

# Partners in Crime

## Schools, Neighborhoods and the Formation of Criminal Networks

**Stephen B. Billings, University of North Carolina Charlotte**

**David Deming, Harvard University & NBER**

**Stephen L. Ross, University of Connecticut**

Criminal activity is greatly influenced by peer interactions. Patterns of crime across neighborhoods and over time display strong evidence of social interactions (Glaeser, Sacerdote and Scheinkman 1996).<sup>1</sup> A number of recent studies find evidence for peer effects in criminal activity across a wide variety of contexts such as neighborhoods, schools, and juvenile corrections facilities (Ludwig et al 2001, Kling et al 2005, Cook and Ludwig 2006, Bayer, Hjalmarsson and Pozen 2009, Deming 2011, Billings, Deming and Rockoff 2014).<sup>2</sup>

Further, two recent papers contribute to our understanding of a key unresolved question: the underlying mechanism for peer effects in crime. As first noted by Manski (1993), observed peer effects can be driven directly by group behavior (an “endogenous” peer effect), or they can be driven by exogenous attributes of a group.<sup>3</sup> Bayer, Hjalmarsson and Pozen (2009) show that criminal peer effects are stronger when juveniles who have similar criminal expertise are grouped together. Damm and Dustmann (2014) study the impact of growing up in a high-crime neighborhood on adult crime, and find that it is the share of criminals (rather than the number of

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<sup>1</sup> For examples of social interactions in other markets see Bertrand et al. (2000) on welfare program participation, Bayer, Ross and Topa (2008) on labor referrals, Grinblatt, Keloharju and Ikaheimo (2008) on automobile consumptions, and Fletcher and Ross (2012) on health behaviors.

<sup>2</sup> See Ross (2011) for a recent review of the peer effects literature more generally.

<sup>3</sup> Also see Brock and Durlauf (2001) for more recent discussions.

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crimes committed) in one's neighborhood that determines later criminal activity. The findings of both are strongly suggestive of a direct effect of social interactions because the peer effects are mediated by variables that suggest greater returns to or opportunities for social interactions between peers.<sup>4</sup>

In this paper we study the influence of a particularly important social environment – the school – on the formation of criminal partnerships. We match administrative data from Charlotte-Mecklenburg schools (CMS) to arrest and criminal incident and location records, which allows us to determine precisely when individuals commit crimes together. Criminal partnerships are a uniquely valuable behavior to examine when attempting to capture the role of social interactions between peers in determining criminal activity because the partnership could not take place unless the two individuals communicated and chose to commit a crime together, i.e. they engaged in a social interaction related to criminal activity.

Figure 1 displays our key result visually – individuals who live the same physical distance apart are much more likely to be “partners in crime” when they attend the same school and partnerships are much likely occur when individuals who attend the same school live very near each other. Two individuals living 0.5 km apart or less are 4.6 times more likely to form a criminal partnership when they attend the same school. We also find that criminal partnership is much more likely among youth of similar age, race and gender, and among students who shared the same grade and classroom in a school.

To ensure that this relationship is not biased by sorting across school attendance boundaries, we exploit the 2002-2003 redistricting of CMS schools, which changed neighborhood school assignment for more than half of students in the county (Billings, Deming

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<sup>4</sup> Also see Patacchini and Zenou (2009) for a more structural approach where they find that conforming to the criminal activity of self-reported friends contributes to a youth's own criminal activity. They instrument for the criminal activity of friends using the criminal activity of the individuals who the friends report as friends.

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and Rockoff 2014). By restricting our sample to individuals living on either side of a recently redrawn school boundary, we ensure that our results are not biased by sorting on unobserved attributes that might affect the probability of criminal partnership. As we discuss later, our results are robust to a wide variety of alternative sample restrictions and robustness checks.

We also test for the possibility of agglomeration externalities in crime – namely, that the availability of potential partners increases the *overall incidence* of crime. We find that increases in the number of same age, race and gender peers within a 1 km radius significantly increases a student’s own probability of committing a crime, but only when those peers attend the same school. Specifically, we regress whether a student ever committed a crime on the number of proximate potential partners overall and the number of potential partners assigned to the same school. Only the control for same school potential partners explains criminal activity, and only when potential partners are measured based on being the same age, gender and race as the student.

This paper makes two main contributions. Our first contribution is to provide new evidence on the importance of schools as a social setting for criminal network formation. While several other studies find important impacts of schools on criminal behavior (e.g. Jacob and Lefgren 2003, Cullen, Jacob and Levitt 2006, Deming 2011, Billings, Deming and Rockoff 2014), this paper pushes forward on the causal mechanism by demonstrating that schools strongly affect the formation of criminal partnerships even though criminal partnerships are a strongly local phenomenon that arise most frequently among individuals who reside in close proximity. Our results, however, do not rule out school effects on crime through other mechanisms such as changing criminal opportunities or the return to education. In fact, the broad within school peer effects on crime in Charlotte identified by Billings, Deming and Rockoff

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(2013) are primarily concentrated among African-Americans, but the strongest partnership effects in this paper are identified for white and Hispanic students.

Second, we provide evidence consistent with peer effects in crime that are directly driven by changes in peer *behavior* (criminal partnerships), rather than the exogenous characteristics of the group (Manski 1993). We examine the relationship between the presence of potential partners and the likelihood that individual students commit crimes and find that criminal activity is only increased by the proximity of potential partners who attend the same school, are similar in age, and are of the same race and gender.

**Data**

Our sample is comprised of administrative records from Charlotte-Mecklenburg Schools (CMS) for all individual students that attended public school in the county. We limit the sample to students that we observe at age 14 between the 2002-2003 and 2008-2009 school years, as well as students for which we observe a residential address during this period. The data include student gender, race, yearly end-of-grade (EOG) test scores, days absent and days suspended from school. The EOG tests are standardized and administered across the state of North Carolina from 1993 to the present.

This sample allows us to identify the residential location of students two years prior to age 16, which is the age at which criminal offenders in North Carolina are included in the registry of all adult arrests. We link CMS data to arrest registry data for Mecklenburg County from 1998 to 2013 using first and last name as well as date of birth.<sup>5</sup> The arrest data includes

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<sup>5</sup> Our match rate between student and arrest records is 94% and this same matching procedure has been incorporated and verified in Deming (2011) and Billings, Deming and Rockoff (2014) for these two datasets.

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individual names and identifiers,<sup>6</sup> and information on the number and nature of charges. We define “offenders” as students who were arrested during our sample period between the ages of 16 and 21. While this data allow us to observe the future criminal behavior of CMS students, regardless of whether they transfer or drop out of school, they are limited to crimes committed within Mecklenburg County.

Beginning in 2005, the registry of offenders was linked to records of all criminal incidents, so that officers could better understand crime patterns among repeat offenders. This data allows us to identify individuals that were arrested for the same crime. Approximately, 22 % of all reported crimes from 2005-2013 that led to an arrest were committed with one or more partners. Crimes committed by partners are disproportionately burglaries, robberies, and drug offenses.<sup>7</sup>

We use our linked student and arrest data to generate pairs of student offenders identifying whether they are ever criminal partners during our sample period. Specifically, we create a unique observation for every pair of students within three years of age among all students in the county who were ever arrested during our sample period.<sup>8</sup> We exclude pairs less than 130 feet apart since this is the smallest distance upon which we find different school pairs and to remove the influence of siblings and criminals within a single housing or apartment building.<sup>9</sup> Then, we create an indicator variable for a criminal partnership if both individuals were arrested for the same crime. Since our data uniquely links each individual’s arrest back to

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<sup>6</sup> The Mecklenburg County Sheriff (MCS) tracks arrests across individuals using a unique identifier that is established with fingerprinting.

<sup>7</sup> See Appendix Table 1 for the distribution of crime categories for all arrests as well as partnership arrests.

<sup>8</sup> We limit analysis to individuals within 3 years of age since less than 5% of criminal partnerships involve individuals more than 3 year apart. Even with this restriction, the size of this dataset is substantial (over 30 million observations) and thus we limit our analysis to pairs of individuals within certain distance thresholds. For computational ease, some models limit our sample to only non-partner observations that were ever arrested age 16-18. Results are unchanged if we limit non-partner observations to only individuals ever arrested age 19-21.

<sup>9</sup> Our regression coefficients are slightly larger in magnitude if we include these pairs.

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the Charlotte-Mecklenburg Police Department (CMPD)'s reported crime database, it allows us to determine if two individuals were arrested for the same crime even if each member of the partnership was arrested at different times, as well as rule out situations where individuals were arrested at the same time, but were not acting together to commit a crime.

We define residential neighborhoods within Mecklenburg County using 373 Block Groups from the 2000 Census. We identify 129 Block Groups that were bisected by middle and high school attendance zone boundaries that were newly drawn under redistricting in the summer of 2002. Our primary analysis involves the sample of offenders who attended public school at age 14 and resided in one of these bisected block groups between the 2002-2003 and 2008-2009 school years. We also consider a sample based on all individual students who reside in one of those block groups prior to the fall of 2002 at any age and are age 14 or older sometime between 2002-2003 and 2008-2009. However, the assigned school in this sample is quite noisy due to the high rates of residential mobility among our sample of student offenders. Estimates based on this second sample are shown in the appendix.<sup>10</sup>

Table 1 provides descriptive statistics for our sample. Panel 1 presents arrest data for ages 16-21, and panel 2 presents basic individual demographics, education outcomes, and school and neighborhood attributes. The first column shows means for the full sample of students, the second column presents means for all offenders, and the final column presents means for all offenders who were arrested for committing a crime with one or more partners.

The arrest rates among our sample of students are high, with 17 percent of the sample ever being arrested and 3 percent of the sample being arrested for violent crimes.<sup>11</sup> Among those

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<sup>10</sup> See Figures A2 and A3 and Table A6, which are comparable to Figures 3 and 5 and Table 7 using our primary sample.

<sup>11</sup> Based on the FBI Uniform Crime Reporting, we classify violent crimes as assault, kidnapping, rape and robbery, while property crimes are auto theft, burglary, fraud/forgery, larceny and criminal trespassing (attempted burglary).

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students ever arrested, the incidence of violent crime is 19 percent, but jumps to 34 percent for offenders who commit crimes with partners. The overall rate of individuals ever involved in a criminal partnership for our sample of offenders is 28 percent, with partner crimes tending to be more serious in nature as most of them are categorized as violent or property crimes. Offenders involved in criminal partnerships average 4.26 arrests and 1.23 unique partners.

Offenders are more likely to be male, black, have low test scores, more absences and suspensions, reside in poorer neighborhoods, and reside near more same age and same age-same school peers than all students. Other attributes are broadly similar between all offenders and those offenders involved in criminal partnerships.

Our main dataset for examining criminal partnerships is constructed by taking our sample of offenders (which are restricted to only CBG bisected by new boundaries in 2002) and merging each individual in that sample with all offenders  $j$  from our full CMS sample who are within three years of age of individual  $i$ .

Tables 2 and 3 present descriptive statistics for the sample of matched pairs who live within 1 kilometer of each other based on assigned school and on school attended respectively.<sup>12</sup> The first three columns present the subsample of all offender pairs, all pairs who attend the same school and all offender pairs who attend different schools. The final three columns present the means for subsamples of pairs who were arrested together in the commission of a crime. Based on the sample sizes and the number of partnerships in the last two columns, partnerships are also substantially more frequent when offenders attend the same school. Tables 2 and 3 present student demographics for pairs of offenders and shows some differences in the distribution of

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<sup>12</sup> One kilometer is identified as the threshold for which the relationship between distance and probability of partnership approaches zero in our dataset.

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students attributes between partners and non-partners. Partners are more likely to be similar in age, both male, same race and both reside in single-family residences.

To formally test if being assigned to the same school is exogenous to student attributes, we provide a balancing test in Table 4 for our sample of paired offenders given in Tables 2 and 3. Table 4 presents the results of a regression of whether offenders  $i$  and  $j$  are assigned to the same school (column 1) or assigned to the same school and grade (column 2) based on demographic attributes, test scores, suspensions and absences for individual  $j$ , while controlling for census block group fixed effects. Individual coefficients are insignificant and small in magnitude given the large number of pairs assigned to the same school in this sample. Our F-statistics highlights that jointly these coefficients are not statistically different from zero.

**Empirical Strategy**

Our strategy for examining the role of school peers in criminal activity involves taking a sample of individuals that were ever arrested for at least one crime and determining the probabilities that these individuals form criminal partnerships. Formally, our main empirical model is based on a dataset of offenders designated by  $i$  who sorted into the same neighborhood  $n$ , where redistricting caused this neighborhood to be divided by an attendance zone boundary. Each offender in this neighborhood is then matched to all offenders  $j$  (drawn from all offenders in our data) who attend school  $t$ , which may or may not equal  $s$ . A dummy variable  $P$  is set to one if the two individuals  $i$  and  $j$  have ever been arrested together for committing a crime and zero otherwise.

We then ask the following question: Is an individual more likely to commit a crime with an individual who resides nearby if they are also assigned to the same school? Concretely,

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suppose that the probability of criminal partnership depends upon both spatial proximity and school attended:

$$P_{isnkt} = f(d_{ij}) + g(d_{ij})D(s = t) + \varepsilon_{isnkt} \quad (1)$$

where  $f$  and  $g$  are functions that describe the relationship between the probability of partnership and distance ( $d_{ij}$ ) between the two individuals,  $D$  is an indicator for whether the two individuals are assigned to the same school or the same school and grade, and  $\varepsilon_{isnkt}$  is an idiosyncratic error. The function  $f$  captures the reduced form relationship over distance for pairs of offenders who are assigned to different schools, and our function of interest  $g$  captures the effect of school assignment on this relationship. Intuitively, our identification strategy asks whether the probability of criminal partnership between any two offenders who live the same distance apart is greater when they also attend the same school.

In order to generate exogenous variation in school assignment, we focus our analysis on neighborhoods that were bisected by a new school attendance boundary in the summer of 2002 due to court-ordered resegregation.<sup>13</sup> Then, we extend the model by adding a neighborhood fixed effect  $\delta_n$  based on  $i$ 's neighborhood and controls  $X_{jt}$  for the individual  $j$  who is being paired with each individual  $i$  in neighborhood  $n$ , where  $X_{jt}$  includes attributes of  $j$ 's assigned school.

Specifically,

$$P_{isnjt} = f(d_{ij}) + g(d_{ij})D(s = t) + \delta_n + \beta X_{jt} + \varepsilon_{isnjt} \quad \text{if } d_{ij} < \bar{d} \quad (2)$$

The neighborhood fixed effect implies that  $g$  is identified by differences in the frequency of criminal partnership for two offenders who reside in the same neighborhood, but are on opposite

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<sup>13</sup> See Billings, Deming, Rockoff (2014) for a discussion of school reassignment under the end of court-ordered busing in Charlotte-Mecklenburg Schools. The authors show that new school boundaries are not related to observable student attributes.

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sides of the school attendance boundary. Both offenders are paired with additional offenders  $j$  who vary in school assignment and by construction the same school variable is unique for each pair of offenders  $i$  and  $j$ . Moreover, our restriction to *newly formed* school boundaries ensures that the impact of attending the same school on criminal partnership is not biased by sorting across historically stable school assignment zones.<sup>14</sup>

Our initial analyses estimate  $f$  and  $f+g$  by creating a histogram of the distribution of criminal partnership frequency over distance separately for pairs of offenders in the same school and pairs of offenders in different schools. In our follow-up analyses, we restrict our sample to  $j$ 's who reside within a specified distance threshold  $\bar{d}$  of an individual  $i$ , where we specify  $\bar{d}$  based on the distribution of criminal partnership over pairwise distances  $d_{ij}$ . Standard errors for this model and for generalizations of this model are clustered at the neighborhood  $n$  level of individual  $i$  in each pair.

In addition to studying the impact of attending the same school, we also explore whether the probability of criminal partnership is greater when partners are in the same grade, as well as whether they shared a classroom together. However, unlike our results for school assignment and school and birth date implied grade assignment (which are arguably exogenous),<sup>15</sup> assignment to grades and classrooms is potentially biased by sorting and so we treat these results as suggestive. We also examine whether criminal partnership is greater when students share similar characteristics such as race, gender, age and test scores.

Finally, since our analysis is in part motivated by the idea that criminal partnerships may endogenously contribute to high rates of crime, we test whether increased opportunities for

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<sup>14</sup> As robustness tests, we estimate models that include distance bin fixed effects, individual fixed effects for each individual  $j$  as well as models that control for individual  $j$  by neighborhood  $n$  fixed effects.

<sup>15</sup> Same grade in the school assigned models is based on starting kindergarten when an individual is age 5 by September 1<sup>st</sup> and normal grade progression.

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criminal partnership affect the likelihood of committing a crime. Specifically, the likelihood of committing a crime  $C$  is allowed to depend upon the number of students  $N$  who share attributes with potential partners and reside within a specified distance; the number of students  $S$  who share these same key attributes with this student including residential proximity and are assigned to the same school; neighborhood fixed effects  $\delta_n$  and individual controls  $X_{isn}$ .

$$C_{isn} = \alpha_1 N(X_{jt,v-w} = X_{is,v-w} | d_{ij} < \bar{d}) + \alpha_2 S(X_{jt,v-w} = X_{is,v-w} | d_{ij} < \bar{d}, s = t) + \delta_n + \beta X_{isn} + \mu_{isn} \quad (8)$$

where  $N$  and  $S$  are constructed so that they contain the number of students  $j$  who match student  $i$  on attributes  $v$  through  $w$  in the vector  $X_{jt}$  and satisfy the conditioning criteria, distance threshold for  $N$  and both distance threshold and same school for  $S$ .

