

# Peer Delinquency and Student Achievement in Middle School

August 2014

Tom Ahn\*  
Department of Economics  
University of Kentucky  
335X Gatton B&E Building  
Lexington, KY 40506-0034  
thomas.ahn@uky.edu

Justin G. Trogon  
Gillings School of Global Public Health  
University of North Carolina at Chapel Hill  
1101B McGavran-Greenberg Hall  
Chapel Hill, NC 27599-7411  
trogonj@email.unc.edu

## Abstract:

This paper studies the relationship between peer delinquency and student achievement/misbehavior in North Carolina middle schools using detailed panel data. We identify the severity of the delinquent act by using the punishment that was meted out for the offense and calculate the average exposure to peer delinquency. Using this new measure in an Arellano-Bond instrumental variables framework that includes a rich set of controls including student, peer, and teacher characteristics, we find that the a 10% increase in peer delinquent acts resulting in at least an out-of-school suspension is associated with a 19% of a standard deviation decrease in mathematics standardized exams and a 35% increase in incidence of own delinquent acts.

\* Corresponding author.

## Introduction

Peers have an important role in determining students' educational outcomes. Peers' characteristics (e.g., gender, race/ethnicity, language proficiency) are correlated with student achievement.<sup>1</sup> However, despite considerable focus and attention from parents and administrators, the relationship between peers' delinquent behavior and student achievement has been understudied empirically.

Because of the way delinquent behavior is often punished, the net effect of peer delinquency on student achievement may be positive or negative. The offense itself may be disruptive to classroom instruction. If teachers' or administrators' attention and effort are diverted from educational activities toward dealing with frequent disruptions, student achievement is expected to decline.

However, offenses that rise to the level of disciplinary actions may provide a justification for removing the disruptive influence from the classroom, at least temporarily. The removal of peers that are disruptive may benefit the rest of the class and increase achievement. In addition, the punitive measure may have a deterrent effect for the remaining peers as well (Kinsler 2013). Therefore, the effect of peer delinquency on student achievement is an empirical question.

Although many studies have acknowledged the potential role for peer delinquency in determining academic performance (Hoxby, 2000; Gavrila and Raphael 2001; Hanushek et al., 2003; Ding and Lehrer, 2007), we are aware of only a small number of studies that directly investigate it. Figlio (2007) found that behavior problems were associated with increased peer disciplinary problems and reduced peer test scores among 6<sup>th</sup> graders. Neidell and Waldfogel (2010) found that kindergarten classrooms with the highest numbers of students with externalizing problems (as reported by the teacher) had lower math and reading

---

<sup>1</sup> See Angrist and Lang 2004, Booser and Cacciola 2001, Lavy, Silva, and Weinhardt 2012; Hanushek et al. 2003; Imberman, Kugler, and Sacerdote 2012; Burke and Sass 2013, for example.

scores. Carrell and Hoekstra (2010) use the parents' domestic violence records to capture the negative spill-over effects to classmates. Lavy, Paserman, and Schlosser (2012) use prior year retention in the same grade as an instrument for peer delinquency.

In this study, we use administrative data for all public middle schools in North Carolina from 2008-2009 to 2011-2012 to estimate the reduced-form effect of peer delinquency on math and reading end-of-grade (EOG) test scores as well as the student's own delinquent behavior. Our analysis focuses on middle school, when delinquent behaviors can become quite serious (e.g., Gunter and Bakken 2010). Our large sample size also allows for interesting subgroup comparisons.

Identification of the effect of peer delinquency on student delinquency and academic outcomes is challenging. The correlation between peer delinquency on student delinquency could arise from causal effects, reverse causality ("reflection"), or shared context both observed and unobserved to the econometrician (Manski 1993). The correlation between peer delinquency and academic outcomes could be due to non-random sorting of students into schools and classes (e.g., tracking).

We use a combination of fixed effects and instrumental variables to address these challenges.<sup>2</sup> We use first-differences to eliminate unobservable, time-invariant student-level effects. We also first-difference the school-fixed effects to account for possible non-random sorting of students into schools and classes. Even if students are "tracked" into classes or schools based on unobserved ability, the model is identified by changes in the number of offenses over time within a student's cohort. Our specification for academic outcomes also controls for lagged test scores to capture potentially unobserved student ability. To account for common shocks during the school year, we control for student, peer, and teacher

---

<sup>2</sup> A previous version of the paper utilized a fixed-effects value-added approach and generated much smaller point estimates on the impact of peer behavior (Hanushek et al. 2003; Arcidiacono and Nicholson 2005; Ding and Lehrer 2007; Neidell and Waldfogel 2010). See online appendix at <http://sites.google.com/site/tomsyahn/>.

characteristics. Finally, we instrument for peer delinquency and lagged academic outcomes using predetermined values available in our panel data (Arellano and Bond 1991).

## **Data**

We use an administrative data set of North Carolina public schools covering four school years: 2008-2009 through 2011-2012.<sup>3</sup> The data set contains information on all public school students, teachers, and schools in North Carolina. Because the data is collected annually with a unique student identifier, students can be matched across years to create a panel.

We restrict our sample to middle school students (grades 7 and 8). We drop 6<sup>th</sup> grade students from the analysis because this is their first year in middle school. All lagged variables for the first difference equations would necessarily be from different schools. Furthermore, the two-years-ago peer offense, used as an instrument in the Arellano-Bond approach, would be from 4<sup>th</sup> grade. There are virtually no major (suspension-resulting) offenses and a very small number of reported minor offenses for students that young. We drop students in grades with less than 10 students and in schools with less than 30 students. The majority of students in these categories are already placed in alternative schools/programs (schools of last resort).<sup>4</sup>

### *End-of-grade Test Scores*

Two academic outcome variables of interest are standardized exam scores. North Carolina uses standardized scores in its accountability calculations, which is similar to z-scores. In the standard setting year (1993-1994), grade-level scores are rescaled to mean zero, standard deviation one. This score is continued to use as a benchmark for subsequent years,

---

<sup>3</sup> Data restrictions prevent us from going further back in time.

<sup>4</sup> Including these students does not qualitatively change the results.

such that it is feasible for all students (in a particular grade) to score above “zero,” if these students perform better than students in that grade in the standard setting year.<sup>5</sup>

All students in grades 3 through 8 in North Carolina must take EOG exams in reading and mathematics. These scores are aggregated to the level of the school and are used for school report cards, which are published on-line as well as for No Child Left Behind sanction purposes. In addition, the EOG exam scores are part of the final grade calculation for students. In this sense, the exams are high-stakes for schools as well as students.

### *Own Offenses*

We also analyze the effect of peer delinquency on own delinquency. If peer delinquency is “contagious” to other students, the impact is important in its own right, separate from the impact on test scores. We use the Offense-Discipline data described below to more richly capture the degree of delinquency compared to previous studies.

### *Offense-Discipline Data*

Offenses recorded in the administrative data range from disruptive behavior in classes, excessive tardiness, and disrespecting teachers, to physical altercations resulting in serious injury, drug use, bringing (or discharging) weapons in the school, and other serious and/or illegal acts of delinquency.<sup>6</sup> In general, the number and severity of disciplinary incidents increase dramatically starting in middle school. In the North Carolina data, the average number of disciplinary incidents per pupil per academic year in elementary schools is 0.27. As young adolescents transition to a new school building, meet new peers and teachers, and attempt to adjust to a tougher curriculum, the number jumps to 0.88 (see for example, Table 1 (Summary Statistics) or Mushkin et al. 2014).

Each reportable offense is linked to a disciplinary measure meted out by the school administration. The punishments range from detention to expulsion or reporting to law

---

<sup>5</sup> For more details, see <http://www.ncpublicschools.org/docs/accountability/reporting/abc/2011-12/academicchange.pdf>.

<sup>6</sup> See the Appendix for a more extensive list of the most common offenses.

enforcement. All disruptive *behaviors* are not created equal, and merely summing up the number of incidents at the student or peer level does not fully capture the disruptive impact of different types of offenses.

While the seriousness of the offense is readily discernable by the description in many cases, there are a substantial number of incidents where categorization is difficult. For instance, “Property Damage” may indicate simple minor vandalism or extensive damage to school buildings or teachers’ personal property. As such, the discipline meted out to students who commit “property damage” ranges from in-school detention to arrest/expulsion from the school. As another example, the nebulously termed “Disruptive Behavior” is the most oft-reported offense, accounting for roughly eight percent of all reported incidents in middle schools. Over 30% of “Disruptive Behavior” offenses result in before or after-school detention, while approximately 20% of the offenses result in one to ten days of out-of-school suspension.

We categorize student offenses into minor and major categories. Because of the ambiguity in categorizing offenses, we rely instead on the discipline variable. That is, we allow the school to reveal how serious the incident was. Offenses are categorized as major if the punishment is at least an OSS.<sup>7</sup> Two of the most frequently reported offenses for OSS or greater (besides “Disruptive Behavior”) are “Aggressive Behavior” and “Fighting”, while the second most numerous minor offense is “Bus Misbehavior.” The majority (approximately 63%) of reported incidents result in suspension or tougher sanctions.

