Breaking Bad: Mechanisms of Social Influence and the Path to Criminality in Juvenile Jails

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Abstract

Using rich data on youths in juvenile correctional facilities, I conduct a series of tests of peer influence on future crime motivated by three mechanisms: criminal skill transfer, the formation of new criminal networks, and the social contagion of crime-oriented attitudes and behavioral habits. Identifying peer influence off of natural variation in small cohorts within the same facility, I find evidence consistent with the social contagion mechanism: exposure to peers who come from unstable homes and who have behavioral/emotional problems leads to a large increase in crime after release, as well as an increase in crime-oriented non-cognitive factors. I also find evidence consistent with persistent network formation, but only in settings which unite youths from the same local area. Multiple tests of the identifying assumptions support the causal argument.

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1 Introduction

Approximately 45% of adults released from prison find themselves back in prison within three years (Gelb, 2011), with similar rates for juveniles (Mendel, 2011). This revolving door suggests there might be something criminogenic in the experience of incarceration, particularly for youth. Recent evidence supports this: using an instrumental variables approach with random assignment to judges, Aizer and Doyle (2013) and Mueller-Smith (2014) find that both juvenile and adult incarceration leads to an increase in post-release crime for the marginal offender. Several potential explanations have to do with the social experience of incarceration: isolation from the rest of society and around-the-clock exposure to criminally experienced and life-hardened peers. Could social interactions had while incarcerated influence criminal behavior after release? The evidence presented in this paper says a resounding 'yes'.

Attempts to empirically analyze peer effects during incarceration have been limited by scarcity of data. Three papers – Bayer et al. (2009) most notably – have looked at whether exposure to peers with experience in a particular crime category increases the likelihood of offending with that particular crime after release (Damm and Gorinas, 2013; Ouss, 2011). Read as a trio the papers suggest that there is some sort of an effect, but the mechanism is unclear and the results are inconsistent.[1]

Recent years have brought much public discussion about reform of the criminal justice system. While it's not hugely controversial to suggest that the social dynamics of incarceration affect post-release crime, translating this into improved policy requires an understanding of the mechanisms of influence. Using a dataset on youths in juvenile incarceration which is unprecedented in terms of detail and size, I conduct a series of tests of peer influence which are designed to distinguish between three potential mechanisms: criminal skill transfer, persistent network formation, and the social contagion of crime-oriented attitudes and behavioral habits. I find that peer exposure during incarceration has a large, robust, and highly significant effect on both post-release crime and post-release non-cognitive factors. The constellation of evidence is very consistent with the social contagion mechanism, with a role for persistent network formation in correctional settings which unite youths from the same local area.

I identify peer influence using natural variation in small cohorts within the same correctional facility. The identifying assumption is that conditional on facility and time-of-release fixed effects, the variation in peer characteristics is as-good-as-random. I test this assumption carefully in a variety of ways, and the results consistently support

[1] Bayer et al. (2009) find an effect for both skilled and non-skilled crimes, but only for those who already have experience in that crime area. Damm and Gorinas (2013) do not generally find an effect, with the exception being drug crimes if the peer group is defined to be those of similar ages or ethnicities. Ouss (2011) finds an effect both for skilled crimes and violence, with previous experience unimportant. However the variation in peer exposure in this setting is not exogenous, so it is unclear whether this is a causal effect.

the causal argument. Following an 'exogenous effects' model, peer influence is identified using variation in pre-determined peer characteristics (Manski, 1993).

The data is compiled from the Florida's Department of Juvenile Justice (FDJJ), Department of Law Enforcement, and Department of Corrections, and spans all youths released from a juvenile correctional program in that state between July 2006 and July 2011. Besides crime, correctional facility, and demographic information, the data set includes 136 variables describing the youths' home, family, school and social lives. It also includes psychological and non-cognitive measures taken both before and after the incarceration period.

Each mechanism of peer influence generates testable empirical predictions about the *type* of peers which will be influential, the *settings* in which the mechanism is most likely to occur, and the *post-release behaviors* the mechanism will generate. The social contagion mechanism posits that teenagers are influenced by the attitudes, behavioral habits, and social norms of their peers in a way that alters their preferences around crime (Posner, 1997; Bowles et al., 2001a; Heckman et al., 2006). This mechanism predicts that exposure to peers with high levels of aggression or anti-societal attitudes will lead to an increase in both post-release crime as well as crime-oriented non-cognitive factors. Since deep-rooted habits of behavior and thought take a relatively intensive experience to shift, this mechanism is predicted to be important in settings where the youths spend extended periods of time together, isolated from the rest of society.

Under the network formation mechanism teenagers form new criminal connections while incarcerated which persist after release. This expanded criminal network could be beneficial to the 'criminal career' in much the same way that a network is beneficial in the legal economy: sharing knowledge about illicit opportunities, reducing information asymmetries, providing informal credit/insurance, enforcing business agreements, and so forth (Jackson, 2011). Since juvenile crime is predominantly local, this mechanism will be most important in correctional settings which unite youths from the same local area. The influential peers will be those who are already connected to a criminal network (gang members) or those with a high probability of becoming career criminals. Besides post-release crime, this mechanism predicts an increased membership in gangs or other crime syndicates.

Finally, the skill transfer mechanism posits that while incarcerated, teenagers are teaching each other practical criminal skills such as how to disable car alarms or manufacture methamphetamine (Mincer, 1974). As such, this mechanism predicts that exposure to criminally experienced peers will lead to an increase in skilled crime, particularly in correctional settings which provide ample unsupervised time during which skills can be shared.

The conclusions of the paper are established by testing the predictions outlined above. I find that exposure to peers who have grown up in unstable/abusive homes, and who show high levels of aggression and anti-societal attitudes, leads to an increase in post-release crime, an increase in crime-oriented behaviors and attitudes, and a decrease in healthy non-cognitive functioning. This phenomenon shows up in an environment of intense social exposure, and one in which peers are unlikely to have much physical interaction with each other after release. This effect is extremely stable to different specifications, including those that control for the criminal experience of the cohort. The evidence is strongly consistent with the social contagion mechanism and would be difficult to reconcile with either skill transfer or persistent network formation.

I perform a supplementary analysis on day treatment facilities (alternative schools for delinquent youth), a setting which is more conducive to the network formation mechanism since it unites youths from the same local area. I find that exposure to peers with lots of criminal experience or criminal connections leads to an increase in post-release crime and gang affiliation, but only if these peers live close enough to one another to enable physical interaction after release. This effect is strong in day treatment facilities, but also occurs in a more limited way in residential facilities. These effects are best explained by the network formation mechanism.

I do not find evidence to support the skill transfer mechanism.

The research presented here contributes to three strands of academic literature: crime, peer effects, and non-cognitive factors. While scholars have long suspected that peers are influential in criminal behavior, empirical analysis which clearly demonstrates a causal influence is scarce. Research has shown that changes in school, neighborhood or prison can affect crime (Ludwig et al., 2001; Jacob and Lefgren, 2003; Chen and Shapiro, 2007; Billings et al., 2013); assignment to higher security prisons can also lead to an increase in 'criminal-cognitions' (Lerman, 2013). Peer influence is a plausible, although not definitive, explanation for these findings. Quantitative research which attempts to disentangle the different *mechanisms* by which peers influence crime is next to non-existent. In fact, the mechanisms question remains elusive in most areas of peer effects research (Lavy and Schlosser, 2011; Bursztyn et al., 2014). Finally, while many papers have established the importance of non-cognitive factors in predicting education, labor force, or criminal outcomes, the acquisition of these factors remains largely a black box (Blanden et al., 2007; Bowles et al., 2001a; Nagin and Pogarsky, 2004; Heckman and Rubinstein, 2001; Duckworth and Peterson, 2007; Nagin and Pogarsky, 2004). I demonstrate that one determinant in the formation of behavioral habits, attitudes and character traits is peer influence during adolescence. I show that peer influence over these characteristics lasts at least eight months after contact has ceased, and that these newly acquired traits are strongly predictive of criminal activity. I am unaware of any other paper which that shows that peers have a large and lasting causal impact over the development of important non-cognitive factors.

Section 2 discusses the data, assignment to facilities, and peer measures. Section 3 tests the identifying assumptions. Section 4 describes the three proposed mechanisms of peer influence, their testable predictions, and the results of these tests. Section 5 explores heterogeneity and functional form in the social contagion effect and discusses policy implications. I estimate that organizing the incarceration facilities so that the lower risk boys are separated from those with particularly high levels of aggression and emotional disturbances would lead to an 18% reduction in the one year re-incarceration rate, an improvement gained through non-linearities in peer influence.[2]

2 Data, facility assignment, and peer measures

2.1 Data and descriptive statistics

The primary source of data is the Juvenile Justice Information System, which is the central administrative databank for the Florida Department of Juvenile Justice (FDJJ). This provides criminal history, basic demographics, sanctions information (incarceration facility, facility details, etc.), and recidivism data. This data set, which covers all youths released from a FDJJ program between July 2006 and July 2011, has been matched to administrative records from the Florida Department of Law Enforcement and the Florida Department of Corrections. These sources provide information on adult arrests, convictions and sanctions. The final source of data is the Community Positive Achievement Change Tool (C-PACT), which provides information on criminal history, success in school, use of free time, work experience, relationships, family life, drug and alcohol use, mental health, attitudes/behaviors, aggression and social/emotional skills. The C-PACT is used to evaluate the youths' risk-to-reoffend as well as to evaluate the effectiveness of FDJJ programs. C-PACT information is gathered from criminal history records, from a structured interview with the youths, and from the youths' Juvenile Probation Officers (JPO). The JPOs have first hand knowledge of the youth's home, family, school and social lives.

I have the data from the C-PACT examination taken immediately prior to incarceration for all youths from July 2007 to July 2011. Among the youths that I have C-PACT information for, 80% of them have undergone the full examination and 20% have only a shortened version, which includes key questions in most domains but does not include the psychological measures.[3] I also have two full-length post-release C-

[2]Any such experiment would require careful monitoring to ensure that results are as anticipated (Carrell et al., 2013).

[3]The full C-PACT examination is shown in the online appendix, section A. The questions which are highlighted are also found on the shorter evaluation.

PACT examinations for a subset of the youths in residential treatment facilities: one taken immediately after release from the facility and one taken an average of eight months after release.[4] Since the C-PACT examination is administered in the home town by a counselor who is unlikely to have knowledge of the peer cohort (due to the large degree of geographical dispersion in residential facilities) any error in the C-PACT evaluation should be orthogonal to peer characteristics.

The two main outputs of the C-PACT examination are the 'life-risk' score and the 'criminal history' score, which are used by the FDJJ to evaluate the youth's risk-to-reoffend.[5][6] The life-risk score, sometimes referred to in this paper as simply the risk score, describes the extent to which a teenager's life circumstances - home, school and social life - put him/her at risk of criminal behavior. Summary statistics for some of the indicators used to build the life-risk score are shown in Panel A of Table 1: incarcerated parents, foster care placement, physical and sexual abuse, gang affiliation, whether or not s/he is a high school dropout, etc. The criminal history score measures the youth's criminal experience. Summary statistics for some of the indicators used to build the criminal history score are shown in Panel B of Table 1: age at first offense, number and type of previous crimes, and previous periods of incarceration.[7]

I also use a variety of attitude and behavioral measures from the full C-PACT examination as outcome variables. Examples are shown in Panel C of Table 1. These characteristics are summarized by an index of crime-oriented attitudes and non-cognitive factors as well as an index of healthy (crime-protective) non-cognitive factors.[8] For more detailed analysis, I have compiled the questions from the C-PACT into five categories and built measures for each. The 'aggression' category includes all questions having to do with anger, physical or verbal violence, or belief in the necessity of aggression. The 'impulsivity' measure includes all questions having to do with the inability to control impulses or emotional urges. Questions that measure lack of respect for law, the rules of society, authority figures, or the property of others, as well as belief in the necessity of physical or verbal aggression, are captured by the 'anti-societal attitudes' measure. All questions having to do with the ability to get along well with or relate

[4] I have the first post-release C-PACT for 68% of the youths in my sample; this group consists of youths who were released onto probation and whose probation officers correctly followed the guidelines of administering a C-PACT immediately upon release. I have the second post-release C-PACT for 57% of the youths. This group consists of adolescents who stayed on probation for at least three months and had a C-PACT administered some time after the third month.

