Building Criminal Capital behind Bars: Peer Effects in Juvenile Corrections[*]

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Abstract

This paper analyzes the influence that juvenile offenders serving time in the same correctional facility have on each other's subsequent criminal behavior. The analysis is based on data on over 8,000 individuals serving time in 169 juvenile correctional facilities during a two-year period in Florida. These data provide a complete record of past crimes, facility assignments, and arrests and adjudications in the year following release for each individual. To control for the non-random assignment to facilities, we include facility fixed effects, thereby estimating peer effects using only within-facility variation over time. We find strong evidence of peer effects for various categories of theft, burglary, and felony drug and weapon crimes; the influence of peers primarily affects individuals who already have some experience in a particular crime category. We also find evidence that peer effects are stronger in smaller facilities and that the predominant types of peer effects differ in residential versus non-residential facilities; effects in the latter are consistent with network formation among youth serving time close to home.

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I. Introduction

Juvenile crime is a serious problem in modern American society. In 2000, law enforcement agencies throughout the United States made approximately 2.4 million arrests of juveniles under the age of eighteen, or approximately one arrest for every 10 individuals between the ages of thirteen and eighteen (FBI, 2001; Puzzanchera *et al*., 2002). More than 500,000 of these arrests were for property crimes; more than 200,000 were for drug-related violations; and almost 100,000 were for violent crimes (FBI, 2001). On any given day in 1999, over 100,000 juvenile offenders were being held in residential placement (Sickmund, 2002). Concerned with the magnitude of these statistics, a number of researchers have attempted to identify the factors that influence juvenile crime. In particular, studies have often focused on factors illuminated in Becker's economic model of crime (1968), such as the deterrent effect of sanctions, the probability of getting caught, and legitimate sources of income.[1] Few papers, however, have considered how the characteristics and behavior of an individual's peers affect his or her propensity to engage in criminal activity.[2] The purpose of this paper is to provide empirical evidence on such peer effects in juvenile crime. We do so by examining them in a setting where interactions among individuals with criminal experience are likely to be particularly intense: juvenile correctional facilities.

Criminal behavior may be affected by peer effects that occur in the family, in school, on the street corner, in a gang, in the neighborhood, or in prison. Such peer effects may arise from any number of underlying mechanisms related to the social interactions between two individuals or a group of individuals; it is helpful for interpreting the results of our analysis to enumerate some of these mechanisms here.[3] We focus on potential mechanisms related to the criminal

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[1] For example, Levitt (1998) shows that harsher punishments for juveniles are strongly associated with lower rates of juvenile offending for both violent crimes and property crimes. Grogger (1998) finds a negative relationship between market wages and youth crime. Mocan and Rees (1999) study the impact of juvenile arrest rates, unemployment, and family structure on the propensity of juveniles to commit both violent crimes and property crimes.

[2] A notable exception is Case and Katz (1991) who find that family and peer influences operate in a manner such that "likes beget likes." For instance, they find that youths who had family members in jail during the course of their childhood are more likely to be involved in criminal activity or that residence in a neighborhood in which many other youth are involved in crime increases a juvenile's propensity to participate in criminal activity himself.

[3] The theoretical literature in sociology and, more recently, in economics describes many of the potential channels through which social interactions may work. Sutherland (1939) highlights learning from peers, in the form of information, skill acquisition, and behavioral norms; this mechanism is also incorporated into the models of Sah (1991) and Calvo-Armengol and Zenou (2003). Ethnographic studies by Anderson (1990, 1999) and the theoretical model of Silverman (2002) describe social interactions that arise through reputational effects. Criminal gangs and other crime networks may also have productive in addition to learning effects (Sarnecki, 2001; Warr, 2002).

experience of an individual's peers, grouping these mechanisms into three broad categories: (i) those related to a social stigma, (ii) those related to the reinforcement of addictive behavior, and (iii) those related to information dispersion and network formation. Social stigma refers to the impact that an individual's peers have on behavior related to perceived pressures, social norms, and other similar social influences. The standard hypothesis in this case is that when an individual is exposed to peers who regard criminal activity in a negative way, the individual is less likely to participate in such behavior. Similarly, exposure to peers with a greater intensity of criminal experience can reduce or reverse this stigma, thereby increasing the propensity of the individual to participate in criminal activity. Second, especially in the case of drug crimes, addiction or habit-formation may play a significant role in an individual's propensity to recidivate with such a crime. Peer interactions would be important in this case if exposure to peers with similar habits or addictions reinforces an individual's own addiction.

The third mechanism listed above relates to the dissemination of crime-related information through peer interactions, which we label social learning, and the development of criminal networks.[4] Social learning may occur because individuals use the experiences of their peers to update their beliefs concerning the expected benefits or punishments of committing particular crimes, making individuals more or less likely to commit these crimes. Alternatively, social learning may take the form of the acquisition of crime-specific skills and knowledge, such as how to steal a car, how to disconnect a burglary alarm, or how to avoid being caught by the police. In this case, interactions with individuals who have experience committing a particular type of crime may allow an individual to acquire this knowledge more easily, thereby leading to increased activity in the corresponding crime category. Finally, access to individuals with experience in a given criminal activity might assist in the formation or expansion of an individual's criminal network. Networking of this sort is especially important in more complicated criminal activities such as those related to auto theft or illegal drugs, which require a great deal of coordination among manufacturers, distributors, sellers, and users.

While distinguishing the existence and magnitude of peer effects or social interactions has been the focus of a large body of recent empirical research in economics,[5,6] empirical work

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[4] There is a small but growing body of research in economics on social learning and network formation, including Besley and Case (1994), Foster and Rosenzweig (1995), Munshi (1999), and Conley and Udry (2002).

[5] The goal of much of the recent literature in economics has been to deal explicitly with the three traditional difficulties involved in the estimation of social interactions in linear models: the simultaneity (reflection) problem, the non-random selection of individuals into peer groups, and the presence of correlated unobservable factors that affect the behavior or outcomes of everyone in a peer group. Moffitt (2001)

exploring the importance of social interactions in criminal behavior has been relatively limited. The few papers that attempt to provide direct evidence of social interactions are generally subject to serious concerns regarding the non-random selection or assignment of an individual's peers.[7] Indirect evidence of social interactions is provided by Sah (1991) and Glaeser, Sacerdote, and Scheinkman (1996); these authors conclude that social interactions must play an important role in criminal behavior as crime exhibits variation across time and space that is difficult to explain with observable differences in the economic and social environment.[8] Additionally, Jacob and Lefgren's (2003) finding, that school attendance increases the amount of violent crimes but decreases the amount of property crimes, underscores the role played by social interactions in explaining violent crimes.

In light of the paucity of credible direct evidence to date, the central goal of this paper is to estimate the effects of peer characteristics on criminal behavior in a manner that deals directly with the non-random assignment of individuals to correctional facilities and, consequently, to their peers. Specifically, we examine whether the behavior of a juvenile offender after being released from a correctional facility is influenced by the characteristics of individuals with whom he concurrently served time in that facility. The analysis is based on data on over 8,000 individuals serving time in 169 juvenile correctional facilities during a two-year period in Florida. These data provide a complete record of past crimes, facility assignments, and arrests and adjudications in the year following release for each individual.

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provides an excellent overview of these difficulties. See Brock and Durlauf (2001) for a discussion of these issues in a nonlinear context.

[6] A great deal of recent work in the economics of education literature, in particular, has explicitly attempted to deal with the non-random selection of individuals into schools and classrooms. See, for example, Evans, Oates, and Schwab (1992); Hanushek *et al.* (2000); Hoxby (2000); Sacerdote (2001); Zimmerman (2003); Boozer and Cacciola (2001); and Angrist and Lang (2002).

[7] Reiss (1988) and Warr (1996) provide a summary of sociological research based on co-offender surveys, which universally do not control for the non-random selection of peers as well as other endogeneity issues. Thornberry *et al.* (1993, 2003) provide evidence that criminal behavior increases once individuals become members of gangs, but no attempt is made to control for the non-random timing of the decision to join a gang. More recently, Ludwig, Duncan, and Hirschfield (2001) use the Moving to Opportunity experiment to study the effects of neighborhoods on criminal behavior. They find that a shift to a wealthier neighborhood decreases violent while increasing property crimes, but it remains unclear whether their results are driven by changes in private incentives or social interactions. Gaviria and Raphael (2001) find strong evidence of peer-group effects in the crime-related behaviors of drug use, alcohol drinking, and cigarette smoking for a sample of high school students. But there is mixed evidence on the extent to which endogenous sorting across schools inflates their peer effects measures.

[8] Imrohoroglu, Merlo, and Rupert (2001) are able to explain much of the aggregate dynamic variation in crime over the past quarter-century without relying explicitly on social interactions.

Our empirical analysis consists of a series of regressions that relate recidivism in each of a number of crime categories to individual demographic and criminal history characteristics, peer demographic and criminal history characteristics, and interactions between these individual and peer characteristics. To control for the non-random assignment of juveniles to facilities, we include facility fixed effects in these regressions. This ensures that the impact of peers on recidivism is identified using only the variation in the length of time that any two individuals who are committed to the same facility happen to overlap.

Relative to other settings where the estimation of social interactions has proven more difficult, this empirical strategy exploits a unique feature of correctional facilities—namely, that the peer group is constantly evolving over time with the admittance and release of individuals as their sentences begin and expire.[9] As long as the date at which a given individual is assigned to a facility within the two-year sample period is random with respect to the peers in the facility at that time, this empirical strategy properly controls for the non-random assignment of individuals to facilities. We provide a number of different tests of this central identifying assumption, demonstrating among other things that the within-facility variation in peer characteristics is orthogonal to all observable individual characteristics.[10]

We find strong evidence of the existence of peer effects in juvenile correctional facilities. In most instances, these peer effects have a reinforcing nature, whereby exposure to peers with a history of committing a particular crime increases the probability that an individual *who has already committed the same type of crime* recidivates with that crime. When using the entire sample, this form of a reinforcing peer effect is positive and significant for the cases of burglary, petty larceny, misdemeanor drug offenses, and felony sex offenses. However, when using the sample of relatively small facilities, where peer interactions are presumably measured more precisely, this reinforcing peer effect is also positive and significant, or near significant for robbery, felony weapon, and felony drug offenses. In contrast, we find no evidence that exposure to peers with particular criminal histories increases an individual's propensity to recidivate in a

[9] Recent research in other settings has generally relied on particular randomizing events, such as the random assignment of roommates (Sacerdote, 2001) or randomization derived from social experiments such as the Moving to Opportunity experiment in Boston (Katz, Kling, and Leibman, 2001) or the STAR experiment in Tennessee schools (Boozer and Cacciola, 2001). Relying on such events or experiments, however, can severely limit the settings where peer effects can be studied and the generalizability of the findings.

[10] In the context of juvenile correctional facilities, the simultaneity problem (first described by Manski (1993)) is that the influence of peer characteristics, such as the intensity of peer criminal history, cannot be distinguished from the influence of future peer behavior. Because it is impossible to distinguish these types of peer effects without strong *a priori* functional form assumptions, we simply assume that peer effects operate through the influence of peer characteristics rather than subsequent peer behavior.

crime category in which the individual has no prior experience; in our main specifications, the corresponding coefficient is never positive and significant and is in fact negative and significant for robbery and petty larceny. In addition, we find evidence of different types of peer effects in non-residential versus residential facilities. Specifically, there is a strong reinforcing peer effect for the crimes of auto theft, robbery, and felony drug offenses in non-residential facilities; the nature of these crimes is consistent with important network effects in non-residential facilities, which tend to be very close to the residential locations of those assigned to these facilities.

The remainder of the paper is organized as follows. Section II describes the data. Section III outlines our basic empirical methodology, identification strategy, and measurement issues. Section IV presents the main results, and Section V examines a series of policy issues related to these results. Section VI concludes.

II. Data and Juvenile Corrections in Florida

The primary data source for this study is the internal database that the Florida Department of Juvenile Justice (DJJ) maintains for juvenile offenders under its care. We were granted access to the DJJ's records on all youths released from a Florida-based juvenile correctional facility between July 1, 1997 and June 30, 1999. These data provide complete histories of the experience of each individual in the Florida juvenile justice system, including records of all past arrests, adjudications,[11] sentences, and facility assignments. The data also provide some basic socio-demographic information, such as date of birth, race, and zip code of residence at the time of the individual's most recent assignment to a facility. 16,164 youths are included in the full sample.

For each individual in the initial sample, the data detail whether or not the individual recidivates within the first year following release. The type of crime committed upon recidivating, however, is only available if the individual is younger than age eighteen at the date of re-arrest and, thus, still a juvenile in the Florida system. In analyzing post-release criminal behavior, we therefore eliminate from the sample all individuals who are older than age seventeen when released; for all individuals remaining in the sample, we observe if the individual recidivates and (if so) the details of the recidivism offense.[12] While the initial sample contains records for 16,164 individuals, only 9,382 of these individuals remained juveniles for at least one

[11] An adjudication, in the vernacular of the juvenile justice system, is analogous to a conviction in the adult system.

[12] It is possible that individuals who are 14 and older and who commit sufficiently serious crimes will be processed in the adult criminal system. Unfortunately, we cannot observe such recidivism offenses; but the inability to do so should not influence the results regarding relatively minor crimes such as misdemeanor drugs, petty larceny, and burglary.

year after release. For an additional 982 of these individuals, the data are missing facility assignment and, finally, for an additional 184 individuals, the data are missing admit/release date information. Thus, the primary sample used in our analysis contains 8,216 juveniles. However, data for the full set of individuals for whom facility assignment and admit/release date information is available are used in constructing the measures of peer characteristics used in the analysis.

The sample includes not only detailed information on recidivism behavior, but also data on the youths' correctional facility assignments, criminal histories, personal characteristics, and home neighborhoods. Descriptive statistics are presented in Table 1. Measures of overall recidivism can be constructed on the basis of either a subsequent adjudication (conviction) or a subsequent criminal charge. 51 percent of the sample recidivates within a year of release by the former measure, while 67 percent of the sample recidivates within a year by the latter. Because the primary goal of this paper is to study whether exposure to peers with a criminal history in a particular crime category increases an individual's propensity to recidivate in that same crime category, we use a subsequent criminal charge as our definition of recidivism. This characterization permits individuals to recidivate in multiple crime categories (many do) and avoids a series of issues related to adjudication when an individual has been charged in multiple categories.[13] Using this measure of recidivism, Table 1 shows that 14 percent of the sample recidivates with a burglary offense, 12 percent recidivates with a petty larceny offense, and approximately 9 percent recidivates with a felony drug offense, a misdemeanor drug offense, an auto theft, and a grand larceny offense. Because individuals can be adjudicated for multiple offenses simultaneously, the sum of the recidivism rates in all possible crime categories is greater than the overall recidivism rate of 67 percent (i.e. the different possible outcome variables are not mutually exclusive).

Throughout the paper we focus on nine main crime categories: auto theft, burglary, grand larceny, petty larceny, robbery, felony drug crimes, misdemeanor drug crimes, aggravated assault and/or battery and felony weapons crimes, and felony sex crimes. Appendix Table 1 contains descriptions of particular crimes associated with each of these categories. These particular categories are chosen for analysis using three criterion: (i) the offense is serious enough to contribute to the FBI crime index; (ii) the crime is defined well enough to interpret the results; and (iii) enough individuals recidivate with the crime so that the estimation is reasonably precise. Disorderly conduct is not included, for example, because the exact nature of the offense may vary

[13] Analogous specifications to those included in the paper with recidivism defined as a subsequent adjudication yielded qualitatively similar results.

greatly across crimes, and misdemeanor sex offense is not included because only 27 of the 8,216 individuals recidivate with this crime.

The assignment of juveniles to facilities in Florida typically occurs in two steps.[14] First, the judge determines the level of confinement that is appropriate for the individual. There are five risk levels, minimum-, low-, moderate-, high-, and maximum-risk; minimum-risk facilities are non-residential, and all other risk categories are residential. In part, risk-level assignment is based on the characteristics of the juvenile's current offense and past offenses. For instance, individuals whose current offense is a first degree felony, a sex offense, or a firearm-related offense are automatically excluded from the low-risk category. Given this judge-assigned risk level, the Florida Department of Juvenile Justice places the juvenile in a particular program. During our study period, each individual was assigned to one of 169 correctional facilities in Florida. These facilities vary greatly in type: there are halfway houses, group treatment homes, boot camps, contracted day treatment programs, intensive residential treatment programs, sex offender programs, work and wilderness programs, etc. Note that very few of these facilities are what one might consider a jail, where individuals are confined to particular cells.[15] There is some variation in the size of these facilities. The average number of individuals released from a facility is 197 (averaged across the individuals in the sample), with a minimum of 13 and a maximum of 981. The average number of individuals in a facility on a given day is 48, with a large standard deviation of 74; the corresponding median facility size (across individuals), however, is only 20 individuals, as a couple of facilities are particularly large.[16]

The individual characteristics listed in Table 1 provide basic information on the youths' age, gender, race, and sentence length. The criminal history variables in Table 1 encompass all charges formally brought against the youth within the Florida system prior to placement in a correctional facility during the two-year evaluation period. The individual criminal history variables are dummy variables that are equal to one if an individual has *any* history of committing a particular type of offense, regardless of the number of times the individual has committed the offense. Thus, we see that 61 percent of the individuals in the sample have a history of petty larceny, 58 percent have a history of burglary, 37 percent have a history of a felony weapon offense, 13 percent have a history of a felony drug offense, and so on. The neighborhood characteristics variables are constructed using each individual's zip code of residence. With the

[14] See National Center for Juvenile Justice (2003) and Florida Department of Juvenile Justice (2004) for more details.
[15] A detailed description of the different types of facilities can be found in Bayer and Pozen (2004).
[16] We examine specifications below that limit the sample to individuals in facilities with less than 20 peers.

exception of Youth Crime Rate in Zip, which comes directly from DJJ records, these neighborhood measures are derived from the 1990 Census of Population of Housing.

