Peer Delinquency and Student Achievement in Middle School

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Abstract:

This paper studies the relationship between peer delinquency and student achievement in North Carolina middle schools. We define severity of the delinquent act using the associated punishment and calculate the average exposure to peer delinquency. Our identification strategy uses this new measure, a rich set of control variables including student, peer, and teacher characteristics, and a novel instrumental variable that captures the indirect social network impact of peer misbehavior. A 10 percent increase in the number of "major" incidents that a student at an average North Carolina school is exposed to would decrease his or her standardized math score by approximately 6.2 percent of a standard deviation.

1. Introduction

Peers undoubtedly have an important role in determining students' educational outcomes. It is standard practice to include peers' demographic characteristics (e.g., gender, race/ethnicity, poverty status, language proficiency) in any education production function.[1] Parents instinctively "know" about the importance of having good classmates, often making residential decisions at least partly on peer characteristics of the school in the catchment area. Many schools track students by academic ability, resulting in increased segregation along socio-economic lines. Disciplinary policies are often aimed at isolating troublesome students away from the rest of the student body, to mitigate potential negative influences. However, despite considerable focus and attention from parents and administrators, the relationship between peers' delinquent behavior and student achievement has been understudied empirically.

Although many studies have acknowledged the potential role for peer delinquency in determining academic performance (Hoxby, 2000; Gaviria 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 6th 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 scores. Carrell and Hoekstra (2010) use the parents' domestic violence records to capture the negative spill-over effects to classmates. Carrell, Hoekstra, and Kuka (2016) also look at the long-run impacts of these spill-over effects. Lavy, Paserman, and Schlosser (2012) use prior year retention in the same grade as an instrument for peer delinquency. Kinsler (2013) studies

[1] See Angrist and Lang 2004, Boozer and Cacciola 2001, Lavy, Silva, and Weinhardt 2012; Hanushek et al. 2003; Imberman, Kugler, and Sacerdote 2012; Burke and Sass 2013, for example.

the potential deterrent effect and academic improvement arising from punishing and removing delinquent peers from the classroom in a structural model.

In this study, we use administrative data of public middle schools in North Carolina from 2009-2010 to 2011-2012 to estimate the reduced-form effect of peer delinquency on math and reading end-of-grade (EOG) test scores. Delinquent behaviors can become quite serious in middle school (e.g., Gunter and Bakken 2010), and most delinquent students in high school already have a long established pattern of offenses and punishments. Therefore, middle school is the natural place to study the early negative impacts of serious peer misbehavior (Loeber and Hay 1997).

Identification of the effect of peer delinquency on academic outcomes is challenging (Angrist 2014). The correlation between peer delinquency and academic outcomes could be due to true causal effects, non-random sorting of students into schools and classes (e.g., tracking by ability or segregating delinquent students), or shared context both observed and unobserved by the econometrician (Manski 1993).

To address these challenges, we use a combination of fixed effects, more detailed data, and a novel instrument.[2] We use 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 characteristics.

[2] A previous version of the paper utilized a fixed-effects value-added approach and generated 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). Another specification that used first differences and Arrellano-Bond (1991) type instruments yielded qualitatively similar results. These results are available in the online appendix: sites.google.com/site/tomsyahn/.

Most importantly, we use a new instrument that captures the delinquent behaviors of a student's current peers' peers from the previous academic year to whom the student is never exposed. Under the assumption that delinquent behavior spreads through social networks (Figlio 2007), the delinquent behaviors of these "peers of peers" provide exogenous variation in a student's exposure to peer delinquency that is orthogonal to the student's outcomes because he/she has never been a direct peer of these "peers of peers." This instrument effectively captures the causal component of peer delinquency on own academic outcomes.[3]

In addition, because the instrument uses the same delinquency data from the administrative data set, it has the advantage of being easily reproducible across other education systems that collect similar academic and behavioral data. Most of the studies mentioned above use variables unique to their data (such as the availability of students' first names or parental criminal records) to instrument or proxy for peer delinquency. Because the causal mechanism we seek to uncover is the transmission of the negative impacts of delinquent behavior from student to student, our peer of peers' misbehavior is a more direct measure of this peer effect.

We find that peer delinquency negatively impacts a student's test scores. An increase by ten percent in the average number of major (suspension-resulting) delinquent acts by peers at a representative school in North Carolina results in a 6.2 percent of a standard deviation decrease in math test scores. A similar sized increase in the average number of any reportable delinquent acts by peers leads to a 5.3 percent of a standard deviation decrease in math test scores.

Section 2 describes the data used in the study. Section 3 presents the econometric model and a detailed analysis of the instrument used. We present results in section 4 and conclude in section 5.

[3] Gibbons and Telhaj (2008) and Lavy et al. (2012) are the only other examples of studies that exploit the re-mixing of compulsory school transitions and use information of peers who had different peers beforehand, to estimate peer effects.

2. Data

We use an administrative data set of North Carolina public schools covering four school years: 2009-2010 through 2011-2012.[4] 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 analytic sample to 6th grade students. We use these students because they are in the first year of middle school. Using middle school data is important because there are fewer major offenses for students below 5th grade. The fact that these students have moved to a new school this academic year is important for our identification strategy, because this (involuntary) change results in a wide-scale remixing of peers. 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).[5]

End-of-grade Test Scores

Two academic outcome variables of interest are standardized exam scores. North Carolina uses standardized scores, which are similar to z-scores, in its accountability calculations. 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, 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.[6]

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

[4] Data and computational restrictions prevent us from going further back in time.
[5] Including these students does not qualitatively change the results.
[6] For more details, see http://www.ncpublicschools.org/docs/accountability/reporting/abc/2011-12/academicchange.pdf.

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.

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.[7] 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 0.72 (see for example, Table 1 (Summary Statistics) of this study or Mushkin et al. 2014). Unsurprisingly, misbehavior in 5th grade is strongly correlated with misbehavior in middle school.

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 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

[7] See the Appendix for a more extensive list of the most common offenses.

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 out of school suspension (OSS).[8] 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 (for example, see Figlio 2007) 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 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. Figure 1, which plots the histogram

[8] See the Appendix for a complete list of disciplinary measures.

of number of offenses per student conditional on committing at least one offense, shows clearly that a large fraction of students are one-time (or rare) offenders.

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 10th 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/grade *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:

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

This measure has the advantage of mitigating measurement problems described above.

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 show 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). More importantly, the scale of differences across major and all offenses is clearly revealed. While the mean exposure for number of students committing major and all offenses are similar, the mean exposure for the number of all offenses is about one-and-half times the exposure to major offenses.

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 years of the sample, and the (unobservable) disciplinary harshness of the principal should be captured in the school dummy.[9] 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.[10]

Explanatory Variables

In addition to student offenses, we control for gender, ethnicity, free or reduced price lunch (FRL) status, and limited English proficiency (LEP) status. 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

For our main analysis, we focus on students with less than or equal to two OSS per academic year. These students are likely the most susceptible to the negative influence of peer delinquency; students with multiple OSS *per semester* are likely the source of the

[9] The unconditional probability of a principal transferring to a different school in North Carolina during the study period is below eight percent.

[10] One method of eliminating this issue would be to focus only on offenses that automatically trigger a law-enforcement response, such that a principal would have no control over the severity of the punishment. Unfortunately, our sample of 6th graders had very few incidents which required police intervention. This may be an exploitable mechanism if the focus were on older students.

problem. We lose about 7 percent of student observations by restricting the sample in this way.[11] We also report results on the full sample of students in the Appendix. In both sets of analyses, all students, including the repeat offenders, are included in the grade-level means used for peer offenses (Equation 1).

Table 1 presents descriptive statistics for students and teachers in our sample. Among 6th grade students in North Carolina with two or fewer OSS per year, the average student committed approximately 0.25 offenses per year. Of these, approximately 60 percent were major offenses that 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 percent of students were non-white. The state had a relatively small number of LEP students, at about five 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.

3. Methods

Our initial model of outcomes is given by equation (2) below:

$$A_{ijst} = A_{ijst-1}\varphi + \bar{O}_{ist}\alpha + X_{ist}\beta + T_{jst}\gamma + \bar{A}_{ist-1}\theta + \bar{X}_{ist}\delta + \rho_s + \tau_t + \varepsilon_{ijst} \quad (2)$$

The dependent variable A_{ijst} represents the standardized test score in reading or mathematics for student *i*, teacher *j*, school/grade *s*, and school year *t*. We include the

[11] The average number of OSS among the excluded students is approximately 5 times in an academic year.

student's prior year test score (A_{ijst-1}) to proxy for the stock of education achievement built up until this year. The main peer characteristic we are interested in is the average number of offenses committed by peers, $\bar{O}_{ist}$. X_{ist} represents student characteristics, T_{jst} represents teacher characteristics, $\bar{A}_{ist-1}$represents average peer prior year test score, and $\bar{X}_{ist}$ represents student peer demographic characteristics.[12] In addition, we include school/grade and year fixed effects, ρ_s and τ_t, respectively. The idiosyncratic error is ε_{ijst}.

If students were truly randomly assigned to peer groups, and if students' own academic outcomes were purely causally impacted by peer behavior and demographic characteristics, OLS parameters from equation (2) would yield the impact of peer delinquency on own academic outcomes.

In matrix notation, we can write equation (2) as:

$$\boldsymbol{A_t} = \boldsymbol{\beta D_t} + \boldsymbol{\alpha G_t O_t} + \boldsymbol{\delta G_t Z_t} + \boldsymbol{\rho_s} + \boldsymbol{\tau_t} + \boldsymbol{\varepsilon_t} \qquad (3)$$

The matrix $\boldsymbol{D_t}$ contains last year test scores and own and teacher demographic characteristics. The matrix $\boldsymbol{Z_t}$ contains peer averages for last year's test score and student demographics. The matrix $\boldsymbol{G_t}$is a N x N interaction-matrix which identifies student i's peer group. N is the total number of students in the sample. If two students i and k are peers (i.e., in the same grade and school), $G(i,k) = G(k,i) = \frac{1}{n_s - 1}$ and $G(i,k) = G(k,i) = 0$ if they are not peers. n_s is the size of the peer group for the pair of students. Conditional on school fixed effects, students are randomized into grades based on age, mitigating the effects of endogenous selection of peers.[13]

There is reason to believe that student achievement and the level of classroom disruptions will be determined together. For instance, if students with disciplinary problems

[12] Excluding peer's last year test scores does not qualitatively alter the results.
[13] Note that N is not subscripted. It is defined over the entire state. Therefore, $\boldsymbol{G_t}$ is an approximately 45,000 x 45,000 matrix. While this is overkill for an OLS specification (as defining peers at the school level will suffice), defining peers at the state level becomes necessary for our instrument scheme.

