lower OOS and ISS rates and how that will positively affect all students by drawing on existing literature.

2 Data

2.1 Dataset

To attempt an analysis on school expenditures and disciplinary punishment, I manipulated public school data from the 2015-2016 school year (United States Department of Education 2018). These data are collected by the Civil Rights Data Collection (CRDC) for use by the U.S. Department of Education and other policy and research agencies. The dataset was gathered in 2017 and last updated on September 28, 2018. The raw data includes 96,360 schools and 1,836 school attributes including school name, location and type; grades offered between preschool and grade 12; population of the school segmented by race and gender; type of classes and sports available; total instances of bullying, absenses, offenses, suspension and expulsions; special education and gifted and talented programs; and financial expenditures of personnel and non-personnel (NPE). Using `R` (R Core Team 2020), `tidyverse` (Wickham et al. 2019), `tidyr` (Wickham 2021), `devtools` (Wickham, Hester, and Chang 2020) and `dplyr` (Wickham et al. 2021), I cleaned and extracted the necessary data to complete an exploratory analysis and modelling.

2.2 Variables

To begin, I removed any school that was labelled alternative, charter, magnet, special education, or juvenile justice facility as I concentrated on schools that were publicly funded and adhered to the same rules and regulations. I then filtered schools that only offer grades 9-12, excluded schools that offer partial grades (ex. grades 10-12) and eliminated schools that offer preschool to grade 8 in order to limit the scope and examine similar schools. The analysis would be unbalanced if schools that only offer two grades were being compared to schools that offer four grades. Unfortunately, Hawaii and the District of Columbia were not included in the dataset after filtering by grade because there are no schools that only offer grades 9-12. In these states, schools either offer more grades, fewer grades or are ungraded, according to the dataset. Additionally, I removed columns that focused on special education and conducted the analysis without racial attributes, although this could be another area of analysis in the future especially as it is well documented that race and disabilities have an adverse affect on suspension rates. Finally, I removed any attributes regarding classes, sports, absences, offenses and bullying.

Before adding calculations of the data, I removed any schools that did not report their financial records. Schools that reported -5 signified that there were missing values but also an action plan for providing the necessary data for the subsequent school year. I then began combining columns to produce new variables that sum enrollment and the number of ISS and OOS as the number of enrollment and suspensions were categorized by gender. Additionally, I calculated new variables that would yield an standardizing affect on schools. For example, schools that have many instances of ISS could have more students in general. To adjust for this, I found the number of ISS per 100 students. I repeated this equation for the number of days missed due to OOS and number of instances of single OOS (SINGOOS) and multiple OOS (MULTOOS). I included on the number of days missed into the analysis as it contributes to the severity of school suspensions rather than just the number given. Finally, I determined the amount each school spends per student by dividing the total spent on personnel and non-personnel by the total enrolled. I also applied the calculation to the total spent on type of personnel to better understand where a school spends the majority of funds. These types of personnel include teachers, administration, support services and instructional aid. In all expenditure variables, I focused on dollar amounts without federal funding (WOFED) as federal funding is a minority of total funding and it is determined by a number of factors. Comparatively, dollar amounts without federal funding are largely determined by state and local funding which prioritizes location and the demographics of each neighbourhood.

2.3 Missing Data

It is crucially important to discuss the data that were purposefully excluded and that were under or unreported by the contributing schools. The decision to combine columns regardless of race, gender of disability has a variety of consequences. Namely, it could provide an additional analysis of the circumstances and address a larger portion of the hypothesis and theory. For example, a school with a high count of days missed due to OOS could have severely punished only one minority student in a majority white school population, highlighting extreme instances of discriminatory disciplinary practices. This type of analysis will not be reflected in the model and could be a property of causality. It should be noted that it is a necessary and urgent area of study, as many studies indicate that demographics are a substantial factor in suspension rates.

In addition, schools that underreport or do not report data at all could severely affect the results. Data quality is dependent on truthful and reliable self-reporting. In the raw data, there are schools that disclose a $1,000 spend on personnel salary in the 2015-2016 school year and ones that disclose a spend of over four hundred million dollars. These outliers can lessen or inflate the extent of association between expenditures and suspensions. For the latter data point, after calculating the spend per student, it recorded $2346486.911/student so I excluded the extreme outlier as I believe it was due to poor reporting. Additionally, schools that do not report any data raise questions of biases. There could be a type of school that is not reporting their numbers and could potentially be concealing some significant figures.

2.4 Plots

To initially better understand the data, I found the ten states with the highest number of enrollments and then plotted the total number of suspensions of those ten states using `ggplot2` (Wickham 2016) and `gridExtra` (Auguie 2017) to arrange them. In doing so, I compared the discrepancies between enrollment and suspensions as there should be a correlation between number enrolled and number of suspensions: those that have more numbers will more likely have more suspensions as well. Figure @tab(fig:statesuspensions) and Figure @tab(fig:statesuspensions2) present mostly as we would expect - the ten states with the highest enrollment can be seen in nearly all graphs which plot the number of ISS and OSS. Texas has the highest number of students from grades 9 to 12; they also have the highest number of ISS and OSS. There are, however, a few differences. California is particularly interesting, with the second highest number of enrolled students yet the lowest number of ISS. Additionally, Georgia has the fifth highest enrollment yet the second highest number of ISS and the third highest number of both Single OOS and Multiple OOS. This roughly signifies that 10% of enrolled students in Georgia receive one instance of ISS.