In addition, all offense-committing *students* are not equally disruptive. Calculating the fraction of peers that commit one or more offenses (as some previous studies have done) gives the same weight to a one-time offender and those who cause persistent disruptions. Indeed, if the majority of disruptions are committed by one or a few students in the peer

---

<sup>7</sup> See the Appendix for a complete list of disciplinary measures.

group, the academic environment may appear to be relatively disruption free, and the impact of each disruption (as counted by number of students committing infractions) will be overestimated. Our data clearly shows that while there are many students who commit many reportable offenses in an academic year, there are also many students who appear only once in the data. In fact, the number of students who commit one offense per year is double the number of students who commit more than five reportable offenses (See Figure 1).

The mix of minor and major offenses also varies by student. For example, among students who commit at least 8 offenses per year (which places them at the top 10<sup>th</sup> percentile of offenders), about 15% of these students *only* engage in potentially “minor” infractions, such as truancy or cell phone use. On the other hand, the remainder engages in more potentially disruptive behavior, such as fighting or possession of controlled substances. Figure 2 is a histogram of the fraction of offenses committed by a student that is considered major. The two mass points at zero and one show that a large fraction of students only commit minor or major offenses, exclusively. Roughly 30% of students who commit at least one reportable offense commit a mix of major and minor offenses.

Therefore, we define our measure of peer offense as the average of disciplinary measures meted out by school administration. That is, for student  $i$  in school  $s$  in year  $t$  that has a peer-group (i.e., grade) size of  $G$ , peer offense,  $\bar{O}_{ist}$  is defined as the average number of offenses committed by a grade-mate (who are subscripted by  $g$ ) in the following manner:

$$\bar{O}_{ist} = \frac{\sum_{g=1}^G \text{Offense}_{g \neq i}}{G - 1}$$

This measure has the advantage of mitigating measurement problems described above. In addition, our measure of disruption allows for easier interpretation for policy makers.

We consider two measures of peer offenses ( $\bar{O}_{ist}$ ). One measure of offenses counts all offenses, minor or major. The other measure counts only major offenses. Counting all offenses provides a complete accounting of incidents that required disciplinary actions by the

school. However, the academic effect of minor offenses committed by peers could be small and aggregating and giving equal weight to all offenses may lead to a distorted view of the effect of student misbehavior. In particular, peer groups that engage in many minor offenses (but no major offenses) and peer groups that engage in major offenses (but less minor offenses) will have similar average counts of offenses. Specifications using only major offenses attempt to correct for this issue.

Figures 3 and 4 report histograms of students' average exposure to peer misbehavior using our measures for major offenses (Figure 3) and all offenses (Figure 4). The difference between using the number of offenses vs. the number of students committing offenses can be seen by contrasting Figures 3 and 4 against Figures 5 and 6. Figures 5 and 6 calculate the exposure of students to peers that have committed at least one offense (major and all, respectively). The grouping of repeat offenders with one-time (or few-times) offenders in Figures 5 and 6 results in an exposure density that is skewed more to the right, compared to our exposure specification (Figures 3 and 4).

While our strategy for categorization is clear and simple to implement, there are potential threats to validity. First, the categories of minor and major are somewhat arbitrary. Whether a one-day OSS is "serious enough" to be categorized as a major disciplinary incident is debatable. Unfortunately, we cannot observe OSS at a finer level than "1 to 10 days." More troublesome is the possibility that discipline may be differently applied by each school. For example, the same level of property damage in one school may be categorized as minor, while at another school it may be considered a major offense. The literature has demonstrated that principals may use suspensions to affect accountability outcomes (Figlio 2006), so it stands to reason that they may vary discipline strength strategically. Even if principals are not acting strategically, some may be more inclined to dole out harsher punishment than others. Schools with these disciplinarian principals will systematically over-



count the number of offenses (or at least serious offenses), resulting in an under-estimate of the effect of peer offenses. We attempt to mitigate this potential effect by including a school fixed effect . Most schools will have the same principal across the two to three years of the sample, and the (unobservable) disciplinary harshness of the principal should be captured in the school dummy.<sup>8</sup> In addition, the ability of schools to strategically apply discipline will be bound by societal norms and the law. Strict principal may find it difficult to enforce out of school suspensions for offenses that are deemed “minor” by the community. On the other side, a lax principal will have no choice but to involve law enforcement if the severity of the offense rises to criminal conduct.

### *Explanatory Variables*

In addition to student offenses, we control for free or reduced price lunch (FRL) status, and limited English proficiency (LEP) status. While gender and ethnicity information is also available, the first-difference structure of our model nets out time-invariant characteristics. With these characteristics, we instead perform subgroup analysis. We also define these variables for their peers (at the grade level).

If teachers with certain (observable) characteristics are strategically assigned to certain students, failing to account for this matching can also lead to bias. For instance, the literature has confirmed that inexperienced teachers are more likely to be placed in classrooms with less academically proficient students (Clotfelter et al. 2006). We include the following teacher characteristics: gender, ethnicity, and an indicator variable for first year on the job (i.e., inexperienced teachers).

### *Descriptive Statistics*

An average middle school student in North Carolina committed approximately 0.88 offenses per year (Table 1). Of these, approximately two thirds were major offenses that

---

<sup>8</sup> The unconditional probability of a principal transferring to a different school in North Carolina during the study period is roughly eight percent.

resulted in at least OSS. The relatively large standard deviation for number of offenses indicates that there were a large mass of students at zero offenses per year and many students who committed many more than one offense per year. While a student who committed a minor offense was more likely to commit another minor offense as well as a major offense, the correlation between the number of minor and major offenses committed by a student is quite modest, at 0.40. There were many students who committed only minor offenses and some students who almost exclusively committed major offenses.

About half of the students qualified for free or reduced price lunch. About 50% of students were non-white. The state had a relatively small number of LEP students, at about four percent of the student population. The bottom two panels of Table 1 show that teachers in North Carolina were predominantly female and white. About six percent of teachers were in their first year on the job.

## Methods

Our model of outcomes is given by equation (1):

$$Y_{ijst} = A_{ijst-1}\varphi + \bar{O}_{ijst}\alpha + X_{ijst}\beta + T_{jst}\gamma + \bar{P}_{ijst-1}\delta + \omega_i + \rho_s + \tau_{gt} + \varepsilon_{ijst}. \quad (1)$$

The dependent variable  $Y_{ijst}$  represents the standardized test score in reading or mathematics ( $A_{ijst}$ ) and the number of major or total offenses ( $O_{ijst}$ ) for student  $i$ , teacher  $j$ , school  $s$ , and school year  $t$ . We include the student's prior year test score ( $A_{ijst-1}$ ) to proxy for the stock of education achievement built up until this year.<sup>9</sup> The main peer characteristic we are interested in is the average number of offenses committed by peers,  $\bar{O}_{ijst}$ .  $X_{ijst}$  represents student characteristics,  $T_{jst}$  represents teacher demographic characteristics, and  $\bar{P}_{ijst-1}$  represents lagged student peer characteristics.

---

<sup>9</sup> Although the inclusion of last year's test score relieves the data requirement of including all prior years' determinants of education production, it also introduces potential endogeneity if unobserved components of past test scores are correlated with current year test scores (Todd and Wolpin 2003).

There is reason to believe that student achievement, or student offenses, and the level of classroom disruptions will be determined together. For instance, if students with disciplinary problems are concentrated into a subset of classes, and these students also tend to perform worse academically compared to the rest of the school, we will over-estimate the effect of peer offenses on test scores. Not only can school administrators choose to group students who are low achieving and disruptive strategically, but low academic achievement itself may lead to students acting out. The literature has addressed this issue using instrumental variables and/or unique proxy variables that do not suffer from this simultaneity (See Figlio 2007, Carrell and Hoekstra 2010 and 2012, and Lavy, Paserman, and Schlosser 2012, for example.).<sup>10</sup>

We address this issue in three ways. First, we define our peer group at the grade-level. While principals may be able to select students into particular classes, we assume that grade-level (and school-level) distribution of student characteristics, including likelihood of committing a reportable offense, is taken as given. While it is most natural to think of the disruptive effect of peers at the level of the classroom, the literature has often calculated peer characteristics at the grade level to minimize concerns about sorting across classrooms within a grade (Rothstein 2010). To maintain consistency with previous studies, we also focus on grade-level peers in our preferred specifications.