[5] Florida uses the term 'social history' instead of life-risk, but as this phrase is not very meaningful I will use the term life-risk, or simply risk, in this paper.

[6] These two numerical variables are used to classify youths into four categorical risk-to-reoffend levels.

[7] The questions which are used to build the life-risk score are indicated by an arrow on the left hand side of the C-PACT document in the online appendix, section A. Domain 1 of the C-PACT evaluation shows all questions used to build the criminal history score.

[8] These scores are the average of the standardized 'risky' and 'protective' domain scores for the three C-PACT domains that cover psychological factors.

to others are used to calculate the 'social skills' measure. Finally, 'consideration for the future' measures optimism about the future, consideration of the consequences of actions, as well as the ability to plan and enact goals.[9]

These five measures are predictive of future crime - the first three positively and the latter two negatively. The life-risk score, the criminal history score and both indices of crime-oriented non-cognitive factors (the one taken before entry and the one immediately after exit) also predict future crime, even after controlling for demographic and other criminal history variables. The criminal history score is the strongest predictor of recidivism, although the non-cognitive measures taken immediately after release from the facility also predict recidivism very well.

Figure 1a shows that the life-risk score is only weakly correlated with the criminal history score. This is within a sample of youths who have generally lived very difficult lives and have a lot of criminal experience; the weak correlation among this unique sample should not be interpreted as evidence that crime is only weakly correlated with the level of life-difficulties. In Figure 1b, however, we see that the life-risk score is strongly correlated with the index of crime-oriented non-cognitive factors. This is consistent with research by psychologists which shows that exposure to trauma or high levels of stress during childhood can lead to emotional and behavioral problems throughout life (Evans and Fuller-Rowell, 2013; Felitti et al., 1998).

All of the descriptive statistics shown above are from the sample of youths in residential correctional facilities. Residential facilities have a median occupancy of 40 youths and a median length of stay of eight months. Genders are separated and facilities are either low, moderate, high or maximum security. Youths generally do not leave the facility during the length of their sentence. While residential facilities are the primary focus of this analysis, I conduct supplemental analysis of youths in day treatment facilities. Similar to an alternative school for delinquent youth, the adolescent lives at home but spends weekdays at the day treatment facility, attending classes and participating in rehabilitative programming. The median occupancy is 38, the median length of stay is five months, and genders are mixed within a facility. Descriptive statistics for the two facility types are shown in Table 2. Both facility types are mostly male and African American, with an average age of around 16.5. Youths in day treatment facilities have a slightly lower criminal history and life-risk score than those in residential facilities. Recidivism rates are quite high: 50/60% are re-arrested and 15/21% are re-incarcerated within a year of release for those in day treatment/residential facilities respectively.

I drop all facilities with less than 50 observations, leaving 160 facilities and 12,695 adolescents in the the residential sample and 29 facilities holding 3306 adolescents in

[9] More details on the construction of these measures is provided in the online appendix, section C.

the day treatment sample.[10]

2.2 Facility assignment

If the judge assigns the youth to residential placement, an employee of the FDJJ known as a commitment manager decides which facility to send the youth to. Some facilities specialize in substance abuse, mental health, or sex offense treatment; if the youth has need for such a specialized program this will influence the choice of placement. Co-offenders are intentionally separated, and the commitment manager must choose facilities within a certain security-level category – low, moderate, high or maximum – which has been determined by the judge.

While the research design is similar to those which leverage cohort level variation after controlling for school and grade fixed effects (Hoxby, 2000; Carrell and Hoekstra, 2010) it differs in several ways which bolster identification. First of all, the youth's parents do not have the power to transfer him to another correctional facility in the case of a particularly undesirable peer cohort. The youth is under the jurisdiction of the juvenile justice system. Second of all, the administrator in charge of placing the youth within a residential facility is unlikely to take the peer cohort into account when deciding where to place the youth. Counties sends youths to a median of 62 different residential correctional facilities over the course of a year, and facilities receive youths from a median of 16 different counties. This high degree of geographical dispersion implies that commitment managers have very little knowledge of any particular cohort at any particular time. Third, the residential facilities are so geographically dispersed that local trends in crime will only marginally impact the type of youths present at any one residential facility. Finally, I have access to very detailed information about each facility. If a facility changes management or changes a program name, I include an extra fixed effect in order to account for any potential changes in the distribution of youths assigned to this facility.[11]

If the judge assigns a youth to a day treatment facilities, she will be placed in the one nearest to her home. Day treatment facilities are entirely local implying that local trends in crime will affect the distribution of youths in a facility in a manner not likely to be absorbed by the statewide time trends. For this reason I include facility-specific linear time trends in the main specification for day treatment facilities.

[10] Additional data details can be found in the online appendix, section D.

[11] I have also conducted diagnostic tests of each facility to examine whether the distribution of youths remain stable over time. In a few circumstances there was evidence of non-random sorting that was not explained by a change in management or program name. I either dropped these facilities from the analysis or added a fixed effect to absorb the change in youth's distribution.

2.3 Peer measures

With the exception of Section 5 which explores heterogeneity in functional form, the independent variables are a weighted average of the peer characteristics where the weights are the number of days that the two youths' sentences overlap. The calculation of the peer measures is defined in Equation 1, where $peerSCORE_i$ is the independent variable for person i, $d_{i,k}$ is the number of days that person i's sentence overlaps with person k within the same facility, and $ownSCORE_k$ is the score/trait of person k. For example, a person's peer risk score would be a weighted average of their peers life-risk score.

$$peerSCORE_i = \frac{\sum_{k \neq i} d_{i,k} * ownSCORE_k}{\sum_{k \neq i} d_{i,k}} \tag{1}$$

I use the full four years for which I have C-PACT data (July 1, 2007 – June 30, 2011) in calculating most of the peer measures. However the peer measures are calculated with error for youths released towards the beginning or end of my sample period since the data doesn't cover members of their peer group who were released before the sample period begins or after it ends. In order to minimize bias due to measurement error I drop the youths who were released in the outer ends of my sample period and perform analysis only on those who were released after April 1, 2008 and before September 31, 2010.

Figures 1c and 1d show the standardized distribution of the peer risk/criminal history score in residential facilities, shown in the left-most box-plots labeled 'Total Variation'. The bottom and top lines of the boxes show the 25th and 75th percentile of the distributions, the outer lines show the adjacent values. These raw peer measures are correlated with observable characteristics of the youths, as seen in the second-to-left box-plot labeled 'Endogenous Part of Total Variation' which shows the fitted values of a regression of peer risk/criminal history on a variety of covariates.[12] Figures 1c and 1d also show the distribution of the identifying variation – the residuals from a regression of peer risk/criminal history score on facility and quarter-by-year of release fixed effects. This is shown in the second-to-right box-plots labeled 'Identifying Variation'. While the fixed effects remove a part of the total variation, a sizable amount still remains; the standard deviation of the identifying variation is approximately one third of the standard deviation of the total peer risk score and one quarter of the standard deviation of peer criminal history. Importantly, however, the fixed effects remove the part of the peer measure variation which is correlated with the observable characteristics of

[12]The covariates included are the same as those in the main specification as described in Section 4 with the exception of the person's own risk score when the dependent variable is peer risk and the person's own criminal history score when the dependent variable is peer criminal history. These scores are omitted due to the mechanical negative correlation described in Section 4.

the youth. This can be seen in the right-most box-plot labeled 'Endogenous Part of Identifying Variation', which shows the fitted values from a regression of the identifying variation on the covariates.

3 Identification

Juvenile correctional facilities in Florida are quite small - the median occupancy is 40 youths - implying that the average characteristics of a facility's cohort will fluctuate as youths enter, serve their sentences, and leave. Peer influence is identified using this 'natural' variation that occurs across cohorts within the same correctional facility. The identifying assumption is that the variation in peer characteristics which is left over after both facility and time fixed effects have been accounted for is as-good-as-random. In day treatment facilities, which are more susceptible to local trends, the identifying assumption also conditions on facility-specific linear time controls. This section demonstrates that variation in key independent variables appears as-good-as-random after the fixed effects and time trends have been accounted for.

3.1 Testing for non-random clustering within facilities

I begin by regressing the life-risk and the criminal history score on a set of peer group dummies. Since peer groups are overlapping, the peer group dummies are based on those present in a particular facility within a six month window. This regression is shown in Equation 2 where $ownSCORE_{ijt}$ is the life-risk/criminal history score of person i in facility j who was released in quarter-by-year t, ω_{js} is a dummy which equals one if the person was in facility j during the six month window s, λ_j are facility fixed effects, η_t are quarter-by-year of release fixed effects, and $\mathbb{I}[day](time_{ijt} * \mu_j)$ are facility specific time trends, used only in the regressions involving the sample of youths in day treatment facilities.

$$ownSCORE_{ijt} = \alpha + \omega_{js} + \lambda_j + \eta_t + \mathbb{I}[day](time_{ijt} * \mu_j) + \epsilon_{ijt} \tag{2}$$

I run both an F test for joint significance at the 10% level on ω and a false discovery rate procedure to see if any individual coefficient in the ω vector is rejected when the p-values are adjusted to control for a 10% false discovery rate (Benjamini and Hochberg, 1995). ω contains 528 dummies in the residential sample and 146 dummies in the day treatment sample. Results are shown in Panel A of Table 4, where the first row shows the F statistic for a test of joint significance on ω, the second row shows the probability of seeing a statistic greater than or equal to F under the null, and the third row shows the smallest FDR adjusted p value. The first and second column shows the results for the risk and criminal history score in the residential treatment facilities and the final two columns show the results for day treatment facilities.

As can be seen in Panel A of Table 4, there is no evidence of non-random clustering in risk or criminal history score within either residential or day treatment facilities. The p values for the F test on joint significance range from .11 to .24 and the false discovery rate adjusted p values for individual significance are all greater than .20.

3.2 Testing for correlations between peer type and own type using a 'split-sample cluster bootstrap'

In most circumstances random assignment implies that the dependent variable that has been randomized is orthogonal to the covariates. When the dependent variable is a peer trait this is not the case; random assignment implies an expected negative mechanical correlation between a person's own trait and the average trait of her peers. Guryan et al. (2009) explain intuitively that this has to do with selection without replacement. In any finite population sample, a person with a higher type will be selecting peers from an urn that has a lower average type than a low type person. In a two person sample, the person with the higher type is guaranteed to have the lower type peer and vice versa. Angrist (2013) provides an analytic demonstration of this mechanical negative correlation. As is clear from both the intuitive explanation and the analytical proof, the problem stems from the fact that a person's own type shows up in the average peer type of his group.