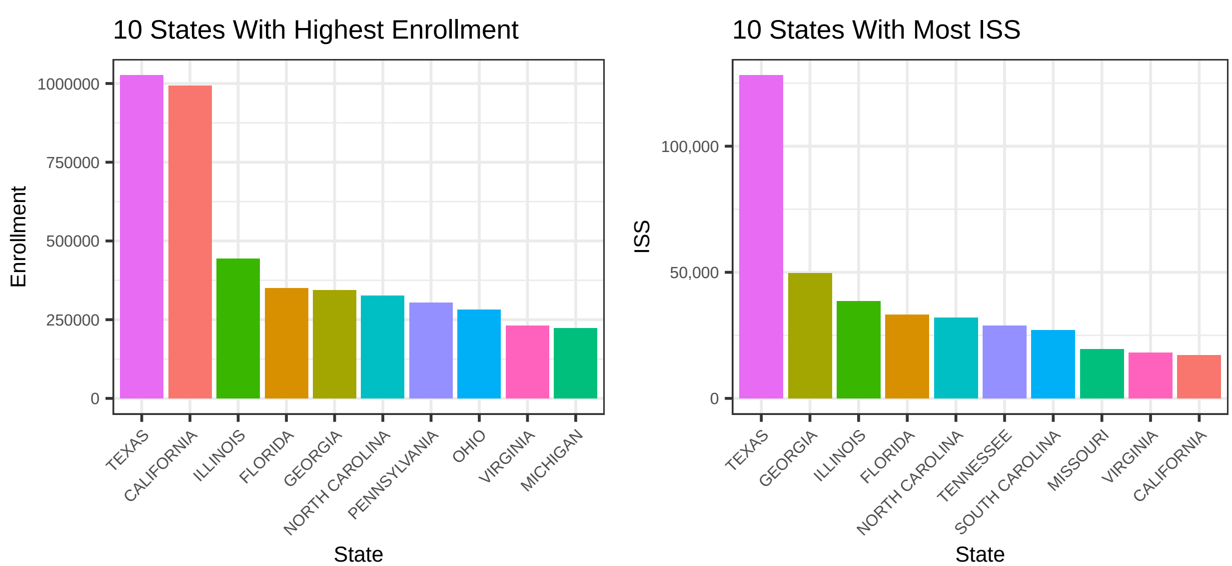


Figure 1: Number of Suspensions in 10 Most Populous Schools

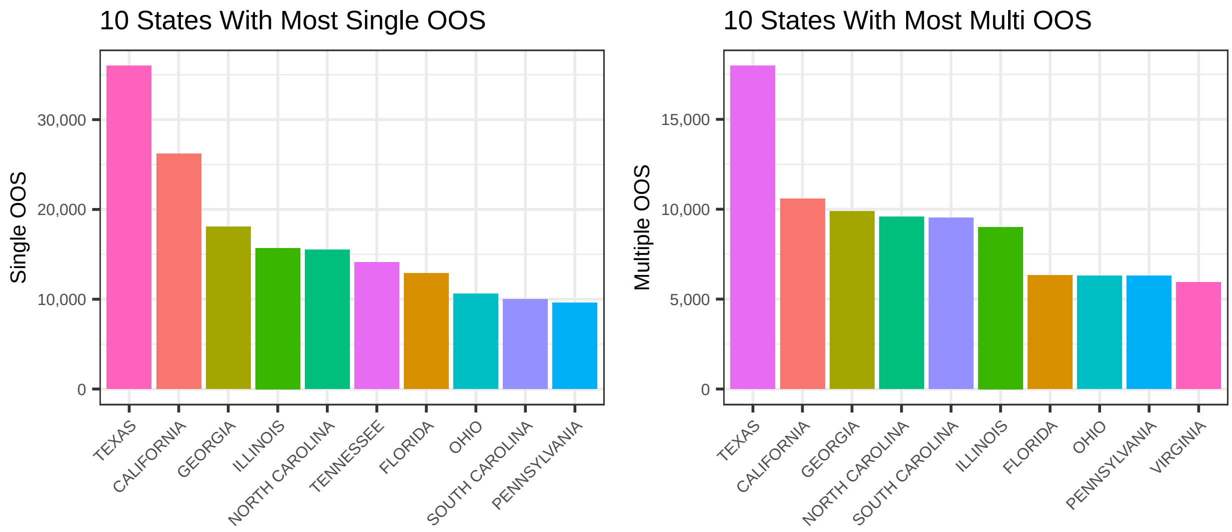


Figure 2: Number of Suspensions in 10 Most Populous Schools

I created similar plots to interpret the relationship between enrollment and how much each state spends on personnel and non-personnel (Figure 3)(Figure 4). Akin to the previous graphs, a high number of students should yield a high spend yet this was not necessarily the case with many of these states. Predictably, both Texas and California had the highest number of enrolled students as well as the highest spend on personnel. Illinois was unexpected as their spend on non-personnel far exceeded other states, even accounting for the fact that they have the third highest enrollment. Although Massachusetts is not included in the cohort of states with the highest enrollment, it does rank as one of the top spending states on personnel and non-personnel.