## **Graphical Results**

We begin with graphical results that display the relationship between distance and the probability of criminal partnerships.<sup>16</sup> Figure 1 plots the probability of a pair of offenders committing a crime together as a function of the distance between the offenders separately for the same and different school subsamples.

For the same school sample, the figure shows that the probability of partnership is high when the offenders are within a few hundred feet of each other, and declines quickly towards zero and is very near to zero once the offenders are 1km away or more. The probability of partnership for offenders who attend different schools is small and does not demonstrate any significant relationship with distance. This constitutes strong *prima facie* evidence that attending

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<sup>16</sup> The distribution of offenders and partners (all as well as subsamples for same/different school) is presented in Appendix Figures A.1, A.2 and A.3. These figures highlight that the sample size for different school pairs increases substantially at larger distances, and for distances within 1km about 15% of our observations are assigned different schools.

the same school increases the likelihood of criminal partnership, even for students who live in the same neighborhoods.

Figure 2 provides conditional probabilities for Figure 1 by controlling for block group fixed effects associated with the residence of offender  $i$  and covariates for the observed attributes of offender  $j$ . There are negligible differences between these conditional and unconditional probabilities. Figure 3 extends this analysis further by comparing the conditional probabilities of same school and assigned grade based on birth date versus different school partnerships. The combination of being in the same school and cohort increases our probabilities of partnership, especially in the 1/2km to 1km interval.

Figures 4 and 5 present the difference between our conditional probabilities of partnerships for same and different school pairs and same school/grade and different school pairs respectively. The 95% confidence intervals are represented by the shaded area. The differences for both figures are statistically significant for pairs who are located within about 1/2km of each other and differences are almost significant again at distances closer to 1 km.<sup>17</sup> Overall, these results highlight a strong positive relationship between shared school assignment and criminal partnerships for individuals that live very close together.

In order to verify that these results are due to school assignment boundaries and not the spatial distribution of offenders, we conduct a falsification test in Figure 6. To implement this test, we randomly shifted all attendance boundaries by between 1 and 2 kms and constructed a new version of Figure 5. We repeated this exercise 500 times in order to create a distribution of false boundary discontinuities and present the average results as a solid line and a 95%

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<sup>17</sup> The standard errors are bootstrapped based on resampling from the data 500 times.

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confidence interval as the shaded area in Figure 6.<sup>18</sup> Figure 6 does not demonstrate any relationship between same school and partnership based on spatially relevant, artificial attendance zone boundaries.

**Regression Results**

Table 5 presents results based on pairs who are within either ½, 1 or 2 kilometers of each other, with the same dependent variable as the figures above: being arrested together for at least one crime. The right hand side variables in the model are assigned to same school and assigned to same school and same grade based on birth date. All models include block group fixed effects for offenders *i* in the bisected block groups and controls for the observable attributes of the paired offenders *j*. Column 1 presents estimates of the partnership model for these subsamples. The coefficients on offenders being assigned to the same school and assigned to the same school and grade are both positive and highly statistically significant for all distance thresholds.

Consistent with our figures, the strongest effects occur for individuals residing within ½ km and effects weaken as we extend distance thresholds out to 2 km. Given the limited number of observations in different schools within ½ km, we focus our analysis on results for 1km. Results at 1 km are more precise than the ½ km results and quantitatively similar magnitudes relative to mean partnership rates. For column 1, being in the same school increases the probability of being criminal partners by 0.21 percentage points and being in the same grade increases this probability by an additional 0.34 percentage points. Overall, being assigned to the same school and grade makes two individuals six times more likely to form a criminal

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<sup>18</sup> The large lower confidence band (shaded area) for less than 1/2km simply reflects the small sample size of different school pairs, which can generate large probabilities of partnerships for only one or two randomly assigned different school partnerships.

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partnership, increasing from a mean probability of 0.0011 for different school pairs to 0.0066 for same school and grade pairs.

The rest of the columns in Table 5 present the model using the number of crimes committed together, if individuals were partners at age 16-18, partners at age 19-21, and finally partnerships for specific crime classifications.<sup>19</sup> Column 2 examines if schools have an effect on the number of partnerships between two offenders. Results for both same school and same school/grade are positive and the magnitudes are larger than other estimates relative to the mean number of partnerships. Partnership effects for both same school and same grade persist except for the 19-21 age samples where effects are primarily at the same school level. The fact that age 16-18 and age 19-21 results differ for same school and grade coefficients is consistent with partnerships being more likely during years that individuals are still in school or recently dropped out of school. Results for crime categories show a consistent role of schools in increasing criminal partnerships for a variety of criminal activities.

Table 6 replicates Table 5 for the 1 kilometer sample using whether partners actually attended the same school, the same school and same grade, and attended at least two classes together.<sup>20</sup> These models all include fixed effects for individual  $j$  since individuals likely attended schools and specific courses based on a number of unobserved attributes.<sup>21</sup> Most of the effects are concentrated among pairs who attended class together, but partnership effects also arise at both the grade and school level. The magnitudes of our effects are larger in these models even though in some cases we lose statistical significance. For column 1, being in the same course, grade and school increase the probability of partnership by 0.0097 percentage points over

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<sup>19</sup> Appendix Table 1 shows results for assigned school by further disaggregated types of crime with assault and burglary generating the largest effects.

<sup>20</sup> Defining same course as at least two classes together provides more precise estimates than other definitions.

<sup>21</sup> To further test if sorting to specific courses is problematic to our results, we created Appendix Table A.2 where we only define same course based on courses required of all students in english, math, science and social studies.

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the mean partnership probability of 0.0016 for different school partners. Again, we find that the effects on 19-21 year old partners are substantially smaller than for 16-18 year old partners.<sup>22</sup>

*Robustness of Results*

Table 7 presents a series of robustness tests for the school assignment model shown in panel 1 and the school attended model in panel 2. The first column presents the main results for the within 1 kilometer sample. The second column presents the model for the same sample, but including fixed effects based on bins for different distances between the individuals in the pair. The third and fourth columns present the model for the ½ kilometer sample, without and with the distance bin fixed effects, respectively. Column 5 presents results for the 1 kilometer sample replacing offender  $j$ 's observable attributes with an individual offender fixed effect. Columns 6 and 7 presents the results for the 1 kilometer sample without and with individual fixed effects where same school assignment is based only on high school. The final column presents estimates controlling for residential block group of offender  $i$  by individual offender  $j$  fixed effects. Results are largely consistent across these models with both distance bin and individual fixed effects generating similar results. The only noticeable difference across these specifications is the smaller magnitude of coefficient when we base school assignment solely of high school. Smaller effects for models where school assignment/attendance only based on high school is consistent with the loss of same school partners that interacted in middle school only. To further validate our story, we ran a few other models designed to test if greater opportunity for interaction amplifies our results. Appendix Table A.4 and A.5 show stronger impacts of schools on

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<sup>22</sup> Appendix Table 3 shows results for school attended by further disaggregated types of crime with significant effects for assault and drug crime partnerships.

partnerships for pairs that attended the same elementary school and for individuals that have a longer tenure in their neighborhood.

One may be concerned with the use of residential address after the newly draw school boundaries in 2002 because of sorting to specific school assignments within a neighborhood. The inclusion of school and individual fixed effects and the fact that Billings, Deming and Rockoff (2014) find minimal residential relocation after redistricting based on changes in school peer composition addresses some of these concerns. Nonetheless, we tested our main results for our sample of students using a student's residential address prior to 2002 and provide results in Appendix Tables A.7 and Appendix Figures A.3 and A.5. Our conclusions regarding the role of schools is still consistent in these models, but we find considerably smaller magnitudes when using these earlier addresses. These attenuated results are due to the large amount of residential movement by our sample of offenders.<sup>23</sup> To further test the concern of post redistricting sorting, we ran a series of models that interacted our school variables with a dummy for individual  $i$  living in the same address since 2001. If our results are driven by individuals sorting into these neighborhoods, we might expect stronger results for the most recent residents who presumably selected into a particular side of the boundary based on across boundary differences. On the other hand, if our results arise from social interactions, we might expect the strongest results to arise between individuals who have resided in this neighborhood the longest and so have the strongest connections to the neighborhood. Table 8 shows stronger effects on pre-2002 residents for both school variables, which is consistent with our main results not being driven by new residents sorting to schools after redistricting, and thus limits concern that post redistricting sorting is generating our results.

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<sup>23</sup> Only 35% of our main sample of offenders live in the same address at age 14 as they did in 2001. Coupled with the fact that we are using pairs of offenders leads to only about 10% of our observations having the same residential information in 2001 as well as at age 14.

### *Partnerships and Student Attributes*

Since offenders may form partnerships based on students attributes, Tables 9 and 10 present results from models where we examine heterogeneity in the likelihood of two offenders partnering together based on same assigned or attended school. We re-estimate our main model from Table 5 including additional controls for the socio-economic/demographic match between the two offenders in any pair, and interact these controls with the assigned to the same school dummy variable. These variables include whether the offenders are assigned to the same grade, have the same gender, same race, whether one or both were suspended and whether one or both reside in single family housing. The effects of same gender are allowed to vary by gender, and the effects of same race are allowed to vary between white, black and Hispanic offenders.

We find strong effects of increased partnership when the offenders in the pair are in the same grade, are both male and are either both white or both Hispanic. The same race effect does not persist for black offenders. We also do not observe any effects associated with suspension or attendance. These results are robust to using number of crimes committed together and for both the 16-18 and the 19-21 age group subsamples. Table 10 repeats this analysis for the attending the same school and being in a class together models. While less strong in some cases, effects continue to be concentrated among partnerships between offenders who are the same age, are both male and are both white or both Hispanic.

### *Criminal Networks*

One way that schools may foster the development of partnerships is through the ability of youth criminals to recruit offenders into criminal partnerships. The existence of youth criminal

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gangs provides an example of strong peer interactions and criminal networks. Ideally, we would be able to measure criminal gangs, but since this type of data is unavailable, we can at least use our partnership data to highlight criminal networks and the role of connected individuals in criminal partnerships. To identify criminal networks, we look at the linkages of 1,665 criminal partners that lived more than 1km apart at age 14.<sup>24</sup> The idea is to see if the network structure can be informative into identifying highly connected individuals. Figure 7 provides summary plots of this network with the degree distribution in the top panel and the distribution of components in this network in the bottom panel. The degree distribution highlights the number of unique partners for an individual and one can see that this network is relatively sparse in connections with about 67% of individuals having only one partner and only 10% having three or more partners. The bottom panel gives the distribution of network components and provides the number of individuals that are connected through a path of partnerships.

Figure 8 plots examples of the components in our network. One can see the tree structure to this network with almost all individuals directly connected by partnership to only one or two other individuals. This network structure is very different than the structure of denser social networks that often have one or a few large connected networks that contain a substantial fraction of the individuals and only a small fraction of individuals in disconnected networks (Jackson, 2008).<sup>25</sup> The relatively sparse nature of our network is likely attributed to both the small neighborhood dynamics of criminal partnerships as well as the fact that criminal partnerships typically lead to incarceration for one or both individuals thus limiting future partnerships due to incapacitation. Given the limited number of nodes with a large amount of

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<sup>24</sup> We focus on partnerships 1km or more to take away any mechanical relationship between networked offenders and probability of partnerships within 1km for later regression analysis.

<sup>25</sup> See Calvo-Armengol, Patacchini, and Zenou (2009) for an example of an analysis that explores the relationship between the centrality of individuals in a dense social network and their outcomes.

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centrality in this network, we focus our analysis on components and simply designate networked offenders based on the size of the component for which an individual belongs. We specify an individual as networked if they belong to a component of size 10 or larger.

Table 11 brings networked individuals into our analysis by designating individual  $j$  as a networked peer if individual  $j$  was involved in partnerships with individuals outside the 1km neighborhood and these partnerships connect individual  $j$  to at least 9 other individuals. Results find higher across boundary partnership rate differences when individuals in bifurcated block groups are paired with networked peers and this relationship is stronger for individuals in the same assigned grade as the networked peer.<sup>26</sup> Effects are strongest for property crime and felony partnerships. Results are slightly weaker in our bottom set of results where we define partnerships based on components of 5 or more criminals.

*Crime Agglomeration*

The higher probability of partnerships in schools provides evidence of direct peer interaction, but we would like to know if this is simply due to schools as a place for finding partners or if the concentration of peers in schools leads to increases in the number of criminals and subsequent partnerships. Therefore, we want to test the influence of same school peer concentration on the probability of becoming an offender.

Tables 12 and 13 present models that build on our analysis by estimating models for the likelihood of individual youths to commit a crime. Specifically, we draw a sample of students from bisected blocks and calculate both the number of potential partners overall and the number

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<sup>26</sup> Regression model for school attended and networked peer finds weaker results, which could be due to the removal of individuals from a school for criminal behavior during the school year. Since we measure school attendance based on spring enrollment, this could lead us to the case of a networked peer splitting time between different schools and thus more muted impacts.

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of potential partners in the same school. We define a student's potential partners in three ways: 1) nearby (within 1 kilometer), similar age/assigned grade students; 2) nearby, similar age/assigned grade students, same race and same gender students; and 3) nearby, similar age, networked peer.

As a balancing test, we regress the number of same school potential partners on the number of potential partners, student observable attributes and block group fixed effects. Table 12 shows that student observables are not able to predict the number of same school potential partners for any of our definitions. Then, we regress ever arrested for a crime on the number of potential partners, the number of same school potential partners, student observable attributes and block group fixed effects.

Table 13 provides three sets of results for our crime models with same school peers indicating the effect of a standard deviation increase in same school peers. Since we want to control for the overall number of peers in the neighborhood and simply vary the number of same school peers, we only present the estimated coefficient on the number of same school peers. When potential partners are defined based on same age/grade, race and gender, we find large positive effects of same school potential partners on the likelihood of any student committing a crime (middle panel), but these effects are not present when potential partners are based only on age (top panel). We also find some effects due to networked peers on violent crimes.

The coefficients on same school, age, race and gender peers indicate that a standard deviation increase (8.3 students) in same school peers increases the probability of ever being arrested by 4.1 percentage points, which indicates a 25% increase in the probability of arrest relative to the average student. A standard deviation increase in the presence of school peers that are same age, race and gender or networked peers increases the probability of arrest for a violent

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crime by 1.8 and 1.3 percentage points respectively. This effect represents a relatively larger increase of 60% and 43% in the probability of arrest relative to the average student.

This is a nontrivial increase in arrest probability, but substantially smaller in relative terms to the increase in partnership probabilities from same school and grade assignment. Notably, our measure of peers provides limited explanation for ever having a crime partner conditional on ever being arrested. Coefficients in columns four through six indicate smaller and insignificant increases in the number of criminal partnerships for criminals. Therefore, having a large pool of potential partners nearby is not leading offenders to simply commit more partnerships crimes overall. Rather, offenders directly interacted with same school peers in criminal activity..

To test if our crime agglomeration results are consistent with the spatial scale of partnership results and also the degree to which our neighborhood definition is well suited for measuring crime agglomeration, we ran a series of regression that redefined our peers as individuals within varying distance bands of 0-1km, 1-2km, 2-3km, 3-4km and 4-5km. Figure 9 presents results for models using the outcome of ever arrested and indicates that only for our less than 1km definition of neighborhood do we say any effects from peers. Results for larger distance bands are all closer to zero and are typically more precisely estimated due to larger number of different school peers. Results for other outcomes are similar to this figure. Additionally, we wanted to test if our measure of peers based on non-shared student attributes would generate weaker coefficients, thus confirming the importance of age, gender and race in defining peers. Figure 10 estimates results for separately for four gender and race groups – black males, black females, white males and white females- using all four groups to define peers. Results indicate stronger effects when defining peers as same gender and race, with black males

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increasing ever being arrested by 9 percentage points for a standard deviation increase in same school-age-race-gender peers. Results weaken as we define peers as female or white, but we do find that different gender and race peers may generate some positive or even negative effects on arrest probabilities. These cross groups effects are likely a function of different peer dynamics between racial and gender groups.

Overall results from our crime agglomeration models support the idea that that higher probability of within school partnerships is likely a result of both better opportunities to find criminal partners as well as more criminals.. These results complement Damm and Dustmann (2014)’s finding that a higher share of criminals within a neighborhood lead to more criminal convictions by extending this finding to schools.

**Conclusion**

In this paper we study the influence of schools and neighborhoods on criminal partnership. We find that two youth who live an equal distance apart are far more likely to be “partners in crime” when they also attend the same school, and these effects are concentrated among use who reside in close physical proximity to each other. This result holds especially strongly for youth of the same age and gender, and for those who also share the same grade and classroom within a school. We also find evidence for agglomeration externalities in crime, which suggests that the social interactions created by the potential for partnerships affect the probability of committing a crime as well as the probability of criminal partnership conditional on crime.

Our results have important implications understanding the determinants of criminal activity. School assignment policies can have unintended effects on neighborhood crime in that drawing boundaries that keep together cohesive neighborhoods with clusters of similar students

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may contribute to higher rates of criminal activity among youth, greater frequency of criminal partnerships among young offenders, and larger criminal networks facilitating future partnerships and crimes. Our results also have implications for the literature on the endogenous effects of social interactions. We demonstrate that the social context of the school affects a key behavior related to criminal activity, criminal partnerships, and show that the relationship between the availability of local peers and criminal activity follows a pattern that is consistent with what we would expect if peers were influencing criminal activity by presenting partnership opportunities. This suggests that interventions which reduce crime among a subset of youth within a school will have a spillover effect on other potential criminals by reducing the opportunities for criminal partnership available to other students who live nearby, leading to a social multiplier that would not exist if the mechanism behind the peer effects were purely social learning or school context.

