Title: Schools or Students? Identifying High School Effects on Student Suspensions

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Evidence is clear that discipline in high school is associated with negative outcomes across the life course. Not only are suspensions related to declining academic trajectories during high school in the form of attendance and academic achievement, students suspended once are also more likely to be suspended again and also substantially increase the likelihood of dropping out of high school (Balfanz, Byrnes, & Fox, 2013; Ekstrom, Goertz, Pollack, & Rock, 1987; Losen & Martinez, 2013; Marchbanks III et al., 2013; Morrison et al., 2001). Through their influence on high-school success and the related increased potential for involvement with the criminal justice system, many scholars identify suspensions as the beginning of a life-course trajectory of deviance and negative outcomes (Balfanz, Spiridakis, Neild, & Legters, 2003; Belfield & Levin, 2007; Pager, Western, & Sugie, 2009; Skiba et al., 2003). Additionally, adolescents as an age-group in particular are sensitive to structural changes and environmental influences making such negative institutional experiences particularly salient during the high school years (Furstenberg, 2000; Harter, 1990; Mortimer, Oesterle, & Kruger, 2005; Roeser, Eccles, & Freedman-Doan, 1999; Seidman & French, 2004). Important, the criminologists also identify the importance of institutions like schools, employment and marriage as potential levers for change in deviant trajectories highlighting the importance of institution-individual relationships (Laub, Nagin, & Sampson, 1998; Laub & Sampson, 1993, 2003; Moffitt, 1993; Weiss & Bearman, 2007). Structures within schools organize behavior and shape climate through the relationships and opportunities developed within these structures. Scholars across multiple fields have identified the importance of individual relationships between students, teachers and other school staff in the way climate influences outcomes above and beyond student attitudes or behavior (Skiba, Peterson, & Williams, 1997; Wu, Pink, Crain, & Moles, 1982).

The plethora of evidence highlighting negative impacts of suspension leaves little room for debate. However, with only a few studies explicitly examining the specific influence of schools on student discipline independent of student behavior itself, this problem guides the following analysis. Namely, it is unclear if students with greater behavioral problems drive greater use of discipline or if greater use of discipline simply belies larger institutional problems. In one case, differences in student behavior are the driving factor in variations in discipline rates at both the student- and school-level. For example, certain schools may enroll harder-to-serve populations with higher rates of behavioral problems before even entering the high school. In the second case, differences in school-level practices may influence variation in discipline rates at the student level regardless of student behavior. While studies on discipline focus on demographic characteristics of schools, they often do not account for more organizational context such as resources and climate. Substantial scholarship shows schools have different levels of resources and school climates and these are generally related to variation in academic outcomes (Bryk & Thum, 1989; Clotfelter, Ladd, Vigdor, & Wheeler, 2006; DiPrete & Mueller, 1981; Lee & Loeb, 2000; Loeb, Kalogrides, & Horng, 2010; Morrison et al., 2001; Rosigno, 1998; Rosigno & Ainsworth-Darnell, 1999); such variation in resources and climate is also likely related to disciplinary practice and outcomes. In an extensive correlational study using a national longitudinal dataset, DiPrete and Mueller (1981) find that a
variety of academic climate measures are strongly related to reduced rates of misbehavior, particularly for boys. More recent studies explicitly explore disciplinary and academic climates finding similar relationships to discipline (Arum, Beattie, Pitt, Thompson, & Way, 2003; Arum & Valez, 2012; Bryk & Thum, 1989; Morrison et al., 2001). Overall, studies on school discipline rarely account for the unique policy climates to which schools are subject. School-level analyses often utilize national or state-level samples while failing to account for unique district and school-level policies (Arum & Valez, 2012; Skiba et al., 2013, 1997). Related, student-level analyses often report aggregate district or state-level discipline rates without accounting for the clustering of certain students into different school environments which likely influence a student’s likelihood of school discipline net the student’s own characteristics.

It is clear that there is variation across schools in suspension rates, yet it is unclear if this is due to the sorting of certain students into certain schools or a result of different school practices. This analysis capitalizes on a natural transition in institutions to identify the way in which schools may influence student behavior throughout the high school trajectory. I utilize static characteristics and information on students preceding their high school career to explore variations in a student’s risk of suspension during the first two years of high school. Specifically I ask: What is the “school effect” on a student’s likelihood of suspension in the first four semesters of high school?