Table 1 also presents descriptive statistics for the measures of peer characteristics. For the most part, the list of peer characteristics parallels the list of individual characteristics (the demographic, criminal history, and neighborhood characteristics). The peer characteristics are calculated as weighted averages of the individual characteristics, where the weights are the number of days an individual is exposed to each peer. Not surprisingly, the average peer group to which an individual is exposed generally reflects the distribution of crimes in the individual criminal histories. Slight differences arise because the individual criminal history measures are averaged over individuals while the peer measures are averaged over days, thus weighting more heavily the crimes of individuals serving longer sentences.

III. Empirical Methodology and Measurement Issues

The primary analysis presented in this paper relates recidivism to vectors of individual characteristics, peer characteristics, and interactions between the two. Recidivism is used as an imperfect proxy for criminal behavior throughout our analysis. Clearly, recidivism is a function of both actual criminal activity and the probability of arrest and adjudication. To the extent that some peer effects take the form of learning to avoid arrest and adjudication, we expect our analysis to *understate* the overall level of increased criminal activity that follows exposure to peers with a greater intensity of experience in a given crime category. On the other hand, it is possible that exposure to peers in prison makes an individual bolder or less cautious in his manner of committing crimes upon release; this type of machismo effect could lead to an increase in arrest rates even if the underlying level of criminal activity has not changed. Despite these issues, recidivism, as previously defined, is the best measure available to us.[17] The general specification that we take to the data can be written as

$$R_{ij} = P_{ij}\alpha + X_{ij}\beta + P_{ij}X_{ij}\gamma + \lambda_j + \varepsilon_{ij} \qquad (1)$$

where R_{ij} is a dummy variable that is equal to one if individual i, having served time in facility j, recidivates; P_{ij} is a vector of peer characteristics; X_{ij} is a vector of individual characteristics; and

[17] An additional issue common to studies using administrative data, and one which we are powerless to do anything about, is the possibility that a juvenile committed multiple crimes at a time (e.g. assault and drug dealing) but is arrested and adjudicated for only one offense (e.g. assault) due to a lack of evidence. The extent to which this is an issue in our study ought to be limited by the fact that we define recidivism in terms of charges rather than adjudication.

λ_j is a facility fixed effect. For each individual, the associated peer characteristics are a weighted average of the characteristics of an individual's peers in a facility, where the weights are equal to the number of days an individual is exposed to each peer in the facility. In this way, because individuals are admitted and released on a regular basis throughout our sample period, the characteristics of the peers to whom any particular individual is exposed vary depending on when exactly that individual enters and leaves a facility.

The inclusion of facility fixed effects in equation (1) controls for the non-random assignment of individuals to facilities as well as any part of the error structure correlated across all of the individuals in a facility. This ensures that the impact of peers on recidivism is identified using only the variation in the length of time that any two individuals held in the same facility happen to overlap.[18] In order for this methodology to yield unbiased peer effects, the timing of the assignment of individuals to facilities, with respect to the particular peers in the facility at that time, must be as good as random within the two-year sample period. We provide a series of exercises designed to demonstrate the validity of this identifying assumption throughout the analysis.

Some Initial Evidence on Our Identifying Assumptions

To provide some initial evidence on the validity of our identifying assumptions, Table 2 reports unbiased estimates of correlations between individual and peer measures that characterize past criminal experience in each of the nine crime categories that serve as the basis for our analysis.[19] To construct an unbiased estimate of the within-facility correlation, we add a fraction of an individual's own characteristics to his own peer measure equal to the average contribution that his characteristics make to the peer measures of others in the same facility.[20] We then

[18] A natural concern that arises when including facility fixed effects is whether there is sufficient variation in the peer measures within facilities to identify peer effects precisely. While the amount of variation in the peer measures does decrease with the inclusion of facility fixed effects, it is not eliminated. This can be seen by comparing the overall standard deviation to the within standard deviation for each peer measure presented in Table 1. The within standard deviation is the standard deviation of the residual peer measures that result from regressing the original peer measures on facility dummies.

[19] A detailed description of the construction of these measures can be found in Appendix 2.

[20] To see why such a correction is needed, consider a setting simpler than the one considered in the paper in which individuals are assigned to M facilities of size N for a fixed and identical length of time. In this case, each individual contributes $1/(N-1)^{th}$ of the characteristics used in constructing the average peer characteristics for each of his peers. This induces a slight mechanical negative correlation between an individual's own characteristics and those of his peers that goes to zero as M grows large. This is essentially the circumstance of the roommate studies, where M is very large and N is quite small. Notice, however, that even in that case a slight negative bias is induced if more than one individual is sampled per room.

estimate the correlation of this measure and individual characteristics.[21] Table 2a displays the raw correlations, that is, between measures that include variation both within and across facilities, while Table 2b shows correlations based only on within-facility variation. In this case, we have first regressed each individual and peer measure on the full set of facility fixed effects, and the correlation of the residuals from these regressions is shown.

The correlation coefficients in Table 2a are in many instances quite large, almost always positive, especially along the diagonal, and statistically significant at the 5 percent level in almost every case. In fact, ignoring the off-diagonal correlations related to felony sex offenses, the correlations shown are positive and significant in every case both on and off the diagonal.[22] In this way, not surprisingly, individuals with more extensive criminal histories are more likely to be assigned to the same facility and facility assignment is especially positively correlated for individuals that have each committed a particular crime.

The corresponding correlation coefficients in the lower panel of the table are typically more than an order of magnitude smaller, negative almost as often as positive, and rarely statistically significant. This implies that the within-facility variation in peer criminal history measures is almost completely orthogonal to an individual's own criminal history. Moreover, given that an individual's own criminal experience is one of the strongest predictors of future criminal behavior and one of the factors most observable to the judges and DJJ officials responsible for the assignment of individuals to facilities, it is very likely that the within-facility variation in peer measures is also orthogonal to other unobserved individual characteristics related to recidivism.

The lack of any systematic correlation in individual and peer criminal history also implies that there is not any undo clustering in the timing of assignment to correctional facilities for individuals with particular criminal histories. Such timing might result not only because of deliberate actions on the part of judges and other DJJ officials, but would also arise naturally if, for example, there were significant trends in the types of crimes being committed in certain parts

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In our setting, individuals are exposed to only a subset of the individuals that come through a given facility. Let this fraction be given by p. In this case, the bias in the sample correlation between individual and peer characteristics is present both when considering the overall sample correlation and the sample correlation within facilities. The bias in the overall sample correlation goes to zero as M gets large, while the bias in the within-facility correlation goes to zero only if p goes to zero. That is, this small sample bias problem would become less significant for estimating the within-sample variation as a greater number of years of data were used in the analysis, but is certainly present in our dataset.

[21] Notice that as the amount of data on a particular facility grows large, this adjustment terms goes to zero, as the average amount that an individual contributes to others in the same facility falls to zero.

[22] The negative correlation between an individual's own history of a felony sex offense and a couple of the other peer measures is due to the fact that Florida maintains a couple of facilities dedicated to rehabilitating sex offenders.

of Florida over this period. Thus, this evidence on the correlation of individual and peer criminal history variables provides a clear support for the key identifying assumption that the within-facility variation in peer characteristics is as good as randomly assigned. We provide a good deal of additional evidence related to this core identifying assumption as we present the results below.

Pre- and Post-Censoring

A final important data-related issue in constructing the peer measures used in equation (1) arises because we only observe individuals who are *released* in the two-year period from July 1, 1997 to June 30, 1999.[23] Thus, for individuals who are released towards the beginning of the sample period, any peers who are released before the sample period begins will not be observed in the data (pre-censoring case). Likewise, for individuals who are released towards the end of the sample period, any peers who are released after the sample ends will be unobserved (post-censoring case). While we are unable to measure each individual's peers exactly, we are able to calculate an unbiased estimate of each individual's peer exposure under the assumption that the within-facility variation in peer characteristics is random with respect to when an individual is assigned to the facility. This, of course, is the central identifying assumption of the paper and we provide a wide variety of evidence related to its validity throughout the paper.

In particular, in order to provide an unbiased estimate of each individual's peers, we estimate each individual's exposure to peers who would have been released either before or after the sample period by using the characteristics of the individuals observed to be released from the facility during the full sample period. In this way, we form the peer measure used in the analysis by averaging (i) the characteristics of those peers actually observed to overlap with the individual and (ii) a properly weighted measure of the estimated characteristics of the peers with whom this individual would have overlapped, but who were released outside of the sample period.[24] This ensures that the peer measure used in the analysis is an unbiased measure of the true peer measure for each individual as long as the sample of individuals released during the study period is not systematically different than those released just before or after it. In this way, while our subsequent peer measure is subject to some measurement error, this error is uncorrelated with the individual characteristics included in the regression. We describe the exact procedure used to

[23] Note that this sample structure does not limit our ability to observe sentences of any length. The individuals that we observe serving longer sentences simply tend to have been admitted earlier, sometimes well before our study period begins.

[24] This procedure relies on the assumption that, conditional on facility assignment, the exact date at which a given individual is assigned to a facility is random with respect to the peers in the facility at that time—an assumption supported by the evidence described throughout the paper.

construct the peer measure, dealing with four separate cases of censoring, in Appendix 1. We also provide evidence below that the remaining measurement error is likely to have a reasonably small effect on the results. In particular, as expected, this form of measurement error appears to have an attenuating effect on the estimated peer effects, but generally does not mask the underlying qualitative pattern of effects.

IV. Results

The earlier discussion of the potential channels through which peers may influence an individual's subsequent criminal behavior informs the empirical specifications that we take to the data.[25] In particular, we consider the following primary specification:

$$R_{ij}^{h} = \beta_0 \left(Offense_{ij}^{h} * Peer\_offense_{ij}^{h} \right) + \beta_1 \left(No\_Offense_{ij}^{h} * Peer\_offense_{ij}^{h} \right) + \beta_2 Offense_{ij}^{h} + P_{ij}\alpha + X_{ij}\gamma + \lambda_j + \varepsilon_{ij} \quad (2)$$

The dependent variable, R^h_{ij}, is a dummy variable for whether or not individual i in facility j recidivates with offense type h. $Peer\_offense^h_{ij}$ represents an individual's exposure to peers with a history of offense type h. $Offense^h_{ij}$ is a dummy variable indicating whether individual i has a history of offense type h himself and $No\_Offense^h_{ij}$ is a dummy variable indicating whether individual i does not have a history of offense type h himself. P_{ij} is a vector of additional peer demographic and criminal history characteristics, including all other crime categories. Similarly, X_{ij} represents a number of individual demographic and criminal history controls, including all other crime categories. Equation (2) is simultaneously estimated for each of nine crime categories using a seemingly unrelated regression (SUR) framework.[26]

While the specification described in equation (2) includes a complete set of controls for individual and peer criminal offenses, the central focus of the analysis below is on the question of whether exposure to peers with a history of committing a particular crime increases the likelihood that an individual recidivates with that same crime. We also aim to distinguish whether or not this effect varies with an individual's own characteristics, particularly an individual's own history of the offense in question. This interaction would, for instance, pick up the reinforcement of

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[25] At earlier stages of the analysis, we explored specifications that did not include the interaction term as well as specifications that considered interactions between peer measures and demographic characteristics such as age, gender, and race.

[26] The standard errors that are reported for this system of regressions that include facility fixed effects are not further adjusted for clustering at the facility level. An analysis of the effects of controlling for clustering in a series of separate regressions had almost no effect on the estimated standard errors for models that included facility fixed effects. In fact, the standard errors on our parameters of interest decreased about as often as they increased.

addictive behavior by others who may share a similar addiction. Moreover, the peer effect mechanisms related to social learning and network formation developed in the introduction suggest that individuals with a prior history in a particular criminal activity may be especially receptive to additional training or to expanding network ties related to this activity. Consider, for example, an individual who already has a high rate of return from stealing cars but has no experience in drug crimes. For this individual, the drug-specific human capital gained from exposure to peers with a history of drug crimes may not provide sufficient incentive to switch from auto theft to drug crimes, as the gap between the rates of return for the two types of crimes may be too large. On the other hand, additional exposure to peers with a history of auto theft may increase this gap in returns (as well as the gap between returns from auto theft and legitimate activity), thereby potentially increasing an individual's propensity to commit auto theft upon release.

While the inclusion of facility fixed effects provides an intuitive way of forcing the peer effects to be identified based on within-facility variation in peer exposure, the inclusion of interactions between individual and peer characteristics require a slightly modified approach. In particular, in estimating the model, we subtract the facility-level mean from the peer measure, thereby ensuring that variation in the peer measure is based only on within-facility variation, regardless of whether the peer measure is included directly or interacted with individual characteristics.[27] It is important to emphasize that we include this form of the interaction term in every specification that includes fixed effects reported in the paper.

Each column of Tables 3a-3d reports the coefficients β_0, β_1, and β_2 for a specification of the type shown in equation (2) for a particular offense type *h*.[28,29] Table 3a reports these coefficients for a specification that includes only these three variables and does not include facility fixed effects; Table 3b adds facility fixed effects and subtracts the facility-level mean

[27] Without this adjustment to the peer measure, the inclusion of facility fixed effects alone would not insulate the estimate of the interaction terms against a subtle form of selection bias. Using the burglary regression as an example, if those individuals with a past history of burglary who were particularly likely to recidivate were also clustered in the same facility (and thus likely to have a high value for peer_burglary), the model would return a positive coefficient on the interaction of individual and peer burglary even if facility fixed effects were included in the regression. Subtracting the facility mean from the peer measure, on the other hand, ensures that the estimated peer effects are based only on within-facility variation.

[28] While we look for evidence of peer effects in particular crime categories (such as grand larceny), it is certainly possible that individuals specialize in groups of particular crime categories (such as all thefts) rather than in just one particular crime category. Appendix Table 2 reports the results of the full impact of an individual's criminal history on the propensity to commit each crime, generally revealing broad specialization across drug crimes as well all forms of theft. This specification corresponds to the one reported in Table 5.

[29] Again, the particular crimes associated with each of these categories are shown in Appendix Table 1.

from the peer measure in the interaction term to ensure that its variation is based only on within-facility variation; Table 3c includes additional controls for peer characteristics; and Table 3d includes additional controls for individual characteristics. Table 3d serves as our baseline specification. The full list of additional individual and peer measures is shown in Appendix Table 2 and includes measures characterizing criminal history in particular crime categories, total number of past felonies, age at first offense, current age, sex, and characteristics of the residential zip code for both the individual and her peers.

We report the key coefficients for these four specifications to highlight a number of aspects of the results. First, a comparison of Table 3a to Table 3b reveals how the results of an analysis that used both across- and within-facility variation in the key peer measure would differ from an analysis using only within-facility variation. A comparison of Table 3b to Table 3c shows that the addition of other peer measures to the specification does very little to the coefficients of primary interest. Finally, a comparison of Table 3c to Table 3d reveals the effect of including individual controls. If such controls are truly uncorrelated with peer measures, the central identifying assumption on which our research design is predicated, the inclusion of individual characteristics should have no effect on the estimated peer effects. In fact the addition of individual controls moves the estimated coefficients on the reported peer measures only slightly, if at all, thus providing additional support for our central identifying assumption.

Specialization

We begin our discussion of the results shown in Table 3 by focusing first on the estimated coefficients on $Offense^h_{ij}$, a variable that indicates whether an individual's own history includes the crime shown in the corresponding column. These measures illustrate the degree to which individuals specialize in crime category *h*. Since the parameter β_2 is reported *at the mean level* of peer characteristics, a test for specialization is simply a test of whether $\beta_2 > 0$. The estimates of β_2 are comparable across the four specifications, declining slightly in magnitude with the inclusion of other individual controls in Table 3d, not surprisingly.

Focusing on the final specification reported in Table 3d, there is evidence of specialization in every crime category, i.e., the coefficients are positive and statistically significant in every instance. The magnitudes of the effects are best understood in relation to the proportion of individuals who recidivate with each crime. For example, having committed a felony drug crime in the past increases one's likelihood of recidivating with a felony drug crime by approximately 21 percentage points; this is relative to the baseline that 9.3 percent of the individuals released from a juvenile facility recidivate with a drug felony within a year.

Similarly, large effect sizes relative to the proportion of individuals who recidivate with a crime can be seen for felony sex crimes (5.4 percentage points versus 1.3 percent of individuals), misdemeanor drug crimes (12 percentage points versus 9 percent), robbery (4.7 percentage points versus 4.5 percent), auto theft (8.1 percentage points versus 9.3 percent), and aggravated assault and felony weapon crimes (7.9 percentage points versus 13.6 percent). While these effects are not the main focus of our analysis, they are certainly broadly consistent with the extensive previous literature related to specialization.