This negative mechanical correlation complicates identification tests as it can obscure positive correlation between own and peer types. Guryan et al. (2009) propose a method to correct for this negative mechanical correlation by controlling for the leave-one-out average score in the 'urn' (pool of potential peers) from which the peers are chosen; in my simulations I find that this technique is very low power (Stevenson, 2015).[13] I present here a 'split-sample cluster bootstrap' method of testing for correlations between own and peer type that does not exhibit negative mechanical correlation under random assignment.[14]. The procedure is similar to a cluster bootstrap method in which instead of single observations being chosen randomly with replacement the

[13] An accounting identity shows that when urn fixed effects are included, as would normally be the case when cohorts are chosen from different populations, this technique is identical to controlling for ones own score scaled by the number of potential peers in the urn. When urn sizes are similar, as in the simulation example presented in Guryan et al. (2009), this added control is almost perfectly correlated with the one's own score. In this situation, controlling for the leave-one-out urn mean eliminates not only the negative mechanical correlation but also greatly reduces the ability to detect potentially problematic positive correlations. While these points are either directly or indirectly made in Guryan et al. (2009) the problems with this technique are worth emphasizing.

[14] A more detailed discussion of this technique, optimized for peer groups which are not overlapping, can be found in Stevenson (2015)

entire cluster (correctional facility) is chosen randomly with replacement (Cameron et al., 2007). However in each iteration the sample is split randomly in two halves: the 'peer' half and the 'analysis' half. The peer scores for the youths in the 'analysis' sample are calculated using only youths in the 'peer' sample. Then these peer scores are regressed on own scores as shown in Equation 3, where $peerSCORE_{ijt}$ refers to the average peer risk/criminal history score of person i in facility j who is released in time period t, calculated only using observations in the 'peer' half of the split sample, and all other variables are as described above. This technique eliminates the negative mechanical correlation and yields an estimate of β which will be centered at zero under random assignment. It works because none of the scores for the 'analysis' group are used in the calculation of the peer scores for their peers; in other words, each youth's score will show up only on one side of the equation. The technique is summarized as follows:

$$peerSCORE_{ijt} = \alpha + ownSCORE_{ijt}\beta + \lambda_j + \eta_t + \mathbb{I}[day](time_{ijt} * \mu_j) + \epsilon_{ijt} \tag{3}$$

1. Randomly split the sample into two groups, a 'peer' group and an 'analysis' group.
2. Calculate the average peer score *only for* the people in the 'analysis' group, and *only using* people in the 'peer' group. Thus for all youths in the 'analysis group', their own score will not show up in the peer score of others.
3. Sample the clusters (facilities) with replacement using a 'pairs cluster bootstrap' technique (Cameron et al., 2007).
4. Run the regression specified in Equation 3, and collect the coefficient $\hat{\beta}$.
5. Repeat steps 1-4 10,000 times.

Panel B from Table 4 shows the results of the split sample test. Row one shows the average $\hat{\beta}$ after 10,000 repetitions, and row two shows the standard deviation of $\hat{\beta}$. A t-test for these estimated parameters would fail to reject the null at any level smaller than 0.54. However, the magnitude of the potential correlation is at least as important is its statistical significance: if it is not possible to rule out a sizable positive correlation between the peer and own scores then the conditional exogeneity assumption is on weaker ground. Row three of Panel B shows the upper bound for a 95% confidence interval on β using the estimated coefficients, row four shows the standard deviation for the risk/criminal history scores and row five shows the standard deviation for the peer risk/peer criminal history scores.[15] The estimates of the upper bound are quite

[15] I did not standardize these since each split of the data set would result in a slightly different scaling, making it difficult to compare the β coefficients.

conservative, since the split-sample technique increases the variance in the estimator, but nonetheless they are tiny in magnitude compared to the magnitudes of the independent and dependent variables. The upper bound of the 95% confidence interval implies that a one standard deviation increase in a person's own score predicts at most a 0.01-0.03 standard deviation increase in average score of their peer cohort, making a confound between own and peer types an unlikely concern.

In results not shown here I conduct tests for correlations between the peer risk/criminal history scores and the covariates. Among the 32 separate tests (eight covariates, two settings, and two peer measures) there are two that are significant at the 10% level, no more than what is expected under random assignment. Furthermore, a joint test of significance in which the peer score is the left hand side variable and all the covariates are on the right easily fails to reject in all four specifications.

4 Mechanisms of peer influence and results

The predictions which are tested in this section vary along three dimensions: the *type* of peers that are expected to be most influential under a certain mechanism, the *setting* in which the mechanism is most likely to show up, and the post-release *outcomes* that correspond with the mechanism. These predictions, as well as the strength of the evidence supporting them, are summarized in table 3.

The generalized specification for the regressions conducted in this section is shown in Equation 4. Y_{ijt} stands for a variety of post-release outcomes for person i in facility j who is release in quarter-by-year t. $peerSCORE_{ijt}$ stands for a variety of weighted average pre-entry peer characteristics as defined in Equation 1. Covariates X_{ijt} include race, gender, ethnicity, age at release, risk score, criminal history score, total number of prior felony charges, total number of prior misdemeanor charges, an index that weighs the seriousness of prior charges and dummies for the category of most serious charge (violent felony, property felony, other felony and misdemeanor). The covariates also include interactions between the facility fixed effects and the risk and criminal history score. Finally, I condition on fixed effects for facility (λ_j), fixed effects for quarter-by-year of release (η_t), and, in the day treatment sample, facility-specific linear time trends ($\mathbb{I}[day](time_{ijt} * \mu_j)$).

$$\begin{aligned} Y_{ijt} = \alpha + peerSCORE_{ijt}\gamma_0 + X_{ijt}\beta_0 + \lambda_j + \eta_t + \\ \mathbb{I}[day](time_{ijt} * \mu_j) + \epsilon_{ijt} \end{aligned} \tag{4}$$

4.1 Social Contagion of Attitudes, Behaviors and Non-cognitive Traits

Mechanism Description: This mechanism captures the influence that peers have over non-cognitive factors related to crime: aggressive behavioral habits, lack of impulse-control, risk preferences, anti-societal attitudes, and so forth. Peers may influence social norms, potentially de-stigmatizing aggressive, non-cooperative, or illegal behavior (Posner, 1997). Peers may also influence identity formation, altering the psychological payoff of different behaviors according to how much they deviate from or support that identity (Akerlof and Kranton, 2000). For example if a youth adopts an 'outlaw' or a 'gangster' self-identity, he is likely to increase behaviors which conform to that image. Peers can also influence beliefs: if a youth has low expectations for success in the 'straight world' then the opportunity cost of crime is lower. Finally, peers may influence the development of social or emotional skills directly through social learning (Ellison and Fudenberg, 1995). The development of anger management, for example, rests on a variety of tricks such as counting to ten before responding, or consciously re-formulating the interpretation of the other person's action. If peers possess few of these skills there are less opportunities by which to learn them.

While all of these channels can directly influence preferences for crime, they may also indirectly influence the net financial returns to crime by influencing the non-cognitive skill set. Different non-cognitive skills may be important for different types of tasks. Characteristics such as aggression are not generally considered skills in the legal economy but may prove beneficial in a line of work where the ability to instill fear in others helps with contract enforcement (drug dealing, for example). Alternatively, peer influence could decrease the opportunity cost of crime by shifting non-cognitive factors away from those valued in the legal economy: persistence, social skills, optimism, etc. (Bowles et al., 2001a; Heckman and Rubinstein, 2001; Nagin and Pogarsky, 2004; Heckman et al., 2006, 2013; Blanden et al., 2007; Moffitt et al., 2011).

Predictions: It is a folk wisdom trope that teenagers are very susceptible to peer influences. Nonetheless, shifting rooted habits of behavior and thought is likely to take a fairly intensive social experience. For this reason the social contagion channel of influence is likely to show up more strongly in residential facilities, where teenagers spend 24 hours a day together isolated from the rest of the world, than day treatment facilities, where they spend the schooldays together but then return to their friends and families. The peers that are most likely to be influential in this mechanism are those with high levels of crime-oriented non-cognitive factors such as aggression or anti-societal attitudes. Exposure to such peers should result not only in an increase in crime, but also an increase in crime-oriented non-cognitive traits.

Results: Table 5 presents the results of a variety of tests related to the social contagion mechanism of peer influence. The tests all are based on the residential facility sample of youths; all independent variables have been standardized for ease of interpretation. I begin by examining the influence of peers with a high life-risk score on recidivism outcomes. As seen in Figure 1a and b, the life-risk score is strongly correlated with crime-oriented non-cognitive factors, but only weakly correlated with criminal experience or skill. Influence of peers with a high life-risk score on post-release crime would thus be more consistent with the social contagion mechanism than with the other mechanisms.

As seen in Panel A of Table 5, exposure to peers with a high life-risk score leads to a large increase in post-release crime. The specification for this regression is shown in Equation 4, where Y_{ijt} stands for five different recidivism dummies indicating whether or not person i is arrested, arrested for a felony, convicted, convicted of a felony, or placed back in a juvenile or adult prison within a year after release.[16] The independent variable ($peerSCORE_{ijt}$) is the weighted average life-risk score of the peer cohort as defined in Equation 1, and the fixed effects and covariates are as described in the introduction to this section.

The magnitude of this effect is comparable in predictive power to an additional 2 or 3 prior felonies on the criminal record. Transferring an adolescent from a peer cohort with an average life-risk score to a cohort whose average life-risk is one standard deviation higher predicts a 16% increase over the mean in the likelihood of being re-incarcerated within a year of release. With p values ranging from 0.003 to 0.021 the effects are also highly significant.[17]

Table 6 shows that the impact peers with a high life-risk score have on recidivism are extremely stable. The regression in the first column includes only fixed effects for facility and quarter-by-year of release. The second through fifth columns add demographics, criminal history variables, the life-risk score, and both the life-risk score and the criminal history score interacted with facility fixed effects. Column 5 includes all the same covariates and fixed effects of the main specification described in the introduction. Column 6 adds extra controls for linear time trends interacted at the facility level and Column 7 includes peer criminal history, peer age, and the percent of peers who are African American or Hispanic. The coefficient magnitude varies only trivially

[16] The various recidivism measures are correlated but still measure different things; the correlation coefficients range from 0.4 to 0.7.

[17] Some of the econometric quirks in peer effects research which were outlined in Angrist (2013) suggest that parametrically estimated standard errors may not be correct. To check this I conduct a permutation test to verify that the standard errors presented in Panel A of Table 5 are not too small. The permutation test involves randomly shuffling the entry dates of youths within their facility, generating randomly assigned counter-factual peer cohorts which should have no effect on post-release outcomes. With each randomly generated permutation I run the five regressions used in Panel A of Table 5. I derive two-tailed p-values from this non-parametric distribution of γ_0 under the null hypothesis. These non-parametrically p-values turn out to be quite similar to those generated parametrically.

across specifications, increasing slightly as controls for own risk score are added (consistent with mechanical negative correlation) and barely budging with the addition of controls for the criminal history score of the peer cohort and facility-specific linear time trends.

The life-risk score is a composite measure that captures many aspects of the youth. Panel B of Table 5 divides the peer risk score into its component parts in an attempt to see which factors are most influential on post-release crime. Columns 1 through 3 look at the impact of peers with gang affiliation, peers from unstable homes, and peers who have experienced abuse or trauma on the likelihood of being convicted of a felony within one year of release.[18] Peers with gang affiliation are not influential in this setting, supporting the hypothesis that this effect is not driven by network formation. The peers that are most influential on future crime are those from difficult or dangerous homes.

Psychologists have found that difficulties in early childhood can have long lasting effects on emotional development and executive functioning. A broadly accepted theory for why this occurs is 'allostatic load' – the idea that if the brain's stress-management system is repeatedly overworked it begins to break down from the strain (McEwen, 1998). Studies have found that even after controlling for socioeconomic factors, the amount of traumatic experiences a person had as a child is a very strong predictor of risky behaviors, mental health issues, poor executive functioning and other undesirable outcomes (Evans and Fuller-Rowell, 2013; Felitti et al., 1998). Research also suggests that behavioral problems stemming from childhood trauma can be contagious: Carrell and Hoekstra (2010) find that classroom exposure to peers who have experienced domestic abuse leads to an increase in misbehavior. While their setting differs from the one analyzed here, the story is similar: difficult life circumstances leads to emotional and behavioral problems with externalities on surrounding youth.