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 (Figlio 2007, Carrell and Hoekstra 2010 and 2012, and Lavy, Paserman, and Schlosser 2012).[14]

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 less manipulable. 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.

Second, our data allows us to include school/grade (ρ_s), and year (τ_{gt}) fixed effects.[15] 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.

Of course, we still have not accounted for the potential endogeneity of peer behavior and peer demographic characteristics (the social effects). To do so, we use the panel data nature of the North Carolina data set, and the fact that a large fraction of students move from elementary schools to middle schools between 5th and 6th grades. Moving and being shuffled into different middle schools, along with the natural turnover in peers that arise from transfers

[14] Some studies take advantage of random assignment of students to peer groups. See Boozer and Cacciola 2001 and Zimmerman 2003, for example.

[15] See Vigdor and Nechyba 2004, Burke and Sass 2013, Lefgren 2004, and Trogdon, Nonnemaker, and Pais 2008 for examples of peer effect estimation using fixed-effects.

into and out of the state's public school system in any given year, means that these students are exposed to a significant number of peers they had no interaction with in the previous academic year. These new peers bring with them exposure to other students from the previous year.

Our key econometric innovation here is that we use $\boldsymbol{G_{t-1}}$ which is the peer group any student was exposed to in the *previous* year. Taking advantage of the relationships generated when $\boldsymbol{G_{t-1}}$ is subtracted from $\boldsymbol{G_t}$ and vice versa, we define a new *indirect* social matrix $\widetilde{\boldsymbol{G_t}} = (\boldsymbol{G_{t-1}} - \boldsymbol{G_t}) > \boldsymbol{0} \cdot (\boldsymbol{G_t} - \boldsymbol{G_{t-1}}) > \boldsymbol{0}$, where the *i*,*j*-th entry signifies a two-step path from student *i* this year to student *j last year* for which there is no direct path between *i* and *j* (i.e., $\widetilde{\boldsymbol{G_t}}$ is a matrix of indicators for intransitive triads). Simulations in the Appendix demonstrate the generation of these two-step paths.[16] When (row-normalized) $\widetilde{\boldsymbol{G_t}}$ pre-multiplies a vector of lagged (*t-1*) characteristics, the resulting column vector represents, for each student, the average lagged characteristic among lagged peers of current peers who are never peers of the student. Because there will be students from (*t-1*) with no path to some students in year *t* (e.g., by moving from elementary to middle school), this matrix generates valid instruments through intransitive triads.[17] An instrumental variable model is estimated using a two-step GMM procedure with errors clustered at the school-cohort level.

For intuition, consider students *i* and k who are peers in year *t*, while students *k* and l, but not *i*, were peers in year *t-1*. The key assumption is that student k's behavior will be correlated with student l's behavior through social influence/peer effects. However, because student i has *never* been exposed to student l, he/she is incapable of impacting student i's outcome, except indirectly through impacting student k. The goal is to remove "reflection" from *i*'s influence on *k*. Student *k* can influence both *i* and *l*. Similar to standard instrumental

[16] Stata/Mata code for simulations is available upon request.
[17] See Bramoulle et al. (2009) for an analogous set up.

variable properties, the main assumption is that l's correlation with i is only through k. Thus, the matrix of peers of peers, $\widetilde{\boldsymbol{G_t}}$, provides valid exogenous variation for identification.

In addition, our framework lessens worries about students sorting into different schools. Unless student i is at school s specifically to avoid meeting student l (who attends some other school $-s$), some central agent specifically split these two students up, or student i's (and student l's) parents specifically located to school catchment zones to avoid each other, all the while being indifferent to exposure to student k, we do not have to worry about sorting at the school/grade level.

Identification Using $\widetilde{\boldsymbol{G_t}}$

Our instrument relies on "indirect peer networks" created when students from different elementary schools meet to become grade-mates in their current middle school. This instrument scheme is feasible if and only if an elementary school sends students to more than one middle school, and more than one elementary school send students to a given middle school. If a single elementary school feeds into a single middle school, there will be no "peers of peers" to construct the instrument. If most of the sample is composed of single elementary to single middle school connections, the variation in "indirect peer network" instrument will arise almost exclusively from transfer students.

While students transferring in to and out of a school in any given year will insure that the composition of peers for a student will change every year, unless transferring students are coming from in-state, the peer composition for these students last year will be unobservable to us. In addition, if there is a systemic reason why students transfer out of their district, this may bias the instrument. For example, if many students (or their parents) choose to transfer because of they do not wish to be continually exposed to the same negative peers in middle school, the indirect peer network instrument for schools with larger transfer populations may have large values for peer delinquency exposure.

Figure 7 shows the distribution of the number of middle schools that 5th grade students will move to from a particular elementary school. On average, an elementary school will send its students to 10.6 different middle schools.[18] Figure 8 shows the distribution of the number of elementary schools from which a particular middle school receives students. A middle school cohort is composed of students originating from approximately 21.3 different elementary schools. There seems to be an adequate degree of “mixing” among peers as they transition from elementary to middle schools.

Figures 9 and 10 show the same distributions as above, restricted to students that move to a middle school within the same district as their elementary school. This isolates peer network formation excluding inter-district or out-of-state transfer students. While the average numbers of sending elementary schools and receiving middle schools decline, there are still roughly 6.9 with-in district receiving district middle schools and 13.8 with-in district sending elementary schools.

Figure 11 shows how many of a middle school student’s current peers were not peers in the previous year. The distribution is bi-modal, with a large mass near 0.8 and another large mass near 0.1. Students with new-peer exposure greater than 0.8 are most likely inter-district transfers. Those with new-peer exposure less than 0.1 are most likely located in small rural districts that usually have one elementary and one middle school. Approximately 68.3 percent of the full sample has a new-peer exposure rate between 0.1 and 0.8.

Figure 12 shows how students within Charlotte-Mecklenburg school district (the largest in the state) move from elementary schools (in blue) to middle schools (in green) forming indirect peer networks. The coloring of the lines connecting the schools represent the number of students moving, with red representing the largest amount of peers moving together. It is evident that elementary schools send students to many middle schools, and middle schools

[18] All students with no prior year record (most likely transfer students from out-of-state or private schools) are considered originating from one school.

accept students from many elementary schools, creating a mix of contemporaneous peers where a sizable fraction are being exposed to each other for the first time.[19]

Robustness checks

In our instrumental variable design, school assignments from 5th to 6th grade should be randomizing students' exposure to delinquent behavior. If the randomization is working, the other covariates should be balanced across different exposures to delinquency and, thus, adjusting for covariates in the regression model should have little to no effect on the coefficient of interest. We report results from five different specifications that build cumulatively from only including school and year fixed effects in the two-stage least squares specification (1) to adding the student's prior year test score (2), own demographic characteristics (3), peer characteristics (4), and subject teacher characteristics (5). Stable estimates for the instrumental variable in the first stage and (instrumented) peer offenses in the second stage would provide evidence in support of the design.

We also conduct falsification tests that use our instrumental variable approach with exogenous, demographic variables as the dependent variable in the second stage. Clearly, peer offenses should not be causing demographic characteristics. Significant coefficients on (instrumented) peer offenses would indicate that our instrumental variable is picking up unobserved factors from the 5th grade school of peers that are correlated with the student composition of the 6th grade school. Insignificant estimates for (instrumented) peer offenses in the second stage would provide evidence in support of the design.

4. Results

First stage regressions results for math scores are presented in Tables 2-1 and 2-2.[20] Table 2-1 has major peer offenses and Table 2-2 has all peer offenses as the dependent variables. The past peer offense instrument performs well. Our instrument is strongly

[19] Network formation for the entire state of North Carolina is available on the online appendix.
[20] As second stage results for reading scores are mostly statistically insignificant, first stage results for reading are presented in the appendix

statistically correlated with current peer delinquency counts across all five specifications. F-statistic calculations on the excluded instrument pass the rule-of-thumb test (F-stat >10). The number of current peer offenses is also negatively correlated with fraction of peers that are female and positively correlated with fraction of peers in poverty status. Interestingly, peer delinquency seems to be mostly unresponsive to teacher observable characteristics. Although it is tempting to conclude that teachers are mostly ineffective in controlling student behavior, we should note that the peer is at the level of the grade, and a subject teacher in middle school instructs a fraction of these students for a fraction of a school day.

Tables 3-1 and 3-2 present our main results for math scores. Once again, we present five specifications that build up from the most parsimonious to the complete model. The parameter on average peer delinquency is stable across the five different specification. The impact of exposure to major peer delinquency is estimated to be around -1.3, and the impact of exposure to all peer delinquency is estimated to be about -0.73. Impact on reading test scores are qualitatively similar but are not statistically significant (see Appendix).[22] Since more of language arts learning is done at the home, away from peers, peer delinquency may have less impact.

The simplest way to interpret these parameter estimates is to calculate the impact on test scores for a “reasonable” increase in peer misbehavior. An increase of 10 percent in average major incidents that a student is exposed to at a representative North Carolina school increases exposure rate to 0.53, increasing the number of suspension-worthy incidents at the school by about a dozen and decreasing his or her math score by approximately 6.2 percent of a standard deviation. Similarly, an increase of 10 percent in the exposure rate to all reportable incidents by 0.072 at the representative school increases the number of delinquent actions by about 20 and decreases a student’s math score by about 5.3 percent of a standard deviation.