Second, our data allows us to include student ( $\omega_i$ ), school ( $\rho_s$ ), and grade-year ( $\tau_{gt}$ ) fixed effects.<sup>11</sup> Even if students are “tracked” into classes or schools based on unobserved ability, the model is identified by changes in the number of offenses over time within a student’s cohort. We eliminate the student fixed effects by first-differencing equation (1):

$$\Delta Y_{ijst} = \Delta A_{ijst-1}\varphi + \alpha\Delta\bar{O}_{ijst} + \Delta X_{ijst}\beta + \Delta T_{jst}\gamma + \Delta\bar{P}_{ijst-1}\delta + \Delta\rho_s + \Delta\tau_{gt} + \Delta\varepsilon_{ijst}, \quad (2)$$

---

<sup>10</sup> Some studies take advantage of random assignment of students to peer groups. See Boozer and Cacciola 2001 and Zimmerman 2003, for example.

<sup>11</sup> See Vigdor and Nechyba 2004, Burke and Sass 2013, Lefgren 2004 for examples of peer effect estimation using fixed-effects.

where  $t = 2010-2011$  and  $2011-2012$ .<sup>12</sup>

Third, we instrument for possible remaining endogeneity using an Arellano-Bond estimation approach. By definition, when  $\Delta A_{ijst}$  is the dependent variable,  $\Delta A_{ijst-1}$  and  $\Delta \varepsilon_{ijst}$  are correlated through their shared term  $\varepsilon_{ijst-1}$ . We also consider  $\Delta \bar{O}_{ijst}$  potentially endogenous due to student tracking in unobserved dimensions (conditional on student, school, and grade-year fixed effects) or due to “reflection” when student offenses is the dependent variable. Our longitudinal data provides us with plausible instruments. Under the assumption that the error term ( $\varepsilon_{ijst}$ ) is serially uncorrelated and lagged academic outcomes and peer offenses are predetermined (i.e., uncorrelated with current and future values of the error term), lagged values of academic outcomes and peer offenses are valid instruments (i.e.,  $A_{ijst-3}$  for  $\Delta A_{ijst-1}$  and  $\bar{O}_{ijst-2}$  for  $\Delta \bar{O}_{ijst}$ ) (Arellano and Bond 1991).

## Results

First stage regressions in Tables 2-1 and 2-2 show that the peer offense instrument performs particularly well for math test and peer offense results. F-statistic calculations on the excluded instruments for math and reading results show that all but one pass the rule-of-thumb test (F-stat >10).

Second stage IV results are estimated using a two-step GMM estimation procedure with errors clustered at the school-cohort level. Tables 3-1 and 3-2 present our main results. For math, a marginal increase in the number of average peer major offenses results in a 3.5 unit decrease in math test scores, and a 3.4 unit increase in own major offenses. If all reportable offenses are considered, math score declines by 0.85 units (although it is only

---

<sup>12</sup> Note that the school and grade-year fixed effects in this first-differences framework takes on values of 1, 0, and -1.

significant at the 90% confidence interval) and own offenses increases by 1.74 units. Results for reading scores are mostly smaller (and/or insignificant).<sup>13</sup>

The simplest way to interpret these results is to calculate the impact on test scores and own behavior for a “reasonable” increase in peer misbehavior. With an average grade size of 260, and a per-student major and all incidents of 0.57 and 0.88, respectively, there are, on average, 229 reportable incidents (148 major offenses) per grade per year.

If the number of major incidents increases by 15 (roughly 10%), standardized math scores decline by about 19 % of a standard deviation. While reading scores are not estimated with statistical significance, the impact is about one third the size compared to math scores. If the total number of incidents (major and minor) increases by 23, math and reading scores decline by about 7.5 % and 5.3% of a standard deviation, respectively. Similar increases in major peer incidents results in a 35% increase in the number of own major offenses, and a 10% increase in all offenses is associated with a 25% increase in the number of overall offenses.

### *Subgroup Specifications*

Our large sample size and rich dataset permit us to split the sample in order to capture the impact of peer misbehavior on particular subgroups of interest. Tables 4-1 to 6-2 split the sample by gender, race, and geography. Tables 4-1 and 4-2 show that males are more likely to be negatively impacted by peer offenses. Male math scores decline more (by a factor of 1.27) compared to female math scores. Own offenses increase at almost 3 times the rate for males compared to females.

---

<sup>13</sup> We present results for impact of peer offense on own offense for both math and reading tests. Note that the RHS and LHS variables, with the exception of the teacher characteristics and previous year test scores, are identical. We present both results for completeness, as well as a fragility check. The magnitudes are quantitatively similar, and more importantly, the relative sizes of the major to minor offense results are close across the two specifications. For further subgroup analyses presented later, we restrict estimates to only own offenses generated using math scores and teachers.

In comparing minority and white students in Tables 5-1 and 5-2, the impact on test scores is mostly statistically insignificant for both groups, but the differential impact on own behavior is very large for minority students, compared to white students. Minority students are 7 to 10 times more sensitive to peer offenses.

Finally, Tables 6-1 and 6-2 examine the impact of peer impact on students in rural schools vs. city schools. Somewhat surprisingly, students at rural schools are impacted much more heavily by peer behavior, compared to students from city schools. Looking at major offenses, rural school students' math scores decline much more (by a factor of 5) compared to city school students' scores. In addition, rural students respond to peer misbehavior by increasing their own delinquent acts, at a rate that is more than 3 times greater than city students.

### **Falsification Tests**

Our results have demonstrated, using a combination of student, school, grade-year fixed-effects, and the Arellano-Bond framework, that peer offenses impact test scores and own behavior. The key identification assumption is that peer offense is exogenous to the outcome variables with the controls and the IV framework. Indeed, most of the literature is focused on finding novel variables that are conceptually unrelated to the outcome variables (except as a channel that impacts peer offense) in order to identify peer influence (Figlio 2007, Carrell and Hoekstra 2010).

In order to buttress the claim that our framework succeeds in estimating the causal impact of peer offense on academic and own behavioral outcomes, we present a series of falsification tests: we estimate the impact of peer demographic characteristics on own demographic characteristics, using our Arellano-Bond framework.

The logic is as follows. If the estimated impact of peer offense on own academic and behavior outcomes are a combination of the true causal effect and a bias term (whether due to

selection, sorting, or the reflection problem), using own outcomes that, by definition, are not influenced by peer characteristics should then leave only the bias term. If our econometric framework successfully mutes the endogeneity bias, the IV estimates should yield statistically insignificant results.

We use own and peer disability and free/reduced price lunch status. Peer disability or poverty status in school should not impact own disability or poverty status, but statistical correlation between the two variables may exist for other reasons.<sup>14</sup>

First, simple OLS regressions using own disability and FRL status as dependent variables and peer averages of these characteristics as controls are presented in the first two columns of Table 7-1 to demonstrate that correlation does exist. Clearly, since there is no causal link between peer disability (FRL status) and own disability (FRL status), the estimated relationship must be purely due to endogeneity bias.

Then, in Table 7-2 and Table 7-3, we replicate our Arellano-Bond framework. First-stage estimates show that the instruments are generally significant, except for the effect of two-year lagged FRL status on the lagged difference in test scores. F-statistics for the instruments are significant, but suggest borderline weak instruments. The second stage results show that parameter estimates on the peer characteristics are statistically insignificant (Table 7-3). That is, the Arellano-Bond framework eliminated the statistical bias between the own and peer demographic characteristic.

## **Discussion**

Our preferred specification estimates of the effect of grade-level peer offenses show that an increase in the average number of offenses committed by peers lowers achievement in reading and mathematics and increases own misbehavior. We find that a 10 % increase in peer major offenses results in a 19% of standard deviation decline in math scores and a 35%

---

<sup>14</sup> Other, more obvious characteristics, such as race or gender, are excluded because we require time-varying characteristics, due to the first-difference framework.

increase in the number of own offenses. Results for reading are weaker and/or smaller, which may be reflective of the fact that education production for reading and language arts occurs more at home.<sup>15</sup> These are sizable impacts.

To put the magnitude of these effects in context, consider the effectiveness of class size reduction. While estimated magnitude of the effect differ by studies, the literature generally agrees that class size reduction by one-half, starting from a class size of twenty, can yield somewhere between 5 to 15 % of a standard deviation increase in student achievement (see Rivkin, Hanushek, and Kain 2005, for example). Therefore, the impact of peer misbehavior seems to be at least as large as a sizeable class-size reduction.

Our paper provides a number of contributions to the small literature on the effect of negative behavioral peer influence. By using the disciplinary measure meted out by the school, we are able to categorize offenses as minor or major more objectively. By counting the average number of incidents (instead of counting the number of students who cause one or more incidents), we get a richer picture of peer-offense. This allows us to examine the effect of different types of peer offenses on student achievement outcomes and behaviors. By using the Arellano-Bond approach while accounting for school level fixed effects, our specification provides more extensive controls for non-random sorting of students into schools and matching of students to classes and teachers while correcting for the endogenous last-year score variable. In addition, we control for important teacher characteristics as well as other own and peer demographic characteristics. In particular, as the literature has shown that students with low achievement often have low income and are frequently placed in classrooms with inexperienced teachers, controlling for these factors is important. In sum, this paper provides a more detailed look at the effect of peer offenses on academic achievement and misbehavior compared to previous research.