In Column 4 of Panel B I test directly whether exposure to peers with crime-oriented non-cognitive traits impacts recidivism. I only have data on pre-entry non-cognitive factors for a subset of the youth, meaning that this independent variable will have a fair amount of measurement error. Nonetheless the coefficient is large in magnitude and significant at the 5% level.

The large majority of youths in residential facilities come from home towns which are far enough apart to prohibit much physical interaction after release, making the network formation mechanism an unlikely explanation for the results shown in Panel A. However approximately 10% of the each youth's cohort comes from the same hometown area. Column 5 tests whether the effects examined in Panel A are being caused by

[18]The final two components of the peer risk score, peers with drug/alcohol problems and peers who are experiencing problems at school, were not found to be statistically significant predictors of future crime.

hometown peers; the independent variable is the weighted average life-risk score of peers within a 20 mile radius of the youth's home zip code. As can be seen, this effect is tiny in magnitude and not statistically significant.

Panels C and D of Table 5 show how exposure to peers with a high life-risk score affects post-release non-cognitive outcomes. In addition to the covariates and fixed effects discussed in the introduction to this section, I include a fully saturated set of controls for the pre-entry non-cognitive factors. I also include both fixed effects and specific time trends for the DJJ unit which conducts the examination in order to absorb some of the incidental variation in grading styles. The dependent variables in Panel C were taken immediately after release from the facility and those in Panel D were taken approximately eight months after release. All dependent variables have been standardized.

Exposure to high risk peers while incarcerated leads to an increase in aggression, impulsivity, anti-societal attitudes and an index score that captures a range of crime-oriented non-cognitive factors. Once again, the magnitude of the effects are considerable: a one standard deviation increase in the peer risk score leads to a 0.11-0.16 standard deviation increase in the various crime-oriented non-cognitive measures and a 0.13 standard deviation decrease in an index score of healthy non-cognitive traits.[19] Furthermore, as shown in Panel D, these effects persist at least eight months post-release. While the magnitudes of the effects are slightly smaller, it is still statistically significant in four of the five specifications despite the smaller sample size. Panel D also shows that the non-cognitive effects captured eight months after release do not appear to be caused by the subset of youths from the same hometown area, suggesting that the influence was exerted predominantly during the incarceration period.

In sum, the evidence presented in this section shows that exposure to peers who have grown up in difficult circumstances, and who show high levels of aggresssion and anti-societal attitudes leads to an increase in recidivism, an increase in crime-oriented behaviors and attitudes, and a decrease in healthy non-cognitive functioning. This phenomenon shows up in an environment of intense social exposure, and one in which peers are unlikely to have much physical interaction with each other after release. This effect is extremely stable to different specifications, including those that control for the criminal experience of the cohort. Considered comprehensively, the evidence is strongly consistent with the social contagion mechanism and would be difficult to reconcile with either skill transfer or persistent network formation.

[19]In results not shown, I also test directly whether exposure to peers with high levels of aggression lead to increased aggression, etc. The results are positive and statistically significant for aggression, anti-societal attitudes, impulsivity, social skills, the index of crime-oriented traits and the index of healthy traits.

4.2 Persistent Network Formation

Mechanism description: One of the defining characteristics of the illegal economy is its covert nature. The conventional methods by which economic information is transmitted - advertising, job posts, credit scores - are unadvisable for those wishing to avoid detection by the law. Information in the illegal economy travels largely through interpersonal connections, implying that the returns to an expansion of the criminal network may be sizable. A criminal network provides benefits similar to those studied in labor economics (Jackson, 2011): transmitting information about opportunities (which house is easy to break into), reducing information asymmetries (who can be trusted not to 'snitch'), connecting buyers with sellers (distributors of weapons or drugs), providing informal insurance (an advance of marijuana after one's supply has been seized), accelerating technology uptake (advanced forms of identity fraud), etc. The lack of a formal venue for contract enforcement suggests an additional role for networks in the illegal economy: contract enforcement via the threat of retaliation.

Predictions: The network formation mechanism posits that incarceration fosters the formation of valuable connections much like business school, or an elite prep school. However, for the connections to be valuable after release, they need to be relevant to a particular criminal market. Most adolescent crime is highly local – few teenagers have criminal operations that are sophisticated enough to span across the state – thus the connections that will be most influential in post-release crime are those with others from the same locality. Network formation is expected to be much more relevant in day treatment facilities, which unite youths from the same local area, than residential facilities, where the average distance between home towns of two peers in the same facility is 100 miles. If the network formation mechanism showed up at all in residential facilities it would likely operate through the small group of peers who return to neighboring home towns after release.

The peers that would be important in the network formation hypothesis are peers who are likely to commit crime after release, or peers who have lots of criminal connections themselves. Since past criminal behavior is the best predictor of future criminal behavior, peers with a high criminal history score are likely to be influential in the network formation mechanism. Peers with gang affiliation are likely to be influential as well, as exposure to these well connected peers could lead to a broader range of connections after release. In addition to post-release crime, the network formation mechanism predicts an increase in gang affiliation and network based crimes such as drug dealing.

Results: Table 7 summarizes the evidence which supports the network formation mechanism of peer influence. All independent variables have been standardized, and all regressions take the basic format outlined in the introduction to this section.

In residential facilities, the overall criminal history of the peer group has no effect on future crime, despite the fact that criminal history is the best predictor of recidivism (see Column 7 of Table 6 and Panel A of Table 8). In day treatment facilities, where the youths are all local, the results are quite different. In Panel A of Table 7 we see that day-treatment exposure to peers with a high criminal history score has a large impact on future crime: a one standard deviation increase in the average criminal history score of the peer cohort predicts a 38% increase over the mean in the likelihood of being convicted of a felony within a year of release. However the day treatment sample is roughly one fourth the size of the residential sample and the peer effects are much noisier. The coefficient on peer criminal history is statistically significant at the 5% level in only two of the five specifications, and statistically significant at the 10% level in another two.

In residential facilities, exposure to peers with gang affiliation has no effect on future crime. In day treatment facilities these well-connected peers are more influential. Panel B shows that day-treatment exposure to peers with gang affiliation leads to an increase in felony conviction and re-incarceration. Although the coefficients are positive in all specifications, the results are only statistically significant in these latter two measures of recidivism.

Returning to the residential setting, I find exposure to peers with a high criminal history score has an effect, but *only if* those peers come from the same hometown area. This is shown in Panel C of Table 7, where the independent variable is the weighted average criminal history score of peers who live within 20 miles of one's own hometown.

In Panel D I test whether exposure to peers with a high criminal history score affects gang membership or drug dealing, which is typically a crime controlled by gangs. While the estimated effects are positive, they are only statistically significant when the facility-specific time trends are removed. In results not shown here I also test whether exposure to gang members increases gang membership or gang-related crimes. The effects are positive but not statistically significant.

Finally Column 5 of Panel D provides a brief robustness check. The regression shown in this column is identical to that shown in Column 4 of Panel A except that all covariates have been removed. The magnitude of the coefficient is quite stable.

In sum, the evidence presented in this section suggests that exposure to peers with lots of criminal experience or criminal connections leads to an increase in post-release crime and gang affiliation, but only if these peers live close enough to one another to enable physical interaction after release. This effect is strong in day treatment centers, but also occurs in a more limited way in residential facilities. While the evidence presented in this section is noisier than that presented in the social contagion mechanism, it is internally consistent and best explained by the formation of new criminal networks which persist after release.

4.3 Criminal Skill Transfer

The theoretical model which underpins this mechanism of peer influence is the classic Mincer model, in which labor market returns increase as skills are acquired (Mincer, 1974). Whereas the skills necessary for employment in the legal economy are generally acquired through school or through job training programs, no such equivalent exists in the illegal economy. Skills are likely gained through experience or through transfer between individuals. Thus the criminal skill transfer theory is based on the idea that correctional facilities can act as a 'school of crime': an informal clearing house for illicit know-how. With lots of time and little to do, inmates may share expertise in areas like disabling car alarms, fencing stolen computers or manufacturing methamphetamine.

Predictions: The criminal skill transfer hypothesis predicts that exposure to criminally experienced peers would lead to an increase in crime.[20] Since the mechanism also requires unsupervised time within the facility during which the youths can teach each other skills, it is more likely in the residential facilities than in day treatment facilities. (Most of the youth's time in the day treatment facilities is under active supervision, either during the school day, or in the after-school programming.) The criminal skill transfer mechanism also predicts that exposure to peers with experience in a particular crime category leads to an increase in the likelihood of recidivating with that particular crime.

Results: Table 8 shows the results of tests related to the skill transfer mechanism. The independent variable in Panel A is the weighted average criminal history score of the entire peer cohort; the sample is from the residential facilities. Since the independent variable captures the criminal experience of the peer cohort – a proxy for skill – a positive and statistically significant impact on recidivism would provide support for the skill transfer mechanism. However the coefficients are small in magnitude, vary in sign, and are not statistically significant.

Panels C-E show how exposure to peers with experience in a particular skill-intensive crime category affects the likelihood of committing that crime after release Following Bayer et al. (2009), I test for heterogenous effects in Panels B and D under the hypothesis that those with previous experience in that particular crime category may be more susceptible. Since the specification in these panels does not involve the

[20] Skilled youths are also less likely to be caught implying that the criminal history score will be an imperfect measure of a youth's true experience. However the probability of getting caught increases with the number of crimes committed and in this paper I assume that the criminal history score is an imperfect but still useful measure of the youth's criminal experience.

life-risk or criminal history score (which are only available in four of the five years for which I have data) I omit these covariates in order to take advantage of the larger sample size.

The outcomes are dummies measuring whether or not the youth is charged or adjudicated guilty for a robbery, felony drug offense, burglary, auto theft, or grand larceny within a year of release. The independent variables vary according the outcome variables, but are all placed in the same row so as to conserve space in the table. For example, when the outcome variable is robbery, the independent variable is the fraction of peers who have committed robbery in the past. In Panels B and D these are interacted with dummies indicating that the youth has also committed robbery in the past (first row) or a dummy indicating the youth has not committed robbery (second row). Following Bayer et al. (2009) I control for previous experience in all the offense categories listed, as well as offense interacted with facility fixed effects. These extra controls, however, make no qualitative difference to the findings.

Of the 20 tests conducted in these four panels, only one is significant at the 5% level, and the sign on that coefficient is negative. These results replicate the findings in Damm and Gorinas (2013) and are not dramatically dissimilar to those in Bayer et al. (2009).[21] Of these five crime categories, Bayer et al. (2009) find effects only for drug offenses and burglary – and only if the youth has previous experience in that particular crime category.[22]

In sum, I do not find evidence to support the skill transfer mechanism. While the lack of supportive evidence may simply be due to low power or measurement error, it could be argued that many criminal skills involve the type of manual techniques that would be difficult to learn in an institutional setting. As anyone who has tried to repair a car or assemble a piece of furniture by reading a manual knows, physical tasks can challenging without physical instruction. Picking locks, disabling alarms or motion detectors, hot-wiring cars – like other physical skills, these techniques are likely best learnt "on the job" as opposed to in whispered conversations in the prison yard.

5 Heterogeneity and policy implications in the social contagion mechanism

In Section 4 we saw that placing teenagers with a cohort which, on average, had a higher degree of behavioral problems and life difficulties lead to an increase in post-

[21]Damm and Gorinas (2013) only finds results for drug crimes if the peer group is narrowly defined to be those of similar age or ethnicity.