[22] We also include in the appendix, estimation results with the habitual offenders included in the sample. Impact of peer delinquency is estimated to be 5 to 15 percent smaller, and only marginally statistically significant.

These are sizable impacts, roughly 50 percent of the estimated achievement gains from cutting class size in half.[24] However, it is worth noting that increasing the exposure rate at the school by 10 percent represents vastly different amounts of relative exposure to peer misbehavior, depending the student's school. Table 1 shows that the exposure rate to major incidents varies from 0 to 5.3, and exposure rate to all incidents varies from 0 to 11. This wide range of average peer delinquency values explains the size of the standard deviations. Figures 13 and 14 show the histograms of exposure rates. The heavily left-skewed distribution shows that a 0.048 and 0.072 increase in major and all delinquent exposure rate means something very different, depending on the status of the reference school. Starting from a school with no major disciplinary issues, a 0.048 increase in major delinquency exposure rate is equivalent to moving from an exemplary school (with zero major incidents) to a school that is roughly at the 8th percentile. On the other hand, starting from a school with major discipline issues (75th percentile), a similar increase in delinquency exposure rate is equivalent to moving to a school that is at the 77th percentile.

These results show that most delinquency is concentrated in a relatively small number of schools. The major delinquency exposure rate at the 75th percentile school is 0.70, which is more than 3.5 times the exposure rate at the 25th percentile school. With two schools that are otherwise identical, this exposure gap of 0.54 equates to a 64 percent of a standard deviation in test scores gap. Because the gap in peer delinquency is so large, even implausibly large improvements in the delinquency exposure rate at the right-tail of the school-grade delinquency distribution (say by moving from 75th percentile to the 50th percentile) that would allow students to improve academic achievement substantially, still leaves a 20 percent of a standard deviation gap in math scores compared to students in schools with better behaved peers (at the 25th percentile).

[24] See Hanushek, Rivkin, and Kain (2005).

One important potential concern with our framework is that the instrument may not be exogenously capturing the impact of contemporaneous peer delinquency through peer of peer's delinquency. For example, the instrument may merely be proxying for the "type" of elementary schools these students came from.[25] The build-up of the model from specification (1) to (5) shows that the impact of the instrumented peer delinquency is robust to the addition of a myriad of pre-determined variables, including own demographic characteristics, peer characteristics, and teacher characteristics. This is evidence that our instrument is randomizing across observed determinants of test scores. Table 4-1 shows that the instrument does not help to predict own characteristics, with the marginal exception for poverty status. While some districts may have larger fractions poverty-status students who are more likely to mix among themselves, that it is only marginally significant (and other characteristics typically associated with higher levels of delinquency, such as minority status or male gender are uncorrelated with instrumented peer delinquency) leads us to be cautiously optimistic that the instrument is truly exogenous.[27] What is perhaps most encouraging here is that instrumented peer delinquency is also not predictive of last year's own test score.

5. 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 mathematics but not reading. We find that a ten percent increase in average exposure to peer major offenses results in a 6.2 percent of a standard deviation decrease in math standardized test scores.

[25] As an (extreme) example, suppose that all elementary schools are segregated by gender. And furthermore, suppose that gender were unobservable to the econometrician. If girls' schools tend to emphasize more collaborative learning than boys' schools, and girls tend to cause less trouble than boys, the instrumented lower peer delinquency measure could capture both the causal impact of lower levels of disruptions (which we are interested in) as well as the impact of more collaborative learning by girls.

[27] It is always possible that some other unobservable characteristic of the elementary school that is correlated with peer of peer's delinquency is being estimated in our IV scheme. Another source of corroborating evidence is the first stage regression results. Individual demographic characteristics, including last year's standardized test scores, and current teacher characteristics are *economically* insignificant predictors of peer delinquency.

To put the magnitude of these effects in context, consider the effectiveness of class size reduction. While estimated magnitude of the effect differs by studies, the literature generally agrees that class size reduction by one-half, starting from a class size of twenty, can yield somewhere between 10 to 15 percent of a standard deviation increase in student achievement (see Rivkin, Hanushek, and Kain 2005, for example). Addressing delinquency directly, then, has the potential to be cost-effective, compared to other traditional means of changing the impact of peer, such as class size reduction, tracking students, or bussing.

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 in a more nuanced and objective manner. 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. 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. Most importantly, we use a novel indirect social matrix in a 2SLS model, allowing us to estimate a consistent estimate of the impact of peer delinquency on academic outcomes. This instrument can be generated in almost any education administrative dataset that contains student level delinquency (or any other behavioral) information, making it more easily accessible and reproducible than previous studies. In sum, this paper provides a more detailed look at the effect of peer offenses on academic achievement and misbehavior compared to previous research.

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.

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Figures and Tables

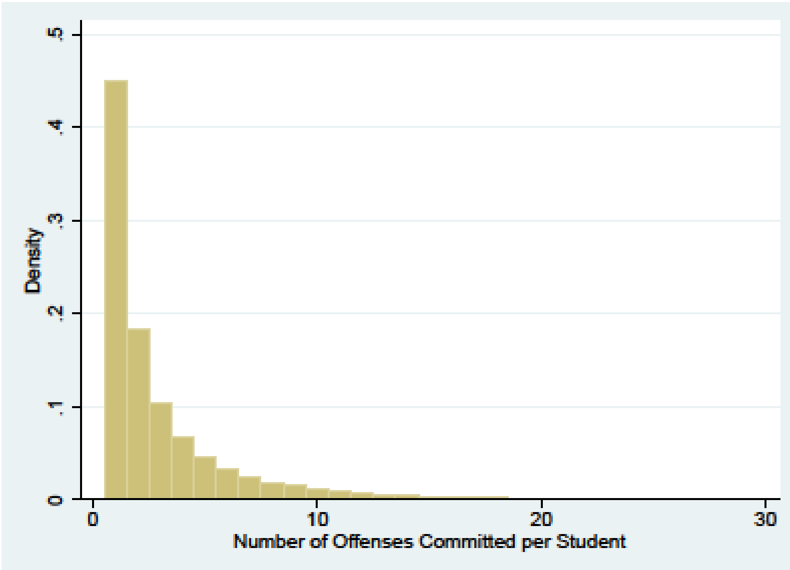

Figure 1: Density of number of offenses committed per academic year, conditional on committing at least one reportable offense. (Top 5% truncated)

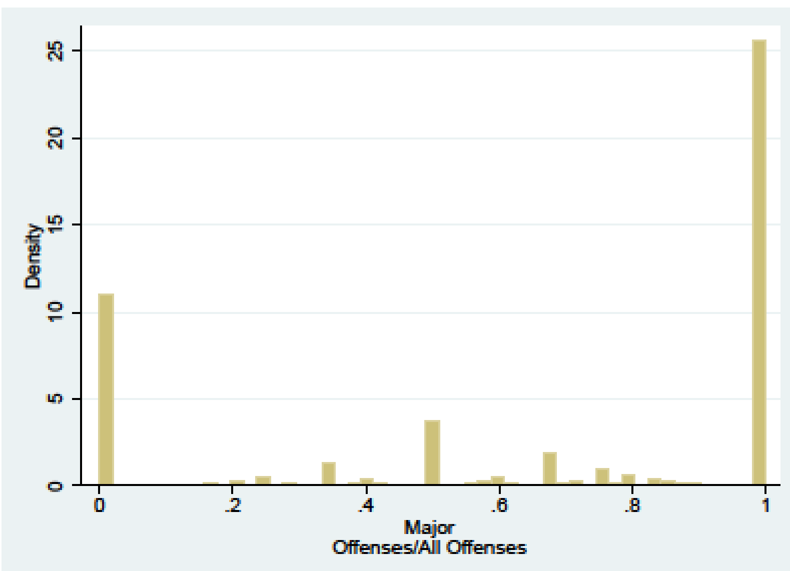

Figure 2: Density of the fraction of offenses committed that are considered "major." (Results in at least an out-of-school suspension.)

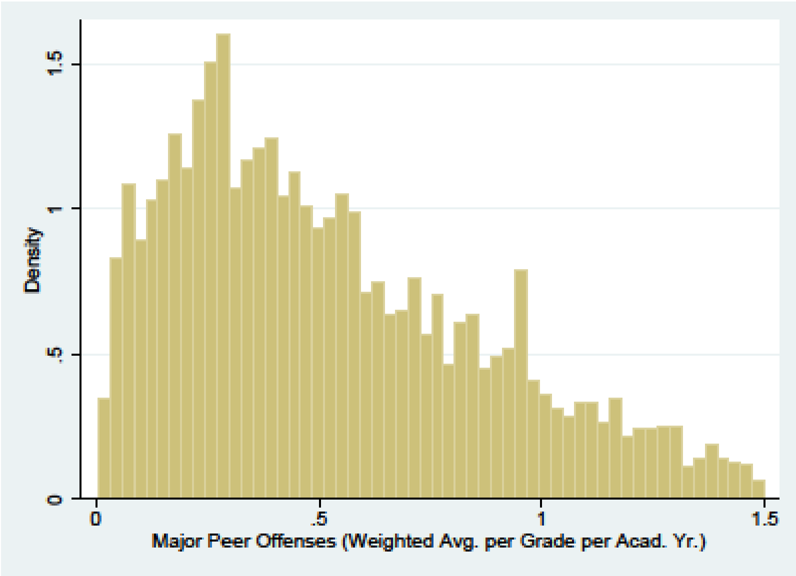

Figure 3: Density of major peer offenses a student is exposed to in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

