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This **writing sample** is an individual assignment I completed for the 'Estimating Impact in Policy Research' course in Spring 2023. The assignment involved coding in STATA, conducting quantitative analysis, and writing a memo with tables and figures. The intended audience for the memo was policy analysts at the Department of Education. The dataset was structured by the professor.

Title

Estimating the Impact of the "Down with Punitive Discipline" Program on School Suspensions in New York City Public Schools (2009-2017)

Introduction

Punitive school discipline may prevent students from adequate education and increase the risk of ending up in prison, disproportionately impacting children of color. Down with Punitive Discipline (DPD) is a program that offers training to school principals on conflict de-escalation and promoting restorative justice. This study aims to evaluate whether the DPD program had an impact on students' suspensions in the New York City (NYC) public school system.

Methods

This study is a longitudinal panel analysis (2009-2017) that examines within-district changes in average student suspensions after implementing the DPD program. The sample includes 22 administrative districts in the NYC public school system. The data were obtained from the NYC Board of Education, consisting of annual district-level totals of student suspensions from 2009 to 2017. The outcome measure is the log-transformed probability of suspensions, while the treatment measure is whether the DPD program was in place in a given district and year between 2009 and 2017. This study begins by presenting descriptive statistics, comparing districts that adopted the DPD program with those that did not. This comparison is accomplished through one-way ANOVA tests and the exploration of time trends. Additionally, simple bivariate regression is used to provide a preliminary understanding. To account for potential district-specific and time-specific effects, a district fixed-effect regression analysis, and a district and time fixed-effect regression analysis were conducted. All analyses were conducted in STATA version 17, with robust adjustment applied, and statistical significance is reported at the .01, .05, and .1 levels.

Results

Descriptive Statistics

Table 1 provides a descriptive summary of the overall and yearly average number of suspensions from 2009 to 2017. For the 10 districts that ever had the DPD program, the average number of suspensions was 1976.69. This is 261.14 fewer suspensions than the average for the 12 districts that never had the DPD program, but the difference is not statistically significant. This gap may be because schools that attended this program had different profiles from those who didn't attend the program. Students in lower-income schools may face resource limitations and a lack of support in addressing life challenges, resulting in higher school suspensions and they are more likely to be encouraged to join the DPD program. [1] Table 1 and Figure 1 display decreasing

[1] *Unequal opportunities: Fewer resources, worse outcomes for students in schools with concentrated poverty*. The Commonwealth Institute. (2021, April 13). https://thecommonwealthinstitute.org/research/unequal-opportunities-fewer-resources-worse-outcomes-for-students-in-schools-with-concentrated-poverty/

mean suspension trends over time across two groups of districts, indicating the possibility of a trend that affected both groups' suspensions, even without the DPD program.

Regression Analyses

To make the findings more interpretable, this study takes the natural log of suspensions as the dependent variable for all the regression models and converts the coefficients to a percent change using the formula of percent change = $(e^{\beta 1} - 1) * 100$. Model 1 in Table 2 shows that on average DPD program implementation was associated with a 37.4% decrease in the likelihood of suspensions, and it is statistically significant at the .01 level. However, this estimate contains omitted variable bias. Model 2 in Table 2 shows that DPD program implementation was associated with a 53.14% decrease in the likelihood of suspensions on average with statistical significance, representing that the Model 1 estimate is biased downward. Thus, after absorbing some time-invariant omitted variables via the fixed effect, the coefficient approached its true value. It indicates that the relationship between the omitted variables and both the likelihood of attending the DPD program and the likelihood of suspension have the same direction. For example, lower-income schools may have higher student suspensions, and they are more likely to be advised to join the DPD program. Model 3 in Table 2 shows that controlling for the time-fixed effects, the coefficient of the DPD on suspension reduces to only a 9.94% decrease in the likelihood on average, and the coefficient is no longer statistically significant. Thus, in Model 2, the coefficient of DPD is biased upwards. Meanwhile, the year coefficients from 2013 to 2017 are negative and statistically significant. The time-fixed effect is negatively associated with suspension but positively associated with DPD, capturing variables that were constant across districts but changed over time. For example, the NYC government may have implemented a law, preventing all districts from over-suspending students; or a city-wide wave may have aroused the consciousness of all districts to limit student suspensions.

Conclusions

There is not sufficient evidence to conclude that the DPD program itself had an impact on school suspension rates. Rather, there was likely some time-related event that happened to all NYC districts across the time and decreased the average student suspension rates, although such effects may vary among different districts.

Limitations

First, this study with panel experimental design may have had limited statistical power because there were only 22 districts over 8 years. Second, omitted time-varying fixed effects within a district and district-varying time effects within a period might have biased the estimates of the analysis and threatened the internal validity. For instance, as principals in a district gain experience, they may generate more effective strategies for promoting positive school dynamics, leading to lower suspension rates and a greater likelihood of joining the DPD program. Third, the impacts are estimated from districts that joined the DPD program, but those are likely to be self-selected, so the estimate may not be generalizable to all districts in NYC, or in other school regions. Fourth, the suspension rates may not be the best measure to capture the DPD program's effect, because suspension rates are affected by many pathways other than the principal's conflict de-escalation skills. Finally, this research did not investigate what event led to the time trends of decreasing school suspensions in NYC. Future research may investigate the possible events and their correlation with the implementation of the DPD program.