Evidence of Peer Effects

The first row of Tables 3a-d reports β_0, the coefficient on the interaction between an individual's history of having committed the relevant offense and the fraction of peers who have ever committed this offense. The second row reports β_1, the coefficient on the interaction between an individual's history of having *not* committed the relevant offense and the fraction of peers who have ever committed this offense.[30] Thus, this parameter reveals how the intensity of exposure to peers with experience in a particular crime category affects the behavior of individuals who *do not have* any prior experience in that crime category. Table 3a, which does not include facility fixed effects, reveals positive and significant peer effects for those without prior experience in a category for six of the nine crime categories. In addition, a joint test rejects the hypothesis of β_1 being equal to zero in each of the nine crime categories with a p-value equal to zero to four digits. As soon as facility fixed effects are included, however, all such evidence vanishes. In the final specification, presented in Table 3d, β_1 is negative as often as it is positive, with no statistically significant evidence of increases in any crime category and statistically significant evidence of a decrease in activity for the case of robbery. One possible explanation for the evidence of negative peer effects in this latter case is that individuals learn that the risk-return tradeoff for robbery is less favorable to the criminal than the tradeoff for other types of property crimes (auto theft, larceny, and burglary).[31] In addition, the hypothesis of β_1 being equal

[30] It is interesting to note that specifications run at an earlier stage of our analysis show that it is whether or not peers have a history of *ever* committing a particular offense, rather than the number of times they have committed the offense, that matters in the context of peer effects. In other words, the peer effects associated with the peers' first offense in a crime category appear to be much more important than the peer effects associated with the third or fourth offense in that category.

[31] Levitt and Lochner (2001) estimate that the average return to both a property crime and a robbery is about $200, but because victims are more likely to report robberies to the police, they assert, there is a higher arrest rate for robbery and more severe punishments conditional on arrest. They estimate that the average sentence length *per crime committed* served by juveniles for robbery is more than twenty times that served for other types of property crimes. An analysis of our data yields similar statistics for sentence

to zero in each category can no longer be rejected, as the corresponding p-value of the joint test is 0.2380.

That these broad crime-specific peer effects measured by β_1 in Table 3a are eliminated when the variation in the peer measures used in the analysis is restricted to within-facility variation implies that the effects based on across-facility variation are mostly driven by the non-random assignment of individuals to facilities rather than true peer effects. The appearance of positive peer effects could easily result, for example, from a process that assigns individuals to facilities based in part on aspects of their propensity to recidivate that are unobserved.

In contrast, in the final specification reported in Table 3d, the parameter estimates for β_0 reported in the first row are positive in almost every case and statistically significant for burglary, petty larceny, misdemeanor drug crimes, and felony sex offenses. This reveals a statistically significant, positive peer effect for individuals who *have* prior experience in a crime category. Thus, exposure to a greater percentage of peers with a history of having committed burglary, for example, increases the likelihood that an individual with prior burglary experience commits burglary upon release.

In order to get a sense of the magnitudes of these reinforcing peer effects, it is helpful to consider the magnitude of these effects relative to the baseline propensity of an individual who has a history of having committed the corresponding crime. The coefficient of 0.16 on the interaction of own and peer offense for burglary, for example, implies that an increase in the fraction of peers with a past burglary offense from the mean of 0.57 to 0.67 would increase the propensity of an individual with a past history of burglary to commit burglary from 0.063 to 0.079. Likewise, the coefficient of 0.21 on the interaction of own and peer offense for misdemeanor drug crimes, for example, implies that an increase in the fraction of peers with a past misdemeanor drug offense from 0.15 to 0.25 would increase the propensity of an individual with a past history of a misdemeanor drug offense to recidivate in this category from 0.120 to 0.141. Finally, a ten percent increase at the mean in the fraction of peers with a felony sex offense would increase the propensity of an individual with a past history of a felony sex offense to recidivate in that category from 0.054 to 0.086. In this way, the estimated magnitudes of these peer effects are certainly sizeable, but also appear to be reasonable given the intensity of peer exposure in these relatively small juvenile correctional facilities.[32]

length (conditional on arrest and a punishment that involves assignment to a correctional facility). A regression of sentence length on recent and past criminal activity is reported in Appendix Table 3.

[32] In a random assignment setting, Kremer and Levy (2003) study these types of interactions when studying the effect of college roommate drinking on GPA; they also find evidence of a large reinforcing peer effect.

Taken as a whole, the evidence presented in Table 3d helps to distinguish between the potential mechanisms through which individuals might be influenced by their peers. The general pattern of this evidence is that exposure to peers with a history of having committed a particular offense has a strong influence on those individuals who already have some experience with that offense but little, if any, impact on individuals with no prior experience in this category. One explanation that fits well with this pattern is that peers may reverse the traditional negative stigma and they may reinforce addictive behavior. Another explanation is that individuals may experience different returns from participation in different types of crimes (or the legitimate sector of the economy) related to natural abilities, opportunities, human capital accumulation, involvement in crime networks, or other factors. In this case, individuals who have a history of committing a particular offense have already revealed themselves to have high returns and, likely, substantial human capital related to this type of crime. Consequently, access to peers who can increase the individual's returns to this type of crime may lead to increased intensity of activity in this type of crime. Access to peers who can increase returns for *another* type of crime may be much less valuable, as this may not decrease the gap in returns between crime categories enough to change an individual's choice of type of crime.[33]

A Further Test of Our Central Identifying Assumption

While it is obviously impossible to test whether unobserved attributes of an individual related to recidivism in a particular crime category are uncorrelated with the within-facility variation in peer measures, it is straightforward to examine whether these peer measures are uncorrelated with observable individual attributes. While Table 2b shows the within-facility correlation between individual and peer criminal histories, the structure of the specifications reported in Table 3 suggests a natural way to combine the information about an individual into a single measure related to recidivism in a particular crime category, thereby providing a much more general test. To construct such a measure, we first regress recidivism in each of the nine crime categories on the full set of individual characteristics determined at the time of assignment

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Specifically, they find that, on average, males assigned to roommates who reported drinking prior to entering college had a one-quarter point lower GPA than those assigned non-drinking roommates. This effect is *four* times as large, a full point GPA, for males who themselves had a history of frequent drinking prior to college. Sacerdote (2001) also examines whether the interaction between own and roommate background has any influence on an individual's own freshman year GPA in college; he finds some evidence that such interactions are important.

[33] Put another way, it is important to distinguish between learning from one's peers and how that learning that gets translated into subsequent criminal behavior. The suggestion here is that an individual may have more to learn in a new crime category; thus, learning in a category in which the individual already has experience may be more likely to be translated into action.

and the full set of facility fixed effects.[34] From these regressions, we calculate a predicted recidivism measure in each crime category for each individual using only the observable individual characteristics. Consequently, this measure of predicted recidivism captures that part of recidivism that can be explained by observable attributes related to an individual's prior criminal history, age, sex, race, age at first offense, and residential neighborhood.

Table 4a reports the results of regressing this measure of predicted recidivism on the two peer measures of primary interest for each crime category; i.e. the two interaction terms. Table 4b repeats these regressions adding facility fixed effects.[35] In Table 4a, the estimated coefficients are positive and significant for each crime category both for the effect of peer criminal history on those *without* a history of the offense and for the effect on those *with* a history of the offense.[36] Thus, clearly, when both across- and within- facility variation in peer characteristics is used in the analysis, there is a strong positive correlation between individual characteristics related to recidivism in a particular crime category and the exposure to peers with a history of crime in that same category.

In Table 4b, on the other hand, where only within-facility variation in peers is used in both measures, we see almost no evidence of correlation between peer characteristics and predicted recidivism. In fact, for individuals without a prior history of having committed the corresponding offense, the coefficients are significant in only two cases, and in all cases the magnitudes are quite small. Thus, to the extent that there is any bias at all, there may be a slight upward bias in β_1 for robbery and felony sex offenses, a bias that would tend to attenuate the negative coefficient on robbery in the main specification shown in Table 3d. None of the coefficients reported in the first row of Table 4b, i.e. those associated with individuals who have a history of committing the offense, are significant. While the coefficient associated with robbery is almost significant, it is actually negative; this implies that, if anything, the estimate of β_0 associated with robbery in our main specification is biased downwards. In general, then, this very strenuous test of our central identifying assumption strongly supports the conclusions that: (i) there is almost no correlation of the within-facility variation in peer measures with the key individual attributes related to recidivism in each crime category and (ii) any analysis of peer

[34] We leave out the total number of days an individual spends in the facility to avoid concerns about the endogeneity of this characteristic.
[35] As described previously, the facility-level mean is subtracted from the peer measure to ensure that the interaction term only captures within-facility variation in the peer measure.
[36] In Tables 4a and 4b, which do not include controls for an individual's own criminal history in the given crime category, we follow the procedure described in the construction of Table 2 in order to obtain unbiased estimates of the correlation of peer characteristics and our measure of predicted recidivism. This procedure involves averaging a small fraction of an individual's own characteristics into his peer measure in order to avoid a mechanical negative correlation between individual and peer characteristics.

effects that incorporates across-facility variation is likely to lead to sizeable biases in the estimated effects, which is exactly what we found in comparing Table 3a to Table 3b.

Peer Effects in Small Facilities

To this point in the paper, we have defined an individual's peer measures to be a weighted average of the characteristics of all other individuals serving time in the correctional facility concurrently with this individual at some point during his sentence. This definition potentially provides a noisy measure of an individual's peer exposure; this would occur if an individual does not actually interact with all of the individuals within a facility or interacts more intensely with certain individuals.[37] Given our specification, which allows the effect of peers to vary with an individual's own characteristics, it is generally not possible to sign the bias that would result if true peer groups consisted of a smaller subset of the individuals within a facility.[38] Therefore, in order to explore whether the estimated peer effects for our main specification are sensitive to any bias resulting from assigning peer measures at the facility level, we present an additional specification analogous to that shown in Table 3d that restricts the sample to only facilities with an average of 20 or fewer individuals concurrently serving sentences.[39]

Table 5 presents the results from estimating equation (2) for the resulting sample of 4,266 individuals in the 115 smallest facilities.[40] Clearly, one would expect there to be greater interaction between all youths in a facility with 10 individuals than in one with 100; thus, restricting the sample to smaller facilities ought to reduce any noise in the peer measure due to variation in intensity of exposure of individuals to one another within a given facility. The results of this specification strengthen the general pattern of the results— namely that the effect of peers on recidivism is significantly greater for individuals with a prior history of having committed the same offense. The interactions between an individual's own experience with an offense and the

[37] Identification of the appropriate peer group is a common problem in the peer effects literature. Arcidiacono and Nicholson (2002) find no evidence that peer groups are formed along racial lines in medical school, though they find some evidence that peer groups are formed along gender lines. Similarly, Sacerdote (2001) examines whether peer effects among college students occur at the room or dorm level.

[38] Manski (1993) points out that it is impossible to identify the true reference group without some a priori knowledge of the way that individuals interact within a larger group, see Section 2.5 in particular. In general, depending on how peer characteristics are defined in the analysis and how individuals actually interact, the mis-specification of the proper reference group can bias the results in any direction.

[39] The full specifications for the results summarized in Table 5 are reported in Appendix Table 2.

[40] One issue in looking at facility size is that we only know the number of individuals released from a facility as opposed to the number of individuals incarcerated in a facility. Using the number of individuals released as a measure of facility size may be an inaccurate reflection of actual facility size since one may expect to see more releases from facilities with shorter sentences. Thus, we create an index of facility size that equals the number of individuals released from a facility multiplied by the average sentence length in each facility. These 4,266 individuals are from facilities with a facility size index less than 15,000.

intensity of exposure to peers with experience in that crime category (i.e. β_0) are now positive in every crime category. This positive reinforcement is now statistically significant or almost significant for robbery, aggravated assault and felony weapon offenses, and felony drug offenses as well as for burglary, petty larceny, misdemeanor drug offenses, and felony sex offenses. As in the case of the entire sample of facilities presented in Table 3d, there is minimal evidence that the intensity of exposure to peers with experience in a particular crime category affects the behavior of individuals who *do not have* any prior experience in that crime category. Using the sample of relatively small facilities, β_1 is still negative more often than it is positive; now there is only weak statistical evidence of a decrease in activity for the case of petty larceny.

In comparison to the results obtained when using the entire sample of facilities, the magnitudes of the reinforcing coefficients are generally either similar in size or greater for this specification based on small facilities. In fact, the coefficient for felony drug offenses increases from 0.13 when using the entire sample to 0.42 when using the sample of small facilities. This makes it such that, as in the case of specialization, the largest reinforcing peer effect occurs for the case of felony drug offenses.[41] The magnitude of this effect implies that for an individual who has a felony drug offense history, increasing the fraction of an individual's peers with a felony drug history from the mean of 0.16 to 0.26, would increase his propensity to recidivate with a felony drug offense from 0.190 to 0.232.[42]

Trends in Crime and the Clustering of Assignment

A potential alternative explanation for the evidence of peer effects described in Table 3d and Table 5 relates to trends in criminal activity. If, for example, there is a general upwards trend in felony drug crimes over the course of our sample, then individuals will likely be exposed to a higher proportion of peers with a history of felony drug crimes and will also be more likely to recidivate with a felony drug crime themselves. While the correlation matrix shown in Table 2 and the implicit test of our identifying assumptions shown in Table 4b provide evidence that this is not likely to be the case, we can also address this possibility directly by estimating a specification that controls for time trends for various regions of the state. In particular, Table 6 presents the results for a specification that includes quarterly time dummies for each of the twenty judicial circuits in Florida; that is, a vector of 160 interactions between eight quarter of release

[41] Additional specifications, not included in the paper, show that the strong evidence of peer effects seen for felony drug crimes is primarily being driven by felony non-marijuana drug crimes.

[42] One may expect the reinforcing peer effects estimated for drug offenses to be especially large since the potential mechanisms described in the introduction are particularly applicable to drug offenses; i.e. addiction is likely to play a large role in drug offenses and crime-specific human capital accumulation and network formation are likely to be particularly important for the distribution of drugs.

dummies and twenty dummies indicating judicial circuit is included in the estimation. Table 6a includes all individuals in the sample while Table 6b again restricts the sample to individuals in small facilities. Comparing the results to those presented in Tables 3d and 5, respectively, we find that there is almost no change in the patterns and the significance of the coefficients in each case. Examining the effects in small facilities, for example, there is still a positive reinforcing peer effect in all crime categories, and it is significant for burglary, felony drug offenses, aggravated assault and felony weapon offenses, and felony sex offenses. Similarly, there is still little evidence that the intensity of exposure to peers with experience in a particular crime category affects the behavior of individuals who *do not have* any prior experience in that crime category. In this way, the estimated peer effects in our main specifications are completely robust to general or localized trends in activity in any of the crime categories considered in our analysis.

A related potential alternative explanation for the evidence of peer effects described in Table 3d and Table 5 concerns the facility assignment of individuals who have committed crimes together. If, for example, individuals who belong to the same gang have similar criminal histories and are sentenced to the same facility at similar times, we might estimate positive interactions between peer and individual criminal history variables in our recidivism regressions even in the absence of peer effects. We address this potential issue by examining clustering in the assignment of individuals to facilities on the basis of residential zip code. As a starting point, it is important to note that individuals are not generally exposed to very many individuals from the same zip code. In particular, of the average of 189 individuals released from a facility, an individual is exposed to an average of only 6 from the same zip code. Thus, individuals from the same zip code generally contribute only about two to three percent of the characteristics used in calculating an individual's peer measures.

Table 7 tests whether there is any undue clustering of release or admit dates for individuals from the same zip code. The upper panel of the table reports the fraction of individuals released or admitted within a certain time period who share the same zip code. Of the individuals released within seven days of one another, 2.8 percent share the same zip code, while of all of the individuals released from the same facility, 2.7 percent share the same zip code. Restricting attention to the set of individuals admitted during the first half of our study period,[43] 2.9 percent of those admitted within seven days of one another share the same zip code, while 2.8 percent of those admitted during the first year of our sample period share the same zip code. In

[43] We restrict the sample to this period because we observe most of the individuals admitted during this period, missing only those serving particularly long sentences. In general, because our sample is based on all individuals released during a two-year period, we are not able to characterize all of the individuals admitted during any particular period.

testing whether the fraction of individuals who share the same zip code is higher for those released or admitted closer to one another in time, we examine the difference between the proportion released (admitted) from the same zip code in a specified time period and the proportion released (admitted) from the same zip code in the overall sample. None of the twelve differences, for the entire sample and the sample of small facilities, reported in the lower panel of Table 7 are statistically significant at the 5 percent level. More importantly, even if these differences were statistically significant, the magnitudes of these differences, which are on the order of 0.1-0.4 percent, would contribute so little to the variation in the peer measures used in our analysis that such neighborhood clustering cannot possibility explain even a small fraction of the results presented in Table 3d and Table 5.