[22]Similar to Bayer et al. (2009), I find results for the crime categories of sex-offense and assault. As these are not skilled crimes I do not include the results in this section.

release crime. In this section I use a more flexible functional form for peer influence in order to determine whether negative externalities can be diminished by sorting the youths differently within incarceration facilities. To explore the impact of peers with different life-risk levels I divide the risk score into bins of two, as seen in Figure 2a. I aggregate the tails of the distribution so that each bin contains at least 10% of the sample. Then for each youth I build six different peer measures: the fraction of peers in each of the six bins. This is expressed in Equation 5, where $frac_i^b$ is the fraction of i's peers (weighted by days) with risk score in bin b.

$$frac_i^b = \frac{\sum_{k \neq i} d_{i,k} * \mathbb{I}[k \in b]}{\sum_{k \neq i} d_{i,k}} \tag{5}$$

Dropping the third bin (so that the fraction of peers with a risk score between six and seven will serve as the reference level) I regress felony conviction on the five peer risk-level variables. The set of covariates and fixed effects are the same as in all the residential facility regressions as specified in Equation 4. I present the results of this regression in graphical form in Figure 2b. The independent variables are represented on the x axis and the coefficient magnitudes are represented on the y axis. The dropped variable is set equal to zero on this graph to serve as a reference point. The shape of the points represent statistical significance, as described in the legend. Each point (each coefficient) represents the marginal impact of having more peers in that particular bin, conditional on the number of peers you have in each other bin. Thus if you experience a 10% increase in the number of the highest risk peers in your cohort, your likelihood of being convicted of a felony increases by 2.5 percentage points. Since an average of 27% of all youths released from incarceration are convicted of felony within a year, the 10% increase in very high risk peers translates into a 9% increase over the mean in felony convictions. While only results for felony conviction are discussed in this section, the functional form for the other recidivism variables are qualitatively quite similar.

This section is presented graphically so that the focus is on looking for descriptive patterns, not on seeking statistical significance of each individual coefficient. Each coefficient represents a relatively low power test, as it is much more difficult to distinguish the impact of peers in two adjacent risk-level bins than it is to identify a general relationship between the risk level of peers and future crime, like the linear-in-means test does.

Figure 2b shows several interesting results. First of all, the coefficients are monotonic and reasonably linear, implying that the effect operates throughout the spectrum and does not solely come from the impact of one type of peer. Second of all, there appears to be an outlier effect, where exposure to particularly high risk peers significantly increases recidivism, even controlling for the fraction of peers in other bins. However these results aggregate both genders, obscuring differences in functional form.

Figure 2c examines how the impact of peer risk on felony conviction differs by gender. The coefficients shown are the result of two regressions, one for boys and one for girls, of felony conviction on the five peer risk level variables. For boys, the fraction of peers with low to moderate risk levels appears to have very little influence, while the fraction of high risk peers increases recidivism markedly. For girls the opposite is true: the fraction of peers with moderate to high risk levels has little influence, but the fraction of peers with very low risk levels decreases recidivism markedly.[23]

It is not immediately clear why girls respond more to positive peer influence than boys do, however this finding corresponds with similar findings in the literature. The benefits of early childhood education – often attributed to the learning of positive non-cognitive skills from teachers and mentors – accrue much more for girls than for boys (Anderson, 2008; Heckman et al., 2013). Kling et al. (2007) finds that moving to higher SES neighborhoods – presumably implying a lower-risk peer group – improves mental health and risky behavior outcomes for girls, while having generally negative effects for boys.

Figures 2d and e show how peers at different risk levels affect felony conviction for youths who are low, medium and high risk themselves. Figure 2d shows the results for boys and Figure 2e shows results for girls. Each graph shows the coefficients from a single regression of felony conviction on the six peer risk level variables interacted with dummies for being in the bottom, middle and top third of the risk distribution. The impact of peers with risk score between six and seven for the low risk youths are dropped from the equations. Small sample sizes make it difficult to draw definitive conclusions about the functional form across the three risk groups.

The non-linearities in the impact of peers with different risk levels suggests that outcomes for low and medium risk boys might be improved by separating them from the boys with higher levels of aggression and emotional disturbance. I divide the male sample into three groups - low risk boys whose life-risk score is five and under, medium risk boys whose score is between six and nine, and high risk boys whose life-risk score is ten or above. For each group of boys I estimate the impact of replacing a low risk peer with a medium or high risk peer, a medium risk peer with a low or high risk peer, or a high risk peer with a low or medium risk peer on their likelihood of being convicted of a felony or re-incarcerated within a year. Using these estimated coefficients, I do a back of the envelope calculation for the expected recidivism rates of each of these three groups under an alternative sorting regime in which the youths are entirely segregated into groups of other similarly ranked youths (low, medium or high risk). I then compare

[23] A test for the equality of coefficients rejects that the influence of very low risk peers is the same across genders at the 5% level, and rejects that the influence of very high risk peers is the same across genders at the 10% level.

these outcomes to those observed in the data, where the average fraction of low risk boys in a facility is 0.33 (with a standard deviation of 0.10), the average fraction of medium risk boys is 0.45 (with a standard deviation of 0.07) and the average fraction of high risk boys is 0.22 (with a standard deviation of 0.09).

I estimate that outcomes are improved for the low and medium risk boys under this alternative method of organizing, while outcomes are worsened for the high risk boys. The net effects, however, are positive. When boys are sorted so that their peers are all in the same risk category, my calculations predict a 16% decrease in the number of boys who are convicted of a felony and an 18% decrease in the number of boys who are re-incarcerated within a year.

An average of 6030 boys are released each year from a residential correctional program in the state of Florida during the years for which I have data (July 2006 to July 2011). 15% of these boys are back in a juvenile incarceration facility within a year of release and 7% are in an adult prison or jail. The average cost of incarcerating an adolescent is $27,000 in a juvenile facility and $15,415 in an adult facility.[24] The estimated yearly savings from fully sorting the youths into low, medium and high risk cohorts would exceed $5.6 million in terms of incarceration costs alone, not counting the social gains of reduced crime. While sorting the youths according to their risk level would lead to a definite welfare loss for high risk boys, this could be potentially offset by increasing their access to evidence-based rehabilitative programming, paid for out of savings from the lower incarceration rates.

These numbers are of course only back-of-the-envelope estimates.[25] Furthermore the youths may respond endogenously to the different peer distributions in ways that are difficult to predict (Carrell et al., 2013). Nonetheless the estimated benefits of separating the lower risk boys from those with higher levels of aggression/anti-societal attitudes are substantial, and as long as the youths are carefully monitored to make sure that the re-sorting is having the expected positive effects, it seems an advisable experiment to undertake.

[24]These cost estimates are generated assuming an eight month stay, which is the average in juvenile facilities. As the length of incarceration in adult facilities is generally longer this is likely to be an underestimate. The yearly cost of incarcerating an adult inmate is $20,553 (Henrichson and Delaney, 2012) and the daily cost of incarceration in a juvenile facility is $97.92 in a non-secure facility and $141.62 in a secure facility (SPLC, 2010).

[25]It could be argued that these numbers are an underestimate since they do not include the social gains of averted crime or the benefits to the youths themselves. On the other hand the practical constraints of implementing the new sorting regime may result in some welfare loss: separating the lower risk boys from the higher risk boys may require placing them in a facility that is too far from home for their parents to be able to visit, for example.

6 Conclusion

This paper presents evidence that social interactions had while incarcerated can have a strong impact on the propensity for crime after release. I find that exposure to peers from unstable homes and who have emotional/behavioral problems leads to a sizable increase in criminal behavior after release as well as an increase in crime-oriented attitudes and behavioral habits. This effect is most consistent with a social contagion mechanism: adolescents are influenced by the attitudes, beliefs, values and behaviors of their peers in a way that alters their criminal propensity. Non-linearities in peer influence suggest that net outcomes can be improved by sorting the youths to minimize negative peer influence. Back-of-the-envelope calculations estimate that separating lower risk boys from higher risk boys would lead to an 18% decrease in the one year re-incarceration rate, with $5.6 million in savings simply from reduced incarceration costs alone.

Although the focus of the paper is on peer influence in juvenile incarceration facilities, I conduct a supplementary analysis on peer influence in day treatment facilities (alternative schools for delinquent youth). Day treatment facilities differ from the residential facilities in a manner that is important for the persistent network formation mechanism: they unite youths from the same local area. In residential facilities I find that exposure to peers with lots of criminal experience leads to an increase in crime after release, but only if those peers live close enough to one another that they are likely to interact after release. This finding is confirmed and expanded upon in day treatment setting: exposure to peers with lots of criminal experience as well as peers with criminal connections (gang affiliation) leads to an increase in crime after release, as well as an increase in gang participation. The finding that this type of peer is only influential when they come from the same local area is consistent with the network formation mechanism.

While the evidence presented in this paper speaks most directly to the question of how to sort youths in order to minimize negative peer influence, it also raises questions about a variety of other important policy questions. Are peer influences in juvenile incarceration damaging enough that home arrest might be a preferable alternative to a group-based form of sanctions? What are the consequences in terms of exposing adolescents to criminally experienced adults when they are placed in an adult jail or prison? If peers are so influential, is there a way to harness this in a positive manner - through mentoring, support groups, or programs which target social cohesion?

Incarceration is a heavily-used tool in the United States criminal justice system. In 2011 there were an estimated 61,423 youths in a juvenile incarceration facility, and 2,240,600 people (both adults and adolescents tried as adults) in state prison, federal prison, or jail (Sickmund et al., 2013; Glaze and Herberman, 2013). Despite the scale of this intervention, much is still unknown about its effects on future outcomes. The evidence presented in this paper underline the fact that youths who are incarcerated are not simply sitting on the shelf: the incarceration period is actively formative. *Who* a teenager is locked up with influences his attitudes towards society, beliefs around law and justice, aggressive behaviors, emotional and social skills. *Who* a teenager is locked up with influences how likely he is to be locked up again, a year after release. While the primary rationale for incarceration is to lower crime through deterrence or incapacitation, the primary experience of incarceration is one of being confined in a small physical space with a particular group of people: criminally experienced and often emotionally troubled. Understanding how this experience affects adolescents is a step towards helping them from getting caught in the revolving door between crime and incarceration.

References

Aizer, Anna and Joseph J. Jr. Doyle, "Juvenile Incarceration, Human Capital and Future Crime: Evidence from Randomly-Assigned Judges," *National Bureau of Economic Research Working Paper*, 2013.

Akerlof, George A. and Rachel E. Kranton, "Economics and Identity," *The Quarterly Journal of Economics*, 2000, *115* (3), pp. 715–753.

Anderson, Michael L., "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American Statistical Association*, 2008, *103* (484), 1481–1495.

Angrist, Joshua, "The Perils of Peer Effects," Working Paper 19774, National Bureau of Economic Research December 2013.

Bayer, Patrick, Randy Hjalmarsson, and David Pozen, "Building Criminal Capital Behind Bars: Peer Effects in Juvenile Corrections," *Quarterly Journal of Economics*, 2009, *124*, 105–147.

Benjamini, Yoav and Yosef Hochberg, "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing," *Journal of the Royal Statistical Society. Series B (Methodological)*, 1995, *57* (1), 289–300.

Billings, Stephen B., David J. Deming, and Jonah Rockoff, "School Segregation, Educational Attainment and Crime: Evidence from the end of busing in Charlotte-Mecklenburg," *The Quarterly Journal of Economics*, 2013.