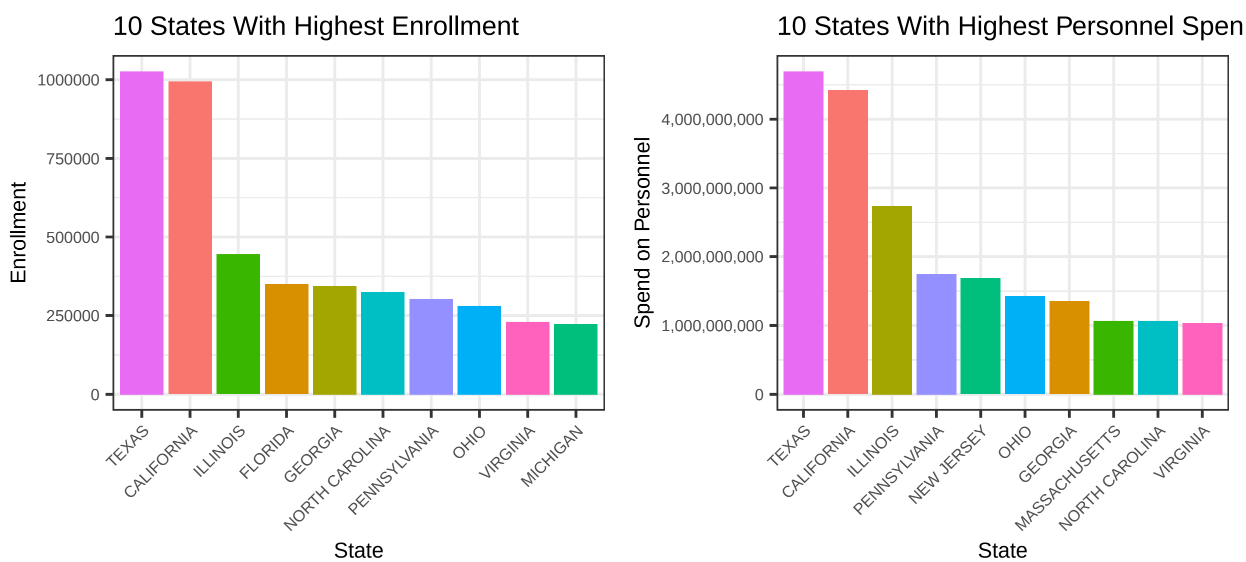


Figure 3: Spend in 10 Most Populous Schools

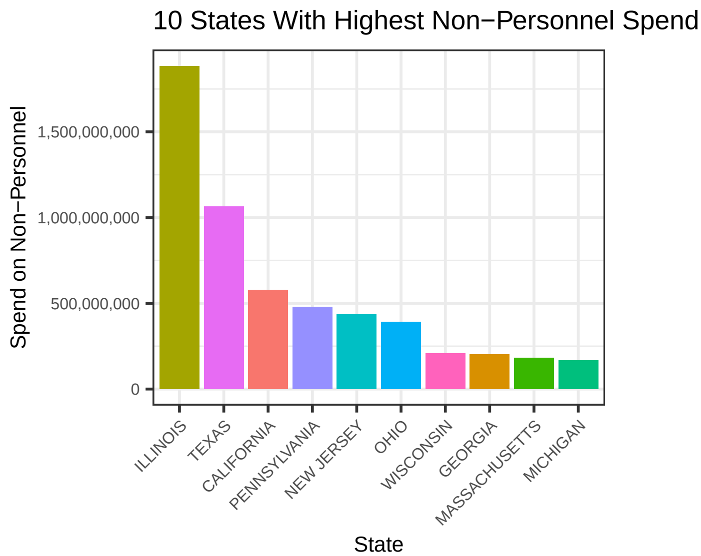


Figure 4: Spend in 10 Most Populous Schools

Although these graphs do not give us information on how spend affects the number of instances of ISS and OOS, it does communicate how states vary in punishment and spend compared to the number enrolled. It also provides some understanding of how states differ in their characteristics based on the discrepancies between enrollment, discipline and spend.

3 Model

3.1 Multiple Linear Regression

In order to understand if a relationship exists between the amount spent per student and the number of suspensions (ISS and OOS), I performed multiple linear regression using `R` (R Core Team 2020). This model was appropriate for an exploratory analysis of quantitative data, allowing for further investigation into the relationship and how that may be conducted in the future. Because I did not use dummy or binary variables, logistic regression was not necessary. Through multiple linear regression, I am unable to decisively conclude results but rather explore if any relationship exists and to the potential strength. I will be using four standard linear regression models, each with separate dependent variables and two predictors as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

In the first model (1), Y is the number of ISS per 100 students, X_1 is the amount spent per student on personnel without federal funding and X_2 is the amount spent per student on non-personnel without federal funding. Additionally, β_0 represents the predicted value of Y when X is 0 and β_1 and β_2 are the expected change to Y when X_1 and X_2 increase. This model is repeated for three other dependent variables (Y): single OOS (2), multiple OOS (3) and number of days missed due to OOS (4).

Additionally, I produced a model to investigate the relationship between ISS and salary of teachers, instructional aid, support services staff and administration. The model is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon$$

Table 1: Model RMSEs

ISS (1)	SINGOOS (2)	MULTOOS (3)	DAYS MISSED (4)	PERSONNEL TYPE (5)
9.51	4.16	3.47	57.92	9.5

Y is the number of ISS per 100 students, X_1 is the amount spent per student on teachers without federal funding, X_2 is the amount spent per student on instructional aid without federal funding, X_3 is the amount spent per student on support services staff without federal funding, and X_4 is the amount spent per student without federal funding. Similarly to the first model, β_0 represents the predicted value of Y when X is 0 and β_1, β_2, β_3 and β_4 are the expected change to Y when X_1, X_2, X_3 and X_4 increase.

3.2 Features

The dependent variables are all calculated from the number of total suspensions and total enrollment at each school. ISS and OOS were chosen to better understand how financial resources and punishment interact with each other. I was interested in ISS and OOS particularly because they are seen as less punitive forms of punishment compared to expulsions. If they are seen as an alternative to expulsions, ISS and OOS could be used more frequently, even though there have been studies done which demonstrate that they still produce adverse consequences for those that are punished and those that go to high-suspending schools. Additionally, to narrow the scope of analysis, I also excluded instances of offenses, such as robbery and assault. As mentioned previously, I kept these variables qualitative and created a per 100 number as to not inflate schools which have high enrollment, and therefore, an increased number of suspensions.