Censoring and Measurement Error

To test the robustness of our measures of peer exposure to the measurement error associated with the censoring of the sample (the fact that we do not observe peers released before the beginning or after the end of our sample period), we estimate equation (2) using only those individuals who are released during the middle year of our sample, December 30, 1997 through December 30, 1998. Because the average sentence length for the sample is less than six months, only a small portion of the peer exposure measure must be estimated for these individuals. The estimated coefficients of interest for this regression are presented in Table 8. The pattern of results is remarkably similar to the main specification presented in Table 3d, continuing to reveal: (i) a positive and significant peer effect for those with a history of the offense for the cases of burglary, misdemeanor drug, and felony sex offenses; (ii) a similarly-sized coefficient on the interaction term associated with petty larceny for those with a history of petty larceny; (iii) minimal evidence of any peer effects for individuals without a history of having committed a particular crime; and (iv) a negative peer effect for robbery for individuals without a history of having committed robbery. While the pattern of results is remarkably consistent, as expected, the magnitudes of the effect sizes in Table 8 are generally greater than those reported in Table 3d. In this way, the form of measurement error induced by the fact that we predict a portion of the peer measure appears to have an attenuating effect on the estimated peer effects, but generally is not sufficient to conceal the general pattern of results.

Residential Versus Non-Residential Facilities

While we do not have enough data to examine peer effects separately for each type of programming used in the state, we are, in fact, able to estimate the model separately depending on whether a facility is residential or non-residential. Individuals in the lowest risk category are assigned to non-residential facilities typically close to their homes (94 percent are in the same county as an individual's residence), while all others are assigned to residential facilities typically much further from home (only 27 percent are in the county of residence). Peer effects might differ in such facilities for a number of different reasons. First, individuals committed to residential facilities may have more time to interact with the other individuals in the same facility. Secondly, the nature of peer effects may vary with the amount of criminal experience of an individual and his peers, which will tend to be smaller in non-residential facilities. Finally, individuals in non-residential facilities tend to be particularly close to home and may form relationships that extend beyond the facilities and onto the street corner even while serving time. Thus, interactions between individuals from non-residential facilities may be particularly likely to lead to more 'hands-on' human capital accumulation or to facilitate involvement in local criminal networks.

Tables 9a and 9b present the results of estimating equation (2) when the sample is restricted to the 6,992 individuals in residential facilities and the 1,224 individuals in non-residential facilities, respectively. Not surprisingly given that they contain over 85 percent of the full sample, the pattern of results for residential facilities generally mirrors the results for the sample as a whole presented in Table 3d. The results presented in Table 9b show that peer effects in non-residential facilities differ dramatically from those in residential facilities. In non-residential facilities, there is evidence of peer effects for those without a history of the offense in the cases of burglary and misdemeanor drug offenses, though the effect for misdemeanor drugs is not quite significant. Moreover, there are significantly positive reinforcing peer effects for auto theft, robbery and felony drug offenses. Thus, in non-residential facilities there is evidence of strong peer effects in the case of auto theft, which has been absent from previous specifications, and evidence of an extremely strong peer effect in the case of felony drug offenses. A potential explanation for these effects is that the crimes of auto theft and felony drugs are largely dependent on network creation and expansion, processes that may be largely facilitated by being sentenced to a non-residential facility, where individuals tend to come from a reasonably small geographic area, thereby enabling them to continue their interactions in the evenings outside of the facility and upon completion of their sentences.[44] While these results are based on a much smaller sample of individuals than the full specification, they point to a particularly problematic

[44] Ayres and Levitt (1998) describe the types of networks that exist in auto theft rings. Stolen cars must be transferred from the individual who steals the car to a chop-shop or another appropriate sales outlet. As in other forms of organized crime, such a transaction may require a level of confidence that the individual will not reveal the network if arrested.

practical concern with the operation of non-residential facilities, which out of necessity must be close to the homes of the individuals assigned to them. Namely, the assignment of individuals to facilities close to home and, therefore, with many other individuals who live within reasonable proximity of one another, may in fact increase subsequent criminal activity through the operation of particularly strong, network-related peer effects.

V. Policy Considerations

Given the strong and robust evidence of reinforcing peer effects in correctional facilities, two policy-related issues merit further examination: the optimal assignment of individuals to facilities and how peer quality is distributed across individuals and facilities. With regards to optimal assignment, our results point to a broad conclusion. The evidence presented in this paper overwhelmingly supports the notion that exposure to peers with experience in a particular crime category has its greatest effect on individuals who themselves already have some experience in that category. Given these results, a policy of optimal assignment should generally involve avoiding the grouping of individuals with others who have a history of committing the same crimes.

To examine whether Florida's assignment of individuals to facilities is generally in line with this recommendation, we return to Table 1, which in addition to reporting means and overall standard deviations for each variable also reports the standard deviation within facilities (eliminating that part of the variation resulting from variation across facilities). As the figures in the table clearly demonstrate, there is almost as much variation in individual experience within facilities as there is in the data as a whole. Thus, during our study period, Florida did not generally isolate individuals who had committed a particular offense, such as a drug offense, in specific facilities.[45] Consequently, Florida's facility assignment mechanism was broadly consistent with a policy aimed at reducing the impact of peer effects in correctional facilities.[46]

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[45] It is interesting to note that subsequent to our study period, Florida did begin using treatment facilities specially designed to handle individuals with drug addiction problems. While our analysis would imply that reinforcing peer effects would generally be greater in such a facility, it is important to stress that the overall impact of a policy of rigorous treatment of drug addictions, which requires individuals with past histories with drug crimes to be housed together, may certainly have the desired effect on recidivism if the program itself is effective. Our analysis points to the reinforcing nature of peer effects related to drug crimes in an institutional setting that was not generally designed to treat drug addiction problems directly.

[46] It is noteworthy that for the one type of crime that Florida did isolate offenders during our study period, sex offenses, the facilities designed to handle sex offenders were remarkably effective at reducing subsequent recidivism with a sex offense. This inference can be made by comparing the results on the interaction term for felony sex offenses in Table 3a and Table 3b. This parameter in Table 3a, which uses both within- and across- variation, and is consequently identified for the most part by the differences in the recidivism of sex offenders in specially designed facilities versus facilities more generally, reveals a strong

The second policy-related issue we consider is how peer quality is distributed across individuals and facilities. Specifically, we explore two types of questions: Are individuals with certain demographic or criminal history characteristics more likely to be exposed to a better or worse peer group? And to what extent is peer quality correlated with facility characteristics such as security level or management type (e.g., private for-profit, private nonprofit, or publicly operated)?

While one could directly examine the distribution of peers across facilities on the basis of any given observable characteristic, we seek to summarize how all the characteristics of one's peers contribute to the propensity to commit particular crimes. To this end, we construct a measure for each facility that summarizes the average impact of the peers in that facility on recidivism of each type of crime. In other words, we use the estimated coefficients from the regression described by equation (2) for small facilities, and presented in Appendix Table 2,[47] to calculate

$$\hat{R}_j^h = \hat{\beta}_0 \left(\overline{Offense}_j^h * \overline{Peer\_offense}_j^h \right) + \hat{\beta}_1 \left(\overline{No\_Offense}_j^h * \overline{Peer\_offense}_j^h \right) + \overline{P}_j \hat{\alpha} \qquad (3)$$

$\hat{R}_j^h$ is the average effect of peer characteristics on recidivism with crime category *h* in facility *j*. To provide a single summary measure of the impact of peers on crime in general, we also create a total crime index, which is a weighted average of $\hat{R}_j^h$ across the nine crime categories. For weights, we use the average sentence length associated with committing each crime, which captures to some degree the seriousness of the crime. Felony sex offenses, robbery, and felony weapon offenses receive the three largest weights, respectively.[48]

negative effect for the interaction term. This effect then turns positive when only within-facility variation is used in Table 3b, thereby implying that these specially designed facilities for sex offenders are particularly effective in reducing recidivism.

[47] We choose to use the estimated peer effects for small facilities, as peer exposure is likely to be more precisely measured in these facilities.

[48] Appendix Table 3 displays the regression used to determine the average sentence length associated with each of the nine crime categories. Sentence length is regressed on individual characteristic variables, dummy variables for the most recent crime committed, and dummy variables for whether a particular crime was committed in the past. All variables are constructed to have mean zero. The weight on felony drug crimes, for example, is then equal to the constant plus the coefficient on having committed a felony drug crime as the most recent offense. The weights are normalized such that their sum is equal to one.

We then regress the estimated peer effect for crime category h, $\hat{R}_j^h$, on a vector of individual characteristics, as in equation (4), and on a vector of facility characteristics, as in equation (5).

$$\hat{R}_j^h = X_{ij}\beta + J_{ij}\gamma + \varepsilon_{ij} \tag{4}$$

$$\hat{R}_j^h = F_j\delta + J_{ij}\gamma + \varepsilon_{ij} \tag{5}$$

The vector of individual characteristics, X_{ij}, includes demographic and criminal history variables; these variables are identical to those included in equation (2). F_j contains two sets of dummy variables—the first indicates the risk level associated with the facility, and the second indicates whether the facility is publicly managed by the state, publicly managed by a county,[49] or privately managed by either a nonprofit or for-profit corporation. J_{ij} is a vector of judicial circuit dummies. A significant and positive coefficient on an individual characteristic implies that this characteristic predicts the assignment to facilities with peers who, on average, increase the propensity to recidivate with a particular crime. Similarly, a significant and positive coefficient on a facility characteristic implies that this type of facility generally contains worse peers. The results from the estimation of equations (4) and (5), for each of the nine crime categories and the total crime index, are presented in Table 10a and Table 10b, respectively.

A number of interesting and significant patterns stand out. First, females are less likely to be exposed to worse peers than males in five of the nine crime categories including the more serious crimes of felony drug offenses, aggravated assault and felony weapon offenses, and robbery. They are more likely to be exposed to worse peers for the cases of auto theft, burglary and grand larceny. It is important to note, however, that these results are based on the assumption that peer effects are the same for males and females. Due to the small number of females in the sample, it is impossible to estimate peer effects separately for females. Moreover, the parameter estimates for all of the main specifications presented in the paper are certainly driven by male individuals. Consequently, we do not wish to make too much of the result for females here.

Somewhat surprisingly, race has almost no effect on the quality of peers conditional on age and criminal experience; if anything black individuals are exposed to marginally better peers. Table 10a also shows that age at exit is significantly and positively correlated with assignment to facilities with worse peers for six of the nine crime categories and the total crime index. An

[49] All county-operated facilities in Florida are boot camps. They are managed directly by their counties' sheriff's departments, with oversight from the DJJ.

Individual who is older at the time of first offense, on the other hand, is assigned to facilities with better peers for five of the nine crime categories and the total crime index

Table 10b reveals that the risk level of the facility that one is assigned to also plays a significant role in determining the quality of an individual's peers. Relative to assignment to minimum and low risk facilities, assignment to moderate risk, high risk, and maximum risk facilities significantly increases exposure to worse peers for almost all types of crimes and the total crime index. This finding fits with that of Chen and Shapiro (2003), which provides evidence based on a regression discontinuity design that assignment of adults to higher risk facilities leads to an increased propensity to recidivate. While not directly comparable, the results presented here imply that Chen and Shapiro's results may be driven in part by increased exposure to worse peers in higher risk facilities. We also find that facility management type does not play a significant role in the assignment of individuals to good or bad peers. Taken together, the results presented in Table 10 imply that peers play an important in reinforcing an individual's involvement in crime as he builds a more extensive criminal career, as an individual's peers grow worse with assignment to higher risk-level facilities and with age and more extensive criminal experience.

VI. Summary and Conclusion

This paper analyzes the influence that juvenile offenders serving time in the same correctional facility have on each other's subsequent criminal behavior. The analysis is based on data on over 8,000 individuals serving time in 169 juvenile correctional facilities during a two-year period in Florida; this data provides a complete record of past crimes, facility assignments, and arrests and adjudications in the year following release for each individual. To control for the non-random assignment to facilities, we include facility fixed effects, thereby estimating peer effects using only within-facility variation over time. We provide a series of exercises throughout the paper designed to demonstrate that the within-facility variation in peer characteristics is as good as randomly assigned, demonstrating that it is orthogonal to all relevant observable individual characteristics. Moreover, we show that our results are robust to concerns about broad or localized variation over time in criminal activity throughout the state and to the possibility that individuals who have committed crimes together are simultaneously assigned to the same facility.

The results provide strong evidence of the existence of peer effects in juvenile correctional facilities. In most instances, these peer effects have a reinforcing nature, whereby exposure to peers with a history of committing a particular crime increases the probability that an individual *who has already committed the same type of crime* recidivates with that crime. When using the entire sample, this form of a reinforcing peer effect is positive and significant for the cases of burglary, petty larceny, misdemeanor drug offenses, and felony sex offenses. When using a sample of relatively small facilities, where we anticipate that peer characteristics are more precisely measured, this reinforcing peer effect is also positive and significant, or almost significant, for robbery, aggravated assault and felony weapon offenses, and felony drug offenses. In contrast, we find no evidence that exposure to peers with particular criminal histories increases an individual's propensity to recidivate in a crime category in which the individual has no prior experience; in our main specifications, the corresponding coefficient is never positive and significant and is actually negative and significant for robbery and petty larceny. In addition, we find evidence of different types of social interactions occurring in non-residential versus residential facilities. Specifically, there is a strong reinforcing peer effect for the more serious crimes of auto theft, robbery, and felony drug offenses in non-residential facilities while there is such an effect for the more minor crimes of burglary and misdemeanor drugs in residential facilities. In addition, we find strong evidence of specialization—for every crime category, having a history of committing a particular crime increases the likelihood that an individual will recidivate with that crime.

While we do not attempt to distinguish explicitly between the many potential mechanisms through which individuals might influence their peers, a few mechanisms do seem particularly capable of explaining the general pattern of our results (primarily the result that exposure to peers with a history of having committed a particular offense has a much stronger influence on those individuals who already have some experience with that offense). One explanation that fits well with this pattern is that peers reinforce addictive behavior, which may explain part of the large reinforcing peer effect for felony drug crimes. Another explanation is that individuals may experience different rates of return from participation in various types of legitimate or illegitimate activities; this variation in returns could be related to natural abilities, opportunities, human capital accumulation, or involvement in criminal networks. In this case, individuals who have a history of committing a particular offense have already revealed themselves to have high returns and, likely, substantial human capital related to this type of crime. Access to peers who can disseminate additional crime-specific knowledge or aid in the expansion of a criminal network may increase the individual's returns to this type of crime, leading him to increase the intensity of his activity in it. On the other hand, access to peers who can increase returns for another type of crime may be unhelpful, as this may not decrease the gap in returns between crime types enough to change an individual's choice of type of crime. Other potential social mechanisms related to stigma or to the general spread of information do not fit the pattern of our estimated peer effects as well.

The results of our analysis have several broad policy implications. First, in the broadest sense, the existence of peer effects in juvenile criminal behavior suggests that any current reduction in crime leads, at least through the correctional system channel, to future reductions in crime by reducing the overall level of crime-related experience. It is important to account for these dynamic benefits when considering the overall benefits of reducing crime in a given period. Notice that this does not imply a good course of action would be to lock up more juveniles for the purposes of deterring crime, as the intense exposure of juvenile offenders to one another in correctional facilities may, through the variety of channels discussed in this paper, increase the amount of criminal behavior upon release.[50] However, other programs for reducing juvenile crime—so long as they do not increase the intensity of juvenile offenders' exposure to one another or so long as they maintain a controlled social environment—might have dynamic benefits that greatly enhance the short-term benefits derived from the decreased criminal behavior of program participants.

Secondly, the evidence presented in this paper overwhelmingly supports the notion that exposure to peers with experience in a particular crime category has its greatest effect on individuals who themselves already have some experience in that category. Thus, while a policy of grouping offenders with others who have committed the same crimes may seem prudent to prevent the learning of new crimes, such a policy may inadvertently increase human capital precisely in those crime categories where it is likely to be of greatest use. Finally, our results point to the fact that non-residential facilities, which tend to serve juveniles from nearby locations, may inadvertently increase subsequent criminal activity through the operation of particularly strong, network-related peer effects, related especially to auto theft and felony drug crimes.

References

Anderson, Elijah. *Streetwise: Race, Class, and Change*. Chicago: Univ. Chicago Press, 1990.

Anderson, Elijah. *Code of the Street: Decency, Violence, and the Moral Life of the Inner City*. New York: W.W. Norton, 1999.

Angrist, Joshua, and Lang, Kevin. "How Important Are Classroom Peer Effects? Evidence from Boston's METCO Program." Working Paper no. 9263. Cambridge, Mass.: NBER, October 2002.

[50] Our paper does not explicitly provide any evidence that the intensity of peer effects is greater inside a correctional facility than on the outside, but one might certainly imagine that this is the case.

Arcidiacono, Peter, and Nicholson, Sean. “Peer Effects in Medical School.” Manuscript. Durham: Duke Univ., 2002.

Ayres, Ian, and Levitt, Steven. “Measuring Positive Externalities from Unobservable Victim Precaution: An Empirical Analysis of Lojack.” *Q.J.E.* 113 (February 1998): 43-77.

Bayer, Patrick, and Pozen, David. “The Effectiveness of Juvenile Correctional Facilities: Public versus Private Management.” Forthcoming *J. Law and Econ.*, 2004.

Becker, Gary. “Crime and Punishment: An Economic Approach.” *J.P.E.* 76 (March/April 1968): 169-217.

Bertand, Marianne; Luttmer Erzo F.P.; and Mullainathan, Sendhil. “Network Effects and Welfare Cultures.” *Q.J.E.* 115 (August 2000): 1019-55.