Blanden, Jo, Paul Gregg, and Lindsey Macmillan, "Accounting for Intergenerational Income Persistence: Noncognitive Skills, Ability and Education*," *The Economic Journal*, 2007, *117* (519), C43–C60.

Bowles, Samuel, Herbert Gintis, and Melissa Osborne, "The Determinants of Earnings: A Behavioral Approach," *Journal of Economic Literature*, 2001, *39* (4), 1137–1176.

__ , __ , and __ , "The Determinants of Earnings: A Behavioral Approach," *Journal of Economic Literature*, 2001, *39* (4), 1137–1176.

Bursztyn, Leonardo, Florian Ederer, Bruno Ferman, and Noam Yuchtman, "Understanding Mechanisms Underlying Peer Effects:Evidence From a Field Experiment on Financial Decisions," *Econometrica*, 2014, *82* (4), 1273–1301.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Bootstrap-Based Improvements for Inference with Clustered Errors," Working Paper 344, National Bureau of Economic Research September 2007.

Carrell, Scott E. and Mark L. Hoekstra, "Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids," *American Economic Journal: Applied Economics*, 2010, *2* (1), 211–28.

_, Bruce I. Sacerdote, and James E. West, "From Natural Variation to Optimal Policy? The Importance of Endogenous Peer Group Formation," *Econometrica*, 2013, *81* (3), 855–882.

_, Richard L. Fullerton, and James E. West, "Does Your Cohort Matter? Measuring Peer Effects in College Achievement," *Journal of Labor Economics*, 07 2009, *27* (3), 439–464.

Chen, M. Keith and Jesse M. Shapiro, "Do Harsher Prison Conditions Reduce Recidivism? A Discontinuity-based Approach," *American Law and Economics Review*, 2007, *9* (1), 1–29.

Damm, Anna Piil and Cedric Gorinas, "Deal Drugs Once, Deal Drugs Twice: Peer Effects on Recidivism from Prisons," Technical Report, Working Paper December 2013.

Duckworth, Angela L. and Christopher Peterson, "Grit: Perseverance and Passion for Long Term Goals," *Journal of Personality and Social Psychology*, 2007, *92* (6), 1087–1101.

Duflo, Esther, Pascaline Dupas, and Michael Kremer, "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya," *American Economic Review*, 2011, *101* (5), 1739–74.

Ellison, Glenn and Drew Fudenberg, "Word-of-Mouth Communication and Social Learning," *The Quarterly Journal of Economics*, 1995, *110* (1), pp. 93–125.

Evans, Gary W. and Thomas E. Fuller-Rowell, "Childhood poverty, chronic stress, and young adult working memory: the protective role of self-regulatory capacity," *Developmental Science*, 2013, *16* (5), 688–696.

Felitti, VJ1, RF Anda, D Nordenberg, Williamson DF, AM Spitz, V Edwards, MP Koss, and JS Marks, "Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults. The Adverse Childhood Experiences (ACE) Study.," *American Journal of Preventative Medecine*, 1998, *14* (4).

Foster, Gigi, "It's not your peers, and it's not your friends: Some progress toward understanding the educational peer effect mechanism," *Journal of Public Economics*, 2006, *90* (89), 1455 – 1475.

Gelb, Adam, "State of Recidivism: The Revolving Door of America's Prisons," Technical Report, Pew Center on the States, Washington, DC April 2011.

Glaze, Lauren E. and Erinn J. Herberman, "Correctional Populations in the United States 2012," Technical Report, Bureau of Justice Statistics December 2013.

Guryan, Jonathan, Kory Kroft, and Matthew J. Notowidigdo, "Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments," *American Economic Journal: Applied Economics*, 2009, *1* (4), 34–68.

Heckman, James J. and Yona Rubinstein, "The Importance of Noncognitive Skills: Lessons from the GED Testing Program," *The American Economic Review*, 2001, *91* (2), pp. 145–149.

_, Jora Stixrud, and Sergio Urzua, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, July 2006, *24* (3), 411–482.

Heckman, James, Rodrigo Pinto, and Peter Savelyev, "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes," *American Economic Review*, 2013, *103* (6), 2052–86.

Henrichson, Christian and Ruth Delaney, "The Price of Prisons: What Incarceration Costs Taxpayers," Technical Report, Vera Institute of Justice January 2012.

Hoxby, Caroline, "Peer Effects in the Classroom: Learning from Gender and Race Variation," Working Paper 7867, National Bureau of Economic Research August 2000.

Hoxby, Caroline M. and Gretchen Weingarth, "Taking race out of the equation: School reassignment and the structure of peer effects," Working Paper, National Bureau of Economic Research 2005.

Imberman, Scott A., Adriana D. Kugler, and Bruce I. Sacerdote, "Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees," *American Economic Review*, 2012, *102* (5), 2048–82.

Jackson, Matthew O., "Chapter 12 - An Overview of Social Networks and Economic Applications," in Alberto Bisin Jess Benhabib and Matthew O. Jackson, eds., , Vol. 1 of *Handbook of Social Economics*, North-Holland, 2011, pp. 511 – 585.

Jacob, Brian A. and Lars Lefgren, "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration, and Juvenile Crime," *American Economic Review*, 2003, *93* (5), 1560–1577.

Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz, "Experimental Analysis of Neighborhood Effects," *Econometrica*, 2007, *75* (1), 83–119.

Lavy, Victor and Anala Schlosser, "Mechanisms and Impacts of Gender Peer Effects at School," *American Economic Journal: Applied Economics*, 2011, *3* (2), pp. 1–33.

Lerman, A.E., *The Modern Prison Paradox: Politics, Punishment, and Social Community*, Cambridge University Press, 2013.

Ludwig, Jens, Greg J. Duncan, and Paul Hirschfield, "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing-Mobility Experiment," *The Quarterly Journal of Economics*, 2001, *116* (2), 655–679.

Manski, Charles F, "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, July 1993, *60* (3), 531–42.

McEwen, Bruce, "Stress, Adaptation and Disease: Allostasis and Allostatic Load," *Annals New York Academy of Science*, 1998.

Mendel, Richard A., "No Place for Kids: The Case for Reducing Juvenile Incarceration," Technical Report, The Annie E. Casey Foundation, Baltimore, MD 2011.

Mincer, Jacob A., *Schooling, Experience, and Earnings*, Columbia University Press, 1974.

Moffitt, Terrie E., Louise Arseneault, Daniel Belsky, Nigel Dickson, Robert J. Hancox, HonaLee Harrington, Renate Houts, Richie Poulton, Brent W. Roberts, Stephen Ross, Malcolm R. Sears andW. Murray Thomson, and Avshalom Caspi, "A gradient of childhood self-control predicts health, wealth, and public safety," *PNAS*, 2011.

Mueller-Smith, Michael, "THE CRIMINAL AND LABOR MARKET IMPACTS OF INCARCERATION: IDENTIFYING MECHANISMS AND ESTIMATING HOUSEHOLD SPILLOVERS," Working Paper July 2014.

Nagin, Daniel S. and Greg Pogarsky, "Time and Punishment: Delayed Consequences and Criminal Behavior," *Journal of Quantitative Criminology*, 2004, *20* (4), 295–317.

Ouss, Aurelie, "Prison as a School of Crime: Evidence From Cell Level Interactions," Technical Report, Working Paper December 2011.

Posner, Richard A., "Social Norms and the Law: An Economic Approach," *The American Economic Review*, 1997, *87* (2), pp. 365–369.

Sickmund, M, T.J. Sladky, W Kang, and C Puzzanchera, "Easy Access to the Census of Juveniles in Residential Placement," Technical Report, Office of Juvenile Justice and Delinquency Prevention 2013.

SPLC, "Fiscal Responsibility: The Key to a Safer, Smarter, and Stronger Juvenile Justice System," Technical Report, Southern Poverty Law Center December 2010.

Stevenson, Megan, "Tests of random assignment to peers in the face of mechanical negative correlation: an evaluation of four techniques," Working Paper March 2015.

7 Tables and Figures

Table 1: Summary statistics on life-risk, criminal history, and non-cognitive indicators

	Male	Female	Total
Panel A: Summary Statistics for the Life-Risk Score			
Dropped out or expelled	0.11	0.13	0.11
Drinks alcohol	0.21	0.27	0.22
Does drugs	0.46	0.44	0.46
Known gang affiliate	0.14	0.10	0.14
Parents w/drug, alc. prob	0.14	0.22	0.15
Parent has been incarcerated	0.45	0.52	0.46
Family member has been incarcerated	0.60	0.67	0.61
Been in foster care/shelter	0.17	0.32	0.19
Ran away or was kicked out	0.42	0.77	0.47
Physically abused	0.16	0.36	0.19
Sexually abused	0.030	0.29	0.065
Panel B: Summary Statistics for the Criminal History Score			
First offense under 14yrs	0.78	0.76	0.77
First offense under 12yrs	0.39	0.33	0.38
Previously incarc.	0.29	0.28	0.29
MS prior- assault	0.39	0.56	0.42
MS prior- burglary	0.35	0.16	0.33
MS prior- robbery	0.14	0.037	0.13
MS prior- drug felony	0.059	0.040	0.057
MS prior- auto theft	0.043	0.080	0.048
MS prior- larceny	0.11	0.30	0.14
MS prior- murder, att. murder	0.0043	0.0029	0.0041
Total prior felony charges	6.06	2.85	5.62
Total prior misdemeanor charges	5.91	4.97	5.78
Panel C: Summary Statistics for the Non-Cognitive Scores			
Low/no hope or aspiration	0.40	0.39	0.40
Impulsive or highly impulsive	0.57	0.64	0.58
Lacks empathy for victim	0.28	0.33	0.29
Lacks respect for other's property	0.17	0.15	0.17
Low tolerance for frustration	0.20	0.36	0.22
Hostile interp. of other's actions	0.50	0.63	0.51
Believe verb. agg. often necessary	0.10	0.21	0.12
Believe phys. agg. often necessary	0.066	0.10	0.071
No/unrealistic goals	0.56	0.55	0.56
Poor situational perception	0.81	0.82	0.81
Poor social skills	0.81	0.79	0.81
Poor emotional skills	0.60	0.65	0.60

The statistic shown is the mean.

Note: This table shows summary statistics by gender on some of the C-PACT indicators used to build the life-risk, criminal history, and non-cognitive scores for 12,695 youths in residential facilities. All variables except for the final two variables in Panel B are dummies indicating whether or not a trait is observed. 'MS prior' is short for 'most serious prior offense'.

Table 2: Summary statistics on demographics, criminal history and recidivism, shown by facility type

	Residential	Day treatment	Total
Pre-determined Variables			
Age at entry	16.5	16.3	16.4
Female	0.14	0.23	0.16
African-American	0.55	0.55	0.55
Hispanic	0.11	0.15	0.12
MS prior-violent felony	0.61	0.45	0.58
MS prior-property felony	0.29	0.31	0.30
Previously incarcerated	0.29	0.22	0.27
Own risk score	7.19	5.38	6.82
Own criminal history score	12.8	8.94	12.0
Recidivism Variables			
Arrest 1yr post	0.60	0.50	0.58
Felony arrest 1yr post	0.44	0.32	0.42
Conviction 1yr post	0.43	0.34	0.41
Felony conviction 1yr post	0.27	0.18	0.25
Re-incarcerated 1yr post	0.21	0.15	0.20

The statistic shown is the mean.

Note: This table shows summary statistics by facility type. There are 12,695 observations for the residential facilities and 3,306 observations for the day treatment facilities. 'MS prior' stands for 'most serious prior offense'. The recidivism variables are dummy variables indicating whether or not the adolescent was arrested/convicted/imprisoned within one year of release.