Setting: Description of the research location.

Using a unique administrative dataset from a large, urban school district in the North East United States, I am able not just to estimate school-level variance, but also to examine some of the student and school-level characteristics that may account for such variance. The data proposed contains multiple observations for students and schools, over time and within a single district policy environment, including a) student-level academic and school participation information b) surveys of parents, teachers and students, and c) infraction-level suspension data by date. Each year of suspension data has roughly 36,000 suspensions district-wide and these students receive an average of just over 2.3 suspensions within a year* and 2.7 infractions per year indicating that often a single suspension will be imposed for the combination of more than one infraction.

(PLEASE INSERT TABLE 1 HERE, APPENDIX B)

Suspension records exist for students in the 9-12 grades and ungraded students who are of age to be in high school but in ungraded programs†. Ninth graders have a slightly higher average of 2.5 suspensions than students in higher grades.

Population / Participants / Subjects: Description of the participants in the study: who, how many, key features, or characteristics.

I conduct this analysis with a single cohort of students who are in 9th grade in the fall of 2009 school year so as to follow them through their high-school career. This sample includes approximately 60,000 students with an average rate of suspension of 15%. The majority of these suspensions are for discretionary offenses (those not mandated for discipline by federal or state

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* I exclude 2013 from this average as it has just under 30,000 suspensions—it is somewhat of an outlier and is excluded from later analysis.

† I remove ungraded students from analysis as they are often in unique, “special education” schools and/or have other unique educational experiences.

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As can be seen in Appendix B-Table 2, the patterns for suspended students broadly match existing literature. (INSERT TABLE 2, APPENDIX B HERE)

For example, while Black students make up approximately 30 percent of this sample, they comprise more than 43 percent of students suspended once and 55 percent of students suspended more than once. Similarly, the rates of suspension for special education students are higher than would be expected\(^\ddagger\). Students who are suspended are also more likely to be chronic absentees and substantially more likely to be overage for their grade.

**Intervention / Program / Practice:** N/A

**Research Design:** Description of the research design.

The use of an HLM strategy such as that used by Ready and Chu (2013) fails to carefully examine school-level variance only providing an empirical average of the school-effect on student suspension rates. I use quasi-experimental, propensity score matching techniques to identify similar students using middle-school academic and behavioral outcomes such as attendance and test scores (Rosenbaum & Rubin, 1983). This framework identifies students based on their likelihood (based on a logistic or Poisson regression model framework) to be suspended at any time during high school with the following model:

\[
Y_{ij} = B_{0j} + B_{1jt}X_{ij} + e_{ij} \quad (1)
\]

In this model, I nest students \((i)\) in their middle schools \((j)\) and then estimate their likelihood of a high school suspension holding certain student characteristics constant. I nest students within middle-school to account for different discipline policies between middle-schools, which would impact both a student’s long-term suspension trajectory and other academic and behavioral outcomes before entering high school (S. Raudenbush & Bryk, 1986; S. W. Raudenbush & Bryk, 2002). Specifically, this model contains a vector of \(X_{ij}\) including student demographic characteristics as well as attendance and academic characteristics from middle school.

A second flaw in HLM analysis is its implicit assumption that all students remain in the sample throughout the period of analysis, or that the attrition is not important. This assumption does not address the possibility that occurrence of the ‘event’ may influence the likelihood of being in the sample at a later period and relatedly, of the event happening more than once. For example, a student who is suspended once in 9\(^\text{th}\) grade may be more likely to transfer schools or dropout as well as to be suspended a second time. After matching, I thus use an Event History (EHA) modeling framework for this analysis conceptually on a logistic regression framework but using a different data structure that not only allows for time-variant measures but, most importantly, adjusts measurement at each time point to take into account the changing population across time points. The analyses in this paper utilize a discrete-time hazard function that calculates the probability that an event will happen at time \(t\) or after time \(t\) to individual \(i\) (Singer and Willett, 2003).

\[
H(t_{ij}) = Pr[T_i = j \mid T_i > = j] \quad (2)
\]

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\(^\ddagger\) Because Special Education and retained students are expected to have higher rates of suspension but are less likely to be included in a ‘first-time 9\(^\text{th}\) grader’ cohort, I currently adjust the data so as to include all students in 9\(^\text{th}\) grade in 2009 including those are in special education/ungraded but have grade 9 recorded on their suspension file.
In the above equation this probability is drawn from a basic logistic regression equation and does not include multi-level modeling§. This analytic strategy also eliminates the need for a multi-level model framework in which I include high school fixed effects as I am using attendance at a different high school as the ‘treatment’ in this analysis and calculating the difference between student risks of suspension for matched pairs to explicitly identify high school ‘effects.’