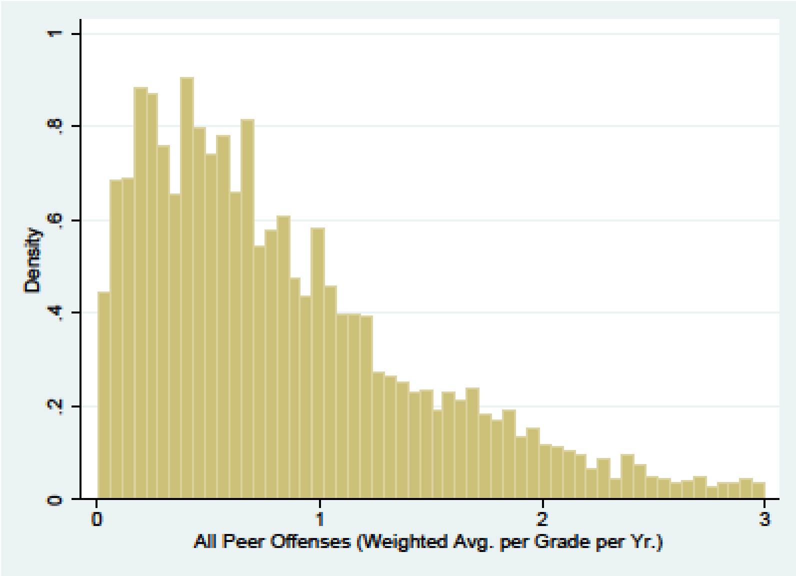

Figure 4: Density of all reportable peer offenses a student is exposed to in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

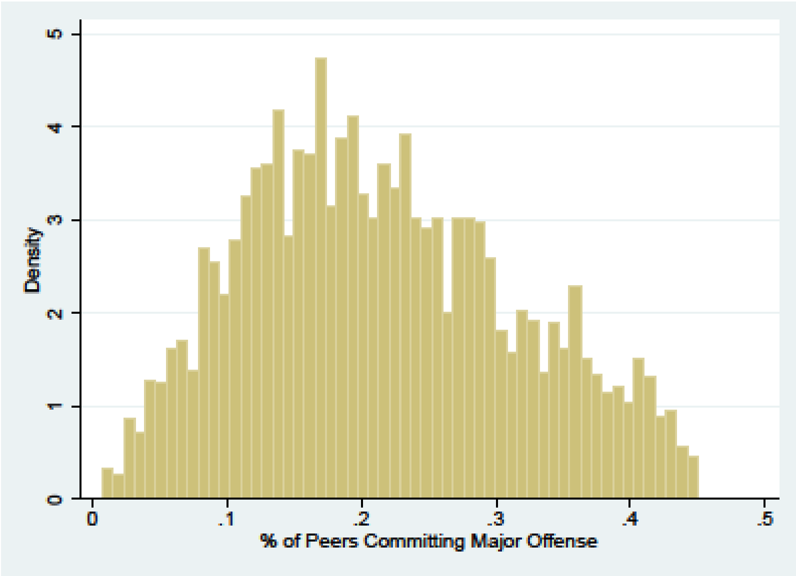

Figure 5: Density of fraction of peers that commit at least one major offense in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

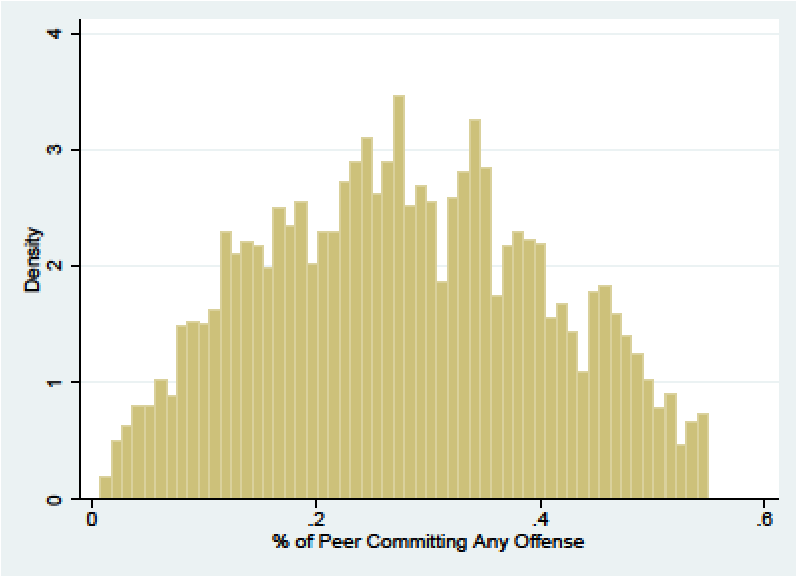

Figure 6: Density of fraction of peers that commit at least one reportable offense in an academic year, conditional on observing at least one peer offense. (Top 5% truncated)

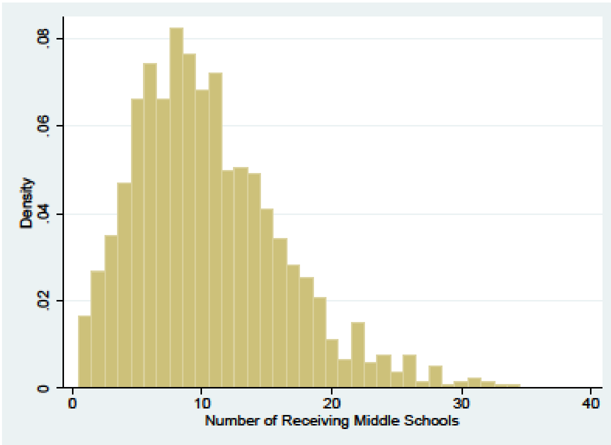

Figure 7: Density of number of middle schools that 5th grade students from one elementary school will move to.

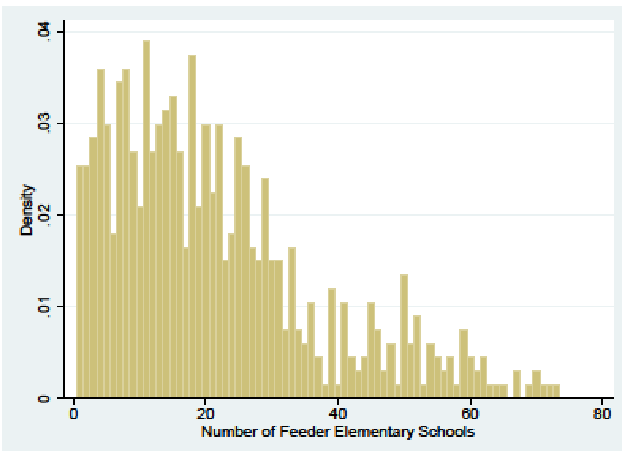

Figure 8: Density of number of elementary schools that students from one middle school come from.

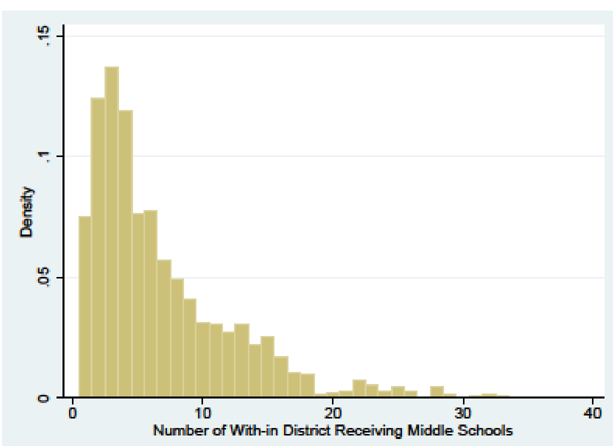

Figure 9: Density of number of middle schools that 5th grade students from one elementary school will move to, conditional on intra-district moves.

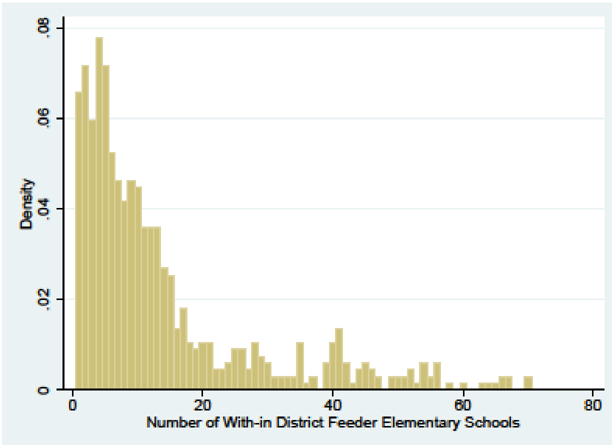

Figure 10: Density of number of elementary schools that students from one middle school come from, conditional on intra-district moves.

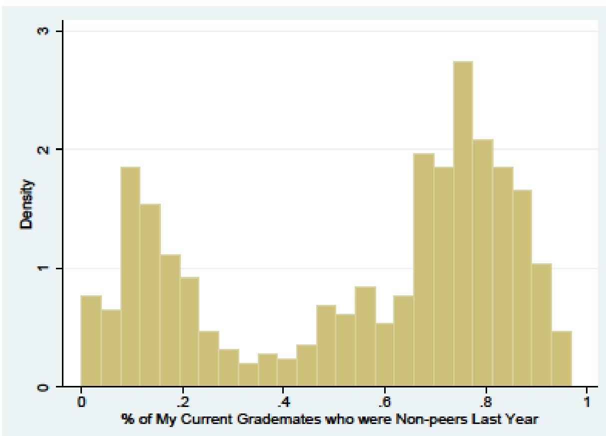

Figure 11: Fraction of middle school current peers who were not peers in 5th grade.

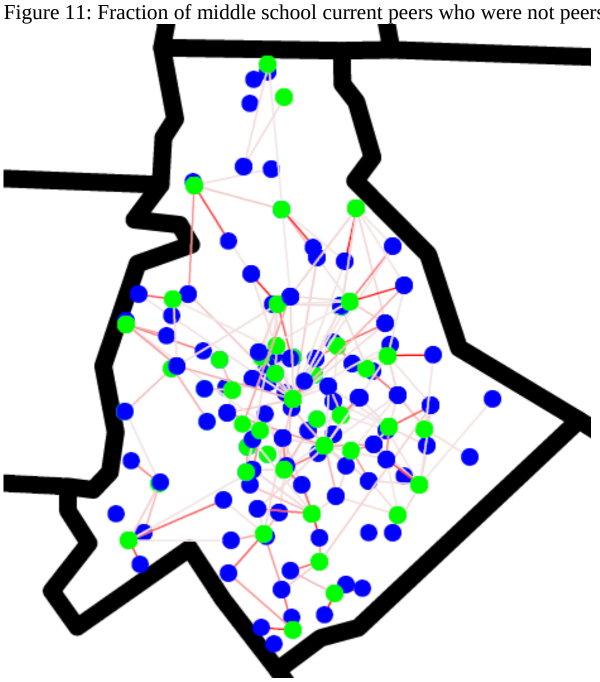

Figure 12: Social network map of Charlotte Mecklenburg school county. Blue dots are elementary schools. Green dots are middle schools. Redder shades of lines connection blue to green dots represent higher number of students moving to a particular middle school.