---

<sup>15</sup> See Jacob 2005, Reback 2008, Rouse et al. 2013, and Ahn and Vigdor 2014, for example.



However, much work remains to be done on this topic. We may have documented the effect of peer offenses, but it is unclear what the prescription would be to improve peer behavior. Indeed, it is not clear what the cost would be (or whether it is even feasible) to effectively deter misbehavior on a large scale. In addition, any observation of offense in the data is really a dyad of offense and disciplinary consequence. We have not attempted to disentangle effect of these two incidents. This study only estimated the reduced form effect of peer delinquency on educational outcomes and not the potential indirect effect through changes in own delinquency. It is clear that a more nuanced understanding of the effect of peer and own delinquency on academic achievement is required.

## References

- Aaronson, Daniel, Lisa Barrow, and William Sander. 2007. Teachers and Student Achievement in the Chicago Public High Schools. *Journal of Labor Economics* 25(1): 95-135.
- Ahn, Tom, and Christopher Jepsen. 2014. Non-English Speaking Peers and Student Achievement in Middle School. Working Paper.
- Ahn, Tom and Jacob Vigdor. 2014. When Incentives Matter Too Much: Explaining Significant Responses to Irrelevant Information. NBER Working Paper # 20321.
- Angrist, J.D. and Lang, K. 2004. Does school integration generate peer effects? Evidence from Boston's Metco program, *American Economic Review*, vol. 94(5): 1613–34.
- Arcidiacono, Peter, and Sean Nicholson. 2005. Peer Effects in Medical School. *Journal of Public Economics* 89: 327–350.
- Arellano M, Bond S. 1991. Some tests of specification for panel data: Monte Carlo evidence and application to employment equations. *Review of Economic Studies*,58: 277–297.
- Boozer, M.A. and Cacciola, S.E. 2001. Inside the 'black box' of Project STAR: estimation of peer effects using experimental data, *Working Paper No. 832*, Economic Growth Center, Yale University.
- Burke, Mary A., and Tim R. Sass. 2013. Peer Effects and Student Achievement. *Journal of Labor Economics* 31(1): 51-82.
- Carrell, S. E., and M. L. Hoekstra. 2010. Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids. *American Economic Journal: Applied Economics*, 2(1): 211-228.
- Carrell, S. E. and M. Hoekstra. 2012. Family Business or Social Problem? The Cost of Unreported Domestic Violence. *Journal of Policy Analysis and Management*, 31:861–875.
- Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2006. Teacher-Student Matching and the Assessment of Teacher Effectiveness. *Journal of Human Resources* 41(4): 778-820.
- Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2007. Teacher Credentials and Student Achievement: Longitudinal Analysis with Student Fixed Effects. *Economics of Education Review* 26(6): 673-682.
- Ding, Weili, and Steven Lehrer. 2007. Do Peers Affect Student Achievement in China's Secondary Schools? *Review of Economics and Statistics* 89: 300–312.
- Figlio, David. 2006. Testing, Crime and Punishment. *Journal of Public Economics* 90(4): 837-851.
- Figlio, David. 2007. Boys Named Sue: Disruptive Children and Their Peers. *Education Finance and Policy* 2: 376–394.

Fletcher, Jason M. 2010. Social Interactions and Smoking: Evidence Using Multiple Student Cohorts, Instrumental Variables, and School Fixed Effects. *Health Economics* 19(4): 466–484.

Gaviria, Alejandro, and Steven Raphael. 2001. School-based Peer Effects and Juvenile Behavior. *Review of Economics and Statistics* 83(2): 257-268.

Gunter, Whitney D., and Nicholas W. Bakken. 2010. Transitioning to Middle School in the Sixth Grade: A Hierarchical Linear Modeling (HLM) Analysis of Substance Use, Violence, and Suicidal Thoughts. *Journal of Early Adolescence* 30(6): 895-915.

Hanushek, Eric, John F. Kain, Jacob Markman, and Steven G. Rivkin. 2003. Does Peer Ability Affect Student Achievement? *Journal of Applied Econometrics* 18: 527–544.

Hanushek, Eric, John F. Kain, and Steven G. Rivkin. 2004. Disruption versus Tiebout Improvement: The Costs and Benefits of Switching Schools. *Journal of Public Economics* 88(9-10): 1721-1746.

Hoxby, Caroline. 2000. Peer Effects in the Classroom: Learning from Gender and Race Variation. NBER working paper no. 7867.

Imberman, Scott, Adriana Kugler, and Bruce Sacerdote. 2012. Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees. *American Economic Review* 102 (5): 2048-2082.

Ishii, Jun, and Steven G. Rivkin. 2009. Impediments to the Estimation of Teacher Value Added. *Education Finance and Policy* 4(4): 520-536.

Jacob, B.A. 2005. Accountability, Incentives, and Behavior: The Impact of High-Stakes Testing in the Chicago Public Schools. *Journal of Public Economics* v.89: 761-796.

Kinsler, Josh. 2012. Assessing Rothstein's Critique of Teacher Value-Added Models. *Quantitative Economics* 3(2): 333-362.

Kinsler, Josh. 2013. School Discipline: A Source or Salve for the Racial Achievement Gap? *International Economic Review* 54(1): 355-383.

Koedel, Cory. 2009. An Empirical Analysis of Teacher Spillover Effects in Secondary School. *Economics of Education Review* 28(6): 682-692.

Lavy, V., Paserman, M. D., and A. Schlosser, 2012. Inside the Black Box of Ability Peer Effects: Evidence from Variation in the Proportion of Low Achievers in the Classroom. *Economic Journal*, 122: 208–237.

Lavy, V., Silva O., and F. Weinhardt. 2012. The Good, the Bad, and the Average: Evidence on Ability Peer Effects in Schools. *Journal of Labor Economics* 30(2): 367-414.

Lefgren, L. 2004. Educational peer effects and the Chicago public schools, *Journal of Urban Economics*, vol. 56(2): 169–91.

Manski, Charles F. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies* 60(3): 531-542.

- Muschkin, C. G., A.N. Beck, and E.J. Glennie 2014. Peer Contexts: Do Old for Grade and Retained Peers Influence Student Behavior in Middle School? *Teachers College Record*, 116(5).
- Neidell, Matthew, and Jane Waldfogel. 2010. Cognitive and Noncognitive Peer Effects in Early Education. *Review of Economics and Statistics* 92(3): 562-576.
- Reback, R. 2008. Teaching to the Rating: School Accountability and the Distribution of Student Achievement. *Journal of Public Economics* 92(5-6): 1394-1415.
- Rivkin, Steven. 2006. Cumulative Nature of Learning and Specification Bias in Education Research. Working Paper.
- Rivkin, Steven G., Hanushek, Eric, and Jacob M. Kain. 2005. Teachers, Schools, and Academic Achievement. *Econometrica* (73):417-458
- Rothstein, Jesse. 2010. Teacher Quality in Education Production: Tracking, Decay, and Student Achievement. *Quarterly Journal of Economics* 125(1): 175-214.
- Rouse, C.E., J. Hannaway, D. Goldhaber, and D. Figlio. 2013. Feeling the Florida Heat? How Low-Performing Schools Respond to Voucher and Accountability Pressure. *American Economic Journal: Economic Policy* v.5: 251-281.
- Todd, Petra E., and Kenneth I. Wolpin. 2003. On the Specification and Estimation of the Production Function for Cognitive Achievement. *Economic Journal* 113(485): F3-F33.
- Trogon, Justin G., James Nonnemaker, and Joanne Pais. 2008. Peer Effects in Adolescent Overweight. *Journal of Health Economics* 27(5): 1388–1399.
- Vigdor, J. and Nechyba, T. 2007. Peer effects in North Carolina public schools, in (L. Woessman and P.E. Peterson, eds.), *Schools and the Equal Opportunity Problem*, pp. 73–101, CESifo Seminar Series. Cambridge and London: MIT Press.
- Zimmerman, D.J. 2003. Peer effects in academic outcomes: evidence from a natural experiment, *Review of Economics and Statistics*, vol. 85(1): 9–23

## Figures and Tables

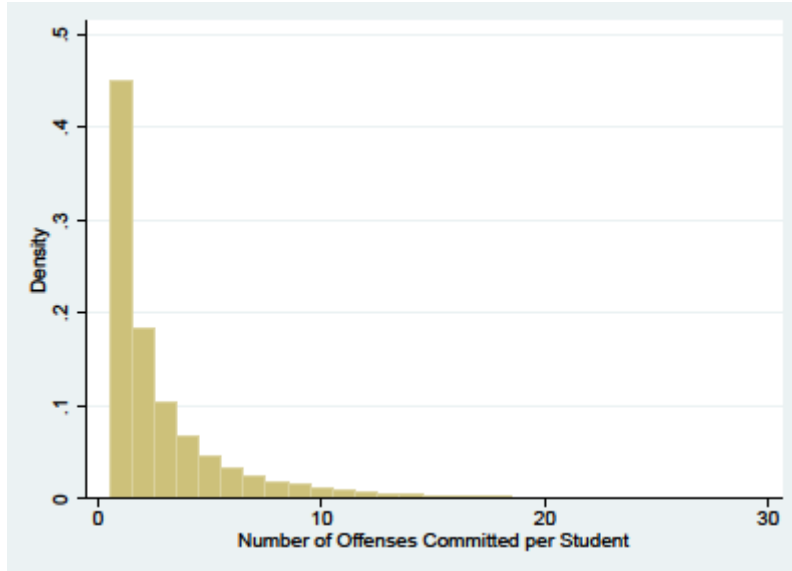


Figure 1: Density of number of offenses committed per academic year, conditional on committing at least one reportable offense. (Top 5% truncated)