**Data Collection and Analysis:** Description of the methods for collecting and analyzing data.
I employ an analytic strategy capitalizing on a longitudinal, administrative dataset for a large urban school district focusing on suspensions during the first two years of high school. A focus on the first two years of high school is driven by two empirical realities: first, the negative impact of a suspension is likely to be much stronger in earlier years of high school where it may influence both placement in academic tracks and peer groups (Balfanz et al., 2013; Balfanz, Herzog, & Mac Iver, 2007; Balfanz et al., 2003; Morrison et al., 2001; Skiba et al., 1997). Also, preliminary analysis of the data used in this paper suggests that the majority of students who will ultimately receive a suspension have received their first suspension by the 10th grade (Table 1, Appendix B).

I calculate the average risk of suspension once they reach high school using a logistic regression model. Once students’ risk of suspension has been calculated, I match students within a particular risk score band (eg 70-80% likely to be suspended) also using pre-high school characteristics. This approach allows me to examine the influence of a school on a student’s likelihood of suspension as if two students with equal likelihood of suspension were assigned to different schools. I then follow these students to different high schools and examine the variation in their observed outcomes (suspensions) over the first four semesters of high school based on high school characteristics.

**Findings / Results:** Description of the main findings with specific details.
Initial findings suggest significant between-school variation in student suspension rates even within this single district.
(INSERT FIGURE 1 APPENDIX B HERE)
As can be seen in the above figure, while the average suspension rate in this cohort’s final school-year was approximately 9.5%, the range of rates goes from 0-almost 50 percent in 2012. Also, (not shown here) descriptive analyses show substantial variation in school suspension rates by school size and the demographic characteristics of a school.

**Conclusions:** Description of conclusions, recommendations, and limitations based on findings.
The impact of organizational structures has a long empirical history of influence on individuals. Much of the literature on suspensions is unable to address variance in school-level discipline based on school-level characteristics due to data limitations. Capitalizing on a recent, large urban administrative dataset this analysis uses both analytic methods rarely used in the study of school discipline and exploits extensive information about schools and students to provide a deeper understanding of these more appropriately estimated school effects on student suspensions.

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§ Initial analyses have tested both fixed and random school-level effects in calculating logodds of suspension in an EHA framework and find little difference between the two methods. Further analysis of model fit will determine the final model specification.
Appendices
Not included in page count.

Appendix A. References
References are to be in APA version 6 format.


Appendix B. Tables and Figures: Not included in page count.

Appendix Table 1: Student-level Suspension Variation

<table>
<thead>
<tr>
<th>Per Student (2009-2012)</th>
<th>Grade 9</th>
<th>Grade 10</th>
<th>Grade 11</th>
<th>Grade 12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Number of Suspensions per Student</td>
<td>2.58</td>
<td>2.30</td>
<td>1.95</td>
<td>1.75</td>
</tr>
<tr>
<td>Average Number of Mandatory Suspensions</td>
<td>0.20</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>Average Number of Aggressive Suspensions</td>
<td>0.93</td>
<td>0.85</td>
<td>0.75</td>
<td>0.68</td>
</tr>
<tr>
<td>Average Number of Low-level Suspensions</td>
<td>1.33</td>
<td>1.18</td>
<td>1.00</td>
<td>0.88</td>
</tr>
<tr>
<td>Average Number of Unique Students Suspended</td>
<td>9772</td>
<td>7765</td>
<td>4002</td>
<td>2642</td>
</tr>
<tr>
<td>Average Number of Suspensions by Grade</td>
<td>16043</td>
<td>11821</td>
<td>5584</td>
<td>3442</td>
</tr>
</tbody>
</table>