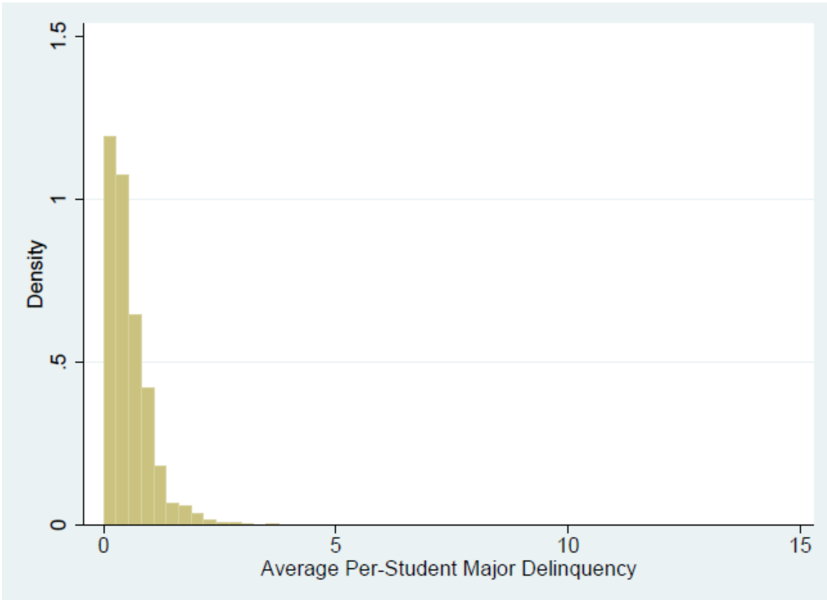

Figure 13: Density of exposure rate to major delinquency.

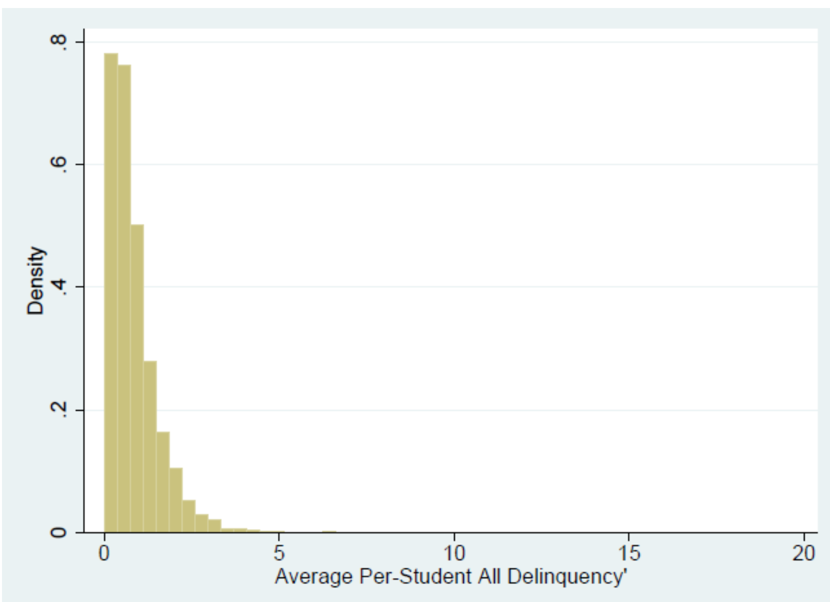

Figure 14: Density of exposure rate to all delinquency.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Academic Outcomes				
Reading Score	0.2468	0.8657	-3.01	2.51
Math Score	0.4241	0.8838	-2.671	2.794
Reading Score last year	0.2228	0.9140	-3.298	2.66
Math Score last year	0.4283	0.9248	-3.011	2.75
Demographic Characteristics				
All Offenses	0.2528	0.6178	0	4
Major Offenses	0.1580	0.4454	0	2
Female	0.5193	0.4996		
White	0.5674	0.4954		
Disabled	0.0785	0.2689		
LEP	0.0490	0.2158		
FRL status	0.5134	0.4998		
Peer Characteristics				
All Offenses	0.7198	0.6256	0	11
Major Offenses	0.4777	0.4032	0	5.333333
Female	0.4895	0.0446	0	0.923077
White	0.5503	0.2775	0	1
Disabled	0.1246	0.0431	0	1
LEP	0.0521	0.0526	0	0.4
FRL status	0.5417	0.2082	0	1
English Teacher				
Female	0.8221	0.3824		
White	0.8431	0.3637		
Inexperienced	0.0583	0.2344		
Math teacher				
Female	0.8221	0.3824		
White	0.8529	0.3542		
Inexperienced	0.0566	0.2310		
Observations	251,248			

Table 2-1: First Stage Regressions (Major Offenses)

	(1)	(2)	(3)	(4)	(5)
Instruments					
Intrans. IV - Major Offenses	0.0582***	0.0582***	0.0577***	0.0603***	0.0700***
	(0.0150)	(0.0150)	(0.0150)	(0.0147)	(0.0177)
Individual Characteristics					
Last Yr. Std. Score		0.0017***	0.0010**	0.0019***	0.0021***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Female			0.0047***	0.0039***	0.0043***
			(0.0008)	(0.0008)	(0.0009)
White			0.0071***	0.0026**	0.0027**
			(0.0011)	(0.0011)	(0.0011)
FRL Status			0.0008	0.0002	0.0002
			(0.0010)	(0.0010)	(0.0010)
LEP			0.0019	-0.0000	0.0007
			(0.0020)	(0.0019)	(0.0021)
Disabled			-0.0018	-0.0005	-0.0003
			(0.0016)	(0.0016)	(0.0017)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0042***	-0.0045***
				(0.0003)	(0.0003)
% Female				-0.4384***	-0.4184***
				(0.0131)	(0.0142)
% White				0.1035***	0.0552***
				(0.0047)	(0.0057)
% FRL				1.0000***	0.9956***
				(0.0127)	(0.0137)
% LEP				-1.1676***	-1.1149***
				(0.0287)	(0.0303)
% Disabled				0.3095***	0.2301***
				(0.0206)	(0.0223)
Teacher Characteristics					
Teacher Female					-0.0125***
					(0.0014)
Teacher Minority					-0.0076***
					(0.0018)
First Yr. Teacher					-0.0081***
					(0.0021)
Constant	0.4897***	0.4891***	0.4823***	0.1397***	0.1816***
	(0.0007)	(0.0008)	(0.0013)	(0.0102)	(0.0112)
Observations	241,494	241,494	241,494	241,494	210,436

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table 2-2: First Stage Regressions (All Offenses)

	(1)	(2)	(3)	(4)	(5)
Instruments					
Intrans. IV - Major Offenses	0.1029***	0.1029***	0.1020***	0.1002***	0.1113***
	(0.0211)	(0.0211)	(0.0211)	(0.0207)	(0.0244)
Individual Characteristics					
Last Yr. Std. Score		0.0036***	0.0023***	0.0039***	0.0045***
		(0.0007)	(0.0008)	(0.0007)	(0.0008)
Female			0.0076***	0.0066***	0.0073***
			(0.0012)	(0.0012)	(0.0013)
White			0.0159***	0.0054***	0.0057***
			(0.0015)	(0.0016)	(0.0016)
FRL Status			0.0019	-0.0000	-0.0001
			(0.0014)	(0.0014)	(0.0015)
LEP			0.0077***	0.0045	0.0061**
			(0.0029)	(0.0028)	(0.0030)
Disabled			-0.0021	0.0005	0.0018
			(0.0024)	(0.0023)	(0.0025)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0056***	-0.0054***
				(0.0004)	(0.0004)
% Female				-0.5775***	-0.4782***
				(0.0191)	(0.0206)
% White				0.2273***	0.1937***
				(0.0068)	(0.0082)
% FRL				1.4267***	1.3284***
				(0.0185)	(0.0198)
% LEP				-1.0772***	-1.0542***
				(0.0418)	(0.0438)
% Disabled				0.7108***	0.5364***
				(0.0300)	(0.0322)
Teacher Characteristics					
Teacher Female					-0.0080***
					(0.0020)
Teacher Minority					-0.0065**
					(0.0025)
First Yr. Teacher					-0.0014
					(0.0030)
Constant	0.7312***	0.7299***	0.7157***	0.0938***	0.1547***
	(0.0011)	(0.0011)	(0.0019)	(0.0149)	(0.0162)
Observations	241,494	241,494	241,494	241,494	210,436

All specifications define peers as students in the same grade. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes school level fixed effects and year dummies.