Besley, Timothy, and Case, Anne. “Diffusion as a Learning Process: Evidence from HYY Cotton.” Manuscript. Princeton: Princeton Univ., 1994.

Boozer, Michael, and Cacciola, Stephen. “Inside the ‘Black Box’ of Project STAR: Estimation of Peer Effects Using Experimental Data.” Economic Growth Center Discussion Paper no. 832. New Haven: Yale Univ., 2001.

Brock, William A., and Durlauf, Steven N. “Discrete Choice with Social Interactions.” *Rev. Econ. Stud.* 68 (April 2001): 235-60.

Calvo-Armengol, Antoni, and Zenou, Yves. “Social Networks and Crime Decisions: The Role of Social Structure in Facilitating Delinquent Behavior.” Manuscript. Barcelona: Universitat Autonoma de Barcelona, 2003.

Case, Anne, and Katz, Lawrence F. “The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youths.” Working Paper no. 3705. Cambridge, Mass.: NBER, May 1991.

Chen, M. Keith, and Shapiro, Jesse M. “Does Prison Harm Inmates? A Discontinuity-Based Approach.” Manuscript. Cambridge, Mass.: Harvard University, 2003.

Conley, Timothy G., and Udry, Christopher R. “Learning about a New Technology: Pineapple in Ghana.” Manuscript. Chicago: Univ. Chicago, and New Haven: Yale Univ., 2002.

Evans, William N.; Oates, Wallace; and Schwab, Robert. “Measuring Peer-Group Effects: A Study of Teenage Behavior.” *J.P.E.* 100 (October 1992): 966-91.

Federal Bureau of Investigation (FBI). “Crime in the United States, 2000: Uniform Crime Reports.” Washington, DC: US Government Printing Office, 2001.

Foster, Andrew D., and Rosenzweig, Mark R. “Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture.” *J.P.E.* 103 (December 1995): 1176-1209.

Gaviria, Alejandro, and Raphael, Steven. “School-Based Peer Effects and Juvenile Behavior.” *Rev. Econ. and Statis.* 83 (May 2001): 257-68.

Glaeser, Edward L.; Sacerdote, Bruce; and Scheinkman, Jose A. "Crime and Social Interactions." *Q.J.E.* 111 (May 1996): 507-48.

Grogger, Jeff. "Market Wages and Youth Crime." *J. Labor Econ.* 16 (October 1998): 756-91.

Hanushek, Eric A.; Kain, John F.; Markman, Jacob M.; and Rivkin, Steven G. "Does Peer Ability Affect Student Achievement?" Working Paper no. 8502. Cambridge, Mass.: NBER, October 2001.

Hoxby, Caroline. "Peer Effects in the Classroom: Learning from Gender and Race Variation." Working Paper no. 7867. Cambridge, Mass.: NBER, August 2000.

Imrohoroglu, Ayse; Merlo, Antonio; and Rupert, Peter. "What Accounts for the Decline in Crime?" Manuscript. Philadelphia: Univ. Pennsylvania, 2001.

Jacob, Brian A., and Lefgren, Lars. "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration and Juvenile Crime." Working Paper no. 9653. Cambridge, Mass.: NBER, April 2003.

Katz, Lawrence F.; Kling, Jeffrey R.; and Leibman, Jeffrey B. "Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment." *Q.J.E.* 116 (May 2001): 607-54.

Kremer, Michael, and Levy, Dan. (2003) "Peer Effects and Alcohol Use Among College Students." Cambridge, Mass.: NBER Working Paper No. 9876.

Levitt, Steven D. "Juvenile Crime and Punishment." *J.P.E.* 106 (December 1998): 1156-85.

Levitt, Steven D., and Lochner, Lance. "The Determinants of Juvenile Crime." In *Risky Behavior among Youths: An Economic Analysis*, edited by Jonathan Gruber. Chicago: Univ. Chicago Press, 2001.

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

Manski, Charles F. "Identification of Endogenous Social Effects: The Reflection Problem." *Rev. Econ. Stud.* 60 (July 1993): 531-42.

Mocan, H. Naci, and Rees, Daniel I. "Economic Conditions, Deterrence and Juvenile Crime: Evidence from Micro Data." Working Paper no. 7405. Cambridge, Mass.: NBER, November 1999.

Moffitt, Robert A. "Policy Interventions, Low-Level Equilibria and Social Interactions." In *Social Dynamics*, edited by Steven N. Durlauf and H. Peyton Young. Cambridge, Mass.: MIT Press, 2001.

Munshi, Kaivan. "Learning from Your Neighbors: Why Do Some Innovations Spread Faster Than Others?" Manuscript. Philadelphia: Univ. Pennsylvania, 1999.

Puzzanchera, Charles; Kang, Wei; Poole, Rowen; and Wan, Yi-chun. "Easy Access to Juvenile Populations." Washington, DC: US Department of Justice, Office of Juvenile Justice and

Delinquency Prevention, 2002. Online: <http://www.ojjdp.ncjrs.org/ojstatbb/ezapop>, last visited June 5, 2003.

Rasmussen, E. "Stigma and Self-Fulfilling Expectations of Criminality." *J. Law and Econ.* 39 (October 1996): 519-43.

Reiss, Albert J. "Co-Offending and Criminal Careers." In *Crime and Justice: A Review of Research*, vol. 10, edited by Michael Tonry and Norval Morris. Chicago: Univ. Chicago Press, 1988.

Sacerdote, Bruce. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *Q.J.E.* 116 (2): 681-704.

Sah, Raaj K. "Social Osmosis and Patterns of Crime." *J.P.E.* 99 (December 1991): 1272-95.

Sarnecki, Jerzy. *Delinquent Networks: Youth Co-Offending in Stockholm*. Cambridge: Cambridge Univ. Press, 2001.

Sickmund, Melissa. *Juvenile Offenders in Residential Placement: 1997-1999*. Washington, DC: US Department of Justice, Office of Juvenile Justice and Delinquency Prevention, 2002.

Silverman, Dan. "Street Crime and Street Culture." Manuscript. Ann Arbor: Univ. Michigan, 2002.

Sutherland, Edwin H. *Principles of Criminology*. Chicago: J.B. Lippincott, 1939.

Thornberry, Terence P.; Krohn, Marvin D.; Lizotte, Alan J.; and Chard-Wierschem, Deborah. "The Role of Juvenile Gangs in Facilitating Delinquent Behavior." *J. Res. Crime and Delinquency* 30 (February 1993): 55-87.

Thornberry, Terence P.; Krohn, Marvin D.; Lizotte, Alan J.; Smith, Carolyn A.; and Tobin, Kimberly. *Gangs and Delinquency in Developmental Perspective*. Cambridge: Cambridge Univ. Press, 2003.

Warr, Mark. "Organization and Instigation in Delinquent Groups." *Criminology* 34 (February 1996): 11-37.

Warr Mark. *Companions in Crime: The Social Aspects of Criminal Conduct*. Cambridge: Cambridge Univ. Press, 2002.

Zimmerman, David J. "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment." *Rev. Econ. and Statis.* 85 (February, 2003): 9-23.

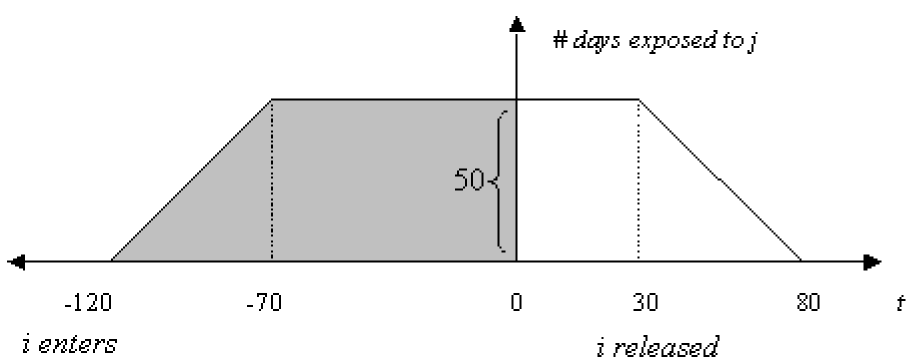
Appendix 1

This appendix describes the exact procedure we use to calculate the peer characteristics used in the analysis. More specifically, when calculating an individual *i*'s peer exposure, we allow each observed potential peer, *j*, in the facility to contribute to this measure in two ways—directly and indirectly. A potential peer contributes directly to the peer measure if his sentence actually overlaps with individual *i*'s sentence, in which case, we weight the relevant peer characteristic, c_j, by the number of days that individual *i* is exposed to the j^{th} peer, d_{ij}. A potential peer also contributes indirectly to the peer measure in certain circumstances, leading to an additional weight, w_{ij}, on the relevant peer characteristic. This weight is based on the fraction of sentences of the length served by the potential peer *j* that would not have been observed for those peers who overlap with the individual. In this way, peer exposure to characteristic c_j is calculated by the following equation

$$Exp_{ij} = \frac{\sum_j (d_{ij} + w_{ij}) \bullet c_j}{\sum_j (d_{ij} + w_{ij})} \tag{A1}$$

We estimate w_{ij} by calculating the expected number of days that individual *i* is exposed to an individual with a sentence the length of individual *j*'s who would have been released either before or after the sample period. In doing so, we make the assumption that each facility is in a steady state with respect to the peers served over the relevant period and that the release date of each individual is randomly distributed across the sample period. The calculation of w_{ij} is best understood by considering an example. Consider individual *i* released 30 days after the sample period begins, having served a sentence of 150 days. Additionally, consider a peer, *j*, in the same facility with a sentence of 50 days. This information is depicted in the following diagram, where the horizontal axis represents time, *t*, and the vertical axis represents the number of days individual *i* would be exposed to peer *j* if peer *j* is released at date *t*.

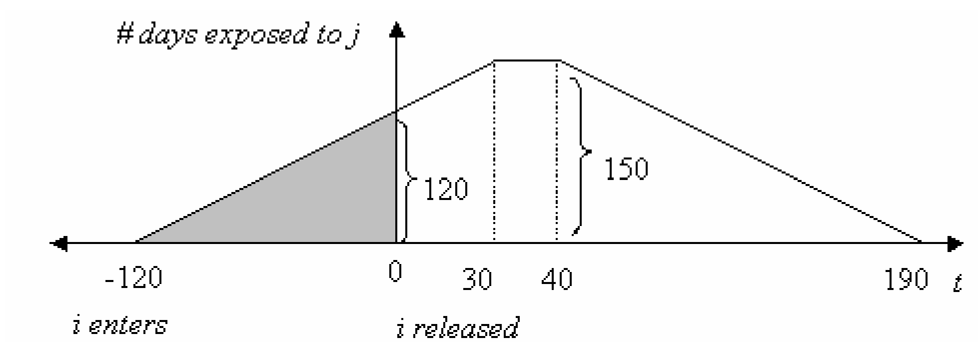
Scenario 1: *date_release[i] <= days_in[i] - days_in[j]*
Example: date_release[i] = 30; days_in[i] = 150; days_in[j] = 50



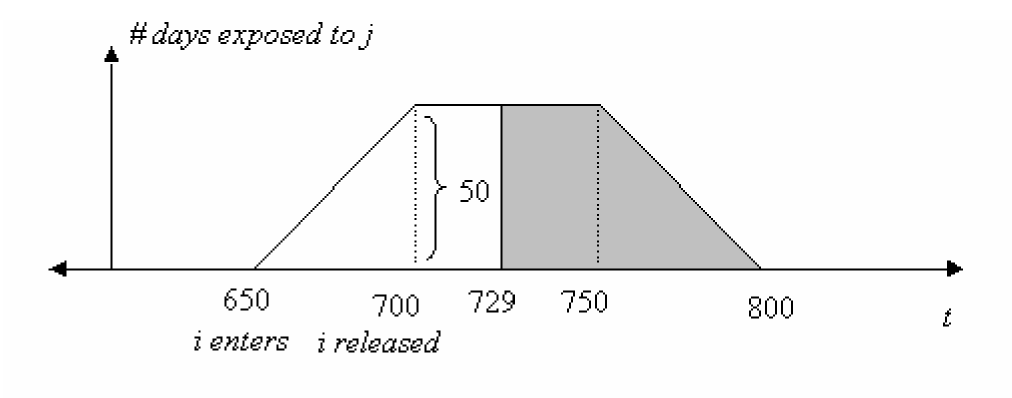
Any individuals who are released before $t = 0$ will be unobserved in the sample. To calculate the average number of days that individual *i* is expected to have been exposed to individual *j*, we simply divide the area of the shaded region by 729 (the number of days in the observed sample). To see this more clearly, imagine, for example, that one individual with a 50-day sentence is released during the sample period. In this case, the probability that such an individual was also released in the 120 days before the sample period is 120/729 and the average exposure of individual *i* to this individual is simply the average height of the shaded region. Thus, the correct weight for individual *j*, w_{ij}, is simply the area of the shaded region (length * average height) divided by 729.

This example depicts the correction made for just one case of pre-censoring. For peers with very long sentences, pre-censoring can occur such that the unobserved region is just the shaded triangular portion of the diagram above. Similarly, there are two cases of post-censoring that parallel those of pre-censoring. The following are examples and diagrams that depict the three additional censoring scenarios. In each scenario, w_{ij} is set equal to the area of the shaded region divided by 729.

Scenario 2: *days_in[i] - days_in[j] < date_release[i] <= days_in[i]*
Example: date_release[i] = 30; days_in[i] = 150; days_in[j] = 160



Scenario 3: *days_in[j] >= 729 - date_release[i] + days_in[i]*
Example: date_release[i] = 700; days_in[i] = 50; days_in[j] = 100



Scenario 4: *729 - date_release[i] <= days_in[j] <= 729 - date_release[i] + days_in[i]*