Table 3: A summary of tests and evidence for the three mechanisms

Social Contagion

Setting	Peer Characteristic	Outcome	Evidence?
Residential	↑ Life-risk score	↑ Crime	Strong
Residential	↑ Life-risk score	↑ Crime-oriented noncogs	Strong
Residential	↑ Life-risk score	↓ Protective noncogs	Strong
Residential	↑ Crime-oriented noncogs	↑ Crime	Strong
Residential	↑ Crime-oriented noncogs	↑ Crime-oriented noncogs	Strong(Not Shown)
Residential	↑ Crime-oriented noncogs	↓ Protective noncogs	Strong(Not Shown)
Residential	↑ Abusive/unstable homes	↑ Crime	Strong

Network Formation

Setting	Peer Characteristic	Outcome	Evidence?
Day	↑ CH score	↑ Crime	Strong
Day	↑ Gang affiliation	↑ Crime	Medium
Day	↑ CH score	↑ Gang affiliation	Medium
Day	↑ Gang affiliation	↑ Gang affiliation	Weak(Not Shown)
Day	↑ CH score	↑ Gang-related crimes	Medium
Residential	↑ CH score, hometown peers	↑ Crime	Medium

Skill Transfer

Setting	Peer Characteristic	Outcome	Evidence?
Residential	↑ CH score	↑ Crime	None
Residential	↑ Specific skilled crime	↑ Specific skilled crime	None
Day	↑ Specific skilled crime	↑ Specific skilled crime	None

Note: This table summarizes the predictions of the various mechanisms as well as the degree to which a prediction is supported by the evidence. For example the first row in the social contagion panel should be interpreted as follows: "The social contagion mechanism predicts that an increase in the life-risk score of the peer group in the residential setting should lead to an increase in crime after release. A test of this prediction provides strong confirmatory evidence." For more details about how these tests relate to the different mechanisms see Section 4. 'CH' stands for 'criminal history'.

Table 4: Identification tests: within-facility cluster test and the 'cluster bootstrap split sample test' for non-random assignment to peers

Panel A: Testing for non-random clustering of types within facilities				
	Residential-Risk	**Residential-Crim. History**	**Day-Risk**	**Day-Criminal History**
F Statistic on ω	1.04	1.08	1.13	1.15
Prob >F under null	0.2423	0.1125	0.1330	0.1082
Smallest FDR p value	0.8258	0.8821	0.4967	0.2034
Panel B: Testing for correlations between own risk/CH score and peer risk/CH				
	Residential-Risk	**Residential-Crim. History**	**Day-Risk**	**Day-Criminal History**
$\hat{\hat{\beta}}$ (Average $\hat{\beta}$: 10,000 reps)	0.0017	0.0018	0.0022	0.0016
$\hat{\hat{\sigma}}_\beta$ (Average $\hat{\sigma}_\beta$: 10,000 reps)	0.0032	0.0028	0.0036	0.0031
Upper Bound, 95% C.I.	0.0081	0.0074	0.0094	0.0078
S.D. Own Score	1	1	1	1
S.D. Peer Score	0.38	0.46	0.31	0.40

Note: Panel A summarizes the results of two different tests for non-random clustering of types within a facility. The first test is an F test for joint significance on a set of peer group dummies. The dependent variable is the risk/criminal history score. The second test is an FDR adjusted test for individual significance on the same set of dummy variables. Panel B summarizes the results for the 'cluster bootstrap split-sample' test of correlation between own risk/criminal history score and the risk/criminal history score of the peers. Descriptions for both techniques can be found in Section 3.

Table 5: Social Contagion

Panel A: Residential Facilities					
	(1) Arrest	(2) Felony Arrest	(3) Convict	(4) Felony Convict	(5) Prison
Peer Risk	0.0377***	0.0405***	0.0312**	0.0349***	0.0344****
	(0.0139)	(0.0137)	(0.0132)	(0.0129)	(0.0100)
Observations	12695	12695	12695	12695	12695
Mean dep. var.	0.60	0.44	0.43	0.27	0.21
Panel B: Residential Facilities: Alternative Specifications					
	Felony Convict	Felony Convict	Felony Convict	Felony Convict	Felony Convict
Peer Gang	0.00927				
	(0.0101)				
Peer Unstable Home		0.0253*			
		(0.0132)			
Peer Abuse/Trauma			0.0293**		
			(0.0133)		
Peer Crim. Noncog				0.0257**	
				(0.0126)	
Peer Risk, Hometown					0.00335
					(0.00541)
Observations	11251	12695	12695	12695	12695
Mean dep. var.	0.27	0.27	0.27	0.27	0.27
Panel C: Residential Facilities: Non-cognitive Outcomes Post-Release					
	Aggr-ession	Anti-Societal Attitudes	Impul-sivity	Crime-Oriented Traits	Healthy Traits
Peer Risk	0.108**	0.160***	0.150***	0.158***	-0.131**
	(0.0493)	(0.0552)	(0.0526)	(0.0528)	(0.0527)
Observations	7035	7035	7035	7035	7035
Panel D: Residential Facilities: Non-cognitive Outcomes 8 Months Post					
	Aggr-ession	Anti-Societal Attitudes	Impul-sivity	Crime-Oriented Traits	Healthy Traits
Peer Risk	0.0984*	0.128**	0.0907	0.128**	-0.123*
	(0.0533)	(0.0565)	(0.0571)	(0.0533)	(0.0621)
Peer Risk, Hometown	-0.0151	0.0151	0.00748	0.000250	0.00234
	(0.0153)	(0.0155)	(0.0196)	(0.0158)	(0.0172)
Observations	5310	5310	5310	5310	5310

Standard errors, clustered at facility level, are shown in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: All regressions are linear and include the full set of covariates and fixed effects shown in Column 5 of Table 6. Panels A/B: The independent variables have been standardized and the dependent variable is binary, indicating whether or not the youth is arrested/convicted/imprisoned within a year of release. Panels C/D: Both the independent and the dependent variables have been standardized. These regressions also include fully saturated controls for pre-entry non-cognitive measures and linear time trends for the DJJ unit which administers the examination.

Table 6: Social Contagion: Stability of effect

	(1) Felony Convict.	(2) Felony Convict.	(3) Felony Convict.	(4) Felony Convict.	(5) Felony Convict.	(6) Felony Convict.	(7) Felony Convict.
Peer Risk	0.0354***	0.0382***	0.0355***	0.0384***	0.0349***	0.0353**	0.0355**
	(0.0132)	(0.0131)	(0.0127)	(0.0129)	(0.0129)	(0.0161)	(0.0167)
Peer CH							-0.0198
							(0.0190)
Perc. Afr.-Am.							-0.102
							(0.0903)
Av. Age							0.0528*
							(0.0311)
Perc. Hisp.							-0.0936
							(0.147)
Facility FE	X	X	X	X	X	X	X
Date FE	X	X	X	X	X	X	X
Demographics		X	X	X	X	X	X
Prior Crimes			X	X	X	X	X
Risk Score				X	X	X	X
Risk x FacFE					X	X	X
CH x FacFE					X	X	X
LinearTT x FacFE						X	X
Observations	12695	12695	12695	12695	12695	12695	12695
R^2	0.0536	0.0709	0.0869	0.0876	0.102	0.110	0.111
Mean dep. var.	0.27	0.27	0.27	0.27	0.27	0.27	0.27

Standard errors, clustered at facility level, are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Peer Risk has been standardized and the dependent variable is a dummy variable indicating whether or not the youth has been convicted of a felony within a year after release. Covariates include facility fixed effects, quarter-by-year of release fixed effects, demographics, criminal history variables and score, risk score, both criminal history and risk score interacted with facility fixed effects, a linear time trend interacted with facility fixed effects, peer criminal history, percent of African American peers, average age of peers and percent of Hispanic peers.

Table 7: Network Formation

Panel A: Day Facilities: Criminal History Score of Peers					
	(1)	(2)	(3)	(4)	(5)
	Arrest	Felony Arrest	Convict	Felony Convict	Prison
Peer CH	0.0646*	0.0427	0.0966***	0.0734**	0.0611*
	(0.0355)	(0.0419)	(0.0322)	(0.0277)	(0.0355)
Observations	3306	3306	3306	3306	3306
Mean dep. var.	0.51	0.32	0.34	0.18	0.15
Panel B: Day Facilities: Peers With Gang Affiliation					
	Arrest	Felony Arrest	Convict	Felony Convict	Prison
Peer Gang	0.0193	0.0267	0.0286	0.0398**	0.0423**
	(0.0221)	(0.0166)	(0.0221)	(0.0181)	(0.0158)
Observations	3306	3306	3306	3306	3306
Mean dep. var.	0.51	0.32	0.34	0.18	0.15
Panel C: Residential Facilities: Peers from Hometown Area					
	Arrest	Felony Arrest	Convict	Felony Convict	Prison
Peer CH, Hometown	0.0130**	0.0136**	0.00877	0.00670	-0.00585
	(0.00649)	(0.00628)	(0.00640)	(0.00501)	(0.00480)
Observations	11251	11251	11251	11251	11251
Mean dep. var.	0.60	0.44	0.43	0.27	0.21
Panel D: Day Facilities: Gang Related Outcomes/Robustness Check					
	Gang	Gang	Drug Off.	Drug Off.	Felony Convict
Peer CH	0.0183**	0.0140	0.0353**	0.0133	0.0610*
	(0.00933)	(0.0109)	(0.0147)	(0.0230)	(0.0286)
Facility FE	X	X	X	X	X
Time FE	X	X	X	X	X
LinearTT x FacFE		X		X	X
Covariates	X	X	X	X	
Observations	2928	1504	1504	2928	3306
Mean dep. var.	0.11	0.11	0.05	0.05	0.18

Standard errors, clustered at facility level, are shown in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: Panels A/B/C: The independent variables have been standardized and the dependent variable is binary, indicating whether or not the youth is arrested/convicted/imprisoned within a year of release. The phrase 'Peer CH, Hometown' refers to the average criminal history score of youths whose zip codes are within 20 miles of one's own zip code. Panel D: The outcomes here are binary and refer to whether or not the youth has joined a gang, committed a drug offense (a gang-related crime), or been convicted of a felony within a year of release. Columns 1 and 4 omit the facility-specific time trends and Column 5 omits the covariates as a robustness check. The regression are linear and, besides the three mentioned, include a full set of covariates and fixed effects as described in Section 4.