Table 3-1: Second Stage Regressions (Major Offenses, Standardized Math Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency					
Avg. # Major Offenses	-1.4856	-1.3748**	-1.3777**	-1.2880**	-1.1810*
	(1.1108)	(0.6985)	(0.6977)	(0.6479)	(0.6653)
Individual Char.					
Last Yr. Std. Score		0.7773***	0.7401***	0.7409***	0.7392***
		(0.0018)	(0.0016)	(0.0019)	(0.0021)
Female			0.0191***	0.0180***	0.0174***
			(0.0039)	(0.0033)	(0.0037)
White			0.0707***	0.0669***	0.0617***
			(0.0058)	(0.0034)	(0.0035)
FRL Status			-0.0984***	-0.0985***	-0.0979***
			(0.0027)	(0.0026)	(0.0027)
LEP			-0.0524***	-0.0545***	-0.0583***
			(0.0056)	(0.0053)	(0.0055)
Disabled			-0.1707***	-0.1689***	-0.1681***
			(0.0047)	(0.0044)	(0.0047)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0072**	-0.0065**
				(0.0029)	(0.0032)
% Female				-0.4344	-0.3947
				(0.2846)	(0.2787)
% White				0.0778	0.0351
				(0.0677)	(0.0390)
% FRL				1.3033**	1.1897*
				(0.6499)	(0.6644)
% LEP				-1.7388**	-1.5246**
				(0.7612)	(0.7462)
% Disabled				0.5435***	0.4955***
				(0.2080)	(0.1643)
Teacher Char.					
Teacher Female					0.0185**
					(0.0092)
Teacher Minority					-0.0757***
					(0.0069)
First Yr. Teacher					-0.0972***
					(0.0076)
Constant	1.1453**	0.7842**	0.8122**	0.2825***	0.2914**
	(0.5438)	(0.3415)	(0.3363)	(0.0937)	(0.1232)
Observations	240,164	240,164	240,164	240,164	209,269
R^2	0.0279	0.5028	0.5071	0.5180	0.5352

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

0.05, *** $p < 0.01$. Includes school level fixed effects and year dummies.

Table 3-2: Second Stage Regressions (All Offenses, Standardized Math Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency					
Avg. # Major Offenses	-0.7234	-0.7280**	-0.7359**	-0.7322**	-0.6954*
	(0.5927)	(0.3637)	(0.3639)	(0.3691)	(0.3891)
Individual Char.					
Last Yr. Std. Score		0.7775***	0.7403***	0.7413***	0.7398***
		(0.0018)	(0.0016)	(0.0020)	(0.0023)
Female			0.0183***	0.0178***	0.0174***
			(0.0035)	(0.0032)	(0.0036)
White			0.0725***	0.0674***	0.0624***
			(0.0064)	(0.0034)	(0.0037)
FRL Status			-0.0981***	-0.0988***	-0.0982***
			(0.0026)	(0.0025)	(0.0027)
LEP			-0.0493***	-0.0512***	-0.0549***
			(0.0059)	(0.0054)	(0.0059)
Disabled			-0.1698***	-0.1679***	-0.1666***
			(0.0044)	(0.0042)	(0.0045)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0058**	-0.0048**
				(0.0022)	(0.0023)
% Female				-0.2945	-0.2351
				(0.2151)	(0.1886)
% White				0.1116	0.1053
				(0.0845)	(0.0764)
% FRL				1.0604**	0.9390*
				(0.5288)	(0.5198)
% LEP				-1.0229**	-0.9401**
				(0.4048)	(0.4171)
% Disabled				0.6669**	0.5972***
				(0.2684)	(0.2168)
Teacher Char.					
Teacher Female					0.0278***
					(0.0048)
Teacher Minority					-0.0713***
					(0.0052)
First Yr. Teacher					-0.0885***
					(0.0054)
Constant	0.9470**	0.6434**	0.6746***	0.1714***	0.1844***
	(0.4334)	(0.2654)	(0.2604)	(0.0429)	(0.0655)
Observations	240,164	240,164	240,164	240,164	209,269

R^2	0.0144	0.5322	0.5372	0.5244	0.5357

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table 4-1: Robustness Check – Falsification Tests with Demographic Characteristics as Dependent Variables.

	Female	White	FRL Status	LEP	Disabled	Last Yr. Score
Avg. # Major Offenses	0.2104	0.6373	1.1435*	0.0831	-0.4203	-0.0179
	(0.6332)	(0.5432)	(0.6301)	(0.2673)	(0.3413)	(1.1014)
Last Yr. Std. Score	-0.0248***	0.1156***	-0.1520***	-0.0386***	-0.0822***	
	(0.0016)	(0.0014)	(0.0016)	(0.0007)	(0.0009)	
Constant	0.4286	0.2390	-0.0026	0.0278	0.3144*	0.3922
	(0.3097)	(0.2657)	(0.3082)	(0.1308)	(0.1669)	(0.5394)
Observations	241,494	241,494	241,494	241,494	241,494	241494
R^2	0.0008	0.0007	0.0737	0.0241	0.0128	0.0039

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table Appendix

Table X-1: Second Stage Regressions (Major Offenses, Standardized Reading Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency Measure					
Avg. # Major Offenses	-0.0767	-0.6043	-0.5626	-0.3823	-0.4092
	(1.0399)	(0.6465)	(0.6406)	(0.5992)	(0.6700)
Individual Characteristics					
Last Yr. Std. Score		0.7649***	0.7188***	0.7186***	0.7170***
		(0.0018)	(0.0015)	(0.0017)	(0.0017)
Female			-0.0066*	-0.0076**	-0.0072*
			(0.0036)	(0.0030)	(0.0037)
White			0.0751***	0.0759***	0.0729***
			(0.0053)	(0.0032)	(0.0033)
FRL Status			-0.0952***	-0.0947***	-0.0931***
			(0.0025)	(0.0024)	(0.0026)
LEP			-0.0963***	-0.0966***	-0.0983***
			(0.0053)	(0.0050)	(0.0055)
Disabled			-0.1992***	-0.1985***	-0.2003***
			(0.0044)	(0.0041)	(0.0045)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0013	-0.0012
				(0.0031)	(0.0031)
% Female				-0.1445	-0.1194
				(0.2625)	(0.2282)
% White				-0.0365	-0.0442
				(0.0625)	(0.0452)
% FRL				0.3339	0.3178
				(0.6018)	(0.5791)
% LEP				-0.5793	-0.7161
				(0.7070)	(0.8921)
% Disabled				0.2600	0.2866
				(0.1924)	(0.2975)
Teacher Characteristics					
Teacher Female					0.0062
					(0.0049)
Teacher Minority					-0.0130**
					(0.0052)
First Yr. Teacher					-0.0360***
					(0.0112)
Constant	0.2874	0.3837	0.3982	0.2259***	0.2412**
	(0.5091)	(0.3163)	(0.3090)	(0.0861)	(0.1204)

Observations	239,845	239,845	239,845	239,845	201,368
R^2	0.0207	0.6168	0.6300	0.6563	0.6498

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-2: Second Stage Regressions (All Offenses, Standardized Reading Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency Measure					
Avg. # Major Offenses	-0.0321	-0.3931	-0.3745	-0.3216	-0.2946
	(0.5722)	(0.3546)	(0.3525)	(0.3567)	(0.3831)
Individual Characteristics					
Last Yr. Std. Score		0.7651***	0.7190***	0.7190***	0.7175***
		(0.0018)	(0.0015)	(0.0018)	(0.0020)
Female			-0.0064*	-0.0071**	-0.0069**
			(0.0033)	(0.0030)	(0.0035)
White			0.0771***	0.0766***	0.0735***
			(0.0063)	(0.0034)	(0.0035)
FRL Status			-0.0950***	-0.0949***	-0.0931***
			(0.0025)	(0.0024)	(0.0026)
LEP			-0.0944***	-0.0950***	-0.0969***
			(0.0059)	(0.0054)	(0.0056)
Disabled			-0.1993***	-0.1984***	-0.2002***
			(0.0043)	(0.0041)	(0.0045)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0015	-0.0011
				(0.0025)	(0.0024)
% Female				-0.1629	-0.1274
				(0.2073)	(0.1928)
% White				-0.0030	-0.0185
				(0.0814)	(0.0689)
% FRL				0.4109	0.3410
				(0.5116)	(0.4906)
% LEP				-0.4787	-0.6022
				(0.3927)	(0.5633)
% Disabled				0.3709	0.3542
				(0.2593)	(0.3248)
Teacher Characteristics					
Teacher Female					0.0054
					(0.0051)
Teacher Minority					-0.0114***
					(0.0043)
First Yr. Teacher					-0.0348***

					(0.0109)
Constant	0.2733	0.3752	0.3951	0.2026***	0.2194***
	(0.4184)	(0.2590)	(0.2524)	(0.0413)	(0.0706)
Observations	239,845	239,845	239,845	239,845	201,368
R^2	0.0104	0.6103	0.6237	0.6362	0.6395

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-3: Summary Statistics (Full Sample)

Variable	Mean	Std. Dev.	Min	Max
Academic Outcomes				
Reading Score	0.1987	0.8834	-3.01	2.51
Math Score	0.3807	0.8991	-2.671	2.794
Reading Score last year	0.1811	0.9246	-3.298	2.66
Math Score last year	0.4037	0.9332	-3.011	2.75
Demographic Characteristics				
All Offenses	0.7083	2.0912	0	72
Major Offenses	0.4636	1.4838	0	65
Female	0.5034	0.5000		
White	0.5514	0.4973		
Disabled	0.0857	0.2799		
LEP	0.0479	0.2135		
FRL status	0.5397	0.4984		
Peer Characteristics				
All Offenses	1.0464	1.5607	0	16.44
Major Offenses	0.7263	1.1501	0	11.75
Female	0.4880	0.0452	0	1
White	0.5416	0.2758	0	1
Disabled	0.1249	0.0432		
LEP	0.0543	0.0534	0	0.39
FRL status	0.5606	0.1973	0	1
English Teacher				
Female	0.9147	0.2793		
White	0.8394	0.3672		
Inexperienced	0.0577	0.2332		
Math teacher				
Female	0.8223	0.3823		
White	0.8494	0.3576		
Inexperienced	0.0585	0.2347		
Observations	230,070			

Table X-4: First Stage Regressions (Full Sample, Major Offenses)