**References**

Bayer, Patrick, Randi Hjalmarsson, and David Pozen, “Building Criminal Capital behind Bars: Peer Effects in Juvenile Corrections,” *The Quarterly Journal of Economics*, 124 (2009), 105–147.

Patrick Bayer & Stephen L. Ross & Giorgio Topa, 2008. "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes," *Journal of Political Economy*, University of Chicago Press, vol. 116(6), pages 1150-1196

Bertrand, Marianne, Erzo Luttmer, and Sendhil Mullainathan (2000), “Network Effects and Welfare Cultures,” *Quarterly Journal of Economics*, 115 (3), 1019-55.

Billings, S. B., Deming, D. J., & Rockoff, J. (2014). School Segregation, Educational Attainment, and Crime: Evidence from the End of Busing in Charlotte-Mecklenburg. *The Quarterly Journal of Economics*, 129(1), 435-476.

Brock, William A. and Steven N. Durlauf (2001), “Interactions-Based Models” in *Handbook of Econometrics*, edited by James J. Heckman and Edward Leamer, Vol. 5, 3297-3380.

**Preliminary – please do not cite or circulate**

Calvo'-Armengol, Antonio, Eleonora Patacchini, and Yves Zenou. (2009). Peer effects and social networks in education. *Review of Economic Studies*, 76, 1239–1267.

Cullen, Julie Berry, Brian A. Jacob, and Steven D. Levitt. "The impact of school choice on student outcomes: an analysis of the Chicago Public Schools." *Journal of Public Economics* 89.5 (2005): 729-760.

Damm, Anna Piil, and Christian Dustmann. "Does growing up in a high crime neighborhood affect youth criminal behavior?." *American Economic Review* 104.6 (2014): 1806-1832.

Deming, D. J. (2011). Better Schools, Less Crime?. *The Quarterly Journal of Economics*, 126(4), 2063-2115.

Fletcher, Jason M., and Stephen L. Ross. Estimating the Effects of Friendship Networks on Health Behaviors of Adolescents (2012). NBER Working Paper No. 18253

Glaeser, Edward L., Bruce Sacerdote, and José A. Scheinkman, "Crime and Social Interactions," *The Quarterly Journal of Economics*, 111 (1996), 507–548.

Grinblatt, Mark, M. Keloharju and S. Ikaheimo. (2008). Social Influence and Consumption: Evidence from the Automobile Purchases of Neighbors. *Review of Economics and Statistics*, 90 (4), pp 735-753.

Jacob, Brian and L. Lefgren "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration and Juvenile Crime," *American Economic Review*, 93 (2003), 1560-1577.

Jackson, M. O., (2008). Social and economic networks. Princeton, NJ: Princeton University Press.

Kling, Jeffrey R., Jens Ludwig and Lawrence F. Katz. "Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Voucher Experiment." *The Quarterly Journal of Economic*. 120:1 (February 2005), 87-130.

Ludwig, Jens; Duncan, Greg J.; and Hirschfield, Paul. "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing-Mobility Experiment." *The Quarterly Journal of Economics*. 116 (May 2001): 655-80.

Ludwig, Jens, and Jeffrey R. Kling, "Is Crime Contagious?" *Journal of Law and Economics*, 50 (2007), 491–518.

Manski, Charles F. "Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* 60.3 (1993), 531-542.

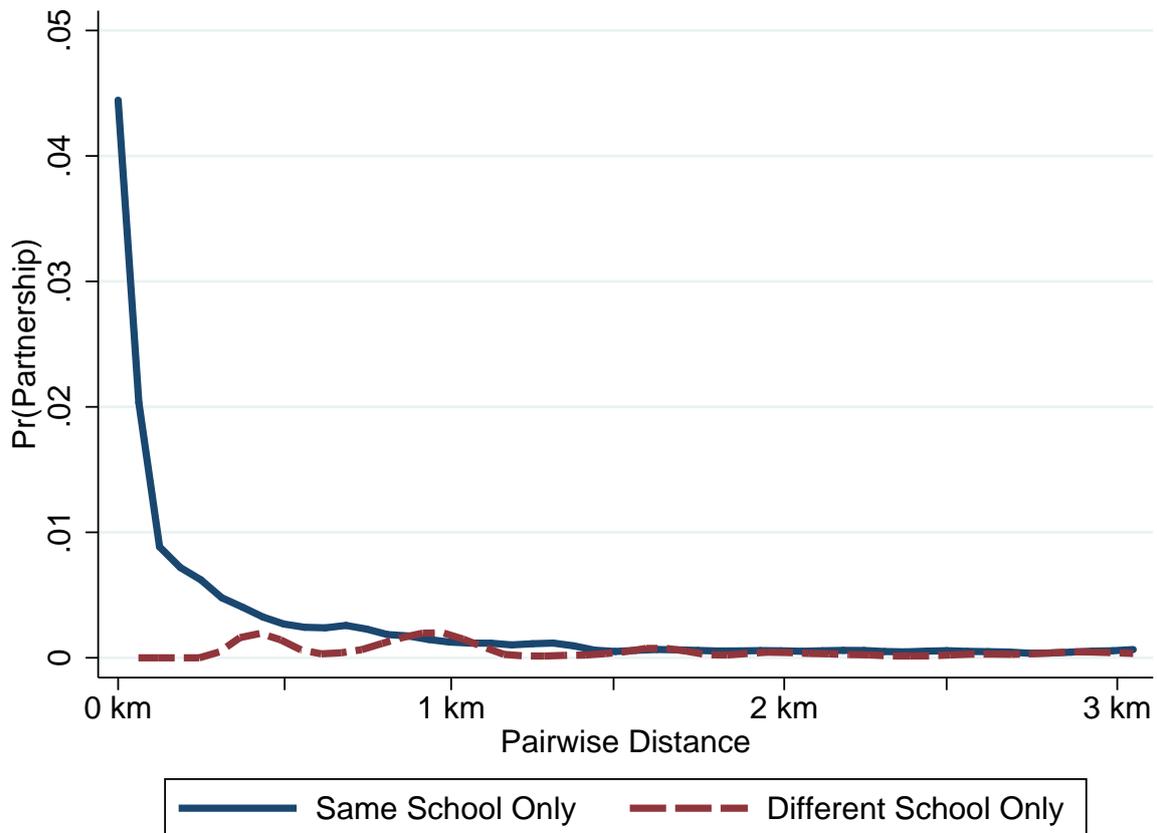
Manski, Charles F. "Economic Analysis of Social Interactions." *Journal of Economic Perspectives*, 14.3 (2000), 115-136.

**Preliminary – please do not cite or circulate**

Patacchini, Eleanora and Yves Zenou. “Juvenile Delinquency and Conformism” *Journal of Law, Economics, and Organization*, 28 (2009), 1-31.

Ross, Stephen L. “Social interactions within cities: Neighborhood environments and peer relationships.” In *Handbook of Urban Economics and Planning* Eds. N. Brooks, K. Donaghy, G. Knapp (2011). Oxford University Press.

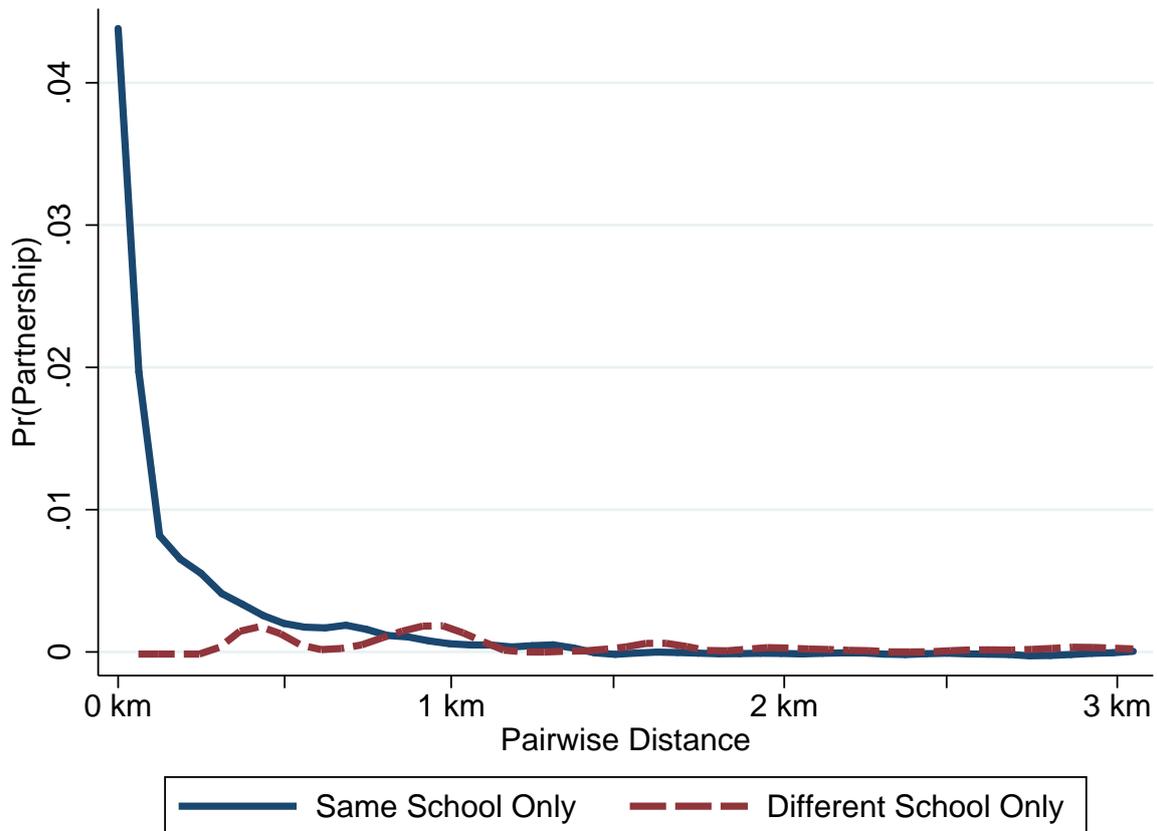
Figure 1: Unconditional Probabilities of Partnership (Same vs. Different Schools)



This figure provides the unconditional probability of same school and different school partnerships by distance b/t partners in a pair.

The sample included in this figure represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 3 km of each other based on school age 14 address and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of non-partner pairs arrested age 19-21.

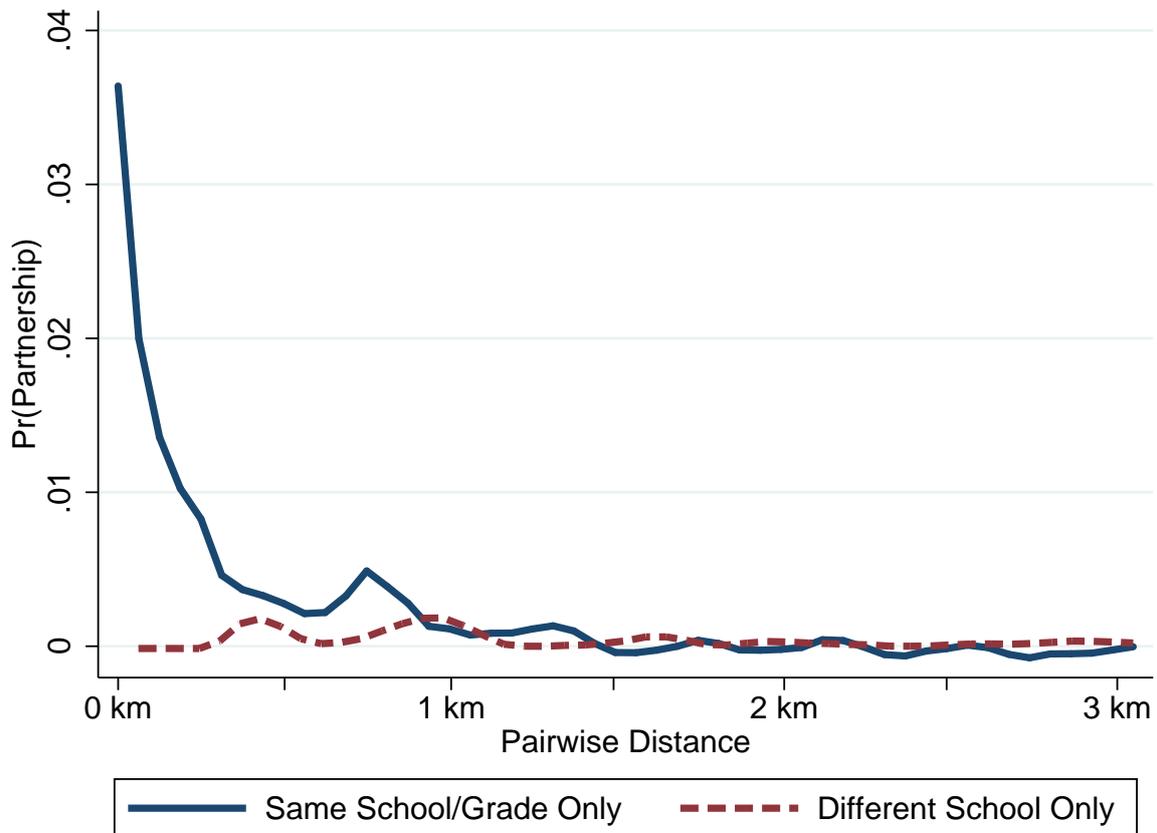
Figure 2: Conditional Probabilities of Partnership (Same vs. Different Schools)



This figure provides the distribution of same school and different school residuals by distance b/t partners in a pair. Residuals calculated using a first stage regression which controls for individual attributes of person  $j$  (gender, race, test scores, absences, suspensions, assigned school fixed effects), school year born fixed effects for  $j$ , and CBG fixed effects for  $i$ .

The sample included in this figure represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 3 km of each other based on school age 14 address and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of non-partner pairs arrested age 19-21.

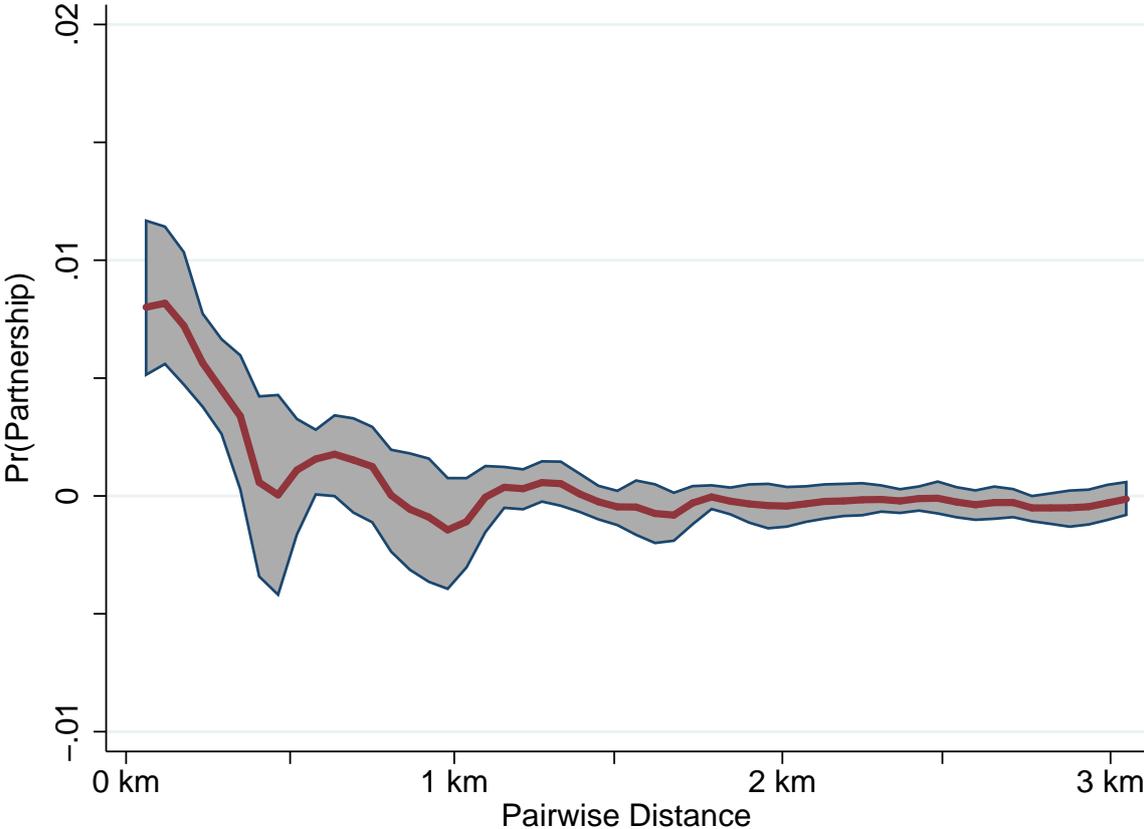
Figure 3: Conditional Probabilities of Partnership (Same School/Grade vs. Different Schools)



This figure provides the distribution of same school and grade, and different school residuals by distance b/t partners in a pair. Residuals calculated using a first stage regression which controls for individual attributes of person  $j$  (gender, race, test scores, absences, suspensions, assigned school fixed effects), school year born fixed effects for  $k$ , and CBG fixed effects for  $i$ . We also include an indicator in individuals  $i$  and  $j$  are the same assigned grade.