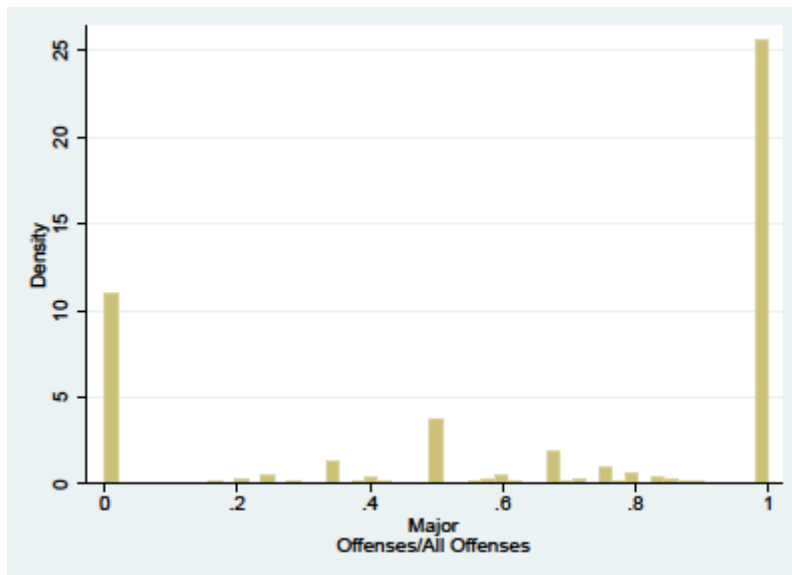


Figure 2: Density of the fraction of offenses committed that are considered "major." (Results in at least an out-of-school suspension.)

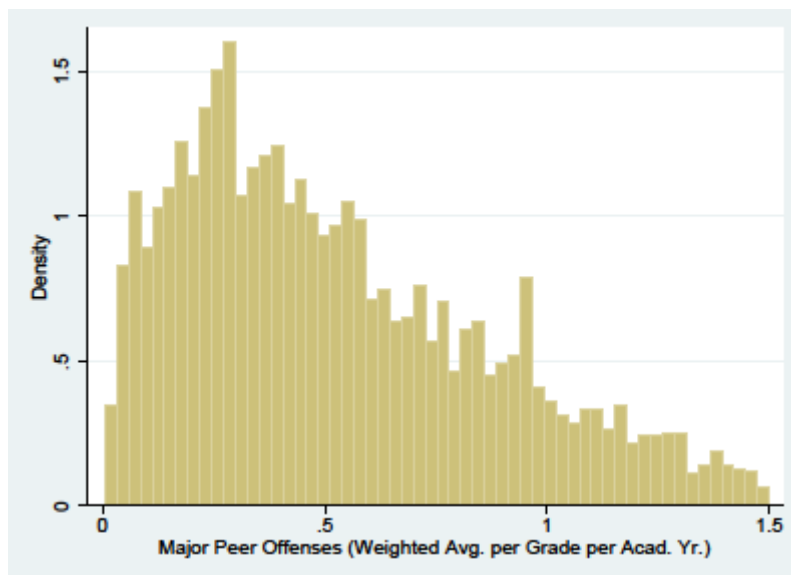


Figure 3: Density of major peer offenses a student is exposed to in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

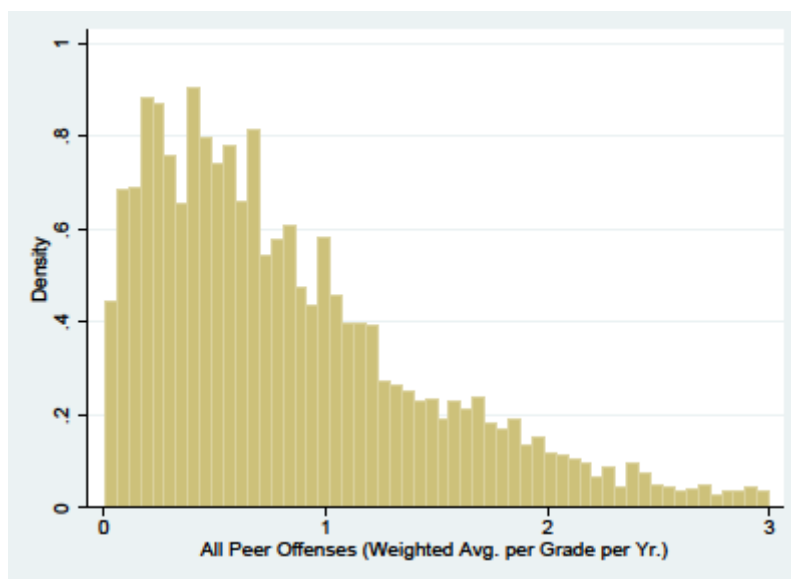


Figure 4: Density of all reportable peer offenses a student is exposed to in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

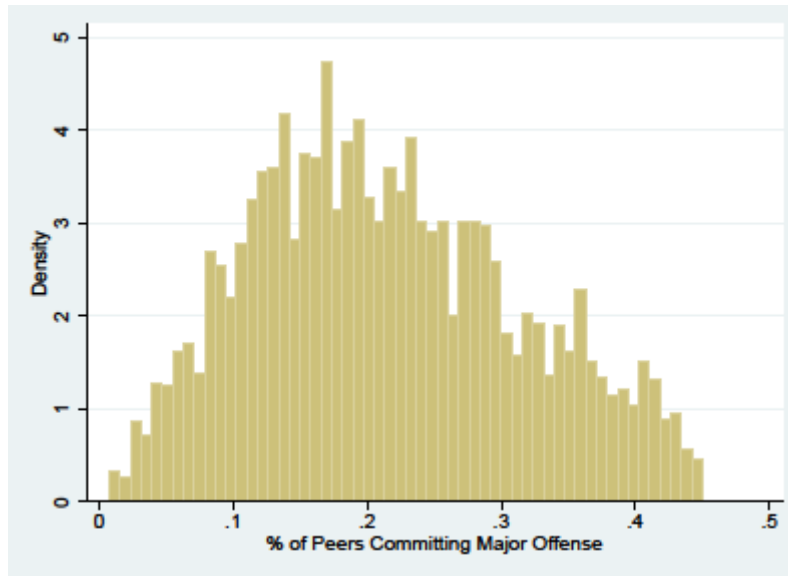


Figure 5: Density of fraction of peers that commit at least one major offense in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

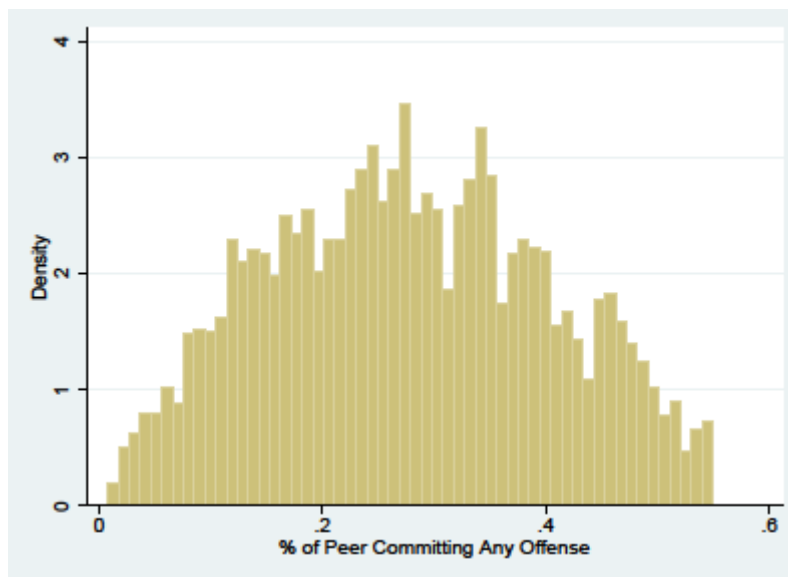


Figure 6: Density of fraction of peers that commit at least one reportable offense in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Academic Outcomes				
Reading Score	0.245	0.909	-3.341	2.682
Math Score	0.547	0.875	-2.737	2.91
Reading Score last year	0.237	0.914	-3.326	2.543
Math Score last year	0.357	0.902	-2.674	2.612