Example: date_release[i] = 700; days_in[i] = 150; days_in[j] = 50

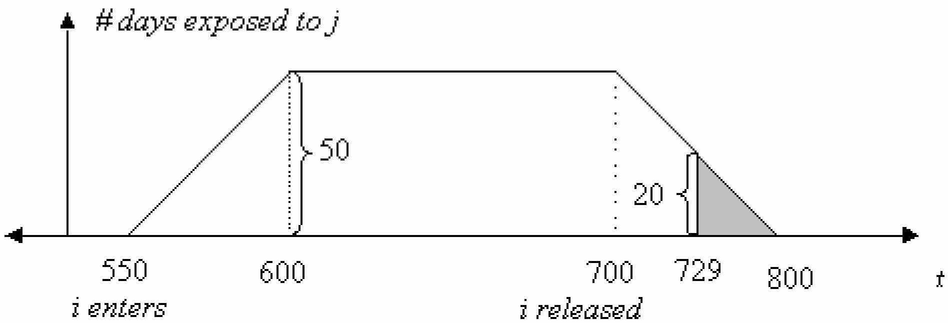


Table 1. Descriptive Statistics

Variable	N	Mean	Standard Deviation: Overall	Standard Deviation: Within	Definition
Recidivism					
Recidivism	8216	.67	.47	.45	1 if client recidivated within one year of release, 0 otherwise
R_Felony Drug	8216	.093	.29	.28	1 if client committed felony drug offense within one year of release, 0 otherwise
R_Misd. Drug	8216	.090	.29	.28	1 if client committed misd. drug offense within one year of release, 0 otherwise
R_Agg. Assault FWpn	8216	.14	.34	.34	1 if client committed aggravated assault or felony weapon offense within one year of release, 0 otherwise
R_Felony Sex	8216	.013	.11	.11	1 if client committed felony sex offense within one year of release, 0 otherwise
R_Auto Theft	8216	.093	.29	.28	1 if client committed auto theft offense within one year of release, 0 otherwise
R_Burglary	8216	.14	.34	.33	1 if client committed burglary offense within one year of release, 0 otherwise
R_Grand Larceny	8216	.094	.29	.29	1 if client committed grand larceny offense within one year of release, 0 otherwise
R_Petty Larceny	8216	.12	.32	.32	1 if client committed petty larceny offense within one year of release, 0 otherwise
R_Robbery	8216	.045	.21	.20	1 if client committed robbery offense within one year of release, 0 otherwise
Facility Characteristics					
# Individuals in Facility per day	14421	48.7	73.5	0	Calculated as number of individuals released multiplied by avg. sentence length in the facility, divided by 729 (total number of sample days)
# Released	14421	196.5	240.5	0	# of individuals released from each facility
Min Risk	14421	.15	.36	0	1 if facility to which client is assigned is designated minimum risk, 0 otherwise
Low Risk	14421	.17	.38	0	1 if facility to which client is assigned is designated low risk, 0 otherwise
Mod Risk	14421	.49	.50	0	1 if facility to which client is assigned is designated moderate risk, 0 otherwise
High Risk	14421	.17	.38	0	1 if facility to which client is assigned is designated high risk, 0 otherwise
Max Risk	14421	.010	.099	0	1 if facility to which client is assigned is designated maximum risk, 0 otherwise
Nonprofit Mgt	14421	.54	.50	0	1 if facility to which client is assigned is managed by a private nonprofit organization, 0 otherwise
For-profit Mgt	14421	.15	.36	0	1 if facility to which client is assigned is managed by a private for-profit organization, 0 otherwise
County Mgt	14421	.091	.29	0	1 if facility to which client is assigned is publicly managed by the county, 0 otherwise
State Mgt	14421	.22	.41	0	1 if facility to which client is assigned is publicly managed by the state, 0 otherwise
Individual Characteristics					
Female	8216	.14	.35	.19	1 if client is female, 0 otherwise
Black	8216	.48	.50	.48	1 if client is black, 0 otherwise
Age First Offense	8216	12.7	2.0	1.8	Client's age in years at first adjudicated criminal offense
Age Exit	8216	15.7	1.0	.87	Client's age in years at exit from facility
Days In	8216	168.5	106.4	64.0	Number of days an individual is in facility
Individual Criminal History Characteristics					
Felonies	8216	4.7	4.6	4.1	Number of felony charges on client's record
Fel Drug	8216	.13	.33	.32	1 if any felony drug charges on client's record, 0 otherwise
Mis Drug	8216	.16	.37	.36	1 if any misd. drug charges on client's record, 0 otherwise
Fel Sex	8216	.067	.25	.24	1 if any felony sex offense charges on client's record, 0 otherwise
Mis Sex	8216	.0095	.097	.096	1 if any misd. sex offense charges on client's record, 0 otherwise
AggAss_Fwpn	8216	.37	.48	.47	1 if any aggravated assault or felony weapon offense charges on client's record, 0 otherwise
Mis Weap	8216	.042	.20	.20	1 if any misd. weapon offense charges on client's record, 0 otherwise
Auto Theft	8216	.26	.44	.16	1 if any auto theft charges on client's record, 0 otherwise
Grlrcn	8216	.35	.48	.46	1 if any grand larceny charges on client's record, 0 otherwise
Plrcn	8216	.61	.49	.48	1 if any petty larceny charges on client's record, 0 otherwise
Burglary	8216	.58	.49	.47	1 if any burglary charges on client's record, 0 otherwise
Robbery	8216	.13	.33	.32	1 if any robbery charges on client's record, 0 otherwise
Escape	8216	.077	.27	.25	1 if any escape charges on client's record, 0 otherwise
Vandalism	8216	.31	.46	.45	1 if any vandalism charges on client's record, 0 otherwise
Disorder	8216	.093	.29	.29	1 if any disorderly conduct charges on client's record, 0 otherwise
Other	8216	.92	.27	.26	1 if any other charges on client's record, 0 otherwise
Individual Neighborhood Characteristics					
Youth Crime Rate in Zip	8216	358	260	247	Total number of juvenile referrals in client's home zip code, FY 2000-01
% Own Race in Zip	8216	.60	.33	.32	% of inhabitants in client's home zip code of same racial group as client, 1990
Per-Cap Inc Race	8216	10710	4331	4180	Median per-capita income of client's racial group in client's home zip code, 1990

Unemployment Rate	8216	.068	.028	.027	% unemployment rate in client's home zip code, 1990
Incarcerated in Zip	8216	109	307	301	Number of people incarcerated in client's home zip code, 1990
Per-Cap Income	8216	12316	3661	3533	Median per-capita income in home zip code, 1990
Peer Demographic Characteristics					
Peer_male	8216	.86	.29	.038	Weighted average of whether or not an individual's peers are male
Peer_age_exit	8216	16.4	.88	.22	Weighted average of the age at exit of an individual's peers
Peer_age1st	8216	13.1	.81	.32	Weighted average of the age at first offense of an individual's peers
Peer Criminal History Characteristics					
Peer_fel	8216	4.7	2.1	.63	Weighted average of the number of felony charges of an individual's peers
Peer_fel_drg	8216	.16	.10	.053	Weighted average of whether an individual's peers have a record of any felony drug offenses
Peer_mis_drg	8216	.19	.11	.065	Weighted average of whether an individual's peers have a record of any misd. drug offenses
Peer_fel_sex	8216	.069	.097	.038	Weighted average of whether an individual's peers have a record of any felony sex offenses
Peer_mis_sex	8216	.010	.023	.016	Weighted average of whether an individual's peers have a record of any misd. sex offenses
Peer_aggass_fwpn	8216	.37	.14	.075	Weighted average of whether an individual's peers have a record of any aggravated assault or felony weapon offenses
Peer_mis_wpn	8216	.042	.038	.028	Weighted average of whether an individual's peers have a record of any misd. weapon offenses
Peer_auto	8216	.27	.14	.066	Weighted average of whether an individual's peers have a record of auto theft
Peer_glrcn	8216	.35	.13	.077	Weighted average of whether an individual's peers have a record of grand larceny
Peer_plrcn	8216	.61	.12	.081	Weighted average of whether an individual's peers have a record of petty larceny
Peer_burg	8216	.57	.16	.079	Weighted average of whether an individual's peers have a record of burglary
Peer_rob	8216	.13	.11	.051	Weighted average of whether an individual's peers have a record of robbery
Peer_vand	8216	.30	.11	.070	Weighted average of whether an individual's peers have a record of vandalism
Peer_dsord	8216	.090	.069	.048	Weighted average of whether an individual's peers have a record of disorderly conduct
Peer_escp	8216	.077	.093	.039	Weighted average of whether an individual's peers have a record of escape
Peer_other	8216	.92	.074	.048	Weighted average of whether an individual's peers have a record of other offenses
Peer Neighborhood Characteristics					
Peer_percapi	8216	10754	1988	810	Weighted average of the per-capita income in an individual's peers' zip codes
Peer_percorin	8216	93	65	42	Weighted average of the number of incarcerated people in an individual's peers' zip codes

NOTE.—Neighborhood characteristics are constructed for Florida zip codes only. Individuals with zip codes from other states are assigned a zero for all neighborhood characteristics, and a dummy variable denoting that an individual has an out-of-state zip code of residence is included in all regressions. This allows us to maintain the full sample for the regressions, and it controls for the potential problem that out-of-state youths are less likely to recidivate in Florida.

Table 2a. Correlations between Peer Variables and Individual Variables

	Fel Sex	Fel Drug	Mis Drug	Auto Thef	Burglary	Grlrcn	Plrcn	Robbery	AggAss_Fwpn
Peer_fel_sex	.3210*	.0122	-.0124	.0107	.0257*	.0305*	-.0187	.0291*	.0245*
Peer_fel_drg	-.0046	.1779*	.1306*	.1320*	.1418*	.0915*	.0665*	.1400*	.0864*
Peer_mis_drg	-.0237*	.1319*	.1638*	.0448*	.0876*	.0445*	.0577*	.0492*	.0044
Peer_auto	-.0092	.1103*	.0491*	.2369*	.1450*	.1265*	.0348*	.1893*	.1268*
Peer_burg	.0208	.1071*	.0672*	.1318*	.2527*	.1530*	.0899*	.1555*	.0892*
Peer_glrcn	.0193	.0858*	.0522*	.1302*	.1719*	.1913*	.0973*	.1023*	.0819*
Peer_plrcn	-.0287*	.0433*	.0400*	.0470*	.1132*	.1087*	.1371*	.0636*	.0678*
Peer_rob	.0143	.1072*	.0431*	.1805*	.1568*	.0957*	.0492*	.2695*	.1396*
Peer_aggass_fwpn	.0202	.0697*	.0079	.1382*	.0944*	.0825*	.0493*	.1567*	.2163*

NOTE. — * indicates that the correlation coefficient is significant at the 5% level or better.

Table 2b. Correlations between Fixed Effects-Transformed Peer Variables and Individual Variables

	Fel Sex	Fel Drug	Mis Drug	Auto Thef	Burglary	Grlrcn	Plrcn	Robbery	AggAss_Fwpn
Peer_fel_sex	.0231*	-.0013	.0001	-.0130	.0070	.0030	.0124	-.0118	-.0026
Peer_fel_drg	.0039	-.0288*	.0204	-.0214	.0064	.0120	.0229*	-.0024	.0117
Peer_mis_drg	.0034	.0217*	.0225*	-.0207	.0078	-.0057	.0115	.0033	.0020
Peer_auto	-.0025	-.0159	-.0157	.0041	.0014	.0226*	-.0120	.0074	-.0131
Peer_burg	-.0011	-.0003	.0031	-.0107	-.0014	-.0161	.0041	.0068	.0029
Peer_glrcn	-.0021	.0134	-.0002	.0141	-.0250*	.0037	-.0038	-.0031	.0019
Peer_plrcn	-.0038	.0097	.0084	-.0064	.0164	-.0048	.0035	.0153	.0102
Peer_rob	-.0083	-.0049	.0018	.0208	.0099	-.0029	.0208	.0086	-.0055
Peer_aggass_fwpn	-.0126	.0102	-.0026	.0048	-.0039	.0062	.0121	-.0017	.0099

NOTE.— All variables have undergone fixed effect transformations (that is, facility averages have been subtracted out). * indicates that the correlation coefficient is significant at the 5% level or better.

Table 3a. Peer Effects and Specialization in the Entire Sample – Without facility fixed effects and any controls

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.13**	0.19**	0.044	0.16**	0.11**	0.67**	0.25**	0.16**	-0.061**
	2.96	*6.52*	*1.16*	*4.23*	*2.58*	*8.34*	*3.66*	*3.96*	*2.98*
No_Offense*Peer_offense (β_1)	.099**	.051	.040	-.035	.068**	.20**	.098**	.059*	.038**
	3.73	*1.61*	*1.43*	*0.81*	*2.97*	*6.36*	*3.04*	*1.82*	*2.13*
Offense (at mean) (β_2)	.088**	.078**	.059**	.043**	.054**	.23**	.13**	.096**	.056**
	11.94	*11.51*	*9.50*	*6.18*	*7.56*	*24.20*	*15.16*	*12.84*	*10.32*
Facility Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Peer Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO
Individual Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0283	.0321	.0155	.0092	.0155	.1080	.0346	.0278	.0137

Table 3b. Peer Effects and Specialization in the Entire Sample – With facility fixed effects but no controls

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.092	0.13**	-0.023	0.14**	0.064	0.19	0.23**	0.071	0.29**
	1.05	*2.30*	*0.36*	*2.45*	*0.70*	*1.32*	*2.23*	*0.97*	*2.45*
No_Offense*Peer_offense (β_1)	.038	-.071	-.018	-.095	-.066	.093	-.046	-.0047	.032
	0.71	*1.14*	*0.39*	*1.41*	*1.43*	*1.56*	*0.89*	*0.08*	*0.94*
Offense (at mean) (β_2)	.083**	.073**	.055**	.041**	.053**	.24**	.13**	.095**	.054**
	11.65	*10.64*	*8.71*	*5.77*	*7.90*	*25.56*	*15.34*	*12.58*	*10.16*
Facility Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peer Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO
Individual Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO
# recidivate with offense	760	1116	770	954	369	762	738	1119	108
% recidivate with offense	9.3%	13.6%	9.4%	11.6%	4.5%	9.3%	9.0%	13.6%	1.3%
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0583	.0628	.0368	.0276	.0447	.1279	.0600	.0527	.0334

NOTE.—Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications are simultaneously estimated as a seemingly unrelated regression (SUR).

Table 3c. Peer Effects and Specialization in the Entire Sample – With facility fixed effects and controls for peer characteristics

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.090	0.16**	-0.047	0.10*	0.038	0.18	0.24**	0.10	0.31**
	1.01	*2.52*	*0.70*	*1.75*	*0.37*	*1.18*	*2.24*	*1.35*	*2.62*
No_Offense*Peer_offense (β_1)	.045	-.038	-.044	-.12*	-.092*	.070	-.035	.027	.042
	0.81	*0.53*	*0.85*	*1.67*	*1.87*	*1.09*	*0.64*	*0.42*	*1.21*
Offense (at mean) (β_2)	.083**	.073**	.055**	.041**	.053**	.24**	.13**	.095**	.054**
	11.57	*10.68*	*8.70*	*5.74*	*7.81*	*25.52*	*15.33*	*12.58*	*10.17*
Facility Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peer Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0602	.0651	.0395	.0295	.0469	.1307	.0620	.0543	.0362

Table 3d. Peer Effects and Specialization in the Entire Sample – With facility fixed effects and controls for peer and individual characteristics

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.084	0.16**	-0.038	0.11*	0.030	0.13	0.21**	0.098	0.32**
	0.94	*2.54*	*0.57*	*1.80*	*0.35*	*0.85*	*2.05*	*1.28*	*2.61*
No_Offense*Peer_offense (β_1)	.044	-.042	-.035	-.11	-.11**	.068	-.036	.014	.039
	0.79	*0.59*	*0.68*	*1.61*	*2.14*	*1.08*	*0.65*	*0.22*	*1.13*
Offense (at mean) (β_2)	.081**	.063**	.044**	.044**	.047**	.21**	.12**	.079**	.054**
	10.26	*6.98*	*5.63*	*5.67*	*6.51*	*21.16*	*13.33*	*9.47*	*9.84*
Facility Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peer Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
# recidivate with offense	760	1116	770	954	369	762	738	1119	108
% recidivate with offense	9.3%	13.6%	9.4%	11.6%	4.5%	9.3%	9.0%	13.6%	1.3%
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0739	.0810	.0542	.0394	.0656	.1619	.0708	.0770	.0389

NOTE.—Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications are simultaneously estimated as a seemingly unrelated regression (SUR).

Table 4a. Test of Identification Strategy for the Full Sample – Regressions of Predicted Recidivism (off of individual characteristics) on the Relevant Peer Measure

Dependent Variable =	Predicted Auto	Predicted Burglary	Predicted Grand Larceny	Predicted Petty Larceny	Predicted Robbery	Predicted Felony Drug	Predicted Misd. Drug	Predicted Agg. Ass. Felony Wpn	Predicted Felony Sex
Offense*Peer_offense (β_0)	0.23**	0.18**	0.12**	0.047**	0.22**	0.94**	0.37**	0.19**	0.083**
	6.19	*6.69*	*5.02*	*3.56*	*10.01*	*5.60*	*6.18*	*4.50*	*4.82*
No_Offense*Peer_offense (β_1)	.043**	.24**	.065**	.069**	.084**	.12**	.086**	.097**	.024**
	2.97	*8.29*	*4.10*	*3.82*	*11.69*	*4.95*	*4.93*	*3.90*	*3.83*
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
F-Statistic	49.73**	159.80**	74.52**	26.31**	115.27**	71.96**	51.20**	60.50**	25.66**
R^2	.1050	.1882	.0571	.0277	.1524	.1540	.1075	.0688	.1544
Facility Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Small Facilities	NO	NO	NO	NO	NO	NO	NO	NO	NO

Table 4b. Test of Identification Strategy for the Full Sample – Regressions of Predicted Recidivism (off of individual characteristics) on the Relevant Peer Measure

Dependent Variable =	Predicted Auto	Predicted Burglary	Predicted Grand Larceny	Predicted Petty Larceny	Predicted Robbery	Predicted Felony Drug	Predicted Misd. Drug	Predicted Agg. Ass. Felony Wpn	Predicted Felony Sex
Offense*Peer_offense (β_0)	0.0016	0.0070	-0.025	0.0010	-0.084	-0.11	0.041	0.0080	-0.048
	0.00	*0.32*	*1.09*	*0.10*	*1.45*	*0.45*	*0.67*	*0.22*	*0.66*
No_Offense*Peer_offense (β_1)	.0086	.0010	.0021	-.0044	.036**	-.025	.0090	.026	.015**
	0.52	*0.03*	*0.18*	*0.29*	*3.42*	*0.70*	*0.59*	*1.21*	*2.97*
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
F-Statistic	0.02	0.01	0.72	0.06	3.85**	0.10	.020	.14	0.70
R^2	.1729	.3109	.1408	.1361	.2143	.1351	.1892	.1601	.2257
Facility Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Small Facilities	NO	NO	NO	NO	NO	NO	NO	NO	NO

NOTE.—Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. The dependent variable is predicted recidivism of the crime labeled at the top of each column. The predicted value for each crime category is calculated from a regression of recidivism with the particular crime category on the entire set of observable individual characteristics and facility fixed effects. This predicted value is then regressed on just the variables presented in these tables.

Table 5. Peer Effects and Specialization in Relatively Small Facilities

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.00070	0.16**	0.022	0.10	0.16	0.42**	0.18	0.13	0.37**
	0.00	*2.30*	*0.28*	*1.57*	*1.56*	*2.62*	*1.55*	*1.55*	*2.59*
No_Offense*Peer_offense (β_1)	-.0044	-.078	-.049	-.13*	-.080	.056	-.065	.012	.060
	0.07	*0.99*	*0.32*	*1.69*	*1.58*	*0.85*	*1.09*	*0.16*	*1.44*
Offense (at mean) (β_2)	.080**	.067**	.037**	.044**	.065**	.19**	.12**	.073**	.062**
	7.54	*5.48*	*3.40*	*4.19*	*6.50*	*14.22*	*9.60*	*6.37*	*7.50*
Facility Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peer Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
# recidivate with offense	365	570	398	483	165	315	362	550	60
# observations	4266	4266	4266	4266	4266	4266	4266	4266	4266
R^2	.0835	.1053	.0632	.0568	.0860	.1616	.0849	.0868	.0520

NOTE.—Since we cannot measure facility size directly, we approximate facility size by creating an index equal to the number of individuals released from a facility multiplied by the average number of days individuals stay in that facility. The sample used in the above specifications includes those individuals in facilities where the average daily population is less than 20. This eliminates approximately half of the sample. Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications are simultaneously estimated as a seemingly unrelated regression (SUR).