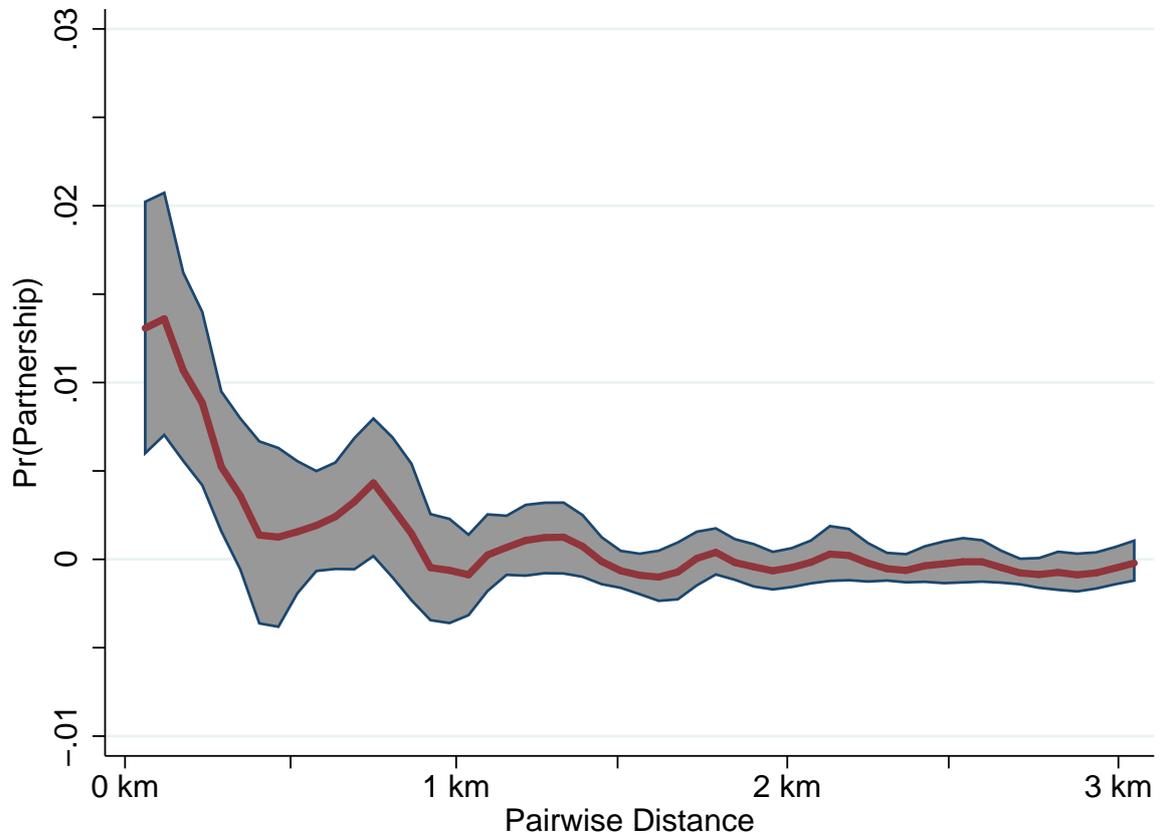
The sample included in this figure represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 3 km of each other based on school age 14 address and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of non-partner pairs arrested age 19-21.

Figure 4: Difference in Conditional Probabilities of Partnership (Same vs. Different Schools)



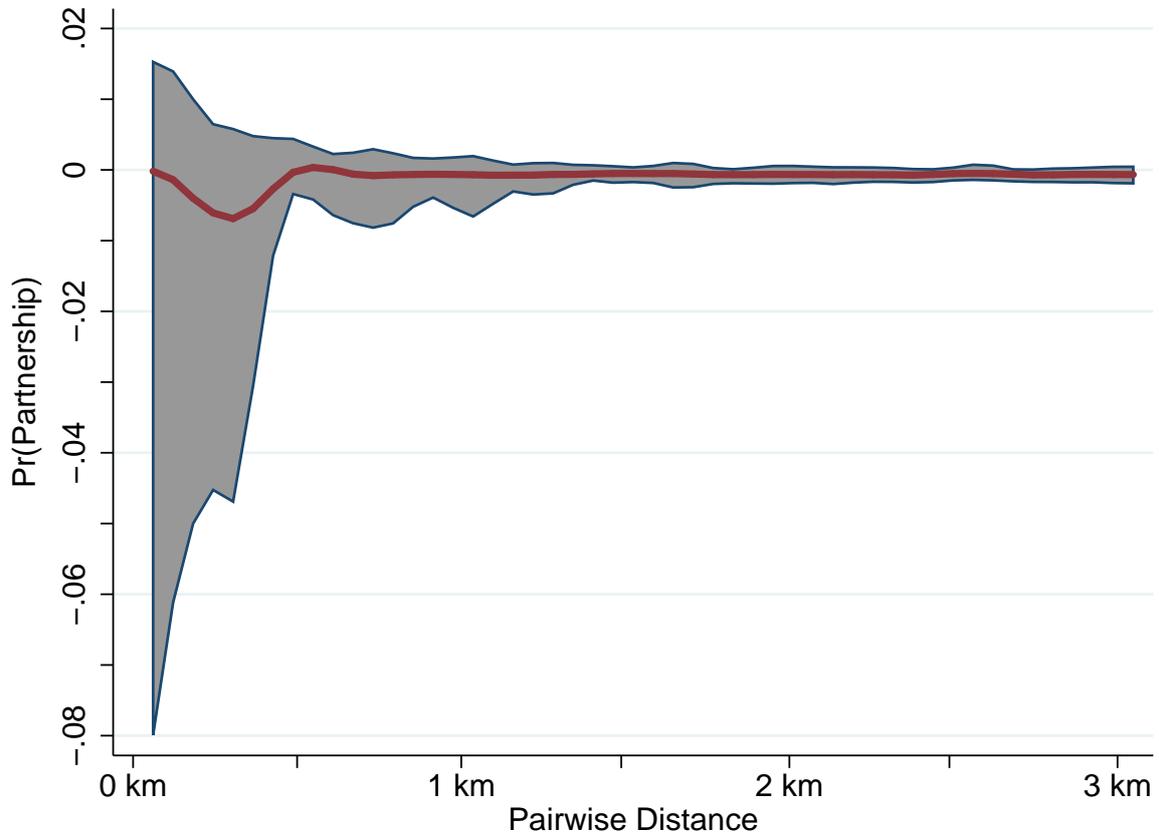
This figure provides the difference in conditional probability (residuals) of partnership between same school and different school pairs. 95% confidence intervals given by shaded area and were generated by resampling data using 500 bootstraps. Kernel-weighted local polynomial smoothing implemented in order to generate a continuous distribution of conditional probabilities.

Figure 5: Difference in Conditional Probabilities of Partnership (Same School/Grade vs. Different Schools)



This figure provides the difference in conditional probability (residuals) of partnership between same school and grade and different school pairs. 95% confidence intervals given by shaded area and were generated by resampling data using 500 bootstraps. Kernel-weighted local polynomial smoothing implemented in order to generate a continuous distribution of conditional probabilities.

Figure 6: Falsification Test



Falsification Test based on randomly shifting school attendance boundaries in all directions by between 1 and 2km. Our original sample of students are then reassigned as same/different schools based on the random boundary shift. With the new school assignments, we calculate the distribution of same school and different school residuals by distance b/t partners in a pair. The solid line indicates the mean difference between same school and different school residuals and shaded areas indicates the range of results (5-95%) based on 500 replications of these random school boundary shifts.

Residuals calculated using a first stage regression which controls for individual attributes of person  $j$  (gender, race, test scores, absences, suspensions, assigned school fixed effects), school year born fixed effects for  $j$ , and CBG fixed effects for  $i$ . Kernel-weighted local polynomial smoothing implemented in order to generate a continuous distribution of conditional probabilities.

NetworkPic.jpg

Figure 7: Criminal Network Plots I

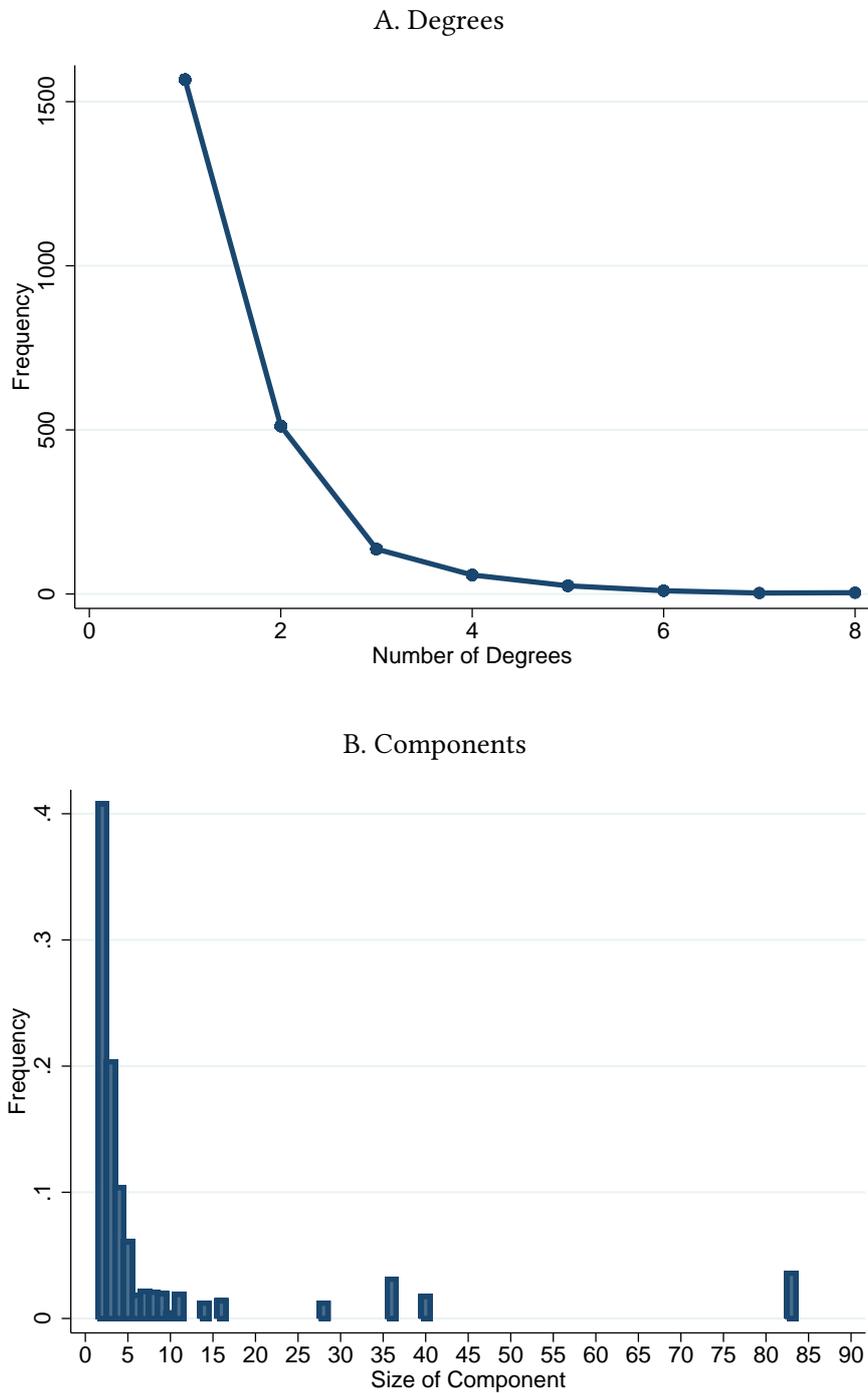


Figure Note: Figure A. provides the distribution of degrees within the network of criminal partners that reside 1km or more apart and Figure B. presents the distribution of components within our network. We include 14 unique components of  $\geq 10$  members. This network is based off of 1,665 unique criminal partnerships for individuals that reside more than 1km apart.

Figure 8: Criminal Network Plots II

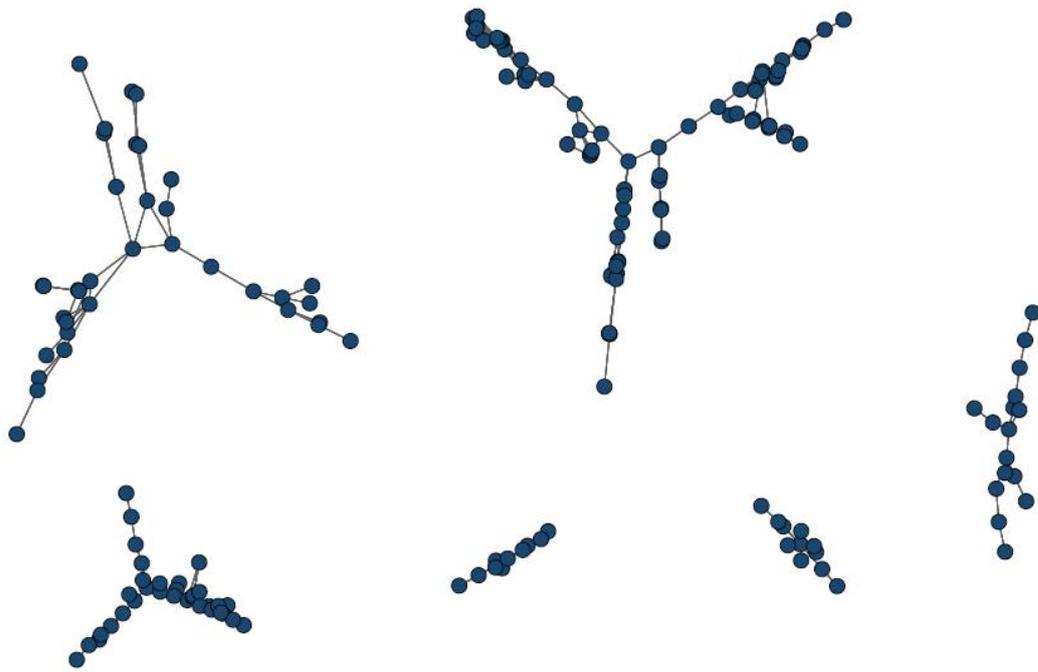
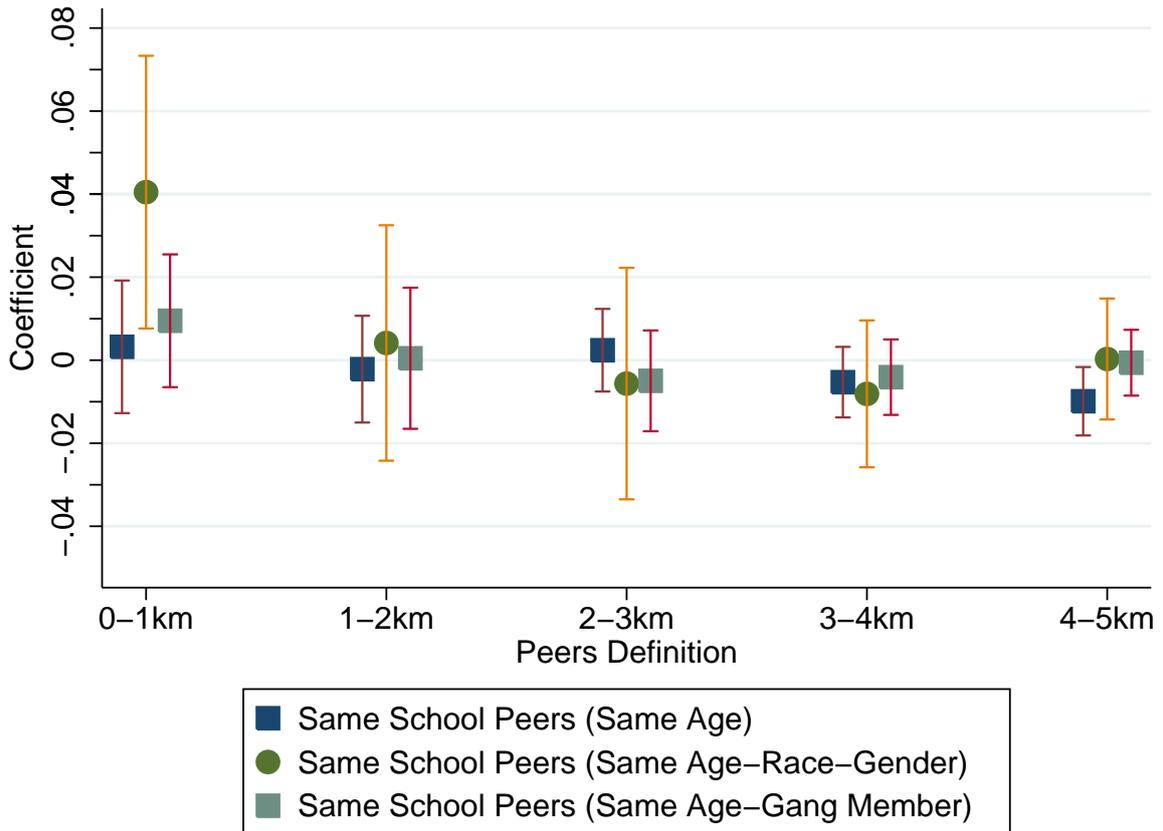