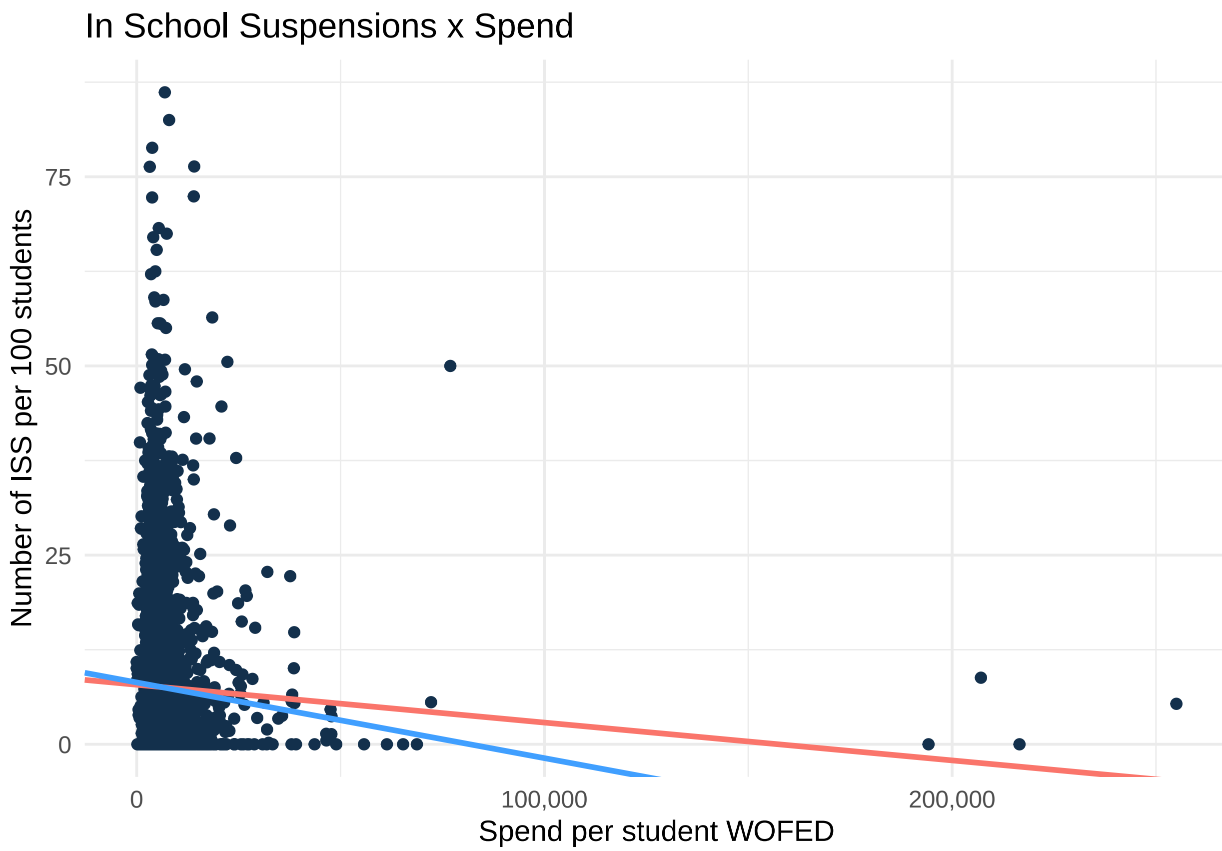
The independent variables focus on the amount spent per student, reflecting the financial resources a school possesses. While some schools may spend more or less than they have, it is at least some indication of their budget. There was the opportunity to use the number of personnel employed, but I wanted a financial representation of the data as well as a comparison between personnel and non-personnel expenditures. This observation would not be able to occur if the number of employed was used because there is no similar characterization of non-personnel. These were the only financial variables included in the raw data, although it would be interesting to see the overall spend of a school. Additionally, there were more data regarding the number of employees including security, nurses and psychologists, that would be an interesting analysis in the future, but was not discussed in the scope of this paper.

3.3 Validation

In order to validate my model, I split my data into test and training sets using `tidymodels` (Kuhn and Wickham 2020) and then calculated the Root Mean Squared Error (RMSE) using `Metrics` (Hamner and Frasco 2018). Unfortunately, all models performed poorly. In the first model (Y = ISS per 100 students), the RMSE was 9.51, which, for this type of data, is extremely large. It indicates that the prediction is off by almost 10 units, or, is off by 10 suspensions from the actual value. The fourth model representing the relationship between days missed due to OOS and amount spent on personnel and non-personnel is particularly inaccurate as it displays an error of 57.92. Table 1 displays RMSEs for the five multiple linear regressions, revealing further inaccurate models. Although the models are poorly performing, I will still explain the results shown and then present a discussion on why it is important and what can be done to get a more accurate understanding of the relationship between financial resources and punishment.

3.4 Threats to Validity

One of the most compelling threats to validity for this particular model is the presence of high-leverage data points. In particular, there are four data points where the spend per student is about $100,000 to $200,000 above the rest of the 8055 observations. Additionally, there were seven high-leverage data points where the spend per student on non-personnel was between \$150 to \$750,000 above the other observations. By removing these data, there is a substantial difference in the model thus potentially misrepresenting the data and invalidating the entire fit. I decided to extract these four and seven data points as they were extremely high-leverage data points but in doing so, I have assumed that this data has been inaccurately reported and it will not be reflected in the model. There is the possibility that these are accurate numbers, thus deleting justifiable data. In Figure @fig(tab:double), I have plotted the two lines of best fit as an example for ISS and spend per student on personnel, one with the outliers (red) and one without (blue). It is clear that these data points have drastically altered the data.



4 Results

The model was run on four independent variables to explore if there is an association with the amount a schools spends on personnel and non-personnel and different types of school suspensions. While ISS are seen as less punitive forms of punishment, they still can lead to missed educational opportunities, ostracization and a decrease in attentiveness. In addition, the amount of OOS, both single and multiple, can inform our understanding of the severity of punishment, especially when observing the number of days missed. There is also access to the type of personnel and the correlated spend per student. Using this data, we can see if there is any association between salary of teachers, administration and support staff and the number of ISS and OOS. In the next two section, I will discuss the results of the models.

4.1 ISS and OOS Results

The first model showed some relationship between instances of ISS and X_1, spend per student on personnel, but not X_2, spend per student on non-personnel. To summarize the results shown in Table 2, presented by huxtable (Hugh-Jones 2021), a one dollar increase in spend per student on personnel β_1 is associated with a -0.00011 decrease in instances of ISS controlling for all the other variables in the model. Although the decrease of the dependent variable seems ineffectual as it is so small, a one dollar increase is a comparatively small increase. Even so, a school would need an additional $10,000 per student to increase the number of ISS by one. Additionally, the β_0 states that if both salary of personnel and non-personnel were held at 0, there would be roughly 8.17 instances of ISS per 100 students. For β_2, a one dollar increase in spend per student on non-personnel is associated with a 0.00004 decrease in instances of ISS, although as mentioned previously, there is a lack of association here. Below Table 2 is the plotted data shown in Figure 5 using scales (Wickham and Seidel 2020) to prepare readable numbers. It captures the amount spent per student on personnel without federal funding on the x-axis and the number of ISS per 100 students of the y-axis. Figure 6 presents the data on amount spent per student on non-personnel without federal funding on the x-axis and the number of ISS per 100 students on the y-axis.

Table 2

	ISS
(Intercept)	**8.17211 *** **
	(0.17452)
SPEND_PER_STUDENT_WOFED	**-0.00010 *** **
	(0.00003)
SPEND_PER_STUDENT_NPE_WOFED	-0.00004
	(0.00004)
N	8048
R2	0.00209
logLik	-29167.88340
AIC	58343.76680

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

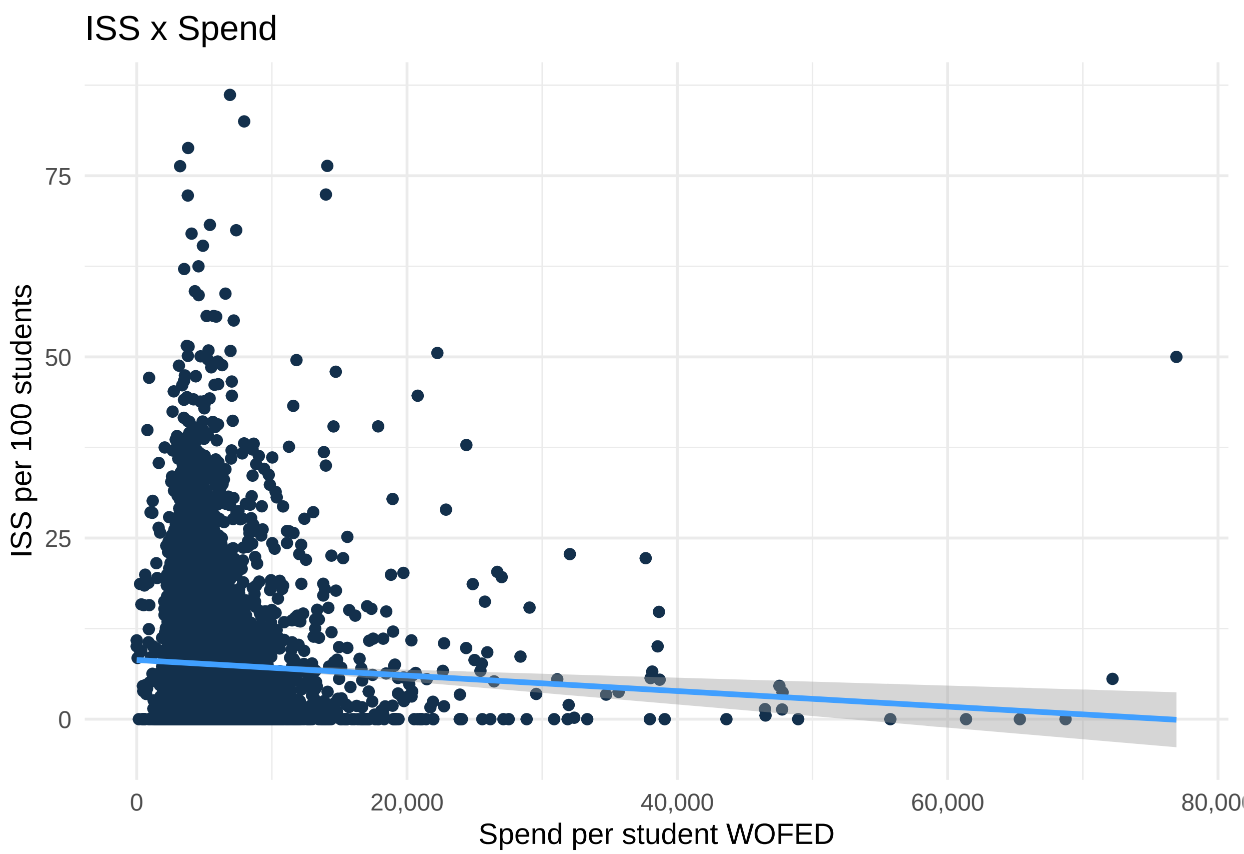


Figure 5: ISS and Spend on Personnel

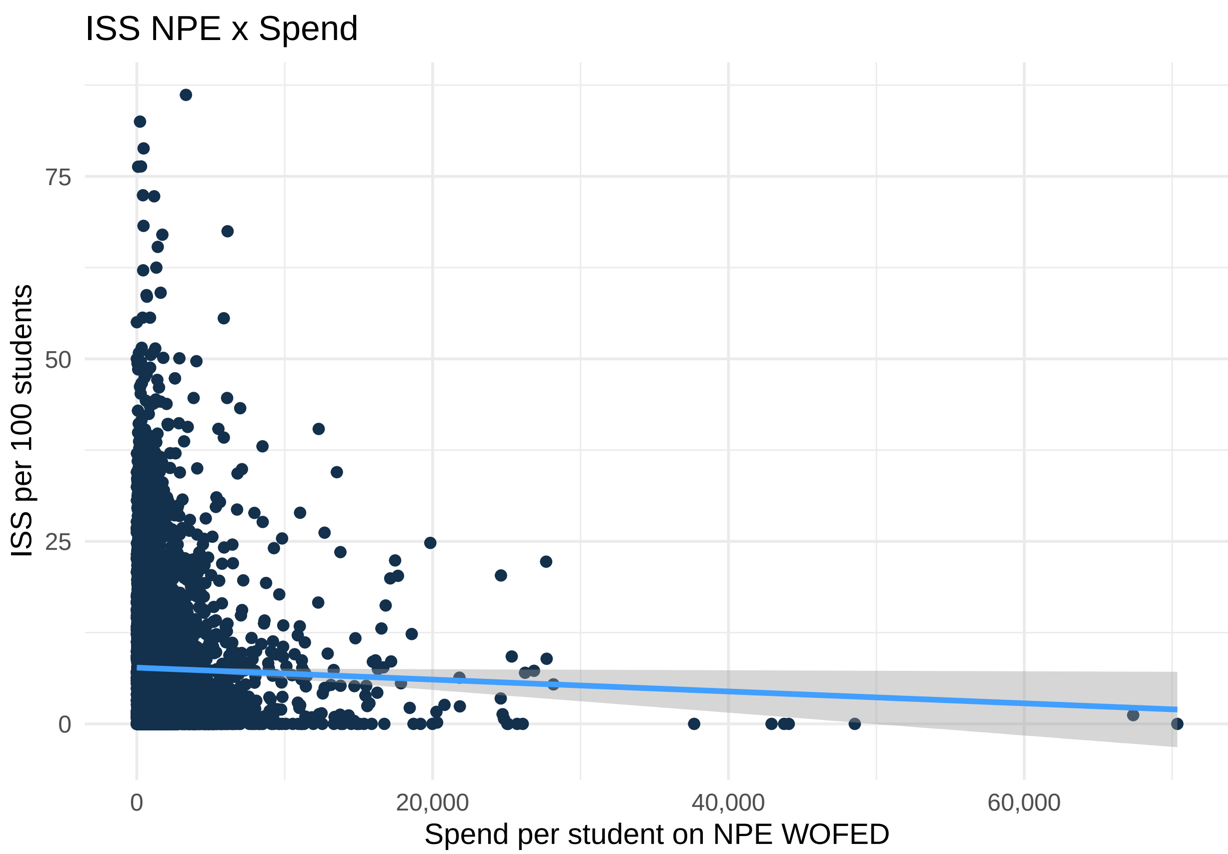


Figure 6: ISS and Spend on Non-Personnel

Both the second and third model (Table 3) reveal no association between instances in single OOS and multiple OOS, respectively, and spend per student on personnel (β_1), however, there is some association between single OOS and spend per student on non-personnel (β_2). A one dollar increase in spend on non-personnel is associated with a -0.00005 decrease in single OOS. Although there is the presense of a p-value less than 0.01, these models only explain that the data is not unusual under this model, rather than proof of a decisive causal relationship. Finally, model four displays some association between number of days missed due to OOS and spend per student on personnel and spend per student on non-personnel. A one dollar increase in spend per student on personnel β_1 leads to a -0.00046 decrease in the number of days missed due to OOS while a one dollar increase in spend per student on non-personnel β_2 produces a -0.00105 decrease in the number of days missed. Additionally, in model 4, β_0 shows that if the sum of spend for both personnel and non-personnel salaries were fixed at 0, there would be 40.16 days missed per 100 students. Figure 7 displays the data of model four, using similar tactics to Figure 5, with the amount spent per student on personnel without federal funding on the x-axis and the number of days missed due to OOS per 100 students of the y-axis. Additionally, Figure 8 plots the amount spent per student on non-personnel without federal funding on the x-axis and the number of days missed due to OOS per 100 students on the y-axis. Unfortunately, in all models, the residual standard percentage error is well over 100%, signifying a poor model fit for the data. As a result, the model leads to inconclusive results and it is indeterminable whether or not school spend has any affect on the number of ISS and OSS with the data provided.

Table 3

	SINGOOS	MULTOOS	DAYS MISSED
(Intercept)	**3.92170 *** **	**2.14359 *** **	**40.16457 *** **
	(0.07860)	**(0.06722)**	**(1.17485)**
SPEND_PER_STUDENT_WOFED	-0.00000	-0.00001	**-0.00046 ***
	(0.00001)	(0.00001)	**(0.00019)**
SPEND_PER_STUDENT_NPE_WOFED	**-0.00005 ** **	-0.00003	**-0.00105 *** **
	(0.00002)	(0.00002)	**(0.00027)**
N	8048	8048	8048
R2	0.00129	0.00065	0.00363
logLik	-22748.12631	-21489.96619	-44514.22047
AIC	45504.25263	42987.93237	89036.44095

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

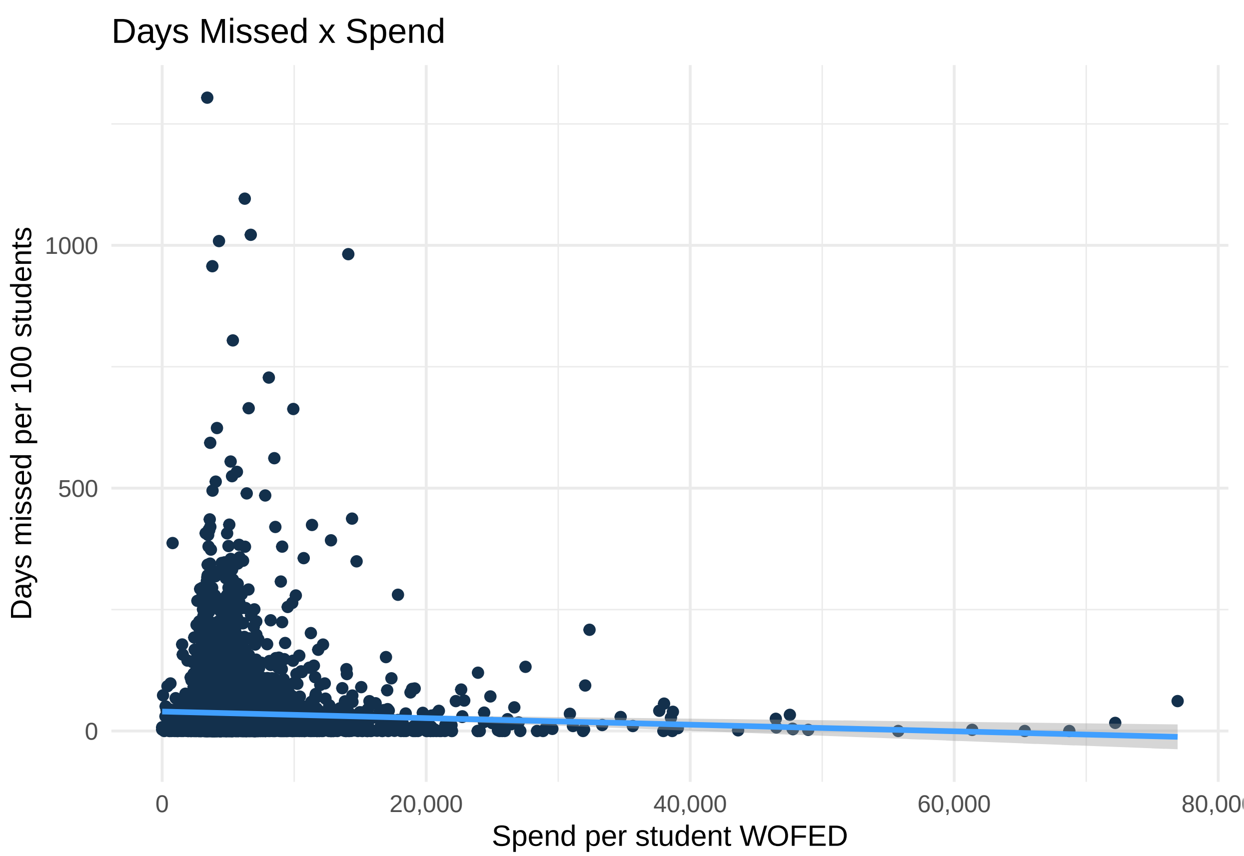


Figure 7: Days Missed and Spend on Personnel

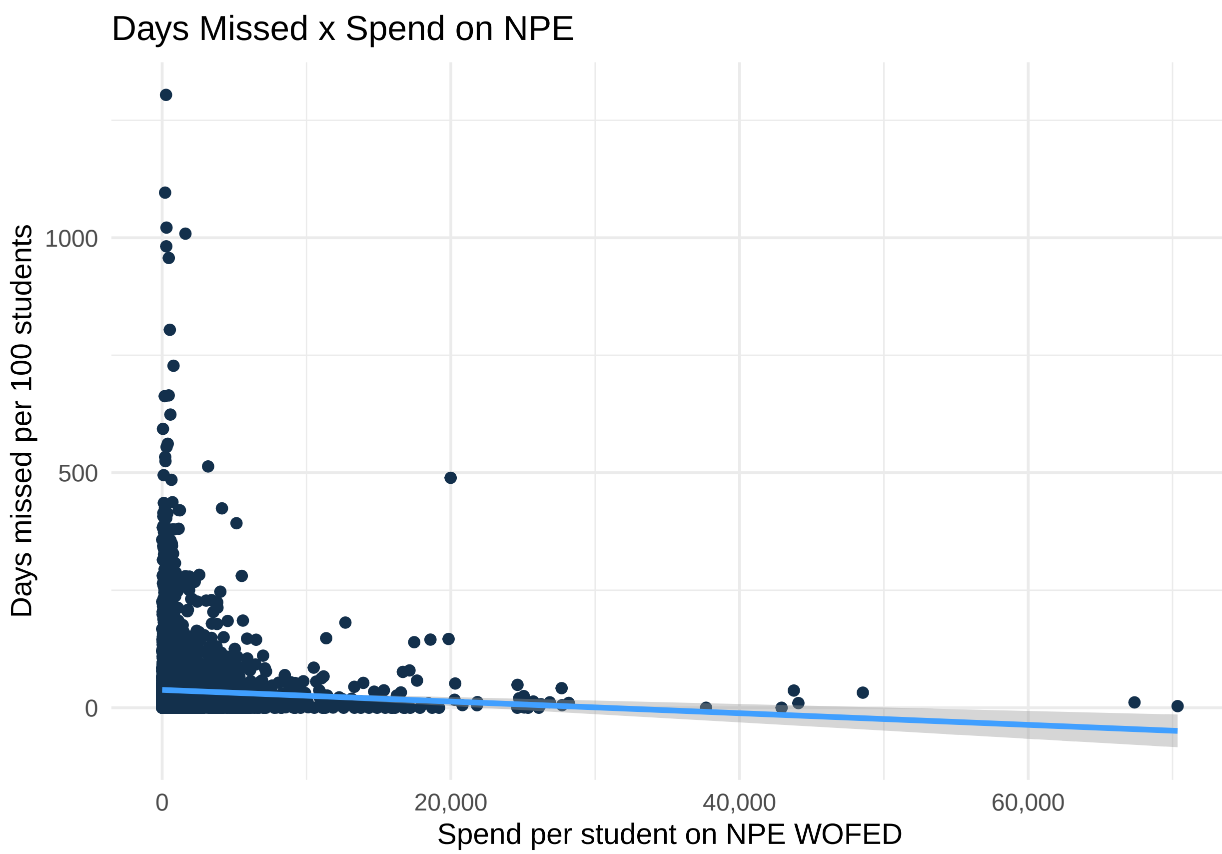


Figure 8: Days Missed and Spend on Non-Personnel

4.2 Salary Results

Although the initial models produced inconclusive results, I wanted to investigate further into the relationship between different salary expenditures and instances of ISS. Following the same multiple linear regression model, I used ISS (Y) as the independent variable and the spend per student on teachers, instructional aid, support services staff and administration as the four dependent variables. The results in Table 4 indicate some relationship between ISS and salary spent on teachers and support services staff, although no association between ISS and salary spent on instructional aids and administration. When all salaries are held at \$0, there are 8.56 instances of ISS per 100 students. A dollar increase in amount spend per student on teachers β_1 produces a -0.00027 decrease in ISS per 100 students. Oddly, a one unit increase in amount spent per student on support services staff β_3 causes an increase of 0.00007 in ISS per 100 students.

These numbers could also be a result of the lack of funding in general to any non-personnel other than teachers. As public schools are consistently underfunded, many institutions do not have the resources to allocate additional funds to assistive personnel. Using `knitr` (Xie 2021), `kableExtra` (Zhu 2020) and `reshape2` (Wickham 2007), Table 5 was created to show the spend on alternative educational roles and how they are far below the resources dedicated to teachers. Although there will generally be a higher number of teachers than support staff, Table 5 indicate that both the mean and the median of instructional aid, support services and administration salary spend is several thousand dollars below that of the salary dedicated to teachers. Additionally, the minimum for instructional aid, support services and administration are \$0 compared to at least \$30.99 for teacher salaries.

Table 4

	ISS
(Intercept)	**8.56054 *** **
	(0.21600)
SPEND_PER_STUDENT_TEACH_WOFED	**-0.00027 *** **
	(0.00005)
SPEND_PER_STUDENT_AID_WOFED	0.00003
	(0.00006)
SPEND_PER_STUDENT_SUP_WOFED	**0.00007 * **
	(0.00003)
SPEND_PER_STUDENT_ADM_WOFED	0.00002
	(0.00002)
N	8048
R2	0.00374
logLik	-29161.22771
AIC	58334.45542

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

5 Discussion

5.1 Summary

Numerous studies have documented the adverse consequences of ISS and OOS. Extreme disciplinary action has been used for not only violent offenses but also minor infractions, which reduce the educational opportunities for students and the subsequent reduction of economic mobility. Although these studies name several factors influences the number of disciplinary actions such as socioeconomic background, ethnicity and attitude toward punishment, this study focuses on the impact of spend on the number of instances of ISS and OOS. Although it is well known that schools are continuously underfunded, getting a better understanding of this insufficient funding on disciplinary action is crucial for endorsing the dire need for more investment. Funding of schools relies on the majority of state and local funding. Local funding is collected