Appendix Table 2: 2009 Cohort Suspension Analysis*

<table>
<thead>
<tr>
<th>Percent within Suspension Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
</tr>
<tr>
<td>---------</td>
</tr>
</tbody>
</table>

**Demographics**

<table>
<thead>
<tr>
<th>Gender</th>
<th>Average</th>
<th>Never</th>
<th>Once</th>
<th>&gt; Once</th>
<th>Discretionary</th>
<th>Mandatory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>51.4</td>
<td>53.1</td>
<td>43.7</td>
<td>39.1</td>
<td>42.2</td>
<td>37.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ethnicity</th>
<th>Average</th>
<th>Never</th>
<th>Once</th>
<th>&gt; Once</th>
<th>Discretionary</th>
<th>Mandatory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hispanic</td>
<td>37.5</td>
<td>37.6</td>
<td>39.2</td>
<td>33.4</td>
<td>36.2</td>
<td>41.9</td>
</tr>
<tr>
<td>Black</td>
<td>30.2</td>
<td>26.9</td>
<td>43.3</td>
<td>55.2</td>
<td>48.7</td>
<td>44.6</td>
</tr>
<tr>
<td>White</td>
<td>14.0</td>
<td>14.9</td>
<td>9.7</td>
<td>7.5</td>
<td>8.8</td>
<td>8.0</td>
</tr>
<tr>
<td>Asian</td>
<td>17.8</td>
<td>20.0</td>
<td>7.3</td>
<td>3.4</td>
<td>5.7</td>
<td>5.0</td>
</tr>
<tr>
<td>Other</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

**Socio-Economic Characteristics**

<table>
<thead>
<tr>
<th>One or More Poverty Indicators</th>
<th>Average</th>
<th>Never</th>
<th>Once</th>
<th>&gt; Once</th>
<th>Discretionary</th>
<th>Mandatory</th>
</tr>
</thead>
<tbody>
<tr>
<td>English Language Learner</td>
<td>65.1</td>
<td>64.0</td>
<td>69.9</td>
<td>73.0</td>
<td>71.0</td>
<td>73.8</td>
</tr>
<tr>
<td>Home Language Not English</td>
<td>7.0</td>
<td>7.1</td>
<td>6.9</td>
<td>5.8</td>
<td>6.5</td>
<td>5.7</td>
</tr>
<tr>
<td>Special Education Student</td>
<td>46.4</td>
<td>49.1</td>
<td>35.6</td>
<td>26.8</td>
<td>31.7</td>
<td>34.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Grade 8 Academics</th>
<th>Average</th>
<th>Never</th>
<th>Once</th>
<th>&gt; Once</th>
<th>Discretionary</th>
<th>Mandatory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enrolled in Public</td>
<td>92.2</td>
<td>91.9</td>
<td>93.5</td>
<td>93.6</td>
<td>93.6</td>
<td>92.7</td>
</tr>
<tr>
<td>Attendance Rate</td>
<td>91.3</td>
<td>91.5</td>
<td>90.4</td>
<td>89.0</td>
<td>89.8</td>
<td>89.4</td>
</tr>
<tr>
<td>Chronic Absentee</td>
<td>3.9</td>
<td>3.3</td>
<td>5.8</td>
<td>9.2</td>
<td>7.2</td>
<td>8.4</td>
</tr>
<tr>
<td>Grade 8 ELA (zscore)</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Grade 8 Math (zscore)</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Overage for Grade 9</td>
<td>24.6</td>
<td>23.3</td>
<td>29.6</td>
<td>34.7</td>
<td>31.6</td>
<td>33.1</td>
</tr>
<tr>
<td>Number of Students</td>
<td>60832</td>
<td>51428</td>
<td>5432</td>
<td>3972</td>
<td>8512</td>
<td>892</td>
</tr>
<tr>
<td>% of Sample</td>
<td>100%</td>
<td>85%</td>
<td>9%</td>
<td>7%</td>
<td>14%</td>
<td>1%</td>
</tr>
</tbody>
</table>

*Not all percentages add up to 100 due to rounding
Appendix Figure 1: Variation in School-level Suspension Rates in 2012

Distribution of PCTSUS

Curve
Normal(Mu=9.6537 Sigma=7.8286)