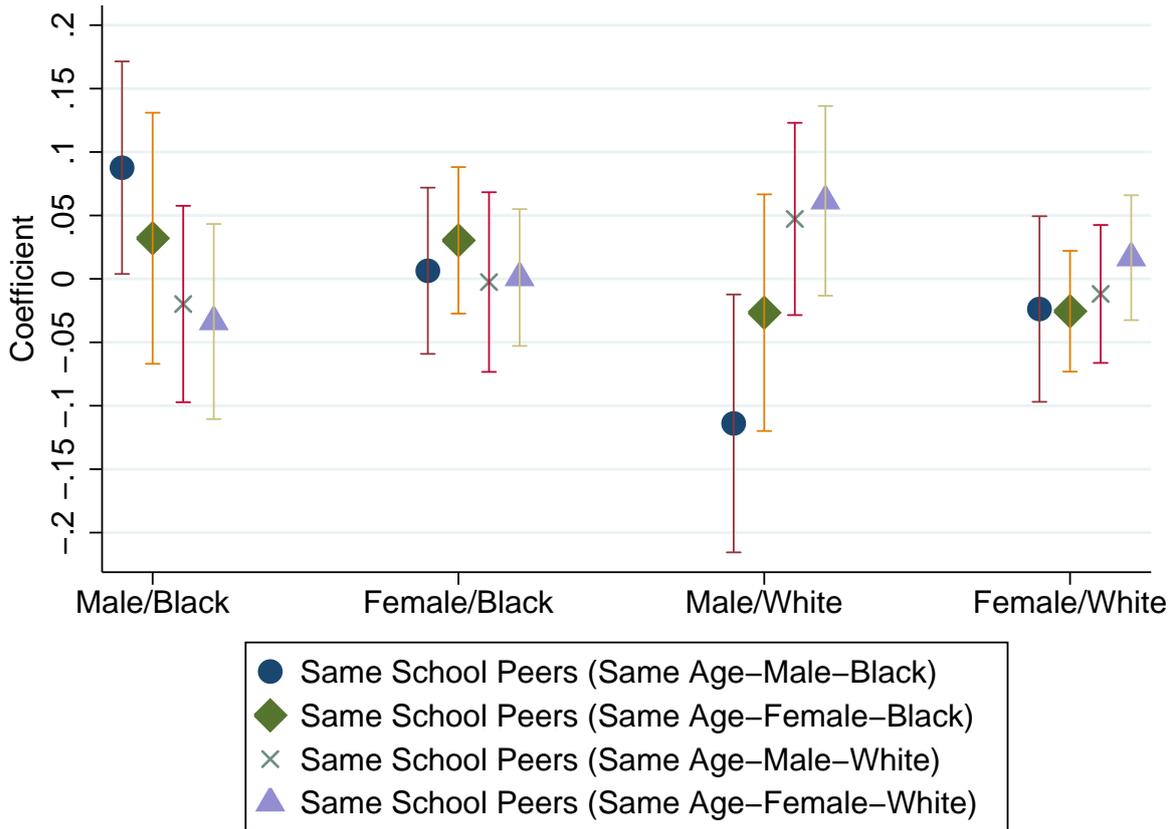
Figure Note: These figures represent examples of different sized components within this network of criminal partnerships.

Figure 9: Crime Model



This figure provides the estimated coefficient of a standard deviation increase in same school and neighborhood peer counts and 95% confidence interval for a series of regression of Equation 4 where we vary definitions of peers based on student attributes as well as distance bands away from an individual upon which to define peers. All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, assigned school fixed effects, and the number of same age peers within a given distance band for a given peer attribute definition. All models include Census Block Group 2000 (CBG) by peer attribute definition fixed effects. Standard errors robust to arbitrary correlation within CBG. Dependent Variable is an indicator for Ever Arrested (16-21).

Figure 10: Crime Model by Gender-Race Groups



This figure provides the estimated coefficient of a standard deviation increase in same school and neighborhood peer counts and 95% confidence interval for a series of regression of Equation 4 where we estimate our crime agglomeration model separately for black males, black females, white males and white females and use peers groups defined by these four gender-race groups for 0-1km neighborhoods. All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, assigned school fixed effects, and the number of same age peers within a given distance band for a given peer attribute definition. All models include Census Block Group 2000 (CBG) by peer attribute definition fixed effects. Standard errors robust to arbitrary correlation within CBG.

Table 1: Summary Statistics - Individuals

	All Students	Ever Arrested	Criminal Partners
<i>Crime Outcomes</i>			
Ever Arrested	0.17 (0.37)	1.00 (0.00)	1.00 (0.00)
Ever Arrested Violent	0.03 (0.18)	0.19 (0.40)	0.34 (0.47)
Ever Arrested Property	0.07 (0.26)	0.42 (0.49)	0.61 (0.49)
Crime Partnership	0.05 (0.21)	0.28 (0.45)	1.00 (0.00)
Number of Arrests	0.48 (1.60)	2.83 (2.91)	4.26 (3.78)
Number of Partners	0.06 (0.31)	0.34 (0.69)	1.23 (0.78)
<i>Background Characteristics</i>			
Male	0.50 (0.50)	0.69 (0.46)	0.76 (0.43)
Black	0.48 (0.50)	0.70 (0.46)	0.81 (0.40)
Hispanic	0.11 (0.31)	0.08 (0.27)	0.07 (0.25)
Single Family Residence	0.79 (0.41)	0.75 (0.44)	0.75 (0.43)
Math Test Score (8th grade)	-0.06 (0.98)	-0.60 (0.84)	-0.73 (0.78)
Read Test Score (8th grade)	-0.04 (0.97)	-0.57 (0.91)	-0.74 (0.89)
Missing Test Score (8th grade)	0.23 (0.42)	0.22 (0.42)	0.21 (0.40)
Total Days Absent (8th grade)	9.15 (11.64)	16.56 (17.03)	19.45 (18.76)
Total Days Suspended from School (8th grade)	2.21 (6.10)	6.89 (10.51)	9.21 (12.50)
All Peers (age +/- 3 years) within 1 km	238.80 (120.96)	259.98 (125.41)	280.23 (124.69)
Same Age Peers within 1 km (0s)	44.97 (21.76)	48.44 (22.44)	50.78 (21.72)
Same Age & School Peers within 1 km	40.36 (20.27)	42.55 (20.84)	44.20 (20.70)
Same Age-Race-Gender Peers within 1 km	11.86 (9.20)	14.37 (9.82)	15.77 (9.90)
Same Age-Race-Gender & School Peers within 1 km	10.57 (8.30)	12.53 (8.78)	13.63 (8.96)
CBG Median HH Income (000s)	56.90 (20.79)	48.73 (18.22)	45.91 (16.83)
People per sq mile (000s)	2.11 (1.82)	2.39 (1.94)	2.57 (1.99)
Observations	34,958	5,867	1,625

Means and standard deviations are reported above. All information regarding housing or Census Block Group (CBG) 2000 neighborhood is based on address at school age 14. School age determined by Charlotte-Mecklenburg Schools (CMS) matriculation policy of starting kindergarten if age 5 by September 1st and we assume normal grade progression. The sample of all students is based on students attending CMS at school age 14 at any time from 2003-2009 and living in a CBG bisected by a new 2002 middle or high school boundary. The column for Ever Arrested and all crime outcomes based on arrests in Mecklenburg County of CMS students age 16 to 21. The column for Criminal Partners is based on those students that were Ever Arrested for a crime for which another student was also arrested for that crime.

Table 2: Pairs by School Assigned

	Non-Partners			Partners		
	All	Assigned Same School	Assigned Different School	All	Assigned Same School	Assigned Different School
Same Age	0.186 (0.39)	0.187 (0.39)	0.180 (0.38)	0.287 (0.45)	0.301 (0.46)	0.048 (0.22)
One Year Apart in Age	0.329 (0.47)	0.329 (0.47)	0.326 (0.47)	0.434 (0.50)	0.423 (0.49)	0.619 (0.50)
Two or Three Years Apart in Age	0.485 (0.50)	0.483 (0.50)	0.494 (0.50)	0.279 (0.45)	0.275 (0.45)	0.333 (0.48)
Both Male	0.494 (0.50)	0.500 (0.50)	0.458 (0.50)	0.842 (0.37)	0.852 (0.36)	0.667 (0.48)
Both Female	0.092 (0.29)	0.090 (0.29)	0.106 (0.31)	0.060 (0.24)	0.052 (0.22)	0.190 (0.40)
One Male, One Female	0.414 (0.49)	0.410 (0.49)	0.436 (0.50)	0.098 (0.30)	0.096 (0.29)	0.143 (0.36)
Same Race	0.705 (0.46)	0.698 (0.46)	0.743 (0.44)	0.825 (0.38)	0.820 (0.38)	0.905 (0.30)
Different Race	0.295 (0.46)	0.302 (0.46)	0.257 (0.44)	0.175 (0.38)	0.180 (0.38)	0.095 (0.30)
Both Suspended (8th Grade)	0.464 (0.50)	0.462 (0.50)	0.474 (0.50)	0.533 (0.50)	0.525 (0.50)	0.667 (0.48)
One Suspended, One Not Suspended	0.428 (0.49)	0.429 (0.49)	0.424 (0.49)	0.344 (0.48)	0.345 (0.48)	0.333 (0.48)
Neither Suspended (8th Grade)	0.108 (0.31)	0.109 (0.31)	0.102 (0.30)	0.123 (0.33)	0.130 (0.34)	0.000 (0.00)
Both in SF Homes	0.550 (0.50)	0.555 (0.50)	0.525 (0.50)	0.743 (0.44)	0.742 (0.44)	0.762 (0.44)
One SF, One Not in SF	0.289 (0.45)	0.276 (0.45)	0.362 (0.48)	0.175 (0.38)	0.174 (0.38)	0.190 (0.40)
Neither in SF Homes	0.160 (0.37)	0.169 (0.37)	0.114 (0.32)	0.082 (0.27)	0.084 (0.28)	0.048 (0.22)
Observations	123,616	104,825	18,791	366	345	21

Means and standard deviations are reported above. We define assigned to the same school as two individuals being assigned to the same middle or high school based on 2002-2003 school attendance boundaries. Same age based on cohort and determined by the school year an individual turned 5 as of September 1st.

The sample included in this table represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 1 km of each other based on school age 14 address and live at least 130 feet apart (minimum distance between two students assigned to different schools) and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. Consistent with figures, we limit non-partner pairs to only those ever arrested age 16-18 and results are similar with the use of non-partner pairs arrested age 19-21.

Table 3: Pairs by School Attended

	Non-Partners			Partners		
	All	Attended Same School	Attended Different School	All	Attended Same School	Attended Different School
In Same Course	0.030 (0.17)	0.084 (0.28)	0.000 (0.00)	0.175 (0.38)	0.267 (0.44)	0.000 (0.00)
Same Age	0.186 (0.39)	0.256 (0.44)	0.148 (0.35)	0.287 (0.45)	0.313 (0.46)	0.238 (0.43)
One Year Apart in Age	0.329 (0.47)	0.409 (0.49)	0.285 (0.45)	0.434 (0.50)	0.492 (0.50)	0.325 (0.47)
Two or Three Years Apart in Age	0.485 (0.50)	0.335 (0.47)	0.568 (0.50)	0.279 (0.45)	0.196 (0.40)	0.437 (0.50)
Both Male	0.494 (0.50)	0.512 (0.50)	0.483 (0.50)	0.842 (0.37)	0.858 (0.35)	0.810 (0.39)
Both Female	0.092 (0.29)	0.084 (0.28)	0.097 (0.30)	0.060 (0.24)	0.058 (0.23)	0.063 (0.24)
One Male, One Female	0.414 (0.49)	0.405 (0.49)	0.420 (0.49)	0.098 (0.30)	0.083 (0.28)	0.127 (0.33)
Same Race	0.705 (0.46)	0.688 (0.46)	0.714 (0.45)	0.825 (0.38)	0.808 (0.39)	0.857 (0.35)
Different Race	0.295 (0.46)	0.312 (0.46)	0.286 (0.45)	0.175 (0.38)	0.192 (0.39)	0.143 (0.35)
Both Suspended (8th Grade)	0.464 (0.50)	0.456 (0.50)	0.468 (0.50)	0.533 (0.50)	0.529 (0.50)	0.540 (0.50)
One Suspended, One Not Suspended	0.428 (0.49)	0.427 (0.49)	0.429 (0.49)	0.344 (0.48)	0.317 (0.47)	0.397 (0.49)
Neither Suspended (8th Grade)	0.108 (0.31)	0.117 (0.32)	0.102 (0.30)	0.123 (0.33)	0.154 (0.36)	0.063 (0.24)
Both in SF Homes	0.550 (0.50)	0.567 (0.50)	0.541 (0.50)	0.743 (0.44)	0.750 (0.43)	0.730 (0.45)
One SF, One Not in SF	0.289 (0.45)	0.281 (0.45)	0.294 (0.46)	0.175 (0.38)	0.150 (0.36)	0.222 (0.42)
Neither in SF Homes	0.160 (0.37)	0.152 (0.36)	0.165 (0.37)	0.082 (0.27)	0.100 (0.30)	0.048 (0.21)
Observations	123,616	44,056	79,560	366	240	126

Means and standard deviations are reported above. We define attended the same school as two individuals matriculating for at least one year at the same middle or high school. Same age based on cohort and determined by the school year an individual turned 5 as of the first day of school. Same course indicates if two individuals took at least two courses together in grades 6-10.

The sample included in this table represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 1 km of each other based on school age 14 address and live at least 130 feet apart (minimum distance between two students assigned to different schools) and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. Consistent with figures, we limit non-partner pairs to only those ever arrested age 16-18 and results are similar with the use of non-partner pairs arrested age 19-21.

Table 4: Balancing Test - Do Observables Explain Assignment to Same School?

	(1) Assigned Same School	(2) Assigned Same School & Grade
Male	0.0012 (0.0050)	-0.0011 (0.0036)
Hispanic	0.0065 (0.0159)	-0.0036 (0.0126)
Black	-0.0072 (0.0075)	-0.0045 (0.0060)
Single Family Residence	-0.0026 (0.0195)	-0.0037 (0.0136)
Math Test Score (8th grade)	-0.0002 (0.0043)	0.0016 (0.0035)
Read Test Score (8th grade)	0.0020 (0.0042)	0.0033 (0.0036)
Total Days Suspended from School (8th grade)	0.0003 (0.0003)	0.0004 (0.0003)
Total Days Absent (8th grade)	-0.0001 (0.0002)	-0.0002 (0.0001)
Observations	123,982	38,560
F-Stat (p-value)	0.92	0.65

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors robust to arbitrary within-CBG correlation in parentheses. We include a total of 129 unique CBGs in our sample.

All regressions include but do not report an indicator for missing a test score, dummies for year individual  $j$  turned age 5 as of 9/1, assigned middle and high school fixed effects for  $j$  and CBG fixed effects for person  $i$ .

We define assigned to the same school as two individuals being assigned to the same middle or high school based on 2002-2003 school attendance boundaries. Same grade is based on starting kindergarten at age 5 and normal grade progression. Column 2 excludes same school, different grade pairs and includes an indicator if individual  $i$  and  $j$  are the same grade. F-statistics reports p-value that all reported covariates are jointly equal to zero.

Table 5: Impact of School Assignment on Criminal Partnerships

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Crime Partner	Number of Partner Crimes	16-18 yr old Partnership	19-21 yr old Partnership	Violent Crime Partners	Property Crime Partners	Felony Partners	Misdemeanor Partners
<u>Pairs <math>\leq</math> 1 km</u>								
Assigned Same School & Grade	0.0034*** (0.0007)	0.0050*** (0.0011)	0.0027*** (0.0007)	0.0006 (0.0004)	0.0012*** (0.0004)	0.0019*** (0.0007)	0.0025*** (0.0007)	0.0013*** (0.0005)
Assigned Same School	0.0021*** (0.0007)	0.0025** (0.0010)	0.0013** (0.0006)	0.0011*** (0.0004)	0.0005 (0.0003)	0.0015*** (0.0005)	0.0015*** (0.0006)	0.0007* (0.0004)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982
<u>Pairs <math>\leq</math> 1/2 km</u>								
Assigned Same School & Grade	0.0034** (0.0016)	0.0055** (0.0022)	0.0029* (0.0016)	-0.0001 (0.0007)	0.0005 (0.0006)	0.0031** (0.0015)	0.0033** (0.0015)	0.0010 (0.0009)
Assigned Same School	0.0044*** (0.0017)	0.0055* (0.0029)	0.0025* (0.0014)	0.0027*** (0.0009)	0.0015*** (0.0005)	0.0030** (0.0015)	0.0034** (0.0014)	0.0014* (0.0008)
Dep. Var (mean)	0.0050	0.0061	0.0036	0.0023	0.0013	0.0033	0.0039	0.0017
Observations	42,601	42,601	42,601	42,601	42,601	42,601	42,601	42,601
<u>Pairs <math>\leq</math> 2 km</u>								
Assigned Same School & Grade	0.0010** (0.0004)	0.0016*** (0.0006)	0.0007* (0.0004)	0.0002 (0.0002)	0.0002 (0.0002)	0.0007* (0.0003)	0.0010*** (0.0003)	0.0001 (0.0003)
Assigned Same School	0.0009*** (0.0002)	0.0010*** (0.0003)	0.0006*** (0.0002)	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0005*** (0.0002)	0.0006*** (0.0002)	0.0003*** (0.0001)
Dep. Var (mean)	0.0014	0.0017	0.0010	0.0006	0.0004	0.0007	0.0009	0.0007
Observations	397,687	397,687	397,687	397,687	397,687	397,687	397,687	397,687

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i. We also include an indicator if individuals i and j are the same assigned grade.