Table 8: Skill Transfer

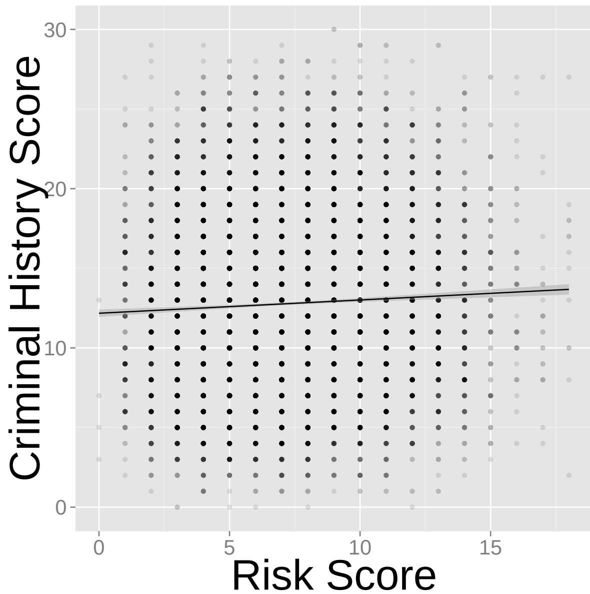
Panel A: Residential Facilities					
	(1) Arrest	(2) Felony Arrest	(3) Convict	(4) Felony Convict	(5) Prison
Peer CH	-0.0121	-0.00831	0.00728	-0.0110	0.00150
	(0.0147)	(0.0151)	(0.0179)	(0.0144)	(0.0164)
Observations	12695	12695	12695	12695	12695
Mean dep. var.	0.60	0.44	0.43	0.27	0.21
Panel B: Residential Facilities - crime-specific skill transfer					
	Robbery	Drug Offense	Burglary	Auto Theft	Grand Larceny
PeerOffense*Offense	0.0250	0.116	0.0836	-0.263	-0.137
	(0.0933)	(0.204)	(0.0592)	(0.241)	(0.179)
PeerOffense*NoOffense	-0.0390	0.000865	0.0355	0.0537	-0.00473
	(0.0471)	(0.0453)	(0.0395)	(0.0436)	(0.0269)
Observations	21288	21288	21288	21288	21288
Mean dep. var.	0.11	0.05	0.31	0.05	0.04
Panel C: Residential Facilities - crime-specific skill transfer					
	Robbery	Drug Offense	Burglary	Auto Theft	Grand Larceny
PeerOffense	-0.0300	0.00657	0.0502	0.0394	-0.0105
	(0.0415)	(0.0444)	(0.0317)	(0.0422)	(0.0265)
Observations	21288	21288	21288	21288	21288
Mean dep. var.	0.11	0.05	0.31	0.05	0.04
Panel D: Day Facilities - crime-specific skill transfer					
	Robbery	Drug Offense	Burglary	Auto Theft	Grand Larceny
PeerOffense*Offense	-0.406**	0.627	-0.0815	0.344	-0.171
	(0.156)	(0.720)	(0.122)	(0.385)	(0.434)
PeerOffense*NoOffense	-0.0444	0.0579	0.00889	0.0445	0.0339
	(0.0791)	(0.0781)	(0.0907)	(0.110)	(0.0702)
Observations	4442	4442	4442	4442	4442
Mean dep. var.	0.09	0.05	0.29	0.05	0.04
Panel E: Day Facilities - crime-specific skill transfer					
	Robbery	Drug Offense	Burglary	Auto Theft	Grand Larceny
PeerOffense	-0.102	0.0923	0.00281	0.0171	0.00765
	(0.0718)	(0.0920)	(0.0716)	(0.102)	(0.0717)
Observations	4442	4442	4442	4442	4442
Mean dep. var.	0.09	0.05	0.29	0.05	0.04

Standard errors, clustered at facility level, are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

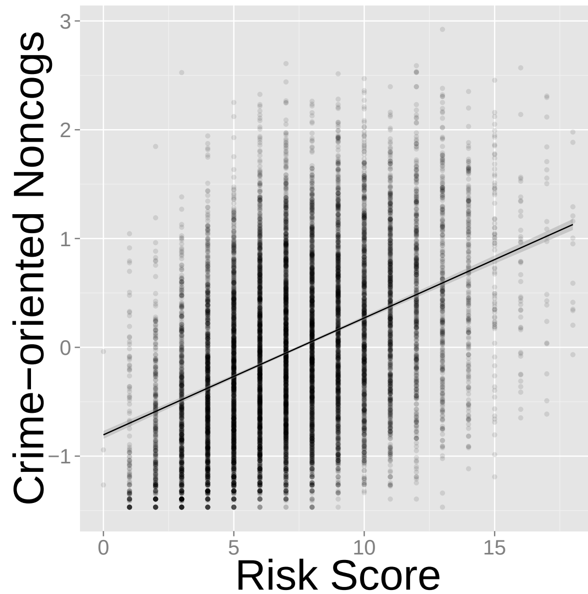
Note: Panel A: The independent variables have been standardized and the dependent variable is binary, indicating whether or not the youth is arrested/convicted/imprisoned within a year of release. Panel B-E: The outcome variables are binary and describe whether the youth commits a robbery, drug offense, burglary, auto theft, or grand larceny within a year of release. The independent variables are standardized and vary according to the outcome variable. For example, when the outcome variable is robbery, the independent variable is the fraction of peers with robbery experience. In Panels B and D this has been interacted with two dummy variables indicating whether or not the youth has robbery experience himself.

Figure 1: Correlations of traits and graphical analysis of identifying variation

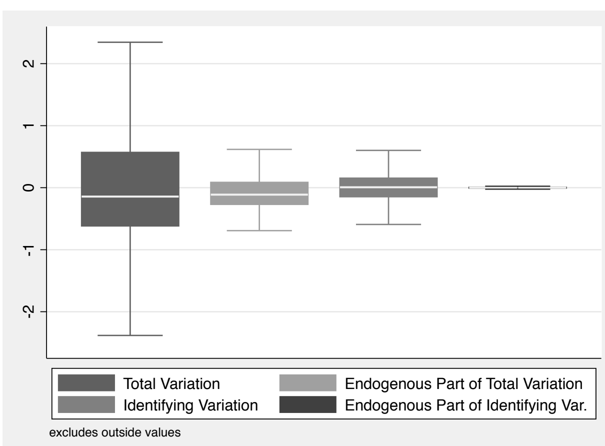
(a) Risk and Criminal History Score



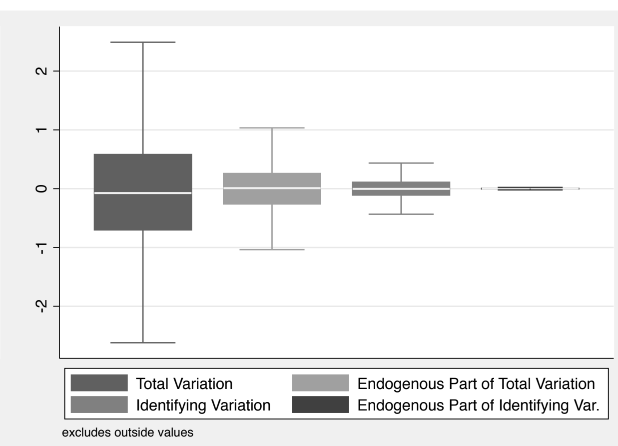
(b) Risk and Crime-Oriented Non-cognitive Index



(c) Peer Risk Score, Breakdown of Variance



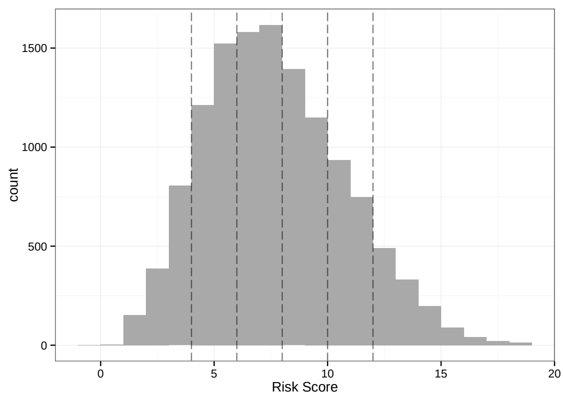
(d) Peer Criminal History Score, Breakdown of Variance



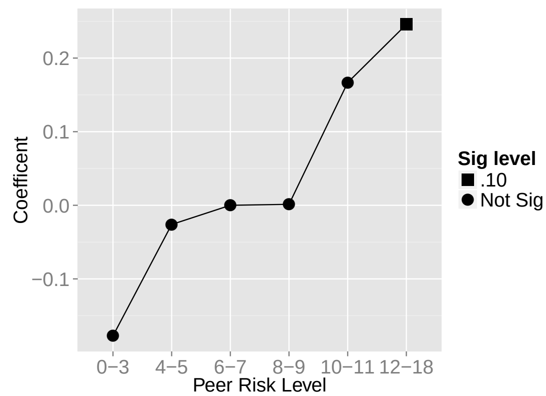
Note: The top row of graphs show the correlation of the life-risk score with the criminal history score and with the index of crime-oriented non-cognitive factors respectively. All three measures are from the examination taken immediately before entry to the facility. In the bottom row of graphs, the left-most box-plot labeled 'Total Variation' shows the distribution of the peer risk (or criminal history) score, standardized. The bottom and top lines of the box show the 25th and 75th percentile of the distribution, the outer lines show the adjacent values. The box-plot labeled 'Endogenous Part of Total Variation' (second to left) show the part of 'Total Variation' which is explained by the covariates. The box-plot labeled 'Identifying Variation' (second to right) shows the residuals of a regression of 'Total Variation' (peer risk or criminal history score) on facility and quarter-by-year of release fixed effects. The box-plot labeled 'Endogenous Part of Identifying Variation' (shown right-most) shows the part of 'Identifying Variation' which is explained by the covariates.

Figure 2: Functional Form and Heterogeneity of the Social Contagion Effect

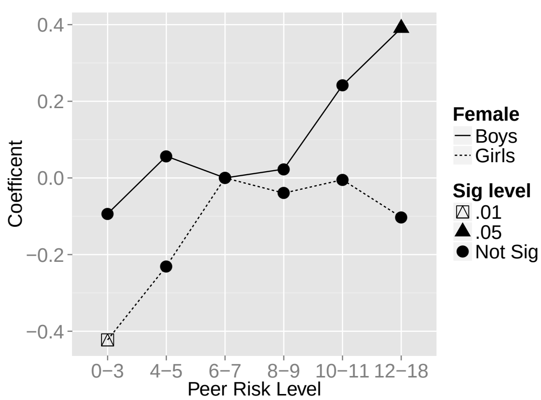
(a) Distribution of Risk Score Divided into Bins



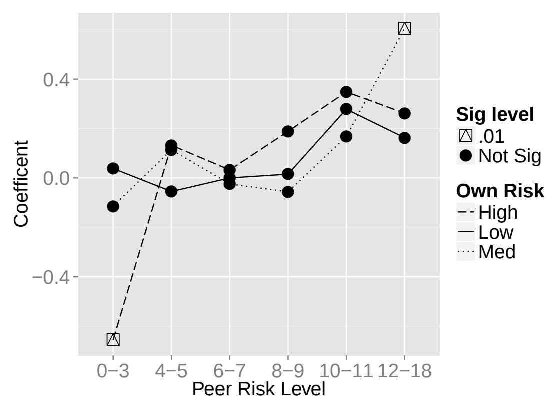
(b) Felony Conviction



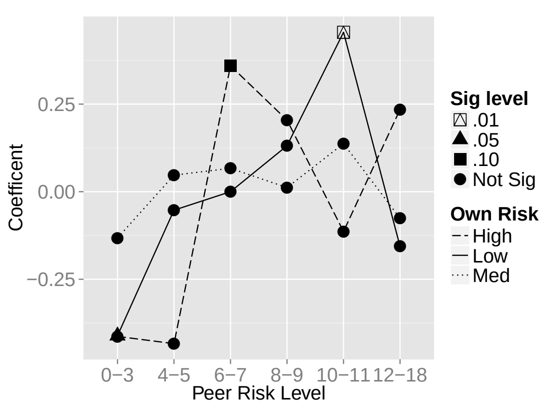
(c) Felony Conviction by Gender



(d) Felony Conviction by Own Risk, Boys



(e) Felony Conviction by Own Risk, Girls



Note: Figure 2a shows the distribution of the risk score; the vertical dotted lines delineate six bins. Figures 2b-e show the coefficients from a regression of felony conviction on the fraction of peers in each of the six bins. Figure 2b shows the full sample, Figure 2c shows results by gender and Figures d and e show results by own risk score. The fraction of peers with risk score between 6 and 7 has been dropped from the regression and is represented by a 0 in the figure. Felony conviction is a dummy variable and the crime-oriented non-cognitive index has been standardized. Each regression includes the full set of covariates and fixed effects as described in Section 4.