Demographic Characteristics				
All Offenses	0.872	2.335	0	77
Major Offenses	0.555	1.608	0	77
Female	0.504	0.500		
White	0.549	0.498		
LEP	0.041	0.198		
FRL status	0.521	0.500		
English Teacher				
Female	0.877	0.328		
White	0.813	0.390		
Inexperienced	0.068	0.252		
Math teacher				
Female	0.738	0.440		
White	0.818	0.386		
Inexperienced	0.061	0.239		
Observations	136,339			

Table 2-1: First Stage Regressions (Math)

	Major Offenses Only				All Offenses			
	Peer Offense		Last Yr. Score		Peer Offense		Last Yr. Score	
<i>Peer characteristics</i>								
% Female	-1.555	***	0.235	***	-2.500	***	0.240	***
	(0.047)		(0.066)		(0.072)		(0.066)	
% White	-0.053	***	0.046	***	-0.020	***	0.044	***
	(0.004)		(0.005)		(0.006)		(0.005)	
% LEP	-0.539	***	0.085		-0.717	***	0.095	
	(0.063)		(0.088)		(0.097)		(0.088)	
% FRL	1.499	***	0.050	*	1.849	***	0.057	**
	(0.020)		(0.029)		(0.031)		(0.029)	
<i>Teacher characteristics</i>								
Female	-0.006	***	-0.010	***	-0.020	***	-0.010	***
	(0.002)		(0.003)		(0.003)		(0.003)	
White	0.006	**	-0.003		0.003		-0.003	
	(0.003)		(0.004)		(0.004)		(0.004)	
Inexperienced	0.011	***	0.018	***	-0.002		0.018	***
	(0.004)		(0.005)		(0.005)		(0.005)	
<i>Individual characteristics</i>								
LEP	0.016		-0.066	***	0.018		-0.065	***
	(0.013)		(0.018)		(0.020)		(0.018)	
FRL student	0.006		0.006		0.002		0.006	
	(0.004)		(0.006)		(0.006)		(0.006)	



<i>Instruments for 2<sup>nd</sup> Stage</i>							
2-Yrs. Avg. # Offenses	0.050 ***	0.027 ***	0.076 ***	0.009 ***			
	(0.004)	(0.005)	(0.004)	(0.004)			
3-Yrs. test score	0.002	-0.005 ***	0.001	-0.005 ***			
	(0.001)	(0.002)	(0.002)	(0.002)			
F-Stat for instruments	83.91	17.42	193.12	8.07			
All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.							

Table 2-2: First Stage Regressions (Reading)

	Major Offenses Only				All Offenses			
	Peer Offense		Last Yr. Score		Peer Offense		Last Yr. Score	
<i>Peer characteristics</i>								
% Female	-2.236	***	0.119	*	-2.845	***	0.121	*
	(0.046)		(0.071)		(0.073)		(0.071)	
% White	-0.011	***	0.018	***	0.041	***	0.018	***
	(0.004)		(0.005)		(0.006)		(0.005)	
% LEP	-0.430	***	0.182	*	-0.407	***	0.184	*
	(0.065)		(0.100)		(0.103)		(0.100)	
% FRL	1.435	***	-0.070	**	1.867	***	-0.069	**
	(0.022)		(0.033)		(0.034)		(0.033)	
<i>Teacher characteristics</i>								
Female	0.003		0.003		0.005		0.003	
	(0.003)		(0.005)		(0.005)		(0.005)	
White	0.003		0.009	**	0.006		0.009	**
	(0.003)		(0.004)		(0.004)		(0.004)	
Inexperienced	0.019	***	0.007		0.038	***	0.007	
	(0.004)		(0.006)		(0.006)		(0.006)	
<i>Individual characteristics</i>								
LEP	0.019		-0.079	***	0.025		-0.079	***
	(0.014)		(0.021)		(0.021)		(0.021)	
FRL student	0.005		-0.011	*	0.000		-0.011	*
	(0.004)		(0.006)		(0.006)		(0.006)	
<i>Instrument for 2<sup>nd</sup> Stage</i>								
2-Yrs. Avg. # Offenses	0.018	***	0.007		0.028	***	0.005	
	(0.004)		(0.006)		(0.004)		(0.004)	
3-Yrs. test score	-0.001		-0.008	***	0.000		-0.008	***
	(0.001)		(0.002)		(0.002)		(0.002)	
F-Stat	10.4		10.42		23.24		10.55	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 3-1: Second Stage Regressions (Math)

Major Offenses Only					All Offenses			
	Std. Score		Own Offense		Std. Score		Own Offense	
<i>Peer characteristics</i>								
# Avg. Offenses	-3.495	***	3.441	***	-0.846	*	1.739	***
	(1.300)		(0.904)		(0.443)		(0.396)	
% Female	-6.793	***	6.68	***	-3.679	**	5.965	***
	(2.464)		(1.722)		(1.601)		(1.453)	
% White	-0.499	***	0.310	***	-0.355	***	0.272	***
	(0.161)		(0.113)		(0.120)		(0.110)	
% LEP	-2.408	**	1.201	*	-1.265		0.848	
	(1.059)		(0.722)		(0.833)		(0.733)	
% FRL	4.887	***	-4.892	***	1.130		-3.207	***
	(1.875)		(1.292)		(0.779)		(0.684)	
<i>Teacher characteristics</i>								
Female	0.065	***	-0.004		0.076	***	-0.025	
	(0.026)		(0.018)		(0.029)		(0.026)	
White	0.039		0.006		0.022		0.040	
	(0.031)		(0.021)		(0.030)		(0.026)	
Inexperienced	-0.135	***	0.074	***	-0.188	***	0.139	***
	(0.045)		(0.031)		(0.058)		(0.053)	
<i>Individual characteristics</i>								
Last Yr. Score	6.332	***	-3.257	**	7.053	***	-5.036	**
	(2.043)		(1.462)		(2.375)		(2.211)	
LEP	0.503	***	-0.331	***	0.504	***	-0.377	*
	(0.203)		(0.142)		(0.213)		(0.194)	
FRL student	-0.030		0.019		-0.052		0.070	*
	(0.041)		(0.027)		(0.044)		(0.039)	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 3-2: Second Stage Regressions (Reading)

Major Offenses Only				All Offenses			
Std. Score		Own Offense		Std. Score		Own Offense	
<i>Peer characteristics</i>							
# Avg. Offenses	-0.927	4.411	***	-0.595	**	2.719	***
	(0.715)	(1.584)		(0.288)		(0.734)	
% Female	-2.142	10.46	***	-1.763	**	8.002	***
	(1.624)	(3.640)		(0.850)		(2.191)	
% White	-0.040	0.112	***	-0.006		-0.002	
	(0.018)	(0.042)		(0.015)		(0.039)	

% LEP	-0.644 (0.398)	1.524 (0.918)	*	-0.486 (0.252)	*	0.444 (0.673)		
% FRL	1.462 (1.045)	-6.443 (2.332)	***	1.242 (0.555)	**	-5.416 (1.427)	***	
<i>Teacher characteristics</i>								
Female	0.002 (0.009)	-0.010 (0.020)		0.002 (0.009)		-0.017 (0.023)		
White	-0.006 (0.009)	0.061 (0.020)	***	-0.005 (0.009)		0.078 (0.023)	***	
Inexperienced	-0.004 (0.017)	-0.046 (0.037)		0.001 (0.015)		-0.038 (0.038)		
<i>Individual characteristics</i>								
Last Yr. Score	1.176 (0.462)	***	-2.401 (1.114)	**	1.128 (0.440)	***	-2.34 (1.209)	*
LEP	0.181 (0.061)	***	-0.294 (0.141)	**	0.174 (0.056)	***	-0.219 (0.148)	
FRL student	0.017 (0.014)		-0.006 (0.031)		0.012 (0.013)		0.042 (0.033)	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 4-1: Robustness Check (Male vs. Female)

	Males / Major Offenses Only				Females / Major Offenses Only						
	Math Score		Reading Score		Own Offense	Math Score		Reading Score		Own Offense	
<i>Peer characteristics</i>											
# Avg. Offenses	-3.325	**	-3.757		5.440	***	-2.614	*	5.305	1.656	***
	(1.605)		(3.768)		(1.971)		(1.444)		(16.010)	(0.474)	
% Female	-7.482	**	-10.62		12.080	***	-4.098	*	9.163	2.585	***
	(3.523)		(10.720)		(4.301)		(2.215)		(27.570)	(0.741)	
% White	-0.435	***	-0.159		0.487	**	-0.417	**	0.251	0.113	*
	(0.169)		(0.127)		(0.211)		(0.199)		(0.701)	(0.067)	
% LEP	-2.529	**	-1.740		2.424		-1.321		-0.158	0.287	
	(1.255)		(1.770)		(1.513)		(1.327)		(1.900)	(0.434)	
% FRL	4.977	**	5.710		-8.140	***	3.274	*	-6.551	-2.237	***
	(2.459)		(5.665)		(2.994)		(1.962)		(20.130)	(0.641)	
<i>Teacher characteristics</i>											
Female	0.020		0.017		0.019		0.132	**	-0.159	-0.0063	
	(0.022)		(0.024)		(0.026)		(0.062)		(0.467)	(0.021)	
White	0.012		0.022		0.015		0.079		-0.210	0.0224	
	(0.028)		(0.019)		(0.034)		(0.061)		(0.568)	(0.020)	