Dependent Variable is an indicator based on column heading. Number of partner crimes indicates the number of times a pair of individuals were arrested for the same crime. 16-18 and 19-21 yr old indicates the age group for which one of the partners belonged at the time of arrest. Property Crime Partnerships include partnerships where at least one individual was arrested for auto theft, burglary, fraud/forgery or larceny. Violent Crime Partnerships include partnerships where at least one individual was arrested for aggravated/sexual/simple assault, rape or robbery. Felony and Misdemeanor based on the severity of the charge at arrest and coded accordingly by the Mecklenburg County Sheriff's Department.

Table 6: Impact of School Attended on Criminal Partnerships

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Crime Partner	Number of Partner Crimes	16-18 yr old Partnership	19-21 yr old Partnership	Violent Crime Partners	Property Crime Partners	Felony Partners	Misdemeanor Partners
Pairs $\leq$ 1 km								
In Same Course	0.0073** (0.0029)	0.0131* (0.0078)	0.0057** (0.0026)	0.0017* (0.0009)	0.0002 (0.0008)	0.0038* (0.0023)	0.0032 (0.0026)	0.0041** (0.0016)
In Same School & Same Grade	0.0015** (0.0008)	0.0018* (0.0010)	0.0019** (0.0007)	-0.0002 (0.0004)	0.0012*** (0.0004)	0.0003 (0.0006)	0.0009 (0.0007)	0.0013*** (0.0004)
In Same School	0.0009* (0.0005)	0.0006 (0.0007)	0.0004 (0.0004)	0.0008** (0.0004)	0.0002 (0.0002)	0.0006 (0.0004)	0.0007 (0.0005)	0.0002 (0.0003)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include fixed effects for individual j, CBG fixed effects for individual i. We define attended the same school as two individuals matriculating for at least one year at the same middle or high school. Same grade is based on a pair of students attending the same grade. Same course indicates if two individuals took at least two courses together in grades 6-10. We also include an indicator in individuals j and k are in the same grade.

Dependent Variable is an indicator based on column heading. Number of partner crimes indicates the number of times a pair of individuals were arrested for the same crime. 16-18 and 19-21 yr old indicates the age group for which one of the partners belonged at the time of arrest. Property Crime Partnerships include partnerships where at least one individual was arrested for auto theft, burglary, fraud/forgery or larceny. Violent Crime Partnerships include partnerships where at least one individual was arrested for aggravated/sexual/simple assault, rape or robbery. Felony and Misdemeanor based on the severity of the charge at arrest and coded accordingly by the Mecklenburg County Sheriff's Department.

Table 7: Other Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Dist. FE	1/2 km	Dist. FE 1/2 km	Student FE	Same HS only	Student FE Same HS only	Student by CBG FE
Assigned Same School & Grade	0.0034*** (0.0007)	0.0034*** (0.0007)	0.0034** (0.0016)	0.0035** (0.0016)	0.0031*** (0.0007)	0.0022** (0.0011)	0.0018* (0.0010)	0.0029*** (0.0007)
Assigned Same School	0.0021*** (0.0007)	0.0011 (0.0007)	0.0044*** (0.0017)	0.0031* (0.0016)	0.0018** (0.0007)	0.0017*** (0.0007)	0.0014** (0.0007)	0.0013 (0.0008)
In Same Course	0.0113*** (0.0034)	0.0113*** (0.0034)	0.0147** (0.0061)	0.0147** (0.0061)	0.0073** (0.0029)	0.0064*** (0.0020)	0.0037** (0.0018)	0.0069** (0.0031)
In Same School & Grade	0.0011 (0.0010)	0.0010 (0.0010)	0.0007 (0.0023)	0.0005 (0.0023)	0.0015** (0.0008)	0.0000 (0.0012)	0.0013 (0.0011)	0.0016* (0.0008)
In Same School	0.0018*** (0.0006)	0.0017*** (0.0006)	0.0037** (0.0019)	0.0037** (0.0019)	0.0009* (0.0005)	0.0014* (0.0008)	0.0006 (0.0007)	0.0008 (0.0006)
Observations	123,982	123,982	42,593	42,593	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i.

School attended models include fixed effects for each school attended (6-10th grade) by person j, except in cases of individual fixed effects (FE). We also include an indicator in individuals i and j are the same assigned or actual grade. Dependent Variable is an indicator for a pair ever being criminal partners. Dist. FE indicates a series of indicator variables for 200 foot intervals of pairwise distances. Same HS indicates that same school only defined based on high schools. Student FE and student by CBG FE is based on individual j.

Table 8: Impact of School Assignment by Resident since 2001

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Crime Partner	Number of Partner Crimes	16-18 yr old Partnership	19-21 yr old Partnership	Violent Crime Partners	Property Crime Partners	Felony Partners	Misdemeanor Partners
Pairs $\leq$ 1 km								
Assigned to Same School/Grade	0.0016** (0.0008)	0.0022** (0.0009)	0.0013* (0.0007)	0.0000 (0.0003)	0.0007* (0.0004)	0.0008 (0.0007)	0.0010 (0.0007)	0.0007 (0.0005)
*Resident since 2001	0.0047*** (0.0014)	0.0076*** (0.0027)	0.0036*** (0.0011)	0.0017* (0.0010)	0.0018** (0.0009)	0.0027*** (0.0010)	0.0039*** (0.0012)	0.0011 (0.0008)
Assigned to Same School	0.0017** (0.0007)	0.0019** (0.0009)	0.0011* (0.0006)	0.0009** (0.0004)	0.0002 (0.0004)	0.0014*** (0.0005)	0.0012** (0.0006)	0.0005 (0.0004)
*Resident since 2001	0.0012* (0.0006)	0.0014 (0.0010)	0.0007 (0.0005)	0.0006 (0.0005)	0.0007** (0.0003)	0.0004 (0.0005)	0.0006 (0.0006)	0.0006 (0.0005)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i. We also include an indicator in individuals i and j are the same assigned grade.

Dependent Variable is an indicator based on column heading. Resident since 2001 based on the years at the same address prior to school age 14 for person i. We also include but do not report the variable *Resident since 2001*, which has a mean of 0.35.

Table 9: Interaction Effects of School Assigned on Criminal Partnerships

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Crime Partner	Number of Partner Crimes	16-18 yr old Partnership	19-21 yr old Partnership	Violent Crime Partners	Property Crime Partners
Assigned to Same School/Grade	0.0034*** (0.0007)	0.0052*** (0.0011)	0.0027*** (0.0007)	0.0007 (0.0004)	0.0014*** (0.0004)	0.0018*** (0.0007)
Assigned to Same School	0.0008 (0.0018)	0.0022 (0.0037)	-0.0001 (0.0015)	0.0015 (0.0011)	0.0005 (0.0009)	0.0008 (0.0014)
*Same Gender*Male	0.0043** (0.0017)	0.0055*** (0.0020)	0.0029* (0.0016)	0.0029*** (0.0008)	0.0014* (0.0008)	0.0022** (0.0011)
*Same Gender	-0.0007 (0.0014)	-0.0009 (0.0014)	-0.0007 (0.0014)	-0.0010* (0.0006)	0.0000 (0.0006)	-0.0005 (0.0010)
*Same Race	0.0105** (0.0047)	0.0246* (0.0147)	0.0105** (0.0044)	0.0024 (0.0018)	0.0026 (0.0017)	0.0055 (0.0039)
*Same Race*Black	-0.0091* (0.0048)	-0.0240 (0.0149)	-0.0095** (0.0044)	-0.0015 (0.0019)	-0.0025 (0.0017)	-0.0052 (0.0041)
*Same Race*Hispanic	0.0029 (0.0060)	-0.0049 (0.0142)	0.0015 (0.0063)	0.0001 (0.0026)	0.0008 (0.0023)	0.0032 (0.0051)
*Both Suspended (8th Grade)	-0.0019* (0.0011)	-0.0018 (0.0015)	-0.0013 (0.0009)	-0.0014 (0.0009)	-0.0006 (0.0006)	-0.0006 (0.0008)
*One Suspended (8th Grade)	-0.0020* (0.0011)	-0.0013 (0.0015)	-0.0015 (0.0009)	-0.0015* (0.0009)	-0.0014* (0.0008)	0.0000 (0.0007)
*Both in SF Homes	0.0020 (0.0013)	0.0008 (0.0028)	0.0020* (0.0010)	0.0005 (0.0006)	0.0007 (0.0007)	0.0011 (0.0010)
*One in SF Home	0.0016 (0.0012)	0.0005 (0.0022)	0.0015 (0.0009)	0.0009 (0.0006)	0.0008 (0.0006)	0.0010 (0.0007)
Observations	123,982	123,982	123,982	123,982	123,982	123,982

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i.

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include indicators for all variables interacted with the assigned to same school variable as well as an indicator for same age whose interaction is given by Assigned to Same School/Grade.

Table 10: Interaction Effects of School Attended on Criminal Partnerships

	(1) Any Crime Partner	(2) Number of Partner Crimes	(3) 16-18 yr old Partnership	(4) 19-21 yr old Partnership	(5) Violent Crime Partners	(6) Property Crime Partners
In Same Course	0.0071** (0.0029)	0.0128* (0.0075)	0.0055** (0.0025)	0.0017* (0.0009)	0.0004 (0.0010)	0.0035 (0.0022)
In Same School/Grade	0.0013* (0.0008)	0.0016 (0.0010)	0.0017** (0.0008)	-0.0002 (0.0004)	0.0011** (0.0004)	0.0001 (0.0006)
In Same School	0.0010 (0.0022)	-0.0023 (0.0048)	-0.0000 (0.0020)	0.0019 (0.0013)	-0.0003 (0.0012)	-0.0006 (0.0018)
*Same Gender*Male	0.0025** (0.0012)	0.0035* (0.0020)	0.0019 (0.0011)	0.0012** (0.0006)	-0.0003 (0.0008)	0.0016** (0.0008)
*Same Gender	0.0014* (0.0008)	0.0014* (0.0008)	0.0012* (0.0007)	-0.0003 (0.0002)	0.0010* (0.0006)	0.0003 (0.0004)
*Same Race	0.0046 (0.0060)	0.0207 (0.0210)	0.0064 (0.0059)	0.0004 (0.0021)	0.0008 (0.0017)	0.0038 (0.0054)
*Same Race*Black	-0.0035 (0.0059)	-0.0194 (0.0207)	-0.0057 (0.0058)	0.0001 (0.0023)	0.0004 (0.0017)	-0.0038 (0.0053)
*Same Race*Hispanic	0.0022 (0.0099)	-0.0108 (0.0252)	-0.0009 (0.0099)	0.0028 (0.0028)	0.0037 (0.0035)	-0.0030 (0.0096)
*Both Suspended (8th Grade)	-0.0007 (0.0014)	0.0011 (0.0023)	0.0004 (0.0013)	-0.0011 (0.0009)	-0.0001 (0.0008)	0.0008 (0.0009)
*One Suspended (8th Grade)	-0.0023* (0.0013)	-0.0006 (0.0024)	-0.0012 (0.0012)	-0.0013 (0.0009)	-0.0007 (0.0009)	0.0001 (0.0008)
*Both in SF Homes	0.0001 (0.0011)	-0.0008 (0.0015)	0.0000 (0.0009)	-0.0002 (0.0008)	-0.0006 (0.0007)	0.0006 (0.0007)
*One in SF Home	-0.0011 (0.0011)	-0.0014 (0.0016)	-0.0006 (0.0009)	-0.0007 (0.0008)	-0.0013 (0.0008)	0.0003 (0.0006)
Observations	123,982	123,982	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include fixed effects for individual j, CBG fixed effects for individual i. All regressions include indicators for all variables interacted with the assigned to same school variable as well as an indicator for same grade whose interaction is given by Attended Same School/Grade.

Table 11: Impact of School Assignment - Networked Peers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Crime Partner	Number of Partner Crimes	16-18 yr old Partnership	19-21 yr old Partnership	Violent Crime Partners	Property Crime Partners	Felony Partners	Misdemeanor Partners
<u>Networked Peer = Component <math>\geq 10</math></u>								
Assigned Same School & Grade	0.0030*** (0.0007)	0.0045*** (0.0009)	0.0023*** (0.0006)	0.0006 (0.0004)	0.0012*** (0.0004)	0.0014** (0.0006)	0.0022*** (0.0007)	0.0008* (0.0005)
*Networked Peer	0.0109* (0.0056)	0.0170* (0.0101)	0.0092* (0.0051)	0.0019 (0.0027)	0.0037 (0.0037)	0.0106** (0.0046)	0.0062 (0.0039)	0.0085* (0.0049)
Assigned Same School	0.0020*** (0.0007)	0.0023** (0.0009)	0.0013** (0.0006)	0.0011** (0.0004)	0.0005 (0.0003)	0.0014*** (0.0005)	0.0013** (0.0006)	0.0008** (0.0003)
*Networked Peer	0.0016 (0.0023)	0.0038 (0.0034)	0.0016 (0.0022)	0.0014 (0.0009)	-0.0002 (0.0017)	0.0023 (0.0015)	0.0029** (0.0013)	-0.0006 (0.0017)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982
<u>Networked Peer = Component <math>\geq 5</math></u>								
Assigned Same School & Grade	0.0029*** (0.0007)	0.0044*** (0.0009)	0.0023*** (0.0007)	0.0005 (0.0004)	0.0012*** (0.0004)	0.0014** (0.0006)	0.0023*** (0.0007)	0.0007 (0.0005)
*Networked Peer	0.0067** (0.0034)	0.0099* (0.0057)	0.0048 (0.0032)	0.0017 (0.0017)	0.0025 (0.0024)	0.0057** (0.0026)	0.0030 (0.0024)	0.0058** (0.0029)
Assigned Same School	0.0019*** (0.0007)	0.0022** (0.0009)	0.0012* (0.0006)	0.0011** (0.0004)	0.0004 (0.0003)	0.0014*** (0.0005)	0.0012* (0.0006)	0.0008** (0.0003)
*Networked Peer	0.0024 (0.0015)	0.0034* (0.0019)	0.0023 (0.0014)	0.0012* (0.0007)	0.0005 (0.0010)	0.0019** (0.0010)	0.0032*** (0.0010)	-0.0005 (0.0009)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. These models include an interaction term that indicates if person j is a networked peer member. A networked peer is defined based on partnership networks from other neighborhoods (individuals >1km apart) and by construction does not specify a networked peer due to within neighborhood partnerships. The top panel of results is based on defining an individual as networked if they are connected through crime partnerships to at least 9 other individuals (component of at least 10 people). The bottom panel of results changes this definition to an individual connected through crime partnerships to at least 4 other individuals (component of at least 5 people). Approximately 3-5% of the individuals matched to our sample of arrestees in neighborhoods bisected by new school boundaries in 2002 are designated potential gang members by these definitions.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i. We also include an indicator in individuals i and j are the same assigned grade. We also include but do not report the dummy variable for networked peer.

Table 12: Crime Agglomeration Models - Balancing Test

	(1) Same School & Age Peers (1 km)	(2) Same School & Age-Race-Gender Peers (1 km)	(3) Same School & Age-Networked Peers (1 km)
Male	-0.0702 (0.0534)		-0.0029 (0.0024)
Hispanic	-0.4666* (0.2414)		-0.0104 (0.0067)
Black	-0.2549* (0.1500)		-0.0008 (0.0039)
Single Family Residence	0.6059 (0.7604)	0.1264 (0.2414)	0.0139 (0.0203)
Math Test Score (8th grade)	-0.0407 (0.0620)	-0.0114 (0.0266)	-0.0002 (0.0021)
Read Test Score (8th grade)	0.0844 (0.0735)	0.0219 (0.0279)	-0.0014 (0.0024)
Total Days Suspended from School (8th grade)	0.0056 (0.0086)	0.0026 (0.0029)	-0.0001 (0.0003)
Total Days Absent (8th grade)	0.0007 (0.0041)	-0.0002 (0.0012)	0.0001 (0.0001)
Observations	34,958	34,958	34,958
F-Stat (p-value)	0.14	0.86	0.84
R <sup>2</sup>	0.93	0.96	0.95

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. The dependent variable in column one indicates the number of same age peers (0s) that live within 1 km and are assigned to the same middle or high school. Column two restricts the definition of peers in column one to only include those individuals that are same gender and same race also. Column 3 defines peers as those individuals connected through crime partnerships (outside of neighborhood) to at least 9 other individuals (component of at least 10 people). The sample used for determining the number of peers is based on all students attending CMS at school age 14 at any time from 2003-2009.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, assigned school fixed effects and the number of same age peers within 1 km in column 1 and the number of same age-race-male peers within 1 km in column 2. Column one includes Census Block Group 2000 (CBG) by age fixed effects. Column 2 includes Census Block Group 2000 (CBG) by age, gender and race fixed effects. Column three includes CBG by year fixed effects. Standard errors robust to arbitrary correlation within CBG.