TABLE 1 - Descriptive Statistics for Administrative District Panel Data: New York City (2009-2017)

Variable		Districts that Ever Took DPD Program (n=10) Mean (SD)	Districts that Never Took DPD Program (n=12) Mean (SD)	P value
Number of Suspensions (2009 - 2017)		1976.69 (2176.47)	2237.83 (905.27)	0.36
Number of Suspensions (Yearly)	2009	2975.2 (1210.83)	3234.33(2848.15)	0.79
	2010	2186.2 (963.05)	2383 (2354.30)	0.81
	2011	3474.1 (1966.95)	3809.08 (3572.11)	0.79
	2012	2451.9 (1487.47)	2838 (3025.45)	0.72
	2013	1694.5 (719.20)	1827.67 (1924.31)	0.84
	2014	1581.5 (762.66)	1798.83 (1781.26)	0.72
	2015	1442.3 (616.71)	1813.67 (1682.20)	0.52
	2016	1140.1 (690.78)	1414.17 (1429.89)	0.59
	2017	844.4 (496.277)	1021.75 (1168.45)	0.66

Note. DPD = Down with Punitive Discipline program.
*** p<0.01, ** p<0.05, * p<0.1 for ANOVA test of no difference between the mean number of suspensions.

Figure 1: Mean Suspensions for Districts that Ever Took and Never Took DPD Program (2009-2017)

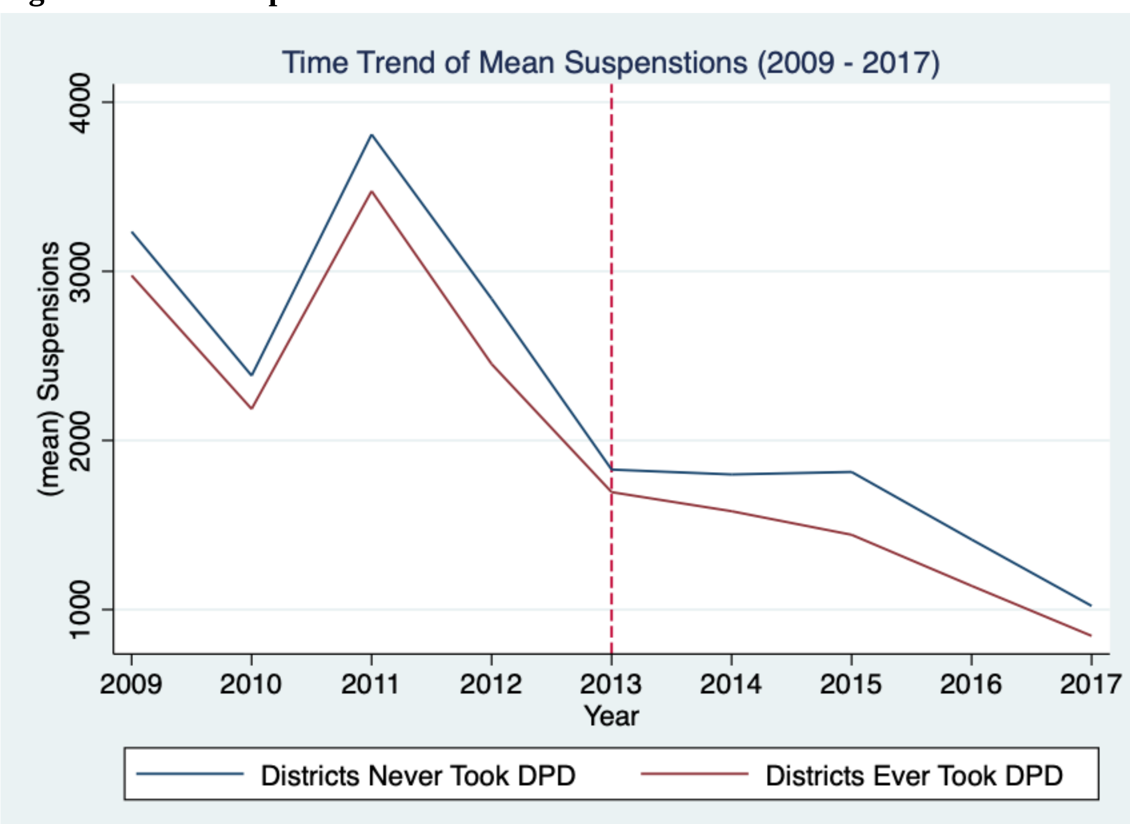

TABLE 2 – Logged Suspension Rates: Ordinary Least Squares (OLS) and Fixed-Effects Regression Results for NYC School Systems (2009-2017)

	Model 1	Model 2	Model 3
Variable	Simple Bivariable Regression	Fixed Effects Regression	Fixed Effects Regression
DPD	-0.468*** (0.106)	-0.758*** (0.051)	-0.104 (0.072)
2010			-0.322*** (0.047)
2011			0.136** (0.057)
2012			-0.219** (0.085)
2013			-0.589*** (0.095)
2014			-0.592*** (0.089)
2015			-0.622*** (0.077)
2016			-0.889*** (0.083)
2017			-1.228*** (0.096)
Constant	7.488*** (0.0575)	7.552*** (0.011)	7.888*** (0.059)
Observations	198	198	198
R-squared	0.075	0.301	0.842
Number of District	22	22	22
District FE		YES	YES
Year FE			YES

Note. DPD = Down with Punitive Discipline program.
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1