	(1)	(2)	(3)	(4)	(5)
Instruments					
Intrans. IV - Major Offenses	0.0568***	0.0568***	0.0564***	0.0592***	0.0692***
	(0.0153)	(0.0153)	(0.0153)	(0.0150)	(0.0182)
Individual Characteristics					
Last Yr. Std. Score		-0.0009*	-0.0011**	-0.0002	0.0000
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Female			0.0010	0.0003	0.0008
			(0.0008)	(0.0008)	(0.0009)
White			0.0053***	0.0009	0.0009
			(0.0011)	(0.0011)	(0.0011)
FRL Status			0.0037***	0.0029***	0.0028***
			(0.0010)	(0.0010)	(0.0010)
LEP			-0.0043**	-0.0061***	-0.0055***
			(0.0020)	(0.0019)	(0.0021)
Disabled			-0.0005	0.0006	0.0008
			(0.0015)	(0.0015)	(0.0016)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0045***	-0.0048***
				(0.0003)	(0.0003)
% Female				-0.4712***	-0.4414***
				(0.0131)	(0.0142)
% White				0.1089***	0.0597***
				(0.0048)	(0.0057)
% FRL				1.0596***	1.0637***
				(0.0126)	(0.0136)
% LEP				-1.2173***	-1.1693***
				(0.0282)	(0.0298)
% Disabled				0.3412***	0.2683***
				(0.0204)	(0.0220)
Teacher Characteristics					
Teacher Female					-0.0132***
					(0.0014)
Teacher Minority					-0.0093***
					(0.0017)
First Yr. Teacher					-0.0086***
					(0.0020)
Constant	0.5115***	0.5118***	0.5067***	0.1389***	0.1722***
	(0.0007)	(0.0008)	(0.0013)	(0.0102)	(0.0112)

Observations	260,547	260,547	260,547	260,547	227,626

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-5: First Stage Regressions (Full Sample, All Offenses)

	(1)	(2)	(3)	(4)	(5)
Instruments					
Intrans. IV - Major Offenses	0.1019***	0.1019***	0.1010***	0.0992***	0.1106***
	(0.0216)	(0.0216)	(0.0216)	(0.0212)	(0.0252)
Individual Characteristics					
Last Yr. Std. Score		-0.0007	-0.0012*	0.0004	0.0011
		(0.0007)	(0.0008)	(0.0007)	(0.0008)
Female			0.0016	0.0007	0.0018
			(0.0012)	(0.0012)	(0.0013)
White			0.0126***	0.0023	0.0025
			(0.0015)	(0.0015)	(0.0016)
FRL Status			0.0064***	0.0042***	0.0040***
			(0.0014)	(0.0014)	(0.0015)
LEP			-0.0015	-0.0046	-0.0029
			(0.0029)	(0.0028)	(0.0030)
Disabled			-0.0002	0.0022	0.0037
			(0.0023)	(0.0022)	(0.0024)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0059***	-0.0058***
				(0.0004)	(0.0004)
% Female				-0.6223***	-0.5060***
				(0.0191)	(0.0206)
% White				0.2403***	0.2082***
				(0.0069)	(0.0083)
% FRL				1.5055***	1.4190***
				(0.0185)	(0.0197)
% LEP				-1.1092***	-1.0953***
				(0.0413)	(0.0433)
% Disabled				0.7492***	0.5752***
				(0.0298)	(0.0320)
Teacher Characteristics					
Teacher Female					-0.0086***
					(0.0020)
Teacher Minority					-0.0080***
					(0.0025)
First Yr. Teacher					-0.0010
					(0.0030)

Constant	0.7692***	0.7694***	0.7583***	0.0983***	0.1463***
	(0.0011)	(0.0011)	(0.0019)	(0.0149)	(0.0163)
Observations	260,547	260,547	260,547	260,547	227,626

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-6: Second Stage Regressions (Full Sample, Major Offenses, Standardized Math Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency Measure					
Avg. # Major Offenses	-1.3589	-1.2594*	-1.2808*	-1.1746*	-1.0663
	(1.1255)	(0.7023)	(0.7030)	(0.6477)	(0.6675)
Individual Characteristics					
Last Yr. Std. Score		0.7772***	0.7378***	0.7388***	0.7369***
		(0.0014)	(0.0015)	(0.0013)	(0.0014)
Female			0.0255***	0.0249***	0.0252***
			(0.0022)	(0.0021)	(0.0023)
White			0.0715***	0.0686***	0.0638***
			(0.0046)	(0.0028)	(0.0029)
FRL Status			-0.1044***	-0.1050***	-0.1043***
			(0.0037)	(0.0032)	(0.0033)
LEP			-0.0514***	-0.0524***	-0.0561***
			(0.0059)	(0.0063)	(0.0063)
Disabled			-0.1706***	-0.1692***	-0.1682***
			(0.0042)	(0.0040)	(0.0042)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0070**	-0.0062*
				(0.0031)	(0.0034)
% Female				-0.4073	-0.3566
				(0.3043)	(0.2939)
% White				0.0656	0.0292
				(0.0710)	(0.0416)
% FRL				1.2461*	1.1346
				(0.6881)	(0.7121)
% LEP				-1.6341**	-1.4221*
				(0.7932)	(0.7864)
% Disabled				0.5588**	0.5243***
				(0.2271)	(0.1879)
Teacher Characteristics					
Teacher Female					0.0222**
					(0.0097)
Teacher Minority					-0.0751***

					(0.0077)
First Yr. Teacher					-0.0953***
					(0.0078)
Constant	1.0643*	0.7395**	0.7803**	0.2490***	0.2397**
	(0.5754)	(0.3593)	(0.3560)	(0.0924)	(0.1172)
Observations	258,853	258,853	258,853	258,853	226,130
R^2	0.0381	0.5298	0.5305	0.5460	0.5631

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-7: Second Stage Regressions (Full Sample, All Offenses, Standardized Math Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency Measure					
Avg. # Major Offenses	-0.6720	-0.6733*	-0.6893*	-0.6799*	-0.6357
	(0.5982)	(0.3651)	(0.3654)	(0.3703)	(0.3917)
Individual Characteristics					
Last Yr. Std. Score		0.7778***	0.7383***	0.7393***	0.7376***
		(0.0012)	(0.0014)	(0.0013)	(0.0015)
Female			0.0253***	0.0250***	0.0255***
			(0.0021)	(0.0021)	(0.0023)
White			0.0734***	0.0690***	0.0644***
			(0.0053)	(0.0028)	(0.0030)
FRL Status			-0.1048***	-0.1056***	-0.1048***
			(0.0034)	(0.0029)	(0.0030)
LEP			-0.0467***	-0.0482***	-0.0520***
			(0.0049)	(0.0051)	(0.0052)
Disabled			-0.1702***	-0.1685***	-0.1669***
			(0.0040)	(0.0040)	(0.0042)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0057**	-0.0047*
				(0.0024)	(0.0025)
% Female				-0.2788	-0.2094
				(0.2310)	(0.1996)
% White				0.1017	0.0984
				(0.0895)	(0.0823)
% FRL				1.0255*	0.9033
				(0.5595)	(0.5586)
% LEP				-0.9572**	-0.8693**
				(0.4175)	(0.4363)
% Disabled				0.6698**	0.6043***
				(0.2832)	(0.2324)
Teacher Characteristics					

Teacher Female					0.0309***
					(0.0050)
Teacher Minority					-0.0701***
					(0.0054)
First Yr. Teacher					-0.0866***
					(0.0051)
Constant	0.8862*	0.6131**	0.6542**	0.1529***	0.1489**
	(0.4599)	(0.2808)	(0.2770)	(0.0435)	(0.0625)
Observations	258,853	258,853	258,853	258,853	226,130
R^2	0.0228	0.5536	0.5558	0.5464	0.5598

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-8: Second Stage Regressions (Full Sample, Major Offenses, Standardized Reading Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency Measure					
Avg. # Major Offenses	0.2640	-0.4102	-0.3796	-0.2039	-0.2192
	(1.0731)	(0.6524)	(0.6472)	(0.6055)	(0.6794)
Individual Characteristics					
Last Yr. Std. Score		0.7690***	0.7211***	0.7212***	0.7200***
		(0.0012)	(0.0014)	(0.0013)	(0.0014)
Female			0.0005	0.0003	0.0003
			(0.0021)	(0.0020)	(0.0023)
White			0.0765***	0.0784***	0.0759***
			(0.0042)	(0.0026)	(0.0028)
FRL Status			-0.1021***	-0.1020***	-0.1002***
			(0.0034)	(0.0030)	(0.0031)
LEP			-0.0880***	-0.0866***	-0.0876***
			(0.0056)	(0.0061)	(0.0074)
Disabled			-0.2000***	-0.1998***	-0.2020***
			(0.0039)	(0.0038)	(0.0042)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0003	-0.0003
				(0.0033)	(0.0033)
% Female				-0.0757	-0.0699
				(0.2841)	(0.2550)
% White				-0.0596	-0.0607
				(0.0664)	(0.0510)
% FRL				0.1507	0.1452
				(0.6443)	(0.6279)
% LEP				-0.3382	-0.4370

				(0.7440)	(0.9511)
% Disabled				0.2165	0.2277
				(0.2122)	(0.3290)
Teacher Characteristics					
Teacher Female					0.0055
					(0.0049)
Teacher Minority					-0.0120**
					(0.0053)
First Yr. Teacher					-0.0370***
					(0.0118)
Constant	0.0699	0.2852	0.3061	0.1982**	0.2095*
	(0.5487)	(0.3336)	(0.3275)	(0.0855)	(0.1214)
Observations	258,487	258,487	258,487	258,487	217,215
R^2	0.0290	0.6494	0.6602	0.6754	0.6717

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Table X-9: Second Stage Regressions (Full Sample, All Offenses, Standardized Reading Scores)

	(1)	(2)	(3)	(4)	(5)
Peer Delinquency Measure					
Avg. # Major Offenses	0.1491	-0.2709	-0.2570	-0.2025	-0.1651
	(0.5844)	(0.3551)	(0.3530)	(0.3583)	(0.3873)
Individual Characteristics					
Last Yr. Std. Score		0.7691***	0.7212***	0.7213***	0.7202***
		(0.0012)	(0.0013)	(0.0013)	(0.0014)
Female			0.0005	0.0003	0.0003
			(0.0021)	(0.0020)	(0.0022)
White			0.0777***	0.0787***	0.0761***
			(0.0051)	(0.0027)	(0.0029)
FRL Status			-0.1019***	-0.1017***	-0.1001***
			(0.0033)	(0.0028)	(0.0030)
LEP			-0.0866***	-0.0862***	-0.0870***
			(0.0048)	(0.0050)	(0.0058)
Disabled			-0.2000***	-0.1996***	-0.2019***
			(0.0039)	(0.0039)	(0.0042)
Peer Characteristics					
Last Yr. Peer Std. Score				-0.0007	-0.0003
				(0.0026)	(0.0025)
% Female				-0.1053	-0.0778
				(0.2228)	(0.2125)
% White				-0.0331	-0.0445
				(0.0864)	(0.0764)

% FRL				0.2400	0.1663
				(0.5421)	(0.5251)
% LEP				-0.3142	-0.3790
				(0.4047)	(0.5865)
% Disabled				0.2995	0.2706
				(0.2741)	(0.3504)
Teacher Characteristics					
Teacher Female					0.0053
					(0.0050)
Teacher Minority					-0.0114***
					(0.0043)
First Yr. Teacher					-0.0360***
					(0.0115)
Constant	0.0903	0.2837	0.3087	0.1893***	0.1997***
	(0.4493)	(0.2730)	(0.2674)	(0.0413)	(0.0720)
Observations	258,487	258,487	258,487	258,487	217,215
R^2	0.0173	0.6445	0.6558	0.6646	0.6676

All specifications define peers as students in the same grade. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Includes school level fixed effects and year dummies.