Table 13: Crime Agglomeration Models

	(1) Ever Arrested	(2) Ever Arrested Violent	(3) Ever Arrested Property	(4) Any Crime Partners	(5) Violent Crime Partners	(6) Property Crime Partners
<hr/>						
Peers = Same Age ( $\leq 1$ km)						
Same School Peers	0.0030 (0.0081)	0.0042 (0.0034)	0.0055 (0.0057)	0.0091 (0.0175)	-0.0108 (0.0131)	-0.0020 (0.0191)
<hr/>						
Peers = Same Age-Race-Gender ( $\leq 1$ km)						
Same School Peers	0.0413** (0.0155)	0.0183** (0.0389)	0.0209* (0.0583)	0.0423 (0.0628)	0.0162 (0.0532)	0.0683 (0.0571)
<hr/>						
Peers = Networked Peer (Component $\geq 10$ )						
Same School Peers	0.0072 (0.0109)	0.0131** (0.0064)	0.0008 (0.0090)	0.0079 (0.0302)	0.0348* (0.0188)	-0.0143 (0.0249)
<hr/>						
Dep. Var (mean)	0.1678	0.0326	0.0713	0.2770	0.1043	0.1474
Observations	34,958	34,958	34,958	5,867	5,867	5,867

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . All coefficients indicate the marginal effect of a standard deviation increase in the number of peers on arrest outcomes. The top panel of results is based on defining an individual's number of peers as those students that are the same age and live within 1 km. The middle panel of results restricts this definition of peers to those individuals that are same gender and same race. The bottom panel of results includes peer counts based on networked peers which are defined as those individuals connected through crime partnerships (outside of neighborhood) to at least 9 other individuals (component of at least 10 people). The sample used for determining the number of peers is based on all students attending CMS at school age 14 at any time from 2003-2009. Each cell indicates a separate regression and we include but do not report coefficients for same neighborhood peer counts.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, assigned school fixed effects.

The top panel includes Census Block Group 2000 (CBG) by age fixed effects. The second panel includes Census Block Group 2000 (CBG) by age, gender and race fixed effects. The bottom panel includes CBG by year fixed effects. Standard errors robust to arbitrary correlation within CBG.

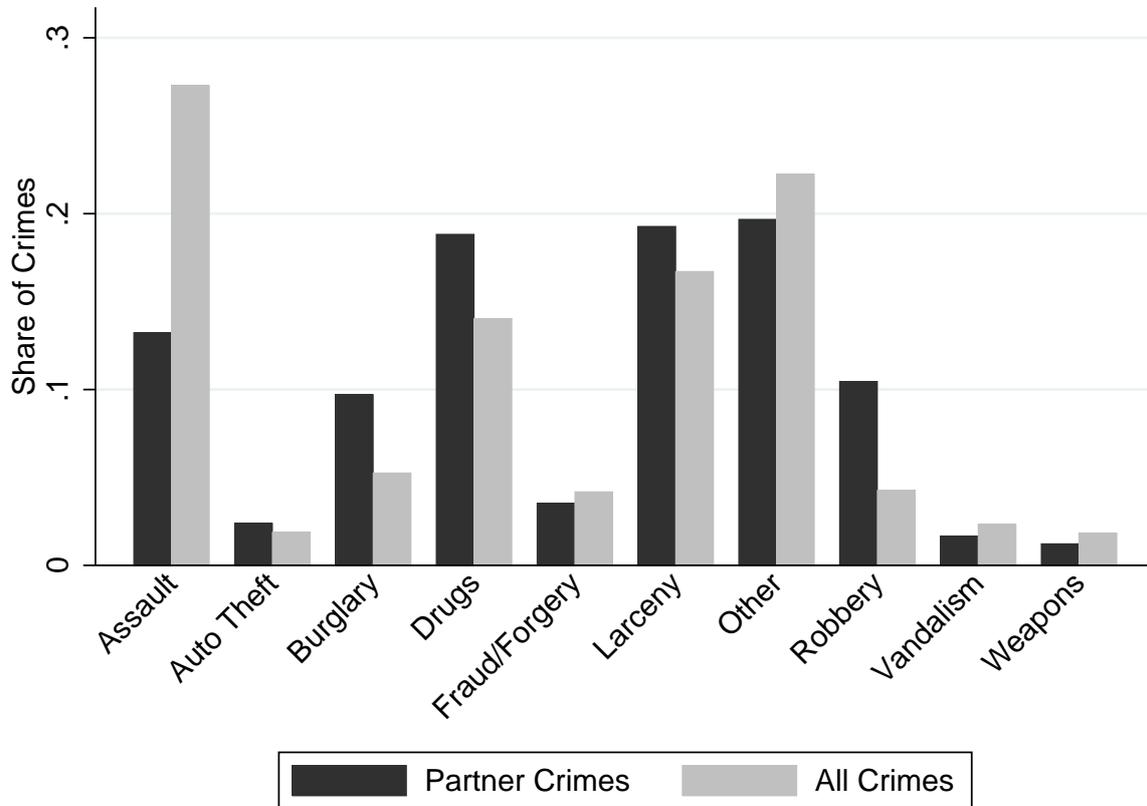
Ever Arrested Property indicates that an individual was arrested for auto theft, burglary, fraud/forgery or larceny between ages 16-21.

Ever Arrested Violent indicates that an individual was arrested for aggravated/sexual/simple assault, rape or robbery between ages 16-21. Partner dependent variables indicate that an individual was arrested for a crime with another individual and we limit this definition to only partnerships within the neighborhood (1km).

Columns 4 through 6 limit our sample to only those ever arrested in order to examine the relationship between the number of peers within 1km and the share of arrestees involved in partner crimes.

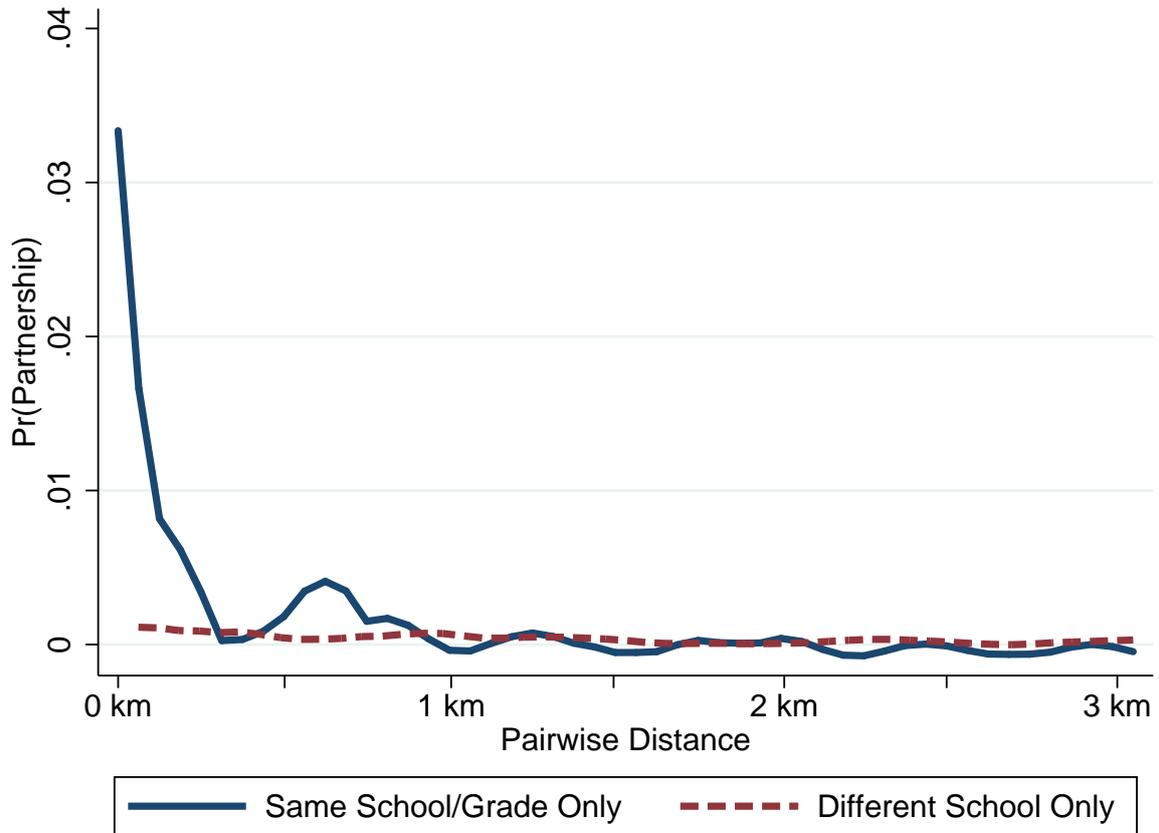
## A. Appendix

Figure A.1: Distribution of Crime Types (Partnership vs. All)



This figure provides the distribution of crime categories for all crimes that led to an arrest in 2005-2013 as well as only those crimes that involve criminal partnerships.

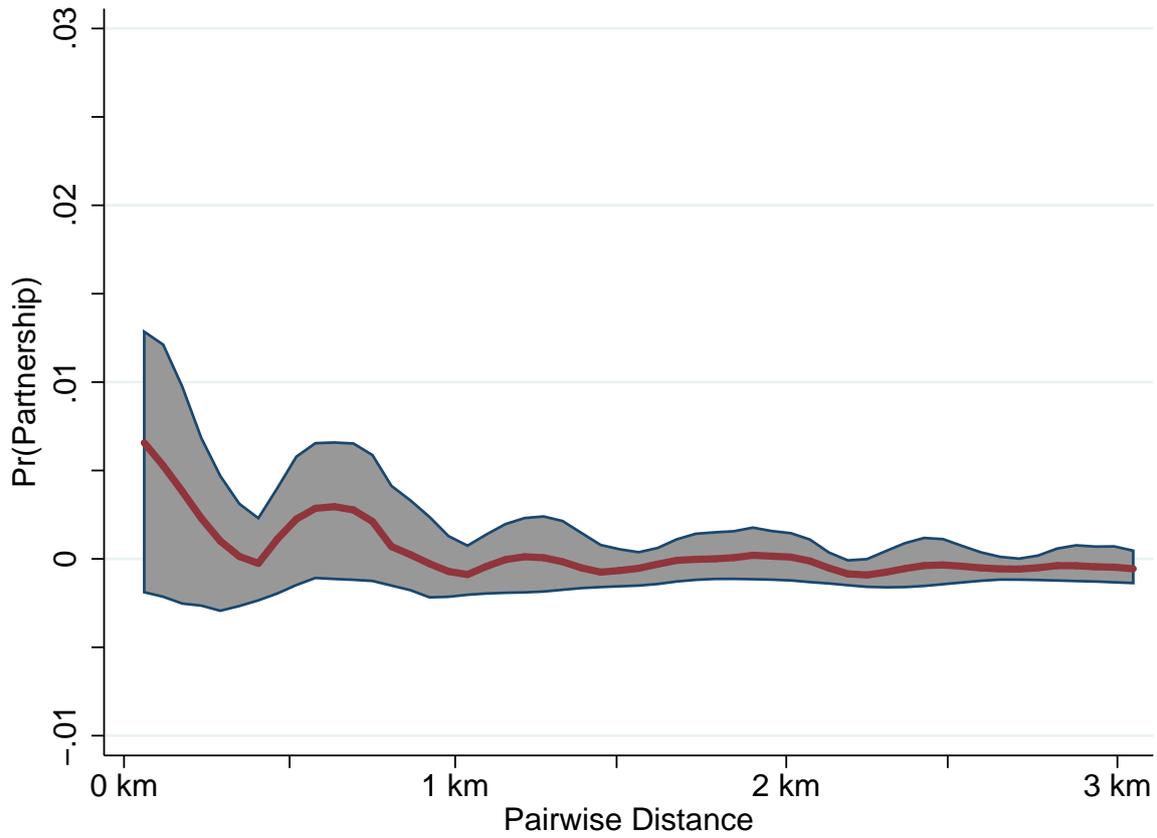
Figure A.2: Conditional Probabilities of Partnership - 2001 Address



This figure provides the distribution of same school and grade, and different school residuals by distance b/t partners in a pair. Residuals calculated using a first stage regression which controls for individual attributes of person  $j$  (gender, race, test scores, absences, suspensions, assigned school fixed effects), school year born fixed effects for  $j$ , and CBG fixed effects for  $i$ . We also include an indicator in individuals  $j$  and  $k$  are the same age.

The sample included in this figure represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 3 km of each other based on 2001 school address and individual  $i$  resides in a CBG bisected by a new middle or high school attendance zone boundary in 2002. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of non-partner pairs arrested age 19-21.

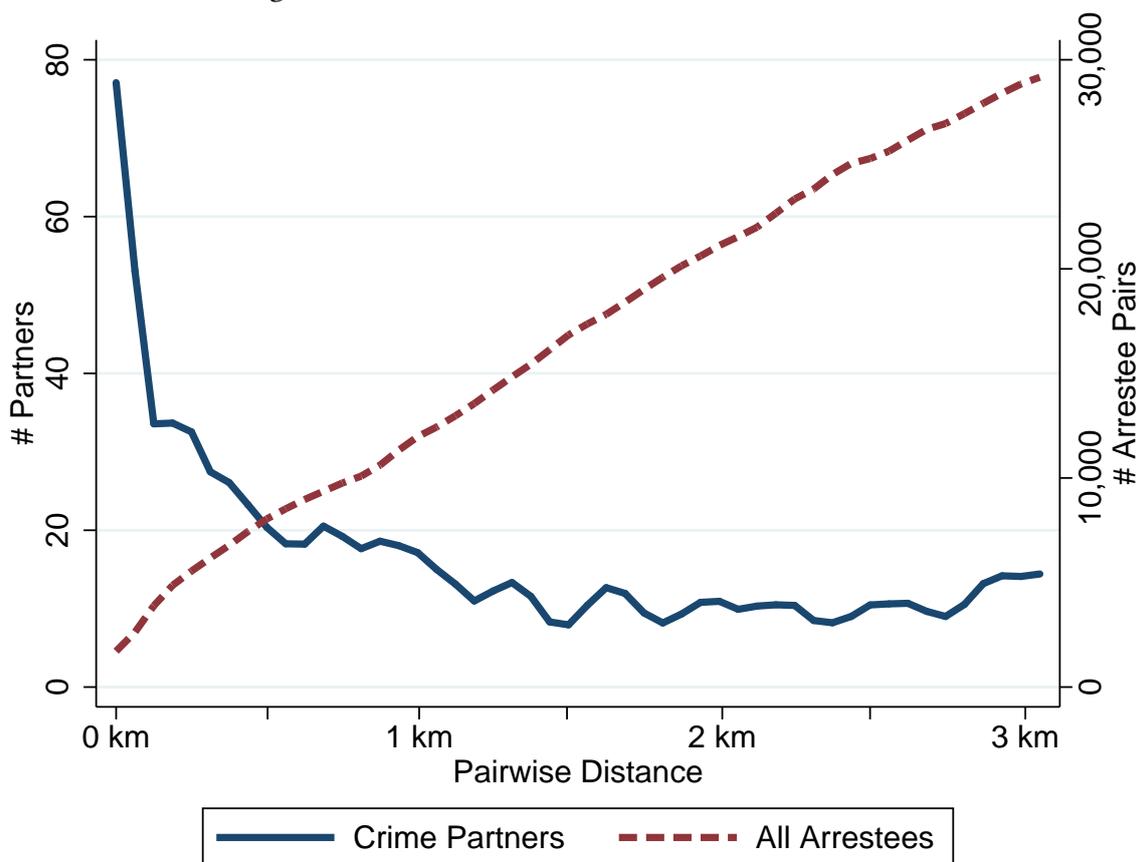
Figure A.3: Difference in Conditional Probabilities of Partnership - 2001 Address



This figure provides the difference in conditional probability (residuals) of partnership between same school and grade and different school pairs. 95% confidence intervals given by shaded area and were generated by resampling data using 500 bootstraps. Kernel-weighted local polynomial smoothing implemented in order to generate a continuous distribution of probabilities.

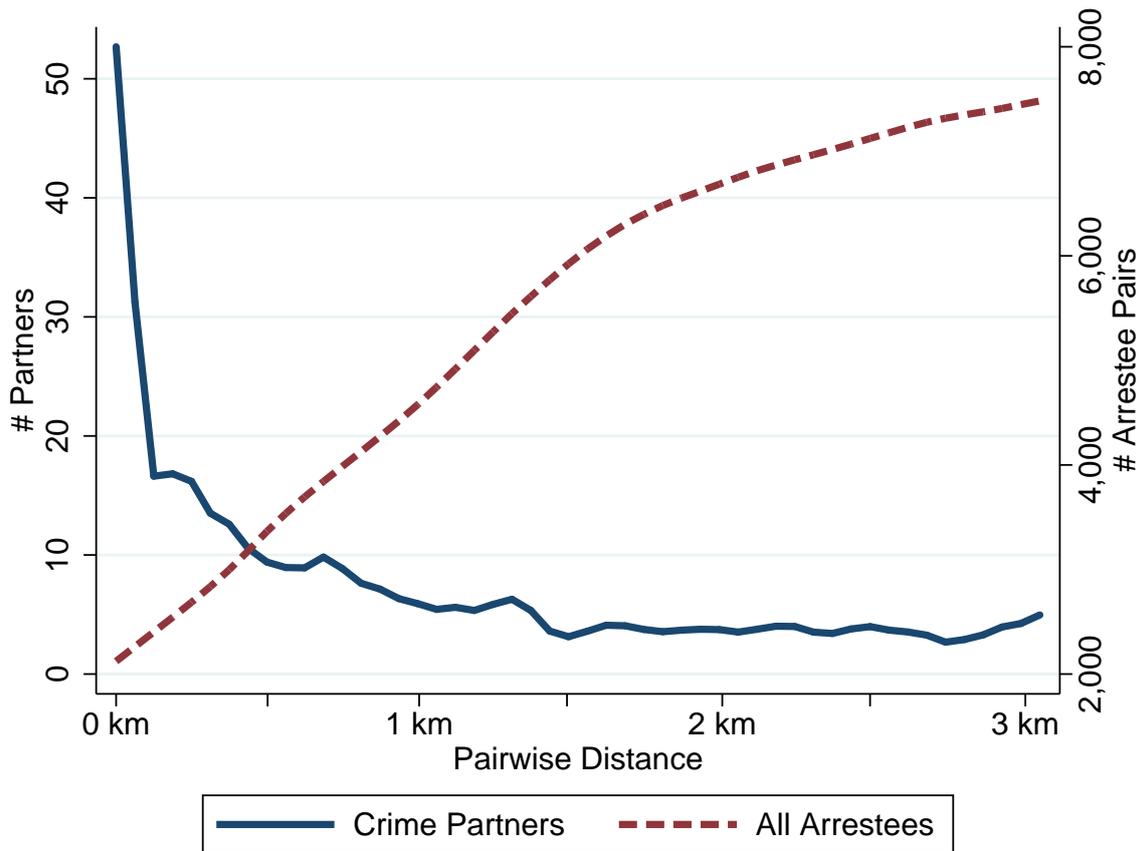
The sample included in this figure represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 3 km of each other based on 2001 school address and individual  $i$  resides in a CBG bisected by a new middle or high school attendance zone boundary in 2002. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of non-partner pairs arrested age 19-21.

