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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 and facility-by-prior offense fixed effects, thereby estimating peer effects using only within-facility variation over time. We find strong evidence of peer effects for burglary, petty larceny, felony and misdemeanor drug offenses, aggravated assault, and felony sex offenses; the influence of peers primarily affects individuals who already have some experience in a particular crime category. We also find evidence 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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"Danbury wasn't a prison. It was a crime school. I went in with a bachelor of marijuana and came out with a doctorate of cocaine." George Jung (Johnny Depp) describing his introduction to cocaine industry in the motion picture *Blow*.

I. Introduction

Understanding the importance and nature of social interactions in criminal behavior not only provides insight into crime as an economic and social phenomenon, it is also important from a policy perspective. Broadly speaking, social interactions are likely to magnify the impact of any changes to economic and social fundamentals, which implies that policy changes are likely to have important dynamic benefits and costs. A better understanding of how criminal knowledge is spread and how criminal networks form can also be used to shape decisions throughout the criminal justice system, such as how to optimally group individuals convicted of various crimes within correctional facilities so as to reduce future recidivism.

Prior empirical research has documented evidence consistent with the possibility that social interactions are of first-order importance in criminal behavior. Glaeser et al. (1996), for example, show that crime exhibits extremely high variance across time and space and that only a small portion of this can be explained by detailed measures of fundamental economic and social conditions.[1] A longstanding criminology literature, starting with Glueck and Glueck (1950), documents a strong positive correlation between individual and peer criminal (delinquent) behavior.[2] But, few papers convincingly document causal effects of peers on one another. Jacob and Lefgren (2003) find that school attendance increases violent crimes but decreases property crimes, which underscores the role played by social interactions in explaining violent crimes. Other research has studied the role of neighborhoods in determining criminal behavior, although it remains unclear in these studies whether the results are driven by changes in private incentives or by social interactions (Case and Katz, 1991; Ludwig et. al., 2001; Kling et. al., 2005).

In light of the limited 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 matching of individuals to their peers. Specifically, we examine whether the behavior of a juvenile offender upon release 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 who served time in 169 juvenile correctional facilities

[1] Glaeser et al. (1996) builds on earlier work on social interactions and crime by Sah (1991) and Murphy, Shleifer and Vishny (1993).

[2] See Akers et. al., 1979; Elliott et. al., 1985; Erickson and Empey, 1965; Jensen, 1972; Matsueda and Heimer, 1987; Tittle et. al. 1986; Voss; 1964; Warr and Stafford; 1991). Reiss (1988) and Warr (1996) provide a summary of sociological research based on co-offender surveys.

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.

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 and facility-by-prior offense 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.[3] 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 tests of this central identifying assumption, demonstrating that: (i) the within-facility variation in peer characteristics is orthogonal to all observable individual characteristics, (ii) the estimated peer effects are completely robust to general or localized trends in criminal activity, and (iii) the estimated peer effects cannot be explained by the facility assignment of individuals who have committed crimes together.

One of the goals of this paper is to understand how crime is spread and the mechanisms underlying this dispersion. Thus, an important feature of our analysis is that it allows crime-specific peer effects to vary with an individual's own criminal experience. In this way, we seek to distinguish between peer effects that reinforce existing criminal tendencies and those that cause individuals to branch out into new areas of criminal activity. Our analysis provides strong evidence of the existence of peer effects in juvenile correctional facilities. In almost every instance, these peer effects are reinforcing in nature: 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. In our main specification, reinforcing peer effects exist for burglary, petty larceny, felony and misdemeanor drug offenses,

[3] Recent research on peer and neighborhood effects in other settings has relied on particular randomizing events, such as the random assignment of roommates (Sacerdote, 2001) or social experiments such as MTