School-To-Prison Pipeline: How can Policy Makers Target the Problem?

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Introduction

The school-to-prison pipeline is an emerging national trend wherein youth are being pushed out of public schools and into the juvenile and criminal legal systems. Zero-tolerance policies and an increased police presence in schools have caused suspension and expulsion rates to skyrocket in the United States (ACLU, 2022). Zero-tolerance policies result in the mandatory expulsion of any student who commits one or more specified offenses, essentially criminalizing minor infractions of school policy. A New York City junior high student was arrested for doodling on her desk with a marker and a 7-year-old Maryland boy was suspended after he chewed his breakfast pastry into a gun shape (St. George, 2013). In the wake of recent school shootings, states have increased the number of police on campuses. These states have vague or non-existent policies governing police interactions with students. Police officers are replacing educators as disciplinarians, endangering the safe educational environment that students deserve.

In 2014, the Obama administration issued guidelines urging schools to abandon strict disciplinary policies that civil rights groups have long said lead to the school-to-prison pipeline. The guidelines recommended that schools draw clear distinctions about the responsibilities of school security personnel, provide opportunities for administrators to develop relationships with students, and end all zero-tolerance policies (Hefling, 2020). Later in 2016, the incoming Education Secretary Betsy DeVos reversed the Obama era guidelines. DeVos argued that the policies put teachers at risk and created disruptive classrooms; her decision was in response to an uptick in school shootings and was heavily criticized (PBS, 2020). Neither policy substantially limited the school-to-prison pipeline.

On any given day, nearly 60,000 youth under the age of 18 are incarcerated in juvenile jails and prisons in the United States (ACLU, 2022). Researchers from Harvard University sought to find whether a causal link exists between students who experience strict school discipline and being incarcerated as an adult, and whether attending a stricter school increases criminal activity in adulthood. The study found that early punishment of misbehavior in school caused an increase in adult crime – ultimately proving that the school-to-prison pipeline exists. Specifically, students that attended stricter middle schools were 3.2 percentage points more likely to be arrested as an adult (Billings and Deming, 2019).

There is a lack of research analyzing the factors that directly influence the youth incarceration population. It is a widely accepted theory that the main drivers of the school-to-prison pipeline are zero-tolerance policies and the increased police presence in schools. However, other factors such as per pupil spending, minority teacher representation, teen pregnancy rates, access to counselors and psychologists, and unemployment rates should be investigated. This paper will analyze youth incarceration rates of California counties. The state of California is divided into fifty-eight different counties; the county is "the largest political subdivision of the state having corporate powers" (California Government Code, 2023). The general role of a county is to deliver the services mandated by the state and federal governments, including health, welfare, and criminal justice enforcement. The two types of California counties are charter counties and general law counties. Charter counties have the autonomy to create and enforce local ordinances, provided the ordinances do not conflict with the general laws of the state. When no charter is adopted, the county is governed by the California General Code. There are currently 13 charter counties and 45 general law counties in California. Due to the division of political and financial responsibility in California and the existence of two different county structures, there are large variations in the county data. This creates a compelling opportunity to utilize this county data to explore the school-to-prison pipeline and its explanatory variables.

I want to test the hypothesis that zero-tolerance policies and an increased police presence in schools is the leading cause of increasing youth incarceration rates. Using data spanning eight years (2010-2018), this paper explores the relationship between county data and youth imprisonment rates. I chose this time period because it was not impacted by the COVID-19 pandemic and there were no changes in county lines. This time period also encompasses the different guidelines set by the Obama and Trump administrations. I used imprisonment per 100,000 youths aged 10-17 as my dependent variable. To build upon the hypothesis and improve the analysis, I collected data on county suspension rates, pupil services, child poverty rates, unemployment rates, number of police in schools, adult incarceration rates, and expenditures per student to use as my independent variables. Youth imprisonment costs in California are substantial, so it is important for legislators to create policies that target the factors primarily responsible for the school-to-prison pipeline.

Literature Review

There are a substantial number of research papers that explore adult incarceration and the societal factors that can be attributed to fluctuations in incarceration rates. There is also an abundance of research on the use of discipline on inmates and its effects on in-prison outcomes. However, few papers look at the relationship between the public school system and the youth incarceration rate. Since counties have the autonomy to set budgets and determine disciplinary policies, California offers the unique opportunity to analyze how differences in public school systems such as per pupil spending and minority teacher representation can affect youth incarceration rates. Unlike the papers I will review and the common theories about the school-to-prison pipeline, I want to examine the direct connection between zero-tolerance policies and youth incarceration.

(1) Long-Run Impacts of School Suspension on Adult Crime

Bacher-Hicks, Billings, & Deming (2019) estimated the net impact of school discipline on student achievement, educational attainment, and adult criminal activity. The study researched whether strict discipline policies exposed children to the criminal justice system or if strict discipline policies acted as a deterrent and limited future harmful behaviors. Using exogenous variation in school assignment caused by a large and sudden boundary change, the study showed that schools with higher suspension rates have substantial negative long-run impacts for students. Specifically, students who attended a school that had a one standard deviation higher suspension rate were 15 to 20% more likely to be arrested and incarcerated as adults.

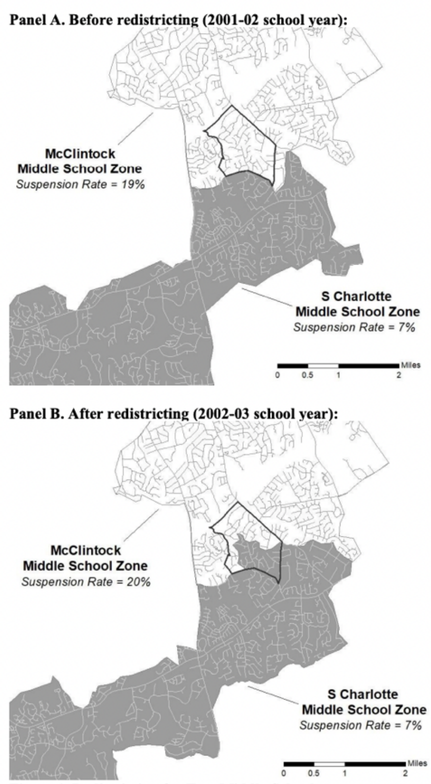


Figure 1. Redistricting for Two Middle Schools

The study found no evidence that school suspension had an impact on students' overall academic achievement. This may be due to a balancing of two opposing forces: negative effects of lost instructional time for the suspended students and positive effects of fewer disruptive peers in the classroom (Kinsler, 2013). However, the research does suggest that suspensions negatively affected educational attainment. Students attending schools with a one standard deviation increase in the suspension effect increased the likelihood that a student dropped out of high school by 1.7 percentage points, a 15% increase. These students were also 11% less likely to attend a four-year college.

The main goal of the paper was to determine the impact on adult criminal activity. Bacher-Hicks, Billings, and Deming found that students attending schools with higher rates of suspension were 20% more likely to be incarcerated as an adult. These students were also arrested more often and incarcerated for longer spells. The negative impact of attending schools with higher suspension rates was largest for minorities and males, contributing to other literature that highlights the racial disparities of the school-to-prison pipeline (Hoffman, 2014).

This research paper looked at the effect strict disciplinary policies had on adult incarceration rates. I replicated some of the processes used in this paper to better understand the impact on youth incarceration rates. Unlike Bacher-Hicks, Billings, & Deming (2019) which focuses on a one-year boundary change, I run a panel regression that uses county data over an eight-year time span. For my models, youth imprisonment is the dependent variable, rather than adult incarceration. My paper also includes factors outside of the school system such as unemployment and child poverty rates, to understand whether the school system, or outside factors, are the biggest determinants of rising youth incarceration rates.

(2) Disciplinary Segregation and Its Effects on In-Prison Outcomes

Solitary confinement has far-reaching, unintended consequences on an individual. Salerno and Zgoba (2019) explored the effects of solitary confinement on in-prison outcomes and recidivism rates among inmates housed in disciplinary segregation. Researchers followed 398 incarcerated individuals and noted the deterrent effects of segregation on program participation (such as adult education programs and reentry services) and future in-prison behaviors. Due to modifications to the restrictive housing unit policies during the period of this study, observations were taken before and after the enactment of policy revisions. Bivariate and multivariate analyses revealed that most inmates did not have a new infraction; however, certain inmates were more likely to receive future discipline.

The effects of disciplinary segregation on institutional misconduct and programming attendance were examined at two points: while the inmate was serving time in disciplinary segregation, and after the return to the general population housing. Most inmates experiencing disciplinary segregation housing were Black (59.0%), once again supporting the literature on racial disparities in disciplinary practices (Kovera, 2019). After returning to general population housing, 26.4% of the sample committed a second disciplinary infraction and the average sanction given was 132 days. The average number of new infractions was less than one for the entire sample. Nearly 47% of all inmates attended programming after their return to general population housing and the average number of programming sessions attended was 3 (*SD* = 7.7).

While this paper is not directly related to my research, the results provide insights on the effects of strict disciplinary policies. The study found that inmates who experienced solitary confinement were more likely to commit future behavioral infractions. These results could be interpreted at the youth level and used to advocate for less strict disciplinary policies in schools. I observe the outcomes of behavioral infractions in California public schools, specifically students who are assigned multiple suspensions.

	New infraction while in disciplinary segregation						New infraction while in general population					
	Step 1 Nagelkerke R^2 = .070			Step 2 Nagelkerke R^2 = .098			Step 1 Nagelkerke R^2 = .115			Step 2 Nagelkerke R^2 = .156		
Predictor	β	*SE*	Exp(*B*)	β	*SE*	Exp(*B*)	β	*SE*	Exp(*B*)	β	*SE*	Exp(*B*)
Age	−0.011	0.014	0.989	−0.022	0.015	0.979	−0.032	0.013	0.968*	−0.019	0.013	0.981
Race												
Black	−0.039	0.351	0.911	0.027	0.355	1.028	−0.040	0.298	0.960	−0.109	0.305	0.896
Hispanic/Latino	0.316	0.426	0.457	0.296	0.429	1.344	0.069	0.379	1.072	0.139	0.387	1.150
Other	−19.820	40,192.97	1.0	−19.210	40,192.97	0.000	23.157	40,192.969	0.000	22.557	10,492.969	0.000
Instant offense												
Weapons	−0.520	0.517	0.595	−0.468	0.520	0.626	−0.094	0.375	0.911	−0.164	0.384	0.849
Property	0.250	0.427	1.284	0.288	0.434	1.334	−0.928	0.455	0.395*	−0.979	0.460	0.376*
Drugs	−0.429	0.532	0.651	−0.351	0.541	0.704	−0.205	0.415	0.814	−0.313	0.419	0.731
Other	0.100	0.425	1.105	0.195	0.431	1.215	−0.309	0.382	0.734	−0.411	0.388	0.663
Number of disciplines on record	0.037	0.013	1.038**	0.037	0.013	1.038**	0.038	0.013	1.039**	0.039	0.013	1.040**
Infraction category												
Category 2	−0.205	0.358	0.815	−0.062	0.365	0.940	0.704	0.359	2.021*	0.537	0.367	1.711
Category 3	0.074	0.443	1.077	0.320	0.460	1.377	1.403	0.423	4.067***	1.130	0.435	3.096**
Category 4	−.639	0.691	0.528	−0.127	0.724	0.881	0.971	0.546	2.640	0.442	0.569	1.555
Category 5	−19.455	20,008.385	0.000	−18.943	19,955.925	0.000	.679	1.218	1.972	0.201	1.224	1.223
Group	—	—	—	0.823	0.318	2.277**	—	—	—	−0.936	0.273	0.392***

Note. Reference categories are as follows: race, White; instant offense, violent; infraction category, Category 1; and Group, 1.
$^*p \le .05$. $^{**}p \le .01$. $^{***}p \le .001$.

Theory and Hypothesis

My overarching research question is: Are strict, zero-tolerance policies and an increased police presence in schools truly to blame for rising youth imprisonment rates? Using suspension rates as a proxy for zero-tolerance policies, I hypothesize that increasing suspension rates will increase youth imprisonment rates. As for police in schools, due to a lack of substantial data, I hypothesize that an increased police presence in schools will not have a significant impact on youth incarceration rates. An alternative hypothesis is that youth incarceration rates are dependent on factors independent of the school system, such as unemployment rates, child poverty rates, and prevalence of teen births in a county. This could indicate that youth incarceration is more dependent on factors that originate at home, rather than at school. I test both hypotheses.

Data and Methods

The variables I used in the regression model are youth imprisonment rates, suspension rates, pupil services, current expenditures per pupil, number of police in schools, certified staff of color, teen birth rate, unemployment rate, child poverty rate, and adult incarceration rate. I collected this data from a variety of government agencies, including the California Department of Education, the California Division of Juvenile Justice, the State of California Employment Development Department, the California Department of Public Health, and the California Department of Corrections and Rehabilitation. Youth imprisonment rate, measured as the number of imprisonments per 100,000 youths aged 10-17, was the dependent variable for this study. I chose to use imprisonments rather than incarcerations as my dependent variable because imprisonment specifically refers to confinement to a jail – while incarceration includes confinement to jail, prisons, mental health facilities, detention centers, and rehabilitation centers. Jails are usually local, short-term holding facilities under the jurisdiction of the county, which is why I focused on imprisonments to jails.

The other variables collected were used as independent variables in the models. Using data from the California Department of Education, suspension rates are measured by the number of suspensions administered by the county divided by the total number of students enrolled at schools in that county. There was limited data on one of the main independent variables, police in schools. For the purpose of the model, the variable 'police in schools' is measured by the total number of law enforcement personnel reported by agencies such as schools and juvenile programs, scaled by the number of schools districts. The variable 'staff of color' refers to the number of certified staff of color in a county per student. To measure pupil spending, I used the current expense per ADA (average daily attendance). By county, the adjusted expenditures are divided by the total ADA to arrive at the cost of education per student per year.

One concern with the data was determining the direction of causality- a correlation between two variables does not indicate which variable is causing which. It is hard to prove causation; it is possible that students who misbehave would have ended up in the juvenile system regardless of strict disciplinary policies. However, Fabelo, Thompson, & Plotkin (2011) found that students who had been suspended or expelled were three times more likely to come into contact with the juvenile probation system the following year than one who was not. To address the issue of causation and using results from Fabelo, Thompson, & Plotkin (2011), the independent variables were collected from the year previous (2010-2017) of the dependent variable (2010-2018). I also included county and year as fixed variables in the panel regression.

Table 1 - Variables

Variables	Description	Years	Unit	Source
Youthimprisonmentrate	The number of imprisonments per 100,000 youths aged 10-17.	2011-2018	Imprisonments per 100,000	California Division of Juvenile Justice
Suspensionrate	The number of suspensions administered by a school divided by the total number of students enrolled at that school.	2010-2017	Percentage	California Department of Education
Pupilservices	The number of pupil support service personnel, including counselors and psychologists per student.	2010-2017	Percentage	California Department of Education
Unemploymentrate	The number of unemployed individuals as a percentage of the labor force.	2010-2017	Percentage	State of California Employment Development Department

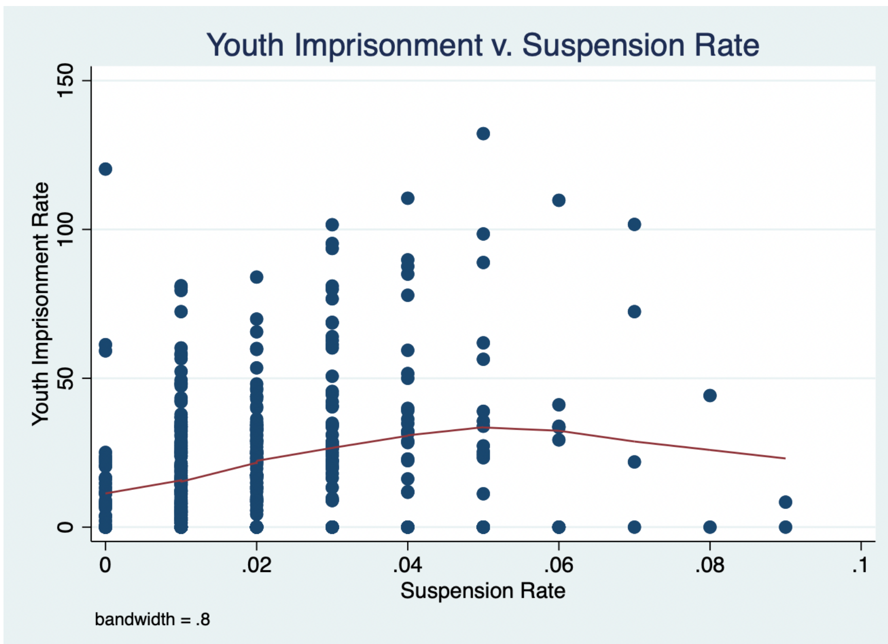
Childpovertyrate	The estimated number of children from birth through age 17 years in families living at or below the federal poverty threshold.	2010-2017	Percentage	California Department of Public Health
Policeinschools	The total number of law enforcement personnel reported by "other" types of agencies such as schools, state rehab centers, and juvenile programs per school district.	2010-2017	Police	The Department of Justice and Criminal Justice Statistics Center
Pupilspending	Calculation of current expense (cost) of education per average daily attendance.	2010-2017	Dollars	California Department of Education
Teenbirthrate	The number of resident live births to mothers ages 13-19 divided by the number of women aged 13-19 in a specified county.	2010-2017	Percentage	California Department of Public Health
Staffofcolor	The number of certified staff of color in a county per student.	2010-2017	Percentage	California Department of Education
Adultincarceration	The adult imprisonment rate from year t-1.	2010-2017	Incarcerations per 100,000	California Department of Corrections and Rehabilitation

Table 2 – Descriptive Statistics, N=464

Variable	Mean	Standard Deviation	Minimum	Maximum
Cummulativeenrollment	111823.8	233061.7	85	1624920
Youthimprisonmentrate	20.59	23.54	0	132.2
Suspensionrate	.0196	.0158	0	.09
Pupilservices	.0023	.00112	0	.0118
Unemploymentrate	.0893	.0432	.023	.293

Childpovertyrate	.189	.0844	0	.701
Policeinschools	4.28	12.85	0	99.5
Pupilspending	10956.46	3620.74	6880	43009
Teenbirthrate	.0173	.0366	0	.266
Staffofcolor	.0090	.0057	0	.0312
Adultincarceration	529.686	248.388	119.8	1568.5

Figure 1 – Lowess Smoother



Using the ‘lowess’ command on STATA, I observed the relatively quadratic relationship between youth imprisonments and the main independent variable, suspension rates. This result is shown in Figure 1. ‘Lowess’ carries out a locally weighted regression of yvar on xvar, displays the graph, and saves the smoothed variable. I used this command to compare the rest of my variables against youth imprisonment rates and determined that all of them had a linear relationship; therefore, I only transformed suspension rates to a quadratic term.

Data Analysis

First, a simple quadratic regression was performed to test the relationship between the dependent variable, youth imprisonments, and the primary explanatory variables, suspension rates and the number of police in schools. Subsequently, three quadratic regression models were performed where different combinations of independent variables were included in addition to suspension rates and police in schools. Each model is a panel regression that sets county and year as fixed effects. Even though most of the variation occurs within counties, not years, both fixed effects are included in each regression. The results are also robust, meaning the influence of outliers is eliminated to provide a more accurate fit for much of the data.

<u>Model 1</u>

Equation 1: $\textit{youthimprisonmentrate} = \beta_0 + \beta_1(\textit{suspensionrate}) + \beta_3\,(\textit{policeinschools}) + u$

Prior to the estimation, I expected youth imprisonments (per 100,000 youths aged 10-17) to increase with an increase in suspension rates. Research pointed towards a positive relationship between youth incarceration and suspension rates, which is reflected in my hypothesis. As mentioned earlier, I hypothesized that the number of police in schools would not have a significant effect on youth incarceration rates. After performing the simple regression, the estimated equation was:

$$\textit{youthimprisonment} = 9.46 + 720.62(\textit{suspensionrate}) + .060(\textit{policeinschools}) + u$$

In this model, the constant coefficient is 9.46 which indicates that if suspension rates and the number of police in schools were zero, then there would be 9.46 imprisonments per 100,000 youths aged 10-17. *Suspensionrate* has a positive coefficient of 720.62, which can be interpreted to mean that increasing a school's suspension rate by 1% increases the number of imprisonments per 100,000 youths aged 10-17 by approximately 720 individuals. *Policeinschools* has a positive coefficient of .060, which means that an increase of one law enforcement official in a school increases the number of youth imprisonments per 100,000 youths aged 10-17 by .060. This supports recent literature that suggests police officers reinforce the school-to-prison pipeline. The R-squared value of this model was .0741, indicating that the correlation between youth imprisonment rate and suspension rates and the number of police in schools is not substantial. *Suspensionrates* and *policeinschools* explain 7.41% of the variation occurring in the dependent variable. Additionally, *suspensionrate* had a z-value of 4.73 and a p-value of 0.000, implying that this variable is statistically significant at the 5% level. *Policeinschools* had a p-value of .718, implying that this variable is not statistically significant at the 5% level. This could be due to the lack of sufficient data for the number of police in schools- a handful of California counties did not report any data for law enforcement officials in school districts.

Model 2

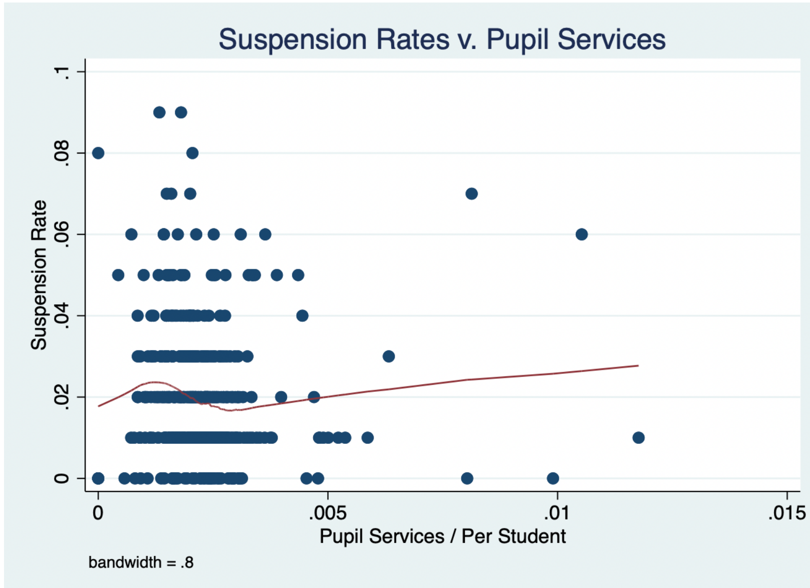
Equation 2: $youthimprisonmentrate = \beta_0 + \beta_1(suspensionrate) + \beta_3\,(policeinschools) + \beta_4\,(pupilservices) + \beta_5\,(pupilspending) + \beta_5\,(staffofcolor) + u$

As in the model above, I expected youth imprisonment rates to increase as suspension rates increased. I also predicted that the number of police in schools would not have a significant effect on youth incarceration rates. For this model, I predicted that youth imprisonments per 100,000 youths aged 10-17 would decrease as *pupilservices*, *pupilspending*, and *staffofcolor* increased. Political activists suggest increasing minority representation in the classroom, spending on students, and the number of social workers and mental health professionals in schools to end the school-to-prison pipeline (ACLU, 2022). Since *pupilservices*, *pupilspending*, and *staffofcolor* were omitted in the first regression, I also predicted that including these variables would impact the outcome of the *suspensionrate* and *policeinschools* coefficients. Omitted-variable bias attributes the effect of the missing variables to those that were included, so adding these new explanatory variables will change the results. After performing the multiple regression, the estimated equation was:

$$\textit{youthimprisonmentrate} = 36.861 + 375.62(\textit{suspensionrate}) + .0145\,(\textit{policeinschools}) + -1451.92(\textit{pupilservices}) + -.00176(\textit{pupilspending}) + 52.87(\textit{staffofcolor}) + u$$

In this model, the constant coefficient is 36.81, which indicates that if all the independent variables were zero, then there would be 36.861 youth imprisonments per 100,000. While *suspensionrate* still had a positive coefficient of 375.62, it decreased from Model 1. The variable is statistically significant at the 5% level with a z-value of 2.26 and p-value of 0.024. The difference in coefficients is due to omitted-variable bias. *Suspensionrate* had some level of covariance with the other, newly added independent variables. This caused the coefficient for *suspensionrate* to be overestimated when the other explanatory variables were omitted. This covariance can be displayed in Figure 2 below. *Policeinschools* still had a positive coefficient of .01453 and was not statistically significant at the 5% level with a p-value of .929. As mentioned above, the lack of substantial data on the number of police in schools most likely contributes to the lack of statistical significance for this variable.

Figure 2 – Covariance



Pupilservices had a negative coefficient of -1451.92, which can be interpreted to mean that increasing the number of pupil services per student by 1% leads to a decrease of approximately 1,451 youth imprisonments per 100,000. This result supports the hypothesis that increasing pupil services, such as counselors and psychologists, decreases the youth imprisonment rate. The variable had a p-value of .112, implying that it is not statistically significant at the 5% level. *Pupilspending* had a negative coefficient of -.00176, meaning a one dollar increase in per pupil spending correlates to a decrease of .00176 youth imprisonments per 100,000 youths. Accordingly, increasing per pupil spending by one hundred dollars leads to a reduction of .176 youth imprisonments per 100,000. While this variable is statistically significant at the 5% level, the increased spending needed to substantially affect youth imprisonment rates is unreasonable. *Staffofcolor* had a positive coefficient 52.87. Increasing the staff of color per student by 1% increases youth imprisonments per 100,000 by 52.87. This result contradicts recent literature that suggests Black, Latino, and Asian American students are less likely to be suspended from school when they have more teachers who share their racial or ethnic background (Bristol and Britton, 2021). However, the result was not statistically significant at the 5% level. This model had an R-squared value of .1086, indicating that these added independent variables do not account for a lot of the variation between youth imprisonment rates and the explanatory variables. *Suspensionrates, policeinschools, pupilservices*, *pupilspending*, and *staffofcolor* explain 10.86% of the variation occurring in the dependent variable.

Model 3

Equation 3: *youthimprisonmentrate* = $\beta_0 + \beta_1$(*unemploymentrate*) + β_2(*childpovertyrate*) + β_3 (*adultincarcerationt1)* + β_4 (*teenbirthrate*) + u

I tested the alternative hypothesis that factors outside of the school system were impacting youth imprisonment rates. Shader (2015) argues that low socioeconomic status, family conflict, absentee parents, and lack of moral guidance are all risk factors for juvenile delinquency. This model included *unemploymentrate, childpovertyrate, adultincarceration1,* and *teenbirthrate;* these variables represent risk factors identified in the study. I predicted that youth imprisonments per 100,000 youths aged 10-17 would increase as *unemploymentrate, childpovertyrate, adultincarceration1,* and *teenbirthrate* increased. After performing the multiple regression, the estimated equation was:

youthimprisonmentrate = 1.33 + 119.28(*unemploymentrate*) + -1.49(*childpovertyrate*) + .034(*adultincarcerationt1)* + 25.99(*teenbirthrate*) + u

Model 3 is another multiple regression that included variables related to the home environment rather than the school environment. The regression no longer included the main explanatory variables *suspensionrate* and *policeinschools*. The constant coefficient was 1.33, indicating that the youth imprisonment rate per 100,000 would be 1.33 if all other variables were zero. *Unemploymentrate* had a positive coefficient of 119.285, which can be interpreted to mean that a 1% increase in the county unemployment rate is correlated with a 119.285 increase in youth imprisonments per 100,000 youths aged 10-17. *Childpovertyrate* had a negative coefficient of -1.487; a 1% increase in the child poverty rate would cause a decrease of 1.487 youth imprisonments per 100,000. *Adultincarcerationt1* had a positive coefficient of .0342, which means that increasing adult imprisonments per 100,000 by one would increase youth imprisonments per 100,000 by .0342. *Teenbirthrate* had a negative coefficient of 25.99, which can be interpreted as a 1% increase in the teen birth rate leads to an increase of approximately 26 youth imprisonments per 100,000. The variable *unemploymentrate* had a z-value of 4.01 and p-value of 0.000, making is statistically significant at the 5% level. The variable *adultincarcerationt1* was also statistically significant at the 5% level with a z-value of 4.69. All other independent variables in this model were not statistically significant at the 5% level. The R-squared value for this model was .077, indicating that the correlation between these independent variables and the dependent variable is nominal. These four variables only explain 7.7% of the variation occurring in the dependent variable.

Model 4

Equation 4: *youthimprisonmentrate* = $\beta_0 + \beta_1$(*suspensionrate*) + β_2(*suspension2*) + β_3 (*policeinschools)* + β_4 (*pupilservices*) + β_5 (*pupilspending*) + β_5 (*staffofcolor*) + β_1(*unemploymentrate*) + β_2(*childpovertyrate*) + β_3 (*adultincarcerationt1)* + β_4 (*teenbirthrate*) + u

The final model included every explanatory variable collected for this paper. I expected to see major changes in the coefficients due to omitted-variable Bias and multicollinearity. After performing the multiple regression, the final estimated equation was:

$$youthimprisonmentrate = 1.951 + 39.12(suspensionrate) + .157\,(policeinschools) + -1628.12\,(pupilservices) + -.005\,(pupilspending) + -10.14(staffofcolor) + 104.35(unemploymentrate) + -5.22(childpovertyrate) + .035(adultincarceration t1) + 13.49(teenbirthrate) + u$$

The only variables that were statistically significant in this model were *unemploymentrate* and *adultincarcerationt1.* The main explanatory variables were no longer statistically significant at the 5% level. *Suspensionrate* experienced a meaningful change in coefficient value, decreasing from 809.65 to 39.12. This indicates that the coefficient value for *suspensionrate* and the impact it had on the variance of youth imprisonment rates in Model 1 was overestimated. The R-squared value for this final model was .2217, the highest R-squared value recorded across all models. When all the explanatory variables related to both the school and the home are included in the multiple regression, the R-squared value indicates an insignificant relationship between these variables and the youth imprisonment rate. The independent variables in the final multiple regression explain 22.17% of the variation occurring in the dependent variable.

Conclusion

Using California county-level data, my study focused on an eight-year time period to investigate the emerging national trend known as the school-to-prison pipeline. By running several panel regressions, I explored the relationship between youth imprisonment rates and the main independent variables: suspension rates and the number of police in schools. Across all models, *suspensionrate* and *policeinschools* have a positive coefficient, supporting the hypothesis that zero tolerance policies and the increased police presence in schools are positively correlated with youth imprisonment rates. The variable *suspensionrate* was statically significant for the first two models. This means that the relationship between *youthimprisonmentrate* and *suspensionrate* is attributed to factors other than chance. The variable *policeinschools* is not statistically significant in any of the models. As mentioned earlier, the lack of substantial and sufficient data on the number of police in each California public school could have affected the statistical significance of the results. Other independent variables that were statistically significant include *unemploymentrate, adultincarceration1,* and *pupilspending*.

I faced a variety of limitations that highlight the opportunity for further research. Due to a lack of available data, I analyzed the school-to-prison pipeline at the county level. I believe that it would be more effective to focus on individual school districts; county-level data does not differentiate between specific schools. For example, collecting data on each public school in Los Angeles County could offer more accurate insights into the relationship between youth imprisonment rates and suspension rates. I also had to scale variables by different factors (per student vs. per school district) which could have affected the results. Another possible avenue for future research is looking at the difference between Obama era and Trump era guidelines. Each administration implemented different policies to target the school-to-prison pipeline. A difference-in-difference test could be applied to determine the effectiveness of these policies.

This paper has several important economic implications for future policies. While the R-squared values for the four models were not substantial, some of the variables were statistically significant and it would be worth targeting these factors in future legislation. In 2018, the total youth imprisonment costs in California were $183.1 million. The average total imprisonment costs per juvenile felony arrest for California counties was $9,316. Using the results found in Model 1, reducing suspension rates by 1% could save a county on average $6.7 million per year. This money could be reallocated towards pupil services, such as counselors and psychologists in schools, which my paper showed to greatly reduce youth imprisonment rates. Policy makers should focus on legislation that provides students with more resources and strikes down zero-tolerance policies that unfairly increase suspension rates.

References

Study Confirms School-to-Prison Pipeline - US news & world report. (n.d.). Retrieved February 6, 2023, from https://www.usnews.com/news/education-news/articles/2021-07-27/study-confirms-school-to-prison-pipeline

Bacher-Hicks, A., Billings, S., & Deming, D. (2019). The School to Prison Pipeline: Long-run Impacts of School Suspensions on Adult Crime. https://doi.org/10.3386/w26257

Morgan H. Restorative Justice and the School-to-Prison Pipeline: A Review of Existing Literature. *Education Sciences*. 2021; 11(4):159. https://doi.org/10.3390/educsci11040159

Berlowitz, M. J., Frye, R., & Jette, K. M. (2015). Bullying and zero-tolerance policies: The school to prison pipeline. *Multicultural Learning and Teaching*, *12*(1), 7–25. https://doi.org/10.1515/mlt-2014-0004

Mbekeani-Wiley, M. (n.d.). *Handcuffs in hallways - shriver center on poverty law*. Retrieved March 27, 2023, from https://www.povertylaw.org/wp-content/uploads/2019/08/handcuffs-in-hallways-final.pdf

Berlowitz, M. J., Frye, R., & Jette, K. M. (2015). Bullying and zero-tolerance policies: The school to prison pipeline. *Multicultural Learning and Teaching*, *12*(1), 7–25. https://doi.org/10.1515/mlt-2014-0004

Bureau, U. S. C. (2022, May 18). *Per pupil spending continues to increase in 2020*. Census.gov. Retrieved March 26, 2023, from https://www.census.gov/newsroom/press-releases/2022/per-pupil-spending.html

Ending the school-to-prison pipeline. NEA EdJustice. (2021, April 20). Retrieved March 26, 2023, from https://neaedjustice.org/ending-the-school-to-prison-pipeline/

Fabelo, T., Plotkin, M., & Thompson, M. (2011). *Breaking schools rules - CSG justice center - CSG justice center*. Retrieved April 10, 2023, from https://csgjusticecenter.org/wp-content/uploads/2020/01/Breaking_Schools_Rules_FAQ.pdf

Flannery, M. E. (n.d.). *The school-to-prison pipeline: Time to shut it down*. NEA. Retrieved March 26, 2023, from https://www.nea.org/advocating-for-change/new-from-nea/school-prison-pipeline-time-shut-it-down

Georgetown Law Library. (n.d.). *Guides: California resources: Local governments*. Local Governments - California Resources - Guides at Georgetown Law Library. Retrieved April 18, 2023, from https://guides.ll.georgetown.edu/c.php?g=275786&p=1838520#:~:text=There%20are%20currently%2013%20charter,by%20the%20California%20Government%20Code.