Table 6a. Robustness: Peer Effects in the Entire Sample with Controls for Judicial Circuit Specific Time Trends in Crime

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.12	0.16**	-0.029	0.090	0.010	0.15	0.21*	0.091	0.31**
	1.36	*2.43*	*0.44*	*1.49*	*0.00*	*0.99*	*1.89*	*1.18*	*2.55*
No_Offense*Peer_offense (β_1)	.049	-.065	-.0042	-.11	-.12**	.11*	-.044	.028	.040
	0.86	*0.91*	*0.08*	*1.63*	*2.43*	*1.64*	*0.77*	*0.43*	*1.14*
Offense (at mean) (β_2)	.079**	.062**	.042**	.043**	.044**	.21**	.11**	.077**	.055**
	10.08	*6.87*	*5.40*	*5.56*	*6.03*	*20.90*	*12.94*	*9.15*	*10.12*
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.1025	.1048	.0733	.0618	.0841	.1864	.0924	.0972	.0689

Table 6b. Robustness: Peer Effects in Small Facilities with Controls for Judicial Circuit Specific Time Trends in Crime

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.064	0.14**	0.054	0.080	0.13	0.36**	0.17	0.15*	0.32**
	0.62	*1.92*	*0.69*	*1.25*	*1.32*	*2.20*	*1.46*	*1.75*	*2.26*
No_Offense*Peer_offense (β_1)	.0073	-.12	-.038	-.13*	-.087*	.037	-.068	.030	.051
	0.12	*1.48*	*0.63*	*1.70*	*1.66*	*0.54*	*1.12*	*0.41*	*1.18*
Offense (at mean) (β_2)	.080**	.063**	.034**	.044**	.064**	.18**	.11**	.070**	.061**
	7.58	*5.13*	*3.14*	*4.20*	*6.45*	*13.71*	*9.15*	*6.18*	*7.39*
# observations	4266	4266	4266	4266	4266	4266	4266	4266	4266
R^2	.1379	.1516	.0964	.0976	.1188	.2020	.1223	.1255	.1008

NOTE.—Since we cannot measure facility size directly, we approximate facility size by creating an index equal to the number of individuals released from a facility multiplied by the average number of days individuals stay in that facility. The sample used in the specifications presented in Table 6b includes those individuals in facilities where the average daily population is less than 20 while the entire sample is used in Table 6a. This eliminates approximately half of the sample. Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications include facility fixed effects and are simultaneously estimated as a seemingly unrelated regression (SUR). In addition, these specifications include a detailed set of demographic and criminal history controls at both the individual and peer levels. These specifications include eight quarter of release dummies, 20 judicial circuit dummies, and a full set of interactions between the two.

Table 7. Robustness: Test for Clustering of Individuals by Five Digit Zip Codes in All Facilities and Small Facilities

	Release Date				Admit Date			
	All Facilities		Small Facilities		All Facilities		Small Facilities	
	Observations	Mean in 5-digit zip	Observations	Mean in 5-digit zip	Observations	Mean in 5-digit zip	Observations	Mean in 5-digit zip
Within 7 days	7,185	0.0284	3,461	0.0317	3,553	0.0292	1,689	0.0297
Within 14 days	7,808	0.0290	3,920	0.0312	3,938	0.0291	1,961	0.0311
Within 21 days	8,102	0.0290	4,163	0.0310	4,096	0.0297	2,099	0.0325
Overall	8,216	0.0273	4,266	0.0295	4,148	0.0278	2,148	0.0301

NOTE.— The value in each cell represents the proportion of individuals who have a peer released (admitted) from the same facility that is from the same zip code during the specified time period.

	Release Date				Admit Date			
	All Facilities		Small Facilities		All Facilities		Small Facilities	
	Observations	5-digit Difference from Overall	Observations	5-digit Difference from Overall	Observations	5-digit Difference from Overall	Observations	5-digit Difference from Overall
Within 7 days	7,185	0.0022 *1.34*	3,461	0.0039 *1.43*	3,533	0.0027 *1.22*	1,689	0.0016 *0.50*
Within 14 days	7,808	0.0026 *1.91*	3,920	0.0034 *1.62*	3,938	0.0022 *1.36*	1,961	0.0027 *1.06*
Within 21 days	8,102	0.0022 *1.86*	4,163	0.0023 *1.27*	4,096	0.0023 *1.80*	2,099	0.0033 *1.48*

NOTE.— The value in each cell represents the difference between the mean presented in the corresponding cell in the above panel and the mean for the overall sample period. Note that the mean for the overall sample period is calculated using the sample of individuals who have at least one peer released (admitted) within 7, 14, and 21 days, respectively. The absolute value of the p-value corresponding to each difference is presented in italics.

Table 8. Robustness: Individuals Released during the Middle Year of the Sample

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	-0.038	0.21**	0.021	0.090	0.12	-0.12	0.43**	0.050	0.74**
	0.30	*2.16*	*0.20*	*0.94*	*0.73*	*0.54*	*2.79*	*0.42*	*3.79*
No_Offense*Peer_offense (β_1)	-.0071	-.10	-.012	-.11	-.19**	.16	-.090	-.070	.10*
	0.08	*0.93*	*0.14*	*1.07*	*2.40*	*1.53*	*1.06*	*0.69*	*1.71*
Offense (at mean) (β_2)	.086**	.067**	.033**	.042**	.055**	.22**	.14**	.065**	.065**
	7.80	*5.33*	*3.01*	*3.91*	*5.29*	*15.47*	*11.38*	*5.35*	*8.01*
# observations	4057	4057	4057	4057	4057	4057	4057	4057	4057
R^2	.0950	.1081	.0824	.0637	.0947	.1928	.1056	.1039	.0635

NOTE.—The regressions above use just those 4,057 individuals who were released between December 30, 1997 and December 30, 1998 and who were younger than 17 at the time. Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications include facility fixed effects and are simultaneously estimated as a seemingly unrelated regression (SUR). In addition, these specifications include a detailed set of demographic and criminal history controls at both the individual and peer levels.

Table 9a. Peer Effects in Residential Facilities

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	-0.0010	0.17**	-0.015	0.070	-0.037	0.060	0.25**	0.11	0.29**
	0.00	*2.43*	*0.20*	*1.17*	*0.32*	*0.36*	*2.16*	*1.30*	*2.29*
No_Offense*Peer_offense (β_1)	.074	-.13	-.0094	-.18**	-.11**	.086	-.091	.011	.057
	1.20	*1.62*	*0.16*	*2.22*	*2.02*	*1.18*	*1.44*	*0.16*	*1.56*
Offense (at mean) (β_2)	.080**	.061**	.042**	.044**	.046**	.21**	.12**	.081**	.056**
	9.37	*6.13*	*4.93*	*5.20*	*5.79*	*20.03*	*12.79*	*8.89*	*9.71*
# observations	6992	6992	6992	6992	6992	6992	6992	6992	6992
R^2	.0731	.0776	.0509	.0394	.0641	.1676	.0705	.0798	.0426

NOTE.—Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications include facility fixed effects and are simultaneously estimated as a seemingly unrelated regression (SUR). In addition, these specifications include a detailed set of demographic and criminal history controls at both the individual and peer levels. Note that these specifications only include individuals from residential facilities.

Table 9b. Peer Effects in Non-Residential Facilities

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.69**	0.19	-0.17	0.17	0.41*	0.66*	0.090	0.052	0.49
	3.45	*1.28*	*1.00*	*1.16*	*1.88*	*1.91*	*0.33*	*0.24*	*0.85*
No_Offense*Peer_offense (β_1)	-.11	.38**	-.16	.087	-.029	.035	.20	.011	-.17
	0.80	*2.49*	*1.43*	*0.60*	*0.24*	*0.28*	*1.63*	*0.07*	*1.52*
Offense (at mean) (β_2)	.076**	.076**	.052**	.040**	.065**	.14**	.090**	.064**	.032*
	4.02	*3.71*	*2.65*	*2.17*	*3.87*	*5.21*	*3.75*	*3.16*	*1.70*
# observations	1224	1224	1224	1224	1224	1224	1224	1224	1224
R^2	.1136	.1512	.1124	.0837	.1368	.1589	.1228	.0839	.0465

NOTE.—Each column represents a different specification; Offense and Peer_offense vary across specifications. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft) while Peer_offense in this specification is Peer_auto (exposure to peers with a history of auto theft). Note that the peer_offense measures are constructed such that they have a mean of zero. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level All specifications include facility fixed effects and are simultaneously estimated as a seemingly unrelated regression (SUR). In addition, these specifications include a detailed set of demographic and criminal history controls at both the individual and peer levels. Note that these specifications only include individuals from non-residential facilities.

Table 10a. Individual Determinants of Peer Quality

	R_Hat Auto	R_Hat Burg	R_Hat Grlrcn	R_Hat Plrcn	R_Hat Rob	R_Hat Fdrg	R_Hat Mdrg	R_Hat Agg. Ass. Fwep	R_Hat Fsex	R_Hat Tot Crime Index
Female	0.06563***	0.05323***	0.04854***	-0.01642***	-0.01750***	-0.02711***	-0.04991***	-0.04010***	0.00169	0.00265
	(9.54)	(8.18)	(7.55)	(3.59)	(5.74)	(5.36)	(9.12)	(6.80)	(0.90)	(1.60)
Black	-0.00150	-0.00239*	-0.00408**	-0.00060	-0.00028	0.00193*	0.00298***	0.00000	-0.00241*	-0.00088
	(1.37)	(1.94)	(2.54)	(0.45)	(0.29)	(1.70)	(2.83)	(0.00)	(1.68)	(1.48)
Age_exit	0.01069***	0.00713***	0.02050***	0.01153***	-0.00304***	0.00052	-0.00718***	-0.00158	0.00240***	0.00428***
	(5.30)	(3.79)	(5.72)	(5.74)	(3.22)	(0.33)	(3.58)	(1.57)	(2.96)	(6.02)
Age1st	0.00022	-0.00031	-0.00008	-0.00120**	-0.00122***	-0.00140***	-0.00109***	0.00006	-0.00049*	-0.00059***
	(0.74)	(0.99)	(0.19)	(2.57)	(4.26)	(3.87)	(4.24)	(0.21)	(1.89)	(3.43)
Felonies	0.00005	0.00035*	0.00023	0.00128***	0.00082***	0.00151***	0.00064***	0.00046**	0.00032***	0.00059***
	(0.25)	(1.77)	(0.95)	(4.68)	(3.87)	(5.74)	(4.00)	(2.61)	(4.32)	(6.08)
Fel Sex	-0.00604**	0.01006*	0.00386	-0.00715	0.01098***	0.00745***	0.00201	0.00770***	0.01881	0.00652**
	(2.17)	(1.71)	(0.62)	(1.25)	(2.71)	(2.71)	(0.54)	(3.38)	(1.64)	(2.19)
Mis Sex	0.00065	0.00378	0.00546	0.01331*	0.01340***	0.00157	-0.00135	-0.00806**	-0.00371	0.00237
	(0.16)	(0.93)	(0.99)	(1.95)	(2.63)	(0.34)	(0.43)	(2.43)	(1.24)	(1.02)
Fel Drug	0.00049	-0.00202	0.00087	0.00632***	0.00090	0.00843***	0.00212*	0.00315**	0.00084	0.00211***
	(0.40)	(1.30)	(0.59)	(3.96)	(0.86)	(4.01)	(1.74)	(2.19)	(1.03)	(3.15)
Mis Drug	0.00023	-0.00360***	-0.00187	-0.00071	-0.00048	0.00041	0.00073	-0.00015	-0.00050	-0.00068
	(0.23)	(3.47)	(1.39)	(0.62)	(0.68)	(0.32)	(0.77)	(0.18)	(0.63)	(1.43)
Fel Weap	0.00029	-0.00284**	-0.00133	0.00267**	0.00166**	0.00280**	0.00304***	0.00429***	0.00157***	0.00133**
	(0.28)	(2.59)	(0.86)	(2.00)	(2.05)	(2.26)	(2.83)	(4.85)	(2.85)	(2.56)
Mis Weap	-0.00099	0.00016	0.00068	-0.00032	-0.00002	-0.00120	-0.00030	0.00163	0.00109	0.00018
	(0.54)	(0.09)	(0.22)	(0.14)	(0.01)	(0.55)	(0.17)	(1.08)	(1.11)	(0.18)
Auto	0.00107	0.00091	0.00287**	0.00130	0.00000	0.00167	-0.00062	-0.00036	-0.00101**	0.00051
	(1.01)	(0.91)	(2.45)	(0.97)	(0.00)	(1.15)	(0.65)	(0.39)	(2.17)	(1.01)
Grlrcen	-0.00199**	-0.00089	-0.00173	0.00046	-0.00007	0.00163*	0.00134*	0.00173**	-0.00027	-0.00002
	(2.18)	(1.04)	(1.33)	(0.47)	(0.13)	(1.73)	(1.71)	(2.10)	(0.82)	(0.05)
Plrcen	-0.00090	-0.00275***	-0.00302**	0.00278***	0.00017	0.00042	0.00196**	0.00227***	-0.00020	0.00002
	(0.82)	(2.70)	(2.29)	(3.07)	(0.28)	(0.39)	(2.01)	(3.19)	(0.41)	(0.05)
Burglary	-0.00055	0.00319**	-0.00159	0.00052	-0.00136	-0.00059	0.00052	0.00143	-0.00147	-0.00008
	(0.53)	(2.45)	(1.05)	(0.41)	(1.63)	(0.52)	(0.51)	(1.57)	(1.18)	(0.15)
Robbery	-0.00030	0.00105	-0.00143	0.00668**	0.00377*	0.00541***	0.00136	0.00041	-0.00113	0.00151
	(0.22)	(0.65)	(0.70)	(2.54)	(1.85)	(2.62)	(1.10)	(0.31)	(0.78)	(1.53)
Escape	0.00820***	-0.00012	0.00315	0.01251***	0.00899***	0.01070***	0.00744***	-0.00529**	0.00184*	0.00481***
	(3.22)	(0.06)	(1.07)	(3.88)	(4.24)	(4.05)	(3.81)	(2.18)	(1.79)	(3.95)
Vandalism	0.00024	0.00003	0.00055	0.00134	0.00016	0.00008	-0.00110	0.00131*	0.00027	0.00033
	(0.27)	(0.03)	(0.40)	(1.12)	(0.24)	(0.07)	(1.11)	(1.76)	(0.41)	(0.72)
Disorder	-0.00179	-0.00270	-0.00199	-0.00179	-0.00058	0.00039	0.00075	-0.00056	-0.00110	-0.00107*
	(1.08)	(1.48)	(1.02)	(1.11)	(0.53)	(0.26)	(0.49)	(0.45)	(0.86)	(1.86)
Other	-0.00287	-0.00220	-0.00526	0.00236	0.00098	0.00057	0.00211	-0.00003	-0.00303	-0.00101
	(1.48)	(0.87)	(1.59)	(0.85)	(0.57)	(0.26)	(0.92)	(0.03)	(0.67)	(0.79)
Constant	0.02139	0.03219	0.29576***	0.24852***	0.01551	-0.12292***	-0.09386***	0.16323***	0.15025***	0.08412***
	(0.64)	(1.04)	(5.10)	(7.66)	(0.88)	(4.73)	(2.80)	(10.32)	(21.69)	(8.00)
Observations	4266	4266	4266	4266	4266	4266	4266	4266	4266	4266
R-squared	0.59	0.44	0.47	0.35	0.40	0.33	0.51	0.47	0.14	0.27

NOTE.—The absolute values of t-statistics are in parentheses. The standard errors used to calculate the t-statistics are corrected for clustering within facilities. ** represents significance at the 5% level and * represents significance at the 10% level. All specifications also include a set of judicial circuit dummies.