Inexperienced	-0.071 *	0.072	0.060	-0.249 **	-0.238	0.0491
	(0.037)	(0.090)	(0.044)	(0.116)	(0.671)	(0.039)
<i>Individual characteristics</i>						
Last Yr. Score	3.841 ***	1.165	-3.605 **	8.344 **	9.922	-1.372
	(1.386)	(1.011)	(1.771)	(4.042)	(28.440)	(1.388)
LEP	0.293 *	0.123	-0.341	0.543 *	0.788	-0.153
	(0.169)	(0.128)	(0.208)	(0.326)	(2.000)	(0.109)
FRL student	0.040	0.023	-0.029	-0.170 *	0.175	0.0328
	(0.044)	(0.041)	(0.053)	(0.101)	(0.490)	(0.035)

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 4-2: Robustness Check (Male vs. Female)

	Males / All Offenses			Females / All Offenses		
	Math Score	Reading Score	Own Offense	Math Score	Reading Score	Own Offense
<i>Peer characteristics</i>						
# Avg. Offenses	-0.746 *	-1.246 *	2.423 ***	-0.466	0.215	0.915 ***
	(0.403)	(0.722)	(0.622)	(0.639)	(1.264)	(0.294)
% Female	-3.267 **	-4.503 *	8.840 ***	-2.412	0.72	2.946 ***
	(1.570)	(2.646)	(2.422)	(1.922)	(3.010)	(0.903)
% White	-0.253 ***	-0.031	0.341 ***	-0.337 *	0.120	0.111
	(0.082)	(0.027)	(0.129)	(0.193)	(0.188)	(0.092)
% LEP	-1.266 *	-0.672	2.305 **	-0.430	-1.196	-0.623
	(0.732)	(0.469)	(1.118)	(1.370)	(2.104)	(0.627)
% FRL	1.246	2.560 *	-4.813 ***	0.150	0.086	-1.568 ***
	(0.776)	(1.449)	(1.181)	(1.182)	(1.847)	(0.541)
<i>Teacher characteristics</i>						
Female	0.017	0.015	0.033	0.171 *	-0.078	-0.0578
	(0.020)	(0.014)	(0.030)	(0.090)	(0.151)	(0.043)
White	0.006	0.018	0.048	0.067	-0.119	0.039
	(0.025)	(0.012)	(0.038)	(0.068)	(0.195)	(0.031)
Inexperienced	-0.102 ***	0.040	0.122 **	-0.334 *	-0.106	0.115
	(0.034)	(0.036)	(0.053)	(0.173)	(0.198)	(0.082)
<i>Individual characteristics</i>						
Last Yr. Score	3.736 ***	0.752 *	-4.430 **	10.13 *	6.074	-3.438
	(1.184)	(0.425)	(1.906)	(5.670)	(10.870)	(2.739)
LEP	0.297 **	0.103	-0.440 *	0.571	0.604	-0.153
	(0.150)	(0.075)	(0.234)	(0.396)	(0.918)	(0.187)
FRL student	0.025	-0.003	0.002	-0.221	0.117	0.105
	(0.150)	(0.018)	(0.056)	(0.139)	(0.205)	(0.068)

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 5-1: Robustness Check (Minority vs. White Students)

	Minority / Major Offenses Only				White / Major Offenses Only			
	Math Score	Reading Score	Own Offense		Math Score	Reading Score	Own Offense	
<i>Peer characteristics</i>								
# Avg. Offenses	-5.566 (3.575)	5.772 (9.596)	6.776 (3.355)	**	0.561 (0.586)	0.261 (1.005)	0.722 (0.347)	**
% Female	-7.837 (4.911)	13.18 (21.920)	9.807 (4.595)	**	2.648 (1.349)	** (2.511)	0.836 (0.795)	1.241
% White	-0.860 (0.521)	* (1.171)	0.658 (0.485)		0.258 (0.089)	*** (0.038)	-0.005 (0.051)	0.00629
% LEP	-5.594 (3.719)	5.381 (8.799)	5.477 (3.421)		0.497 (0.781)	-0.557 (0.277)	** (0.470)	-0.962 **
% FRL	9.185 (5.972)	-9.919 (16.500)	-11.260 (5.596)	**	-0.615 (0.645)	0.008 (0.964)	-0.699 (0.380)	* 
<i>Teacher characteristics</i>								
Female	0.020 (0.041)	0.106 (0.205)	0.013 (0.037)		-0.038 (0.026)	0.007 (0.016)	0.0112 (0.015)	
White	0.083 (0.067)	0.120 (0.218)	-0.047 (0.063)		-0.003 (0.027)	-0.004 (0.014)	0.0163 (0.016)	
Inexperienced	-0.045 (0.066)	-0.039 (0.111)	0.047 (0.059)		0.050 (0.045)	-0.028 (0.033)	-0.00133 (0.026)	
<i>Individual characteristics</i>								
Last Yr. Score	7.37 (4.133)	* (19.860)	-11.52 (3.937)		-5.567 (1.202)	*** (0.325)	0.589 (0.681)	* 
LEP	0.290 (0.239)	-0.727 (1.364)	-0.315 (0.221)		-0.902 (0.350)	*** (0.105)	0.083 (0.203)	0.153
FRL student	-0.106 (0.094)	-0.061 (0.159)	0.088 (0.087)		-0.015 (0.030)	0.004 (0.013)	0.00775 (0.018)	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 5-2: Robustness Check (Minority vs. White Students)

	Minority / All Offenses				White / All Offenses			
	Math Score	Reading Score	Own Offense		Math Score	Reading Score	Own Offense	
<i>Peer characteristics</i>								
# Avg. Offenses	-2.321 (1.572)	4.809 (15.160)	4.221 (1.866)	**	-0.358 (0.283)	-0.338 (0.299)	0.581 (0.235)	***
% Female	-6.241 (4.057)	15.45 (48.490)	10.860 (4.807)	**	0.457 (0.907)	-0.885 (0.965)	1.355 (0.754)	*
% White	-0.557 (0.340)	0.972 (3.176)	0.586 (0.402)		0.203 (0.068)	*** (0.011)	-0.018 (0.055)	

% LEP	-3.347 (2.458)	7.692 (23.740)	4.512 (2.862)	1.061 (0.822)	-0.318 (0.355)	-0.372 (0.685)
% FRL	4.333 (3.052)	-11.390 (35.870)	-8.688 *** (3.606)	0.479 (0.442)	0.645 * (0.359)	-0.868 *** (0.367)
<i>Teacher characteristics</i>						
Female	0.014 (0.042)	0.215 (0.705)	0.017 (0.048)	-0.051 * (0.030)	0.018 (0.011)	-0.00491 (0.024)
White	0.077 (0.065)	0.206 (0.667)	-0.030 (0.078)	-0.019 (0.030)	-0.001 (0.011)	0.00941 (0.025)
Inexperienced	-0.137 * (0.080)	0.013 (0.200)	0.186 * (0.098)	0.040 (0.044)	0.003 (0.024)	-0.0165 (0.036)
<i>Individual characteristics</i>						
Last Yr. Score	8.21 * (4.657)	-22.82 (71.660)	-8.595 (5.646)	-4.511 *** (1.238)	0.725 ** (0.359)	0.324 (0.979)
LEP	0.274 (0.235)	-1.431 (4.690)	-0.340 (0.278)	-0.929 *** (0.361)	0.095 (0.108)	0.219 (0.292)
FRL student	-0.135 (0.235)	-0.088 (0.367)	0.173 (0.128)	-0.010 (0.030)	0.007 (0.014)	0.0433 * (0.025)

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 6-1: Robustness Check (Rural vs. City)

	Rural / Major Offenses Only			City / Major Offenses Only		
	Math Score	Reading Score	Own Offense	Math Score	Reading Score	Own Offense
<i>Peer characteristics</i>						
# Avg. Offenses	-7.003 ** (3.221)	0.68 (1.107)	5.716 *** (2.021)	-1.439 ** (0.665)	-1.565 (1.089)	1.556 *** (0.565)
% Female	-12.64 ** (5.804)	1.758 (2.625)	9.489 *** (3.620)	-2.926 *** (1.140)	-3.527 (2.449)	3.31 *** (0.987)
% White	-0.656 *** (0.282)	0.005 (0.048)	0.423 *** (0.179)	-0.325 *** (0.106)	0.077 (0.053)	0.135 (0.089)
% LEP	-7.040 ** (3.193)	0.637 (1.438)	3.715 * (1.986)	-0.642 (0.718)	0.256 (0.379)	0.131 (0.584)
% FRL	9.204 ** (4.274)	-0.591 (1.312)	-7.012 *** (2.651)	1.951 * (1.080)	2.397 (1.672)	-2.723 *** (0.905)
<i>Teacher characteristics</i>						
Female	-0.035 (0.059)	-0.017 (0.025)	0.079 ** (0.036)	0.032 (0.023)	-0.011 (0.016)	0.0313 * (0.018)
White	0.133 * (0.075)	-0.021 (0.019)	-0.095 ** (0.048)	0.022 (0.029)	0.000 (0.012)	0.0295 (0.024)
Inexperienced	-0.324 ***	-0.090	0.133 * (0.098)	-0.039 (0.044)	-0.102 (0.024)	0.0509 * (0.036)