Figure A.4: Distribution of Pairwise Distances - All



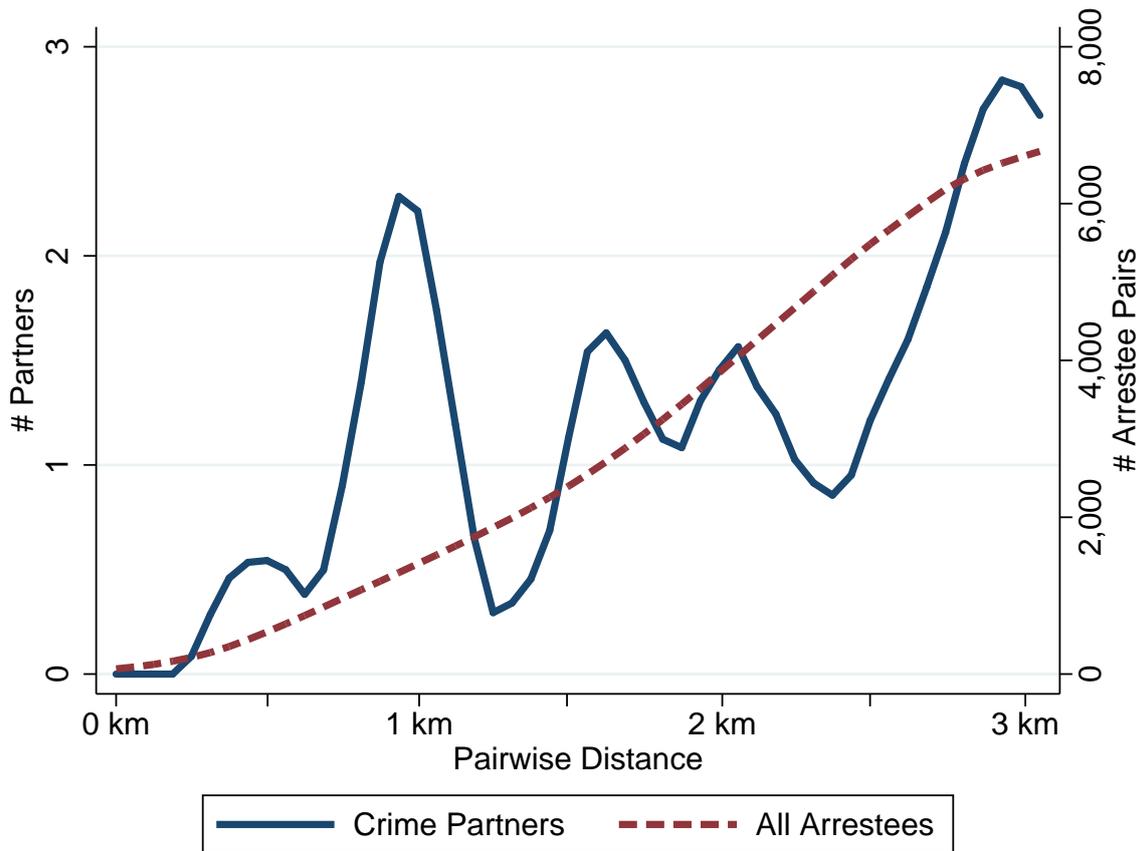
The sample included in this figure represents all unique pairs of individuals arrested between age 16-21 who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart) based on age 14 address and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of only those arrested age 19-21.

Figure A.5: Distribution of Pairwise Distances - Same School Only



The sample included in this figure represents all unique pairs of individuals arrested between age 16-21 who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart) based on age 14 school address, assigned to the same schools and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of only those arrested age 19-21.

Figure A.6: Distribution of Pairwise Distances - Different School Only



The sample included in this figure represents all unique pairs of individuals arrested between age 16-21 who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart) based on age 14 school address, assigned to different schools and individual  $i$  resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. For computational ease, we limit non-partner pairs to only those ever arrested age 16-18, but results are similar with the use of only those arrested age 19-21.

Table A.1: Impact of School Assignment on Partnerships by Types of Crime

	(1) Assault Crime Partner	(2) Burglary Crime Partner	(3) Drug Crime Partnership	(4) Robbery Crime Partnership	(5) Theft Crime Partnership	(6) Other Crime Partnership
<u>Pairs <math>\leq</math> 1 km</u>						
Assigned Same School & Grade	0.0010*** (0.0003)	0.0018*** (0.0006)	0.0006* (0.0004)	0.0002 (0.0003)	0.0000 (0.0003)	0.0004 (0.0002)
Assigned Same School	0.0003 (0.0002)	0.0009** (0.0005)	0.0000 (0.0002)	0.0002* (0.0001)	0.0005 (0.0003)	0.0000 (0.0002)
Dep. Var (mean)	0.0004	0.0010	0.0006	0.0004	0.0006	0.0002
Observations	123,982	123,982	123,982	123,982	123,982	123,982
<u>Pairs <math>\leq</math> 1/2 km</u>						
Assigned Same School & Grade	0.0009* (0.0005)	0.0023** (0.0010)	-0.0000 (0.0004)	0.0001 (0.0006)	0.0002 (0.0009)	0.0004 (0.0004)
Assigned Same School	0.0008* (0.0005)	0.0025*** (0.0007)	0.0001 (0.0002)	0.0001 (0.0006)	0.0012 (0.0014)	0.0002 (0.0002)
Dep. Var (mean)	0.0007	0.0020	0.0006	0.0007	0.0013	0.0002
Observations	42,601	42,601	42,601	42,601	42,601	42,601
<u>Pairs <math>\leq</math> 2 km</u>						
Assigned Same School & Grade	0.0002 (0.0002)	0.0007** (0.0003)	0.0003* (0.0002)	0.0000 (0.0001)	-0.0000 (0.0001)	0.0000 (0.0001)
Assigned Same School	0.0001** (0.0001)	0.0004** (0.0001)	0.0001* (0.0001)	0.0002*** (0.0000)	0.0001 (0.0001)	0.0001 (0.0001)
Dep. Var (mean)	0.0002	0.0004	0.0003	0.0002	0.0003	0.0001
Observations	397,687	397,687	397,687	397,687	397,687	397,687

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual k turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i. We also include an indicator in individuals i and j are the same assigned grade.

Dependent Variable is an indicator based on column heading.

Table A.2: Impact of School Attended *with only required courses*

	(1) Any Crime Partner	(2) Number of Partner Crimes	(3) 16-18 yr old Partnership	(4) 19-21 yr old Partnership	(5) Violent Crime Partners	(6) Property Crime Partners	(7) Felony Partners	(8) Misdemeanor Partners
<u>Pairs <math>\leq</math> 1 km</u>								
In Same Course (required)	0.0079** (0.0039)	0.0163 (0.0118)	0.0065** (0.0032)	0.0019 (0.0013)	0.0012 (0.0012)	0.0036 (0.0028)	0.0042 (0.0036)	0.0044** (0.0021)
In Same School & Same Grade	0.0018** (0.0008)	0.0021** (0.0009)	0.0021*** (0.0007)	-0.0001 (0.0004)	0.0011** (0.0004)	0.0005 (0.0006)	0.0010 (0.0006)	0.0014*** (0.0004)
In Same School	0.0009* (0.0005)	0.0007 (0.0006)	0.0004 (0.0004)	0.0008** (0.0004)	0.0002 (0.0002)	0.0006 (0.0004)	0.0007 (0.0005)	0.0002 (0.0003)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include fixed effects for individual j, CBG fixed effects for individual i. We also include an indicator in individuals i and j are the same grade. Dependent Variable is an indicator based on column heading. We define attended the same school as two individuals matriculating for at least one year at the same middle or high school. Same grade is based on a pair of students being assigned to the same grade. Same course indicates if two individuals took at least two courses together in grades 6-10.

Same course in these models is restricted to required courses in english, math, science and social studies.

Table A.3: Impact of School Attended on Partnerships by Types of Crime

	(1) Assault Crime Partner	(2) Burglary Crime Partner	(3) Drug Crime Partnership	(4) Robbery Crime Partnership	(5) Theft Crime Partnership	(6) Other Crime Partnership
<u>Pairs <math>\leq</math> 1 km</u>						
In Same Course	0.0011 (0.0010)	0.0012 (0.0014)	0.0025** (0.0011)	0.0000 (0.0004)	0.0023 (0.0019)	-0.0004 (0.0004)
In Same School & Same Grade	0.0008** (0.0003)	-0.0002 (0.0004)	0.0004 (0.0003)	0.0002 (0.0003)	0.0005 (0.0004)	0.0005* (0.0003)
In Same School	0.0001 (0.0001)	0.0004 (0.0003)	0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0003)	-0.0001 (0.0001)
Dep. Var (mean)	0.0004	0.0010	0.0006	0.0004	0.0006	0.0002
Observations	123,982	123,982	123,982	123,982	123,982	123,982

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include fixed effects for individual  $j$ , CBG fixed effects for individual  $i$ . We also include an indicator in individuals  $i$  and  $j$  are the same grade. Dependent Variable is an indicator based on column heading. We define attended the same school as two individuals matriculating for at least one year at the same middle or high school. Same grade is based on a pair of students being assigned to the same grade. Same course indicates if two individuals took at least two courses together in grades 6-10.

Table A.4: Impact of School Attended *with elementary schools*

	(1) Any Crime Partner	(2) Number of Partner Crimes	(3) 16-18 yr old Partnership	(4) 19-21 yr old Partnership	(5) Violent Crime Partners	(6) Property Crime Partners	(7) Felony Partners	(8) Misdemeanor Partners
<u>Pairs <math>\leq</math> 1 km</u>								
In Same Elem. School/Grade	0.0011 (0.0025)	-0.0019 (0.0032)	0.0026 (0.0024)	-0.0010 (0.0014)	0.0012 (0.0013)	-0.0011 (0.0021)	-0.0008 (0.0019)	0.0018 (0.0019)
In Same Elem. School	0.0026** (0.0012)	0.0040** (0.0017)	0.0013 (0.0009)	0.0020** (0.0010)	0.0004 (0.0004)	0.0025** (0.0012)	0.0015 (0.0010)	0.0017** (0.0007)
In Same Course	0.0072** (0.0029)	0.0132* (0.0078)	0.0055** (0.0026)	0.0016* (0.0009)	0.0002 (0.0008)	0.0038* (0.0023)	0.0032 (0.0026)	0.0039** (0.0016)
In Same School & Same Grade	0.0016** (0.0008)	0.0021** (0.0010)	0.0018** (0.0008)	-0.0002 (0.0004)	0.0011*** (0.0004)	0.0004 (0.0006)	0.0010 (0.0007)	0.0011*** (0.0004)
In Same School	0.0008 (0.0005)	0.0006 (0.0007)	0.0004 (0.0004)	0.0007** (0.0004)	0.0002 (0.0002)	0.0006 (0.0005)	0.0007 (0.0005)	0.0001 (0.0003)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include fixed effects for individual  $j$ , CBG fixed effects for individual  $i$ . We also include an indicator in individuals  $i$  and  $j$  are the same grade. Dependent Variable is an indicator based on column heading. We define attended the same school as two individuals matriculating for at least one year at the same middle or high school. Same grade is based on a pair of students being assigned to the same grade. Same course indicates if two individuals took at least two courses together in grades 6-10.

Same school elementary and Same school/grade elementary are based on attending the same elementary school.

Table A.5: Impact of School Assignment by Years in Neigh

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Crime Partner	Number of Partner Crimes	16-18 yr old Partnership	19-21 yr old Partnership	Violent Crime Partners	Property Crime Partners	Felony Partners	Misdemeanor Partners
<i>Pairs ≤ 1 km</i>								
Assigned to Same School/Grade	0.0011 (0.0008)	0.0025** (0.0012)	0.0007 (0.0007)	0.0001 (0.0004)	0.0007 (0.0005)	0.0005 (0.0007)	0.0009 (0.0008)	0.0004 (0.0004)
*Years at Address	0.0006*** (0.0002)	0.0007** (0.0003)	0.0005*** (0.0002)	0.0002 (0.0001)	0.0002* (0.0001)	0.0003** (0.0002)	0.0004** (0.0002)	0.0002 (0.0001)
Assigned to Same School	0.0014** (0.0007)	0.0014* (0.0008)	0.0011* (0.0006)	0.0007* (0.0004)	0.0001 (0.0004)	0.0010** (0.0005)	0.0012** (0.0005)	0.0003 (0.0004)
*Years at Address	0.0002 (0.0001)	0.0003* (0.0002)	0.0001 (0.0001)	0.0001* (0.0001)	0.0001* (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Dep. Var (mean)	0.0030	0.0036	0.0022	0.0013	0.0008	0.0016	0.0021	0.0012
Observations	123,982	123,982	123,982	123,982	123,982	123,982	123,982	123,982

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person j. We also include an indicator in individuals i and j are the same assigned grade.

Dependent Variable is an indicator based on column heading. Years at address defined as the number of years at the same address prior to school age 14 for person i. We also include the variable years at address for all regressions. The average number of years at address is 3.6 years.

Table A.6: Other Models - 2001 Address

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Dist. FE	1/2 km	Dist. FE 1/2 km	Student FE	Same HS only	Student FE Same HS only	Student by CBG FE
Assigned Same School & Grade	0.0004 (0.0011)	0.0004 (0.0011)	-0.0003 (0.0017)	-0.0003 (0.0017)	-0.0003 (0.0011)	-0.0002 (0.0010)	-0.0008 (0.0011)	-0.0003 (0.0011)
Assigned Same School	0.0011** (0.0004)	0.0005 (0.0004)	0.0022** (0.0009)	0.0017* (0.0009)	0.0010** (0.0004)	0.0013*** (0.0003)	0.0010*** (0.0003)	0.0008* (0.0005)
In Same Course	0.0062*** (0.0021)	0.0061*** (0.0021)	0.0054 (0.0045)	0.0053 (0.0044)	0.0034** (0.0017)	0.0049*** (0.0015)	0.0027** (0.0012)	0.0029* (0.0017)
In Same School & Grade	0.0011 (0.0008)	0.0011 (0.0008)	-0.0013 (0.0019)	-0.0014 (0.0019)	0.0014** (0.0007)	-0.0008 (0.0019)	0.0006 (0.0017)	0.0015* (0.0008)
In Same School	0.0016*** (0.0005)	0.0015*** (0.0005)	0.0030** (0.0013)	0.0029** (0.0013)	0.0010*** (0.0004)	0.0023** (0.0011)	0.0011 (0.0008)	0.0010** (0.0004)
Dep. Var (mean)	0.0017	0.0017	0.0027	0.0027	0.0017	0.0017	0.0017	0.0017
Observations	93,332	93,332	34,221	34,221	93,332	93,332	93,332	93,332

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors robust to arbitrary within-CBG correlation in parentheses.

The sample included in this table represents all pairs of arrested individuals (age 16-21) who are three years or less apart in age (less than 5% of criminal partners are more than 3 year apart), live within 1 km of each other based on 2001-2002 school address and live at least 130 feet apart (minimum distance between two students assigned to different schools) and individual i resides in a CBG bisected by a new 2002 middle or high school attendance zone boundary. We limit analysis to pairs where both individuals are enrolled in CMS in 2001 as well as at age 14. Consistent with figures, we limit non-partner pairs to only those ever arrested age 16-18 and results are similar with the use of non-partner pairs arrested age 19-21.

All regressions include controls for gender, race, 8th grade reading and math test scores, indicator if missing a test score, days suspended (8th grade), total days absent (8th grade), single family home indicator, indicator for year individual j turned age 5 as of 9/1, assigned middle and high school fixed effects, and CBG fixed effects for person i.

School attended models include fixed effects for each school attended (6-10th grade) by person j, except in cases of individual fixed effects. We also include an indicator in individuals i and j are the same age or in the same grade. Dependent Variable is an indicator for a pair ever being criminal partners. Dist. FE indicates a series of indicator variables for 200 foot intervals of pairwise distances. Same HS indicates that same school only defined based on high schools. Student FE is based on individual j.