Data 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

Simulation Appendix:

Example: Two-Step Pathways Generation of $\widetilde{\boldsymbol{G_t}} = (\boldsymbol{G_{t-1}} - \boldsymbol{G_t}) > \boldsymbol{0} \cdot (\boldsymbol{G_t} - \boldsymbol{G_{t-1}}) > \boldsymbol{0}$

```
. /* 9 kids. 1-5 and 6-9 are the current grade groupings. NOTE: Variation in grade size.
>    Last year, even numbers and odd numbers were together in elementary school.
>    For example, student 1 has connections to students 2-5 this year and 3,5,7, and 9 last year.
>    Student 1 has no direct connections to 6 or 8. But last year, student 1's current classmates
2 and 4 were exposed to students 6 and 8.
>    Thus, there are intransitive triads involving student 1:
>         •     1-2-6
>         •     1-2-8
>         •     1-4-6
>         •     1-4-8
:
: /* Current grades: 1-5 and 6-10 */
:         current = (1,1,1,1,1,0,0,0,0 \ 1,1,1,1,1,0,0,0,0 \ 1,1,1,1,1,0,0,0,0 \
1,1,1,1,1,0,0,0,0 \ 1,1,1,1,1,0,0,0,0 \ 0,0,0,0,0,1,1,1,1 \ 0,0,0,0,0,1,1,1,1 \ 0,0,0,0,0,1,1
> ,1,1 \ 0,0,0,0,0,1,1,1,1)
:         _diag(current,0)
:         current
[symmetric]
       1   2   3   4   5   6   7   8   9
    +-------------------------------------+
  1 |  0                                  |
  2 |  1   0                              |
  3 |  1   1   0                          |
  4 |  1   1   1   0                      |
  5 |  1   1   1   1   0                  |
  6 |  0   0   0   0   0   0              |
  7 |  0   0   0   0   0   1   0          |
  8 |  0   0   0   0   0   1   1   0      |
  9 |  0   0   0   0   0   1   1   1   0  |
    +-------------------------------------+
:         rownum = rowsum(current)
:         rownum
       1
    +-----+
  1 |  4  |
  2 |  4  |
  3 |  4  |
  4 |  4  |
  5 |  4  |
  6 |  3  |
  7 |  3  |
  8 |  3  |
  9 |  3  |
    +-----+
:         curr_norm = current :/ rownum
:         curr_norm
[symmetric]
                 1             2             3             4             5             6             7             8             9
    +-----------------------------------------------------------------------------------------------------------------------------+
  1 |            0                                                                                                                |
  2 |          .25             0                                                                                                  |
  3 |          .25           .25             0                                                                                    |
  4 |          .25           .25           .25             0                                                                      |
  5 |          .25           .25           .25           .25             0                                                        |
  6 |            0             0             0             0             0             0                                          |
  7 |            0             0             0             0             0   .3333333333             0                            |
  8 |            0             0             0             0             0   .3333333333   .3333333333             0              |
  9 |            0             0             0             0             0   .3333333333   .3333333333   .3333333333             0  |
: /* Last year grades: odds and evens */
:         lag = (0,0,1,0,1,0,1,0,1 \ 0,0,0,1,0,1,0,1,0 \ 1,0,0,0,1,0,1,0,1 \ 0,1,0,0,0,1,0,1,0 \
1,0,1,0,0,0,1,0,1 \ 0,1,0,1,0,0,0,1,0 \ 1,0,1,0,1,0,0,0,1 \ 0,1,0,1,0,1,0,0,0
>  \ 1,0,1,0,1,0,1,0,0)
:         lag
[symmetric]
       1   2   3   4   5   6   7   8   9
    +-------------------------------------+
  1 |  0                                  |
  2 |  0   0                              |
  3 |  1   0   0                          |
```

```
  4 |  0   1   0   0                      |
  5 |  1   0   1   0   0                  |
  6 |  0   1   0   1   0   0              |
  7 |  1   0   1   0   1   0   0          |
  8 |  0   1   0   1   0   1   0   0      |
  9 |  1   0   1   0   1   0   1   0   0  |
:         lag_norm = lag :/ rowsum(lag)
:         lag_norm
[symmetric]
                 1             2             3             4             5             6             7             8             9
    +-------------------------------------------------------------------------------------------------------------------------------+
  1 |            0                                                                                                                  |
  2 |            0             0                                                                                                    |
  3 |          .25             0             0                                                                                      |
  4 |            0   .3333333333             0             0                                                                        |
  5 |          .25             0           .25             0             0                                                          |
  6 |            0   .3333333333             0   .3333333333             0             0                                            |
  7 |          .25             0           .25             0           .25             0             0                              |
  8 |            0   .3333333333             0   .3333333333             0   .3333333333             0             0                |
  9 |          .25             0           .25             0           .25             0           .25             0             0  |
: /* Matrices of only intransitive triads */
:         lag_curr = lag - current
:         lag_curr
[symmetric]
        1    2    3    4    5    6    7    8    9
    +---------------------------------------------+
  1 |   0                                         |
  2 |  -1    0                                    |
  3 |   0   -1    0                               |
  4 |  -1    0   -1    0                          |
  5 |   0   -1    0   -1    0                     |
  6 |   0    1    0    1    0    0                |
  7 |   1    0    1    0    1   -1    0           |
  8 |   0    1    0    1    0    0   -1    0      |
  9 |   1    0    1    0    1   -1    0   -1    0 |
:         /* Boolean relations using 'moremata' package */
:         lag_curr01 = mm_cond(lag_curr :< 0, 0, lag_curr)
:         lag_curr01
[symmetric]
       1   2   3   4   5   6   7   8   9
    +-------------------------------------+
  1 |  0                                  |
  2 |  0   0                              |
  3 |  0   0   0                          |
  4 |  0   0   0   0                      |
  5 |  0   0   0   0   0                  |
  6 |  0   1   0   1   0   0              |
  7 |  1   0   1   0   1   0   0          |
  8 |  0   1   0   1   0   0   0   0      |
  9 |  1   0   1   0   1   0   0   0   0  |
:         curr_lag = current - lag
:         curr_lag
[symmetric]
        1    2    3    4    5    6    7    8    9
    +---------------------------------------------+
  1 |   0                                         |
  2 |   1    0                                    |
  3 |   0    1    0                               |
  4 |   1    0    1    0                          |
  5 |   0    1    0    1    0                     |
  6 |   0   -1    0   -1    0    0                |
  7 |  -1    0   -1    0   -1    1    0           |
  8 |   0   -1    0   -1    0    0    1    0      |
  9 |  -1    0   -1    0   -1    1    0    1    0 |
:         curr_lag01 = mm_cond(curr_lag :< 0, 0, curr_lag)
:         curr_lag01
[symmetric]
       1   2   3   4   5   6   7   8   9
    +-------------------------------------+
  1 |  0                                  |
  2 |  1   0                              |
  3 |  0   1   0                          |
  4 |  1   0   1   0                      |
  5 |  0   1   0   1   0                  |
  6 |  0   0   0   0   0   0              |
```

```
  7 |  0   0   0   0   0   1   0           |
  8 |  0   0   0   0   0   0   1   0       |
  9 |  0   0   0   0   0   1   0   1   0   |
:         intrans = lag_curr01*curr_lag01
:         intrans
       1   2   3   4   5   6   7   8   9
    +-------------------------------------+
  1 |  0   0   0   0   0   2   0   2   0   |
  2 |  0   0   0   0   0   0   2   0   2   |
  3 |  0   0   0   0   0   2   0   2   0   |
  4 |  0   0   0   0   0   0   2   0   2   |
  5 |  0   0   0   0   0   2   0   2   0   |
  6 |  2   0   2   0   2   0   0   0   0   |
  7 |  0   3   0   3   0   0   0   0   0   |
  8 |  2   0   2   0   2   0   0   0   0   |
  9 |  0   3   0   3   0   0   0   0   0   |
: /* Squared matrices in using each sociomatrix */
:         /* Current sociomatrix */
:         curr_norm2 = curr_norm*curr_norm
:         curr_norm2
[symmetric]
                 1             2             3             4             5             6             7             8             9
    +-----------------------------------------------------------------------------------------------------------------------------+
  1 |          .25                                                                                                                |
  2 |        .1875           .25                                                                                                  |
  3 |        .1875         .1875           .25                                                                                    |
  4 |        .1875         .1875         .1875           .25                                                                      |
  5 |        .1875         .1875         .1875         .1875           .25                                                        |
  6 |            0             0             0             0             0   .3333333333                                          |
  7 |            0             0             0             0             0   .2222222222   .3333333333                            |
  8 |            0             0             0             0             0   .2222222222   .2222222222   .3333333333              |
  9 |            0             0             0             0             0   .2222222222   .2222222222   .2222222222   .3333333333  |
```