	(0.116)		(0.103)		(0.077)		(0.038)		(0.065)		(0.031)	
<i>Individual characteristics</i>												
Last Yr. Score	4.5	**	1.131	*	-0.936		4.363	***	0.886		-2.201	*
	(2.110)		(0.663)		(1.398)		(1.387)		(0.592)		(1.202)	
LEP	0.368	*	0.231	***	-0.213		0.380	**	0.141		-0.2	
	(0.220)		(0.094)		(0.142)		(0.179)		(0.093)		(0.150)	
FRL student	-0.003		0.000		-0.039		-0.029		0.023		0.0401	
	(0.054)		(0.018)		(0.034)		(0.044)		(0.020)		(0.035)	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

Table 6-2: Robustness Check (Rural vs. City)

Rural / All Offenses					City / All Offenses							
	Math Score		Reading Score		Own Offense		Math Score		Reading Score		Own Offense	
<i>Peer characteristics</i>												
# Avg. Offenses	-1.107		0.058		1.866	***	-0.38		-5.732		1.1	***
	(0.690)		(0.198)		(0.408)		(0.345)		(10.950)		(0.401)	
% Female	-4.094	*	0.37		4.824	***	-2.503	**	-10.37		4.635	***
	(2.486)		(0.767)		(1.468)		(1.148)		(19.870)		(1.392)	
% White	-0.308	**	-0.024		0.205	**	-0.310	***	0.870		0.219	*
	(0.156)		(0.017)		(0.092)		(0.106)		(1.650)		(0.125)	
% LEP	-3.165		-0.128		1.244		-0.099		4.978		0.453	
	(2.013)		(0.495)		(1.201)		(0.680)		(9.651)		(0.759)	
% FRL	1.457		0.153		-2.540	***	0.299		13.690		-2.889	***
	(1.069)		(0.255)		(0.621)		(0.770)		(26.160)		(0.874)	
<i>Teacher characteristics</i>												
Female	0.118	*	-0.006		-0.033		0.017		-0.023		0.0474	*
	(0.066)		(0.014)		(0.040)		(0.024)		(0.067)		(0.026)	
White	-0.007		-0.017		0.018		0.026		0.093		0.0366	
	(0.050)		(0.015)		(0.030)		(0.031)		(0.182)		(0.035)	
Inexperienced	-0.346	***	-0.035		0.131		-0.062		-0.087		0.0885	**
	(0.148)		(0.027)		(0.089)		(0.040)		(0.157)		(0.045)	
<i>Individual characteristics</i>												
Last Yr. Score	7.232	**	1.116	*	-2.549		4.69	***	2.003		-3.614	*
	(3.686)		(0.637)		(2.205)		(1.561)		(3.932)		(1.905)	
LEP	0.501	*	0.229	***	-0.228		0.368	**	0.410		-0.272	
	(0.304)		(0.090)		(0.182)		(0.186)		(0.754)		(0.218)	
FRL student	-0.088		0.005		0.050		-0.031		0.039		0.0546	
	(0.304)		(0.018)		(0.043)		(0.046)		(0.086)		(0.052)	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.



Table 7-1: Falsification Test: OLS Regressions

	Own FRL		Own Disability	
Peer Characteristic	0.141	***	0.016	***
	(0.008)		(0.008)	

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. Other control variables include: peer gender, race, disabled, FRL, LEP, own gender, race, disabled, FRL, LEP, teacher gender, race, experience, prior test score, school, grade-year dummy variables.

Table 7-2: Falsification Test: First Stage Regressions

	Free/Reduced Price Lunch			Disability		
	Peer FRL		Last Yr. Score	Peer Disability		Last Yr. Score
<i>Instruments for 2<sup>nd</sup> Stage</i>						
2-Yrs. Peer Characteristic	0.116	***	-0.022	0.009	***	0.105 *
	(0.002)		(0.019)	(0.002)		(0.062)
3-Yrs. test score	-0.003	***	-0.007 ***	-0.0002	**	-0.007 ***
	(0.0002)		(0.002)	(0.0001)		(0.002)
F-Stat for instruments	2462.61		8.57	9.68		9.03

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. Other control variables include: peer gender, race, disabled, FRL, LEP, own gender, race, disabled, FRL, LEP, teacher gender, race, experience, prior test score, school, grade-year dummy variables.

Table 7-3: Falsification Test: Second Stage Regressions

	Own FRL	Own Disability
<i>Instrumented Variables</i>		
Peer Characteristic	0.111	-0.802
	(0.106)	(0.443)
Last Yr. Score	-0.157	0.372 **
	(0.129)	(0.177)

All specifications define peers as students in the same grade. Standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. Other control variables include: peer gender, race, disabled, FRL, LEP, own gender, race, disabled, FRL, LEP, teacher gender, race, experience, prior test score, school, grade-year dummy variables.

## Appendix

### A. List of Offenses

Affray

Aggressive behavior

Alcohol Possession

Assault - other

Assault involving the use of a weapon  
Assault on non-student w/o weapon not resulting in injury  
Assault on school personnel not resulting in injury  
Assault on student  
Assault on student w/o weapon and not resulting in injury  
Assault resulting in a serious injury  
Being in an unauthorized area  
Bomb threat 04  
Bullying  
Burning of a school building  
Bus misbehavior  
Cell phone use  
Communicating threats  
Cutting class  
Death by other than natural causes  
Discrimination  
Disorderly conduct  
Disrespect of faculty/staff  
Disruptive behavior  
Distribution of a prescription drug  
Dress code violation  
Excessive display of affection  
Excessive tardiness  
Extortion  
False fire alarm  
Falsification of information  
Fighting  
Gambling  
Gang activity  
Harassment – sexual  
Harassment – verbal  
Hazing  
Honor code violation  
Immunization  
Inappropriate items on school property  
Inappropriate language/disrespect  
Insubordination  
Kidnapping  
Late to class  
Leaving class without permission  
Leaving school without permission  
Misuse of School Technology  
Mutual sexual contact between two students

Other  
 Other School Defined Offense  
 Physical Exam  
 Possession of a firearm or powerful explosive  
 Possession of a weapon (excluding firearms/explosives)  
 Possession of Another Person's Prescription Drug  
 Possession of chemical or drug paraphernalia  
 Possession of controlled substance - cocaine  
 Possession of controlled substance - marijuana  
 Possession of controlled substance - other  
 Possession of controlled substance - Ritalin  
 Possession of counterfeit items  
 Possession of Student's Own Prescription Drug  
 Possession of tobacco  
 Property damage  
 Rape  
 Repeat Offender  
 Robbery with a dangerous weapon  
 Robbery without a dangerous weapon  
 Sale of controlled substance - cocaine  
 Sale of controlled substance - marijuana  
 Sale of controlled substance - other  
 Sale of controlled substance - Ritalin  
 Sexual assault not involving rape or sexual offense  
 Sexual offense  
 Skipping class  
 Skipping school  
 Taking indecent liberties with a minor  
 Theft  
 Truancy  
 Unlawfully setting a fire  
 Use of alcoholic beverages  
 Use of controlled substances  
 Use of counterfeit items  
 Use of narcotics  
 Use of tobacco  
 Violent Assault Not Resulting in Serious Injury

B. List of Disciplinary Consequences: Discipline categories for minor offenses are starred.

Before School Detention\*  
 Boot camp

Bus Suspension\*  
Conference\*  
Corporal Punishment  
Court-ordered Probation  
Day Reporting Center  
Day Treatment Program  
Detention\*  
Expulsion  
Homebound instruction  
Hospital Treatment Program  
ISS - In-School Suspension\*  
ISS Partial Day\*  
LEA Operated Alternative School  
Lunch Detention\*  
Off-site Operated Alternative School  
OSS 10 days or less  
OSS 1-10 Pending Student Hearing  
OSS 11-365 days  
OSS 365 days  
Referral to Community Agency  
Report to Law Enforcement  
Residential Treatment Home or Center  
Restriction of School Privileges\*  
Revoke Driving Privileges\*  
Saturday Academy  
Sent Home Early  
Student Oral Warning\*  
Student Pays Restitution\*  
Student Written Warning\*  
Supervised Activities\*  
Time Out\*  
Tobacco Awareness Class\*  
Work Detail  
Youth Development Center