Table 10b. Facility Determinants of Peer Quality

	R_Hat Auto	R_Hat Burg	R_Hat Grlrcn	R_Hat Plrcn	R_Hat Rob	R_Hat Fdrg	R_Hat Mdrg	R_Hat Agg. Ass. Fwep	R_Hat Fsex	R_Hat Tot Crime Index
Low Risk	-0.01858*	-0.00354	-0.02584*	-0.00794	0.01003**	0.00461	0.01224	0.00154	0.00082	-0.00258
	(1.80)	(0.41)	(1.71)	(1.16)	(2.04)	(0.47)	(1.00)	(0.23)	(0.32)	(1.13)
Mod Risk	-0.00946	-0.00503	-0.01733	0.00894	0.02333***	0.02849***	0.02712**	0.00388	0.00885***	0.00749***
	(0.97)	(0.57)	(1.27)	(1.15)	(5.03)	(3.01)	(2.36)	(0.66)	(2.84)	(3.22)
High Risk	-0.01461	0.00902	0.00621	0.04879***	0.04197***	0.06281***	0.03345***	0.01848**	0.02540**	0.02511***
	(1.22)	(0.78)	(0.45)	(4.00)	(5.91)	(4.69)	(2.77)	(2.01)	(2.11)	(6.61)
Max Risk	-0.00661	0.01583*	0.00949	0.09865***	0.06786***	0.08200***	0.04328***	0.03471***	0.01850***	0.03822***
	(0.66)	(1.86)	(0.86)	(10.58)	(6.35)	(6.50)	(3.82)	(3.46)	(4.23)	(13.16)
Non-profit Mgt	0.00255	-0.00153	-0.00857	-0.01177*	-0.00287	0.00273	0.00176	-0.00001	0.00266	-0.00131
	(0.24)	(0.20)	(0.72)	(1.67)	(0.72)	(0.48)	(0.23)	(0.00)	(1.03)	(0.55)
For-profit Mgt	0.01005	-0.00729	0.00737	0.00676	-0.01054	0.00840	-0.00487	0.00326	0.00106	0.00124
	(0.73)	(0.70)	(0.63)	(0.71)	(1.46)	(0.87)	(0.54)	(0.25)	(0.25)	(0.34)
County Mgt	-0.00129	-0.01375	0.00706	0.02122**	-0.02188***	0.01596**	-0.00352	0.01819*	-0.00274	0.00114
	(0.10)	(1.14)	(0.52)	(2.18)	(4.34)	(2.20)	(0.40)	(1.83)	(0.73)	(0.37)
Constant	0.21308***	0.15325***	0.63740***	0.41616***	-0.06238***	-0.15384***	-0.24394***	0.13001***	0.17127***	0.14099***
	(15.99)	(11.90)	(38.85)	(41.43)	(10.72)	(15.23)	(18.01)	(16.06)	(45.89)	(48.62)
Observations	4266	4266	4266	4266	4266	4266	4266	4266	4266	4266
R-squared	0.12	0.09	0.14	0.50	0.46	0.45	0.18	0.19	0.19	0.52

NOTE.—The absolute values of t-statistics are in parentheses. The standard errors used to calculate the t-statistics are corrected for clustering within facilities. ** represents significance at the 5% level and * represents significance at the 10% level. All specifications also include a set of judicial circuit dummies. Minimum Risk (facilities) is the omitted risk level variable; State Mgt (facilities) is the omitted management type variable.

Appendix Table 1. Examples of Crimes Included in Each Crime Category

Crime Category	Included Crimes
Auto Theft	Vehicle theft (2nd degree); grand theft auto (2nd degree)
Burglary	Burglary of a dwelling structure; Possession of burglary tools; Unarmed burglary of a dwelling; Burglary of unoccupied dwelling
Grand Larceny	Grand larceny in the 1st degree (excluding auto theft); Grand larceny valued between $20,000 and $100,000 (excluding auto theft); Grand larceny valued between $300 and $20,000 (excluding auto theft); Grand larceny of a firearm; 3rd or subsequent petty larceny conviction
Petty Larceny	Shoplifting; 1st or 2nd petty larceny conviction
Robbery	Robbery with firearm or weapon; Robbery/carjacking with firearm or weapon; Robbery (no firearm or weapon); Robbery and residential home invasion; other robbery
Felony Drug	Possession; Possession with intent to sell; Use; Purchase; Distribution; Manufacturing – Includes a variety of drug categories and amounts
Misdemeanor Drug	Possession or distribution of less than 20 grams marijuana; Possession of narcotic equipment; Possession of drug paraphernalia; Possession of legend drugs without a prescription
Aggravated Assault/ Felony Weapon	Aggravated assault and/or battery; Carry concealed weapon; Possession of weapon on school property; Fire a weapon from vehicle; Bomb threat
Misdemeanor Weapon	Openly carrying prohibited weapon; Improper exhibition of a firearm
Felony Sex	Sexual assault/battery; Sexual offense against a child; Lewd and lascivious act; Other felony sex offenses
Misdemeanor Sex	Obscene phone call; Indecent exposure in public; prostitution
Escape	Escape from training school, secure detention, or residential program
Vandalism	Damage property or criminal mischief
Disorderly Conduct	Disturbing the peace; Disturbing a school function; Disorderly intoxication; Conspire to interrupt education

Appendix Table 2. Peer Effects and Specialization in Relatively Small Facilities – REVISED VERSION

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Offense*Peer_offense (β_0)	0.00070	0.16**	0.022	0.10	0.16	0.42**	0.18	0.13	0.37**
	0.00	*2.30*	*0.28*	*1.57*	*1.56*	*2.62*	*1.55*	*1.55*	*2.59*
No_Offense*Peer_offense (β_1)	-.0044	-.078	-.049	-.13*	-.080	.056	-.065	.012	.060
	0.07	*0.99*	*0.82*	*1.69*	*1.58*	*0.85*	*1.09*	*0.16*	*1.44*
Peer_auto		-.045	.013	.0091	-.0093	.058	.0018	.036	-.033
		0.70	*0.23*	*0.15*	*0.25*	*1.21*	*0.03*	*0.56*	*1.44*
Peer_burg	-.0021		.031	-.0025	.0076	-.0039	.00075	.042	.00056
	0.04		*0.61*	*0.05*	*0.23*	*0.09*	*0.02*	*0.72*	*0.03*
Peer_glrcn	-.067	-.029		.00098	.00056	.067	.021	.045	.019
	1.39	*0.50*		*0.02*	*0.02*	*1.56*	*0.44*	*0.79*	*0.91*
Peer_plrcn	.049	-.023	.013		.011	-.0098	.033	.032	.012
	1.10	*0.43*	*0.27*		*0.35*	*0.25*	*0.74*	*0.61*	*0.62*
Peer_rob	-.0064	.012	-.12*	.026		.036	-.016	-.089	-.031
	0.10	*0.15*	*1.72*	*0.34*		*0.60*	*0.24*	*1.11*	*1.08*
Peer_fel_drg	.017	-.069	.00030	.12	-.042		.0094	.070	-.0038
	0.24	*0.82*	*0.00*	*1.44*	*0.87*		*0.13*	*0.83*	*0.13*
Peer_mis_drg	-.025	-.071	-.045	-.083	.082**	.026		-.030	.039*
	0.46	*1.09*	*0.79*	*1.34*	*2.20*	*0.54*		*0.47*	*1.70*
Peer_aggass_fwpn	.034	-.12**	-.012	.0098	.025	-.023	.013		.036*
	0.72	*2.13*	*0.25*	*0.18*	*0.76*	*0.55*	*0.27*		*1.79*
Peer_fel_sex	-.051	.10	.065	-.078	.083	.089	-.015	.096	
	0.55	*0.93*	*0.66*	*0.72*	*1.30*	*1.07*	*0.16*	*0.86*	
Peer_mis_wpn	-.016	-.066	-.11	-.26*	.0071	-.22*	-.052	.0075	.0060
	0.12	*0.43*	*0.79*	*1.76*	*0.08*	*1.89*	*0.41*	*0.05*	*0.11*
Peer_mis_sex	-.26	-.10	.0020	.14	.47**	-.30	-.21	.14	-.12
	1.18	*0.39*	*0.01*	*0.54*	*3.06*	*1.51*	*0.96*	*0.54*	*1.23*
Peer_vand	.016	-.034	-.0069	.11*	-.0028	-.022	-.074	.084	.019
	0.31	*0.55*	*0.13*	*1.82*	*0.08*	*0.47*	*1.44*	*1.36*	*0.85*
Peer_dsord	-.068	-.093	-.017	-.019	-.052	.18**	.14**	.0018	.017
	0.96	*1.09*	*0.23*	*0.23*	*1.07*	*2.85*	*1.98*	*0.02*	*0.54*
Peer_escp	.17*	.034	.10	.12	.076	.065	.076	-.15	.033
	1.83	*0.31*	*1.07*	*1.17*	*1.19*	*0.79*	*0.82*	*1.34*	*0.84*
Peer_other	-.079	-.033	-.082	.0096	.018	.020	.053	-.018	.053*
	1.09	*0.38*	*1.08*	*0.12*	*0.36*	*0.31*	*0.74*	*0.21*	*1.70*
Peer_male	-.056	-.099	-.050	.0095	.0067	.015	.076	.016	-.0074
	0.58	*0.86*	*0.49*	*0.09*	*0.10*	*0.18*	*0.80*	*0.13*	*0.18*
Peer_age_exit	.013	.023	.039**	.028	.0015	.0025	-.0042	-.013	.0022
	0.73	*1.08*	*2.13*	*1.36*	*0.12*	*0.16*	*0.24*	*0.63*	*0.29*
Peer_Percapi	-7.5e-06*	5.0e-06	8.2e-06*	-9.5e-08	3.0e-06	-.000011**	-10e-06**	1.6e-06	1.1e-06
	1.79	*0.98*	*1.84*	*0.02*	*1.03*	*2.81*	*2.37*	*0.32*	*0.61*
Peer_Percorin	-.00011	.0010	2.8e-06	-8.7e-06	.00012**	.000081	.000011	.00013	8.3e-06
	1.27	*1.05*	*0.03*	*0.09*	*2.16*	*1.08*	*0.14*	*1.31*	*0.23*
Peer_age1st	.014	-.0077	.00035	-.0054	-.012	-.010	-.013	.017	.0042
	1.13	*0.52*	*0.03*	*0.38*	*1.43*	*0.94*	*1.07*	*1.16*	*0.79*

Appendix Table 2 (Continued)

Dependent Variable = Recidivate with:	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Agg. Assault FWpn	R_Felony Sex
Auto theft	.080**	.0086	.0052	.000099	.029**	.018*	.030**	.012	.0053
	7.54	*0.68*	*0.46*	*0.01*	*3.98*	*1.93*	*2.86*	*0.98*	*1.17*
Burglary	.0078	.067**	.023**	.013	-.00072	.0075	-.0083	-.025**	.0026
	0.76	*5.48*	*2.12*	*1.15*	*0.10*	*0.82*	*0.82*	*2.02*	*0.60*
Grlrcn	.0049	.034**	.037**	.011	.0035	-.0045	.0011	.0036	.0064
	0.48	*2.77*	*3.40*	*0.90*	*0.49*	*0.49*	*0.11*	*0.30*	*1.45*
Plrcn	.017*	.018*	.029**	.044**	.016**	-.012	.015*	.00069	-.0021
	1.83	*1.67*	*3.05*	*4.19*	*2.58*	*1.79*	*1.66*	*0.06*	*0.55*
Robbery	-.0014	-.022	-.033**	-.0051	.065**	.023*	.0050	.031*	-.0038
	0.09	*1.28*	*2.19*	*0.31*	*6.50*	*1.82*	*0.35*	*1.80*	*0.62*
Fel drug	-.027*	-.060**	-.039**	-.014	.0014	.19**	.025*	.024	.0042
	1.87	*3.48*	*2.60*	*0.83*	*0.15*	*14.22*	*1.77*	*1.42*	*0.69*
Mis drug	-.013	-.026*	-.018	-.032**	-.0045	.022**	.12**	.0073	-.0018
	1.08	*1.79*	*1.46*	*2.31*	*0.55*	*2.02*	*9.60*	*0.51*	*0.35*
AggAss_Fwpn	.0019	.0042	.0037	.0033	.0041	-.00025	-.0060	.073**	-.0041
	0.20	*0.37*	*0.37*	*0.30*	*0.62*	*0.03*	*0.64*	*6.37*	*0.10*
Fel sex	-.0079	-.016	-.038*	.014	-.0059	-.045**	-.037**	.011	.062**
	0.41	*0.71*	*1.88*	*0.66*	*0.45*	*2.66*	*1.97*	*0.47*	*7.50*
Mis weap	.022	-.010	-.0060	-.032	-.0043	.0063	-.0060	-.056**	-.0023
	1.00	*0.39*	*0.27*	*1.29*	*0.29*	*0.33*	*0.28*	*2.17*	*0.25*
Mis sex	.046	.12**	.081*	.11**	.069**	-.017	-.013	-.027	-.026
	1.06	*2.23*	*1.76*	*2.25*	*2.29*	*0.44*	*0.29*	*0.52*	*1.41*
Escape	.048**	-.00059	.0021	-.0082	-.0026	-.0016	-.00083	.042**	-.0023
	2.71	*0.03*	*0.11*	*0.40*	*0.21*	*0.10*	*0.05*	*1.98*	*0.31*
Vandalism	-.012	.0087	.023**	.021*	.0024	-.023**	-.018*	.012	-.0082*
	1.23	*0.73*	*2.23*	*1.88*	*0.36*	*2.58*	*1.83*	*1.06*	*1.95*
Disorder	-.0086	-.012	.0035	.011	.011	.0027	-.0023	.012	-.0014
	0.58	*0.67*	*0.22*	*0.66*	*1.08*	*0.20*	*0.15*	*0.66*	*0.22*
Other	.024	.010	.017	.021	.0055	.020	.0083	.054**	-.00086
	1.57	*0.57*	*1.07*	*1.19*	*0.53*	*1.47*	*0.55*	*2.97*	*0.13*
Female	-.041*	-.061**	-.016	-.0087	-.0067	-.041*	-.050**	-.034	-.019*
	1.75	*2.16*	*0.64*	*0.32*	*0.41*	*1.93*	*2.14*	*1.20*	*1.87*
Black	.047**	.025	.014	.018	.035**	.075**	.016	.086**	.00081
	3.10	*1.35*	*0.89*	*1.01*	*3.33*	*5.47*	*1.03*	*4.70*	*0.12*
Age Exit	-.011**	-.0062	-.0039	-.023**	-.0049	.010**	.0027	-.014**	-.0031
	2.10	*0.98*	*0.71*	*3.77*	*1.34*	*2.20*	*0.51*	*2.29*	*1.37*
Age First Offense	.0010	-.0022	-.0020	.0026	-.0020	-.0042*	-.0057**	-.0056	.00026
	0.35	*0.65*	*0.65*	*0.78*	*1.01*	*1.65*	*1.99*	*1.63*	*0.21*
Days In	.000050	.000028	.000036	.000015	-.000011	.000019	-.000047	-.000074	.000028
	0.67	*0.31*	*0.46*	*0.17*	*0.21*	*0.29*	*0.64*	*0.83*	*0.89*
Felonies	.0022*	.0045**	.00069	.0015	.00035	.000030	.00045	.00046	.00021
	1.64	*2.77*	*0.48*	*0.97*	*0.37*	*0.02*	*0.33*	*0.28*	*0.36*
Youth Crime Rate in Zip	.0025	-.00061	-.0047**	-.0041*	.0031**	.0025	-.00037	.0034	-.00062
	1.27	*0.26*	*2.27*	*1.83*	*2.28*	*1.44*	*0.19*	*1.43*	*0.73*
% Own Race in Zip	.0093	.050*	.019	-.0023	.023	.0014	-.015	.047*	.0064
	0.42	*1.85*	*0.79*	*0.09*	*1.49*	*0.07*	*0.69*	*1.77*	*0.67*
Per-Cap Inc Race	.0018	-.0011	.0027	-.00060	.000098	-.00049	.00033	-.00047	-.00071
	1.06	*0.51*	*1.48*	*0.30*	*0.08*	*0.32*	*0.19*	*0.23*	*0.96*
Unemployment Rate	-.078	-.32	.25	-.034	.028	.051	.44**	-.37	-.13
	0.36	*1.24*	*1.11*	*0.14*	*0.19*	*0.27*	*2.02*	*1.42*	*1.42*
Incarcerated in Zip	.00053	.00075	.0014	.0014	.0028**	-.0021	-.0021	.0050**	.00079
	0.35	*0.41*	*0.88*	*0.82*	*2.71*	*1.58*	*1.40*	*2.78*	*1.23*
# who recidivate with offense:	365	570	398	483	165	315	362	550	60
# observations	4266	4266	4266	4266	4266	4266	4266	4266	4266
R^2	.0835	.1053	.0632	.0568	.0860	.1616	.0849	.0868	.0520

NOTE.—The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications include facility fixed effects.

Appendix Table 3. Determinants of Sentence Length

Dependent Variable =	Days In
Female	-1.1
	0.34
Black	3.9*
	1.81
Age Exit	20.4**
	25.29
Age First Offense	-9.5**
	16.00
Last Felony Sex	133.8**
	17.61
Last Misd. Sex	-5.4
	0.24
Last Felony Drug	-3.9
	0.82
Last Misd. Drug	-17.5**
	3.58
Last Auto Theft	16.0**
	3.81
Last Burglary	24.0**
	6.94
Last Grand Larceny	2.3
	0.59
Last Petty Larceny	-11.0**
	2.92
Last Robbery	47.5**
	8.29
Last Escape	31.7**
	5.28
Last Vandalism	5.6
	1.14
Last Disorder	-18.0*
	1.95
Last Agg. Assault / FWpn	33.3**
	9.12
Last Misd. Weapon	-3.7
	0.28
Last Other	2.4
	0.55
Past Felony Sex	41.9**
	9.07
Past Misd. Sex	14.9
	1.30
Past Felony Drug	-5.4*
	1.66
Past Misd. Drug	-15.2**
	5.44
Past Auto Theft	12.6**
	5.08
Past Burglary	5.0**
	2.06
Past Grand Larceny	8.6**
	3.50
Past Petty Larceny	-2.7
	1.20
Past Robbery	25.6**
	7.60
Past Escape	46.0**
	10.45
Past Vandalism	1.2
	0.49
Past Disorder	.66
	0.18
Past Agg. Assault FWpn	6.5**
	2.76
Past Misd. Weapon	6.0
	1.17
Past Other	-4.1
	0.98
Constant	181.9**
	185.11
# observations	14127
R^2	.1212

NOTE.—The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All variables are constructed such that they have mean zero. This regression uses the entire sample of individuals released from these 169 facilities.