Table 5: Salary Overview Across All Schools

Spend Per Student	Min	Max	Mean	Median	SD
SPEND_PER_STUDENT_TEACH_WOFED	30.99	149564.1	3807.80	3303.80	2853.66
SPEND_PER_STUDENT_AID_WOFED	0.00	108617.0	263.25	109.19	1747.07
SPEND_PER_STUDENT_SUP_WOFED	0.00	152877.2	713.88	408.26	3137.10
SPEND_PER_STUDENT_ADM_WOFED	0.00	200024.1	700.69	394.02	4168.71

from property taxes and other taxes such as sales and income. This automatically leads to a discrepancy as low-income communities collect less property tax from low-priced housing and less sales and income tax from fewer overall purchases. Very few states attempt to equalize school funding, and even in states that do, there is still a large discrepancy with the amount of resources schools receive. A study that can undeniably attest to the negative consequences of aggressive punishment as a result of economic deficiencies can begin to facilitate conversations around strategies and approaches to gaining additional funding for the younger generation. Fair, reliable and quality education can result in a better standard of living for everyone and should be a priority for the future.

Using multiple linear regression, the results revealed some relationship between spend on personnel in instances of ISS and number of days missed. Additionally, there was no association found between spend on personnel in instances of single OOS and multiple OOS, yet some association between spend on non-personnel and instances of single OOS. Despite this relationship and non-relationship, results are not sufficient and causality cannot be determined as linear regression does not establish causal inference, only that there is an association to a degree. I would still argue that the presence of a connection should lead to further investigation and an alternate study that I have outlined in a couple sections below.

5.2 Weaknesses

There are several weaknesses of this study that should be discussed. First, school expenditures rely on funding which is directed by state laws, neighbourhood demographics and socioeconomic factors. By using expenditures, there are already a number of influencing variables between the different schools that make it difficult to find a causal relationship from the provided variables and models. State laws could greatly impact how much funding schools receive, as some states use a leveling feature that gives additional resources to underfunded schools. Secondly, the varying between states, neighbourhoods and schools could additionally add a number of confounding variables that cannot be separated. State political alignment could influence the population's perceptions on punishment. Neighbourhoods could be racially diverse or completely segregated which could similarly impact how discipline is administered, especially as racialized communities already experience higher policing and punishment. The variability between schools and their support or opposition toward severe discipline could also add to the source of high suspension rates.

Thirdly, self-reporting makes it difficult to obtain accurate information. All numbers collected by the Civil Rights Data Collection are reported by the schools' administration. Schools may either underreport their numbers or not report them at all. If the data is incorrectly reported, it could produce misleading results even if all other assumptions of the model are true. Additionally, schools that were excluded from the model due to undisclosed information could impact the results by either influencing a rise or fall in school suspension rates. Unfortunately, lack of reporting would not be able to capture these numbers in the model therefore, the model may be deceptive or inconclusive.

5.3 Causality

To reiterate, although the model suggests that there is some relationship, it is not a representation of a causal relationship. There are a multitude factors that could lead to high suspension rates in schools that are unrelated to the amount spent on personnel and non-personnel. Even when focusing expenditures, there are many variables that determine how much funding a school receives based on state and federal laws. Additionally, demographics of students or school characteristics can influence the number of school suspensions. As previously mentioned, studies have been done that determine high-suspending schools are usually schools from in low-income communities and have a higher population of minority students. Certain studies also indicate that school policies or outlooks towards punishment are a strong measure of how many ISS and OOS are issued each year.

Due to this undeterminable relationship through multiple linear regression, a study that uses experimental design to isolate for monetary variables would be better suited to better understand how funding and spending impacts the number of ISS and OOS. In the hypothetical study, a difference-in-differences methodology would be an appropriate model to observe if suspension rates fall, rise or remain the same with the influx of an additional sum of money. This method would compare the change in outcome overtime in the treated group with the control group. Additionally, it would assume that the differences between the two groups would remain constant without the treatment. The participants would comprise of urban schools in several democratic states, with the treatment group receiving $_______ for one school year and the control group receiving no supplemental funding. The location of the schools is important to avoid non-parallel trends in which the treatment and control are based on differences. If the study were to use schools in both rural and urban areas, it would be difficult to argue parallel trends because of the numerous differences between each geographic area such as number of students, impacts of community, socioeconomic variability, and political polarity. At the end of the school year, a comparison will be conducted between the average number of ISS and OOS in the year before the study and the year of the study. The study would collect similar variables and covariates including number of instances of ISS, single OOS, multiple OOS, days missed due to OOS and amount spent on non-personnel, teachers, instructional aid, support services staff and administration.

Other threats to validity in the study include compositional differences and long-term effects. If the study similarly studies high schools with grades between 9 and 12, then those who graduate and those who are newly admitted will change the composition of the school. There could be an overrepresentation of grade 12 students that receive ISS and OSS, who the graduate and naturally reduce the number of suspensions with or without the subsidy. One way to mitigate this would be to focus on a particular grade that would remain in the school for the two years, for example, grade 10 students. This would then be comparing their suspension rates over time, rather than the entire school, although, this is where long term effects also impact the study. Students who are negatively labelled as high-offending students will not be freed of said label in one year or because of an increase in funds. Student-teacher relationships could shape the outcome of the study. To reduce this effect, participants could instead include grade 9 students who have a new rapport with teachers. Additionally, each new grade cohort of grade 9 students could be studied overtime to understand if there is a lasting effect. Unfortunately, this would be quite costly and unethical to the schools who did not receive financial support.

There are a number of challenges and ethical implications of this study. The most obvious is determining which schools will receive an additional sum of money versus which ones will not. Schools that receive a monetary sum could potentially improve educational opportunities for students, thus the students who attend the control schools would have an artificially produced disadvantage. Additionally, staff of the treatment groups would experience advantages, such as an increase in salary and a subsequent increase in mental health, that it would be unfair to educators of the control schools. Even if the schools are randomly selected based on the critera, certain schools would still have an advantage over the schools that did not. The study could grant control schools a similar subsidy for participating but it would be another expensive cost that would need that support of the study's financers, therefore raising another challenge. The financial undertaking of a study like this would be immense. To find a financer may be extremely challenging as the funds needed to make a substantial difference for the schools would

6 Conclusion

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