Henry, K.-A., Catagnus, R., Griffith, A., & Garcia, Y. (2021). Ending the school-to-prison pipeline: Perception and experience with zero-tolerance policies and interventions to address racial inequality. https://doi.org/10.31219/osf.io/cxt8h

Salerno, L. M., & Zgoba, K. M. (2019). Disciplinary segregation and its effects on in-prison outcomes. *The Prison Journal*, *100*(1), 74–97. https://doi.org/10.1177/0032885519882326

School-to-prison pipeline. American Civil Liberties Union. (2022, April 4). Retrieved March 26, 2023, from https://www.aclu.org/issues/juvenile-justice/juvenile-justice-school-prison-pipeline

Shader, M. (2015). *Risk factors for delinquency: An overview - office of justice programs*. Retrieved April 10, 2023, from https://www.ojp.gov/pdffiles1/ojjdp/frd030127.pdf

Shirrell, Matthew, Travis J. Bristol, and Tolani A. Britton. (2021). The Effects of Student-Teacher Ethnoracial Matching on Exclusionary Discipline for Asian American, Black, and Latinx Students: Evidence From New York City. (EdWorkingPaper: 21-475). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/3jqw-5x05

St. George, D. (2013, March 4). *Anne Arundel second-grader suspended for chewing his pastry into the shape of a gun*. The Washington Post. Retrieved April 18, 2023, from https://www.washingtonpost.com/local/education/anne-arundel-second-grader-suspended-for-chewing-his-pastry-into-the-shape-of-a-gun/2013/03/04/44c4bbcc-84c4-11e2-98a3-b3db6b9ac586_story.html

Western, B. (2021). Inside the box: Safety, health, and isolation in prison. Retrieved March 27, 2023, from http://www.jstor.org/stable/10.2307/27074127?refreqid=search-gateway.

Table 1 - Variables

Variables	Description	Years	Unit	Source
Youthimprisonmentrate	The number of imprisonments per 100,000 youths aged 10-17.	2011-2018	Imprisonments per 100,000	California Division of Juvenile Justice
Suspensionrate	The number of suspensions administered by a school divided by the total number of students enrolled at that school.	2010-2017	Percentage	California Department of Education
Pupilservices	The number of pupil support service personnel, including counselors and psychologists per student.	2010-2017	Percentage	California Department of Education
Unemploymentrate	The number of unemployed individuals as a percentage of the labor force.	2010-2017	Percentage	State of California Employment Development Department
Childpovertyrate	The estimated number of children from birth through age 17 years in families living at or below the federal poverty threshold.	2010-2017	Percentage	California Department of Public Health
Policeinschools	The total number of law enforcement personnel reported by "other" types of agencies such as schools, state rehab centers, and juvenile programs per school district.	2010-2017	Police	The Department of Justice and Criminal Justice Statistics Center
Pupilspending	Calculation of current expense (cost) of education per average daily attendance.	2010-2017	Dollars	California Department of Education
Teenbirthrate	The number of resident live births to mothers ages 13-19 divided by the number of women aged 13-19 in a specified county.	2010-2017	Percentage	California Department of Public Health

Staffofcolor	The number of certified staff of color in a county per student.	2010-2017	Percentage	California Department of Education
Adultincarceration	The adult imprisonment rate from year t-1.	2010-2017	Incarcerations per 100,000	California Department of Corrections and Rehabilitation

Table 2 – Descriptive Statistics, N=464

Variable	Mean	Standard Deviation	Minimum	Maximum
Cummulativeenrollment	111823.8	233061.7	85	1624920
Youthimprisonmentrate	20.59	23.54	0	132.2
Suspensionrate	.0196	.0158	0	.09
Pupilservices	.0023	.00112	0	.0118
Unemploymentrate	.0893	.0432	.023	.293
Childpovertyrate	.189	.0844	0	.701
Policeinschools	4.28	12.85	0	99.5
Pupilspending	10956.46	3620.74	6880	43009
Teenbirthrate	.0173	.0366	0	.266
Staffofcolor	.0090	.0057	0	.0312
Adultincarceration	529.686	248.388	119.8	1568.5

Table 3 provides a summary of all variable coefficients, with p-values in parentheses.

Table 3 – Regression Results Summary

Independent Variables	Model 1	Model 2	Model 3	Model 4
suspensionrate	809.65*** (.000)	443.84** (.024)	—	91.89 (.648)
policeinschools	.060 (.718)	.0145 (.929)	—-	.157 (.293)
pupilservices	—	-1451.92* (.112)	—-	-1628.12* (.067)
pupilspending	—	-.00176*** (.000)	—-	-.005 (.319)
staffofcolor	—	52.872 (.873)	—-	-10.14 (.976)
unemploymentrate	—-	—-	119.28*** (.000)	104.35*** (.009)
childinpovertyrate	—-	—-	-1.49 (.918)	-5.22 (.723)
adultincarceration1	—-	—-	.034*** (.000)	.035*** (.000)
teenbirthrate	—-	—-	25.99 (.625)	13.49 (.808)
Number of Observations	464	464	464	464
R-Squared	.0741	.1086	.077	.2217

Significant at *10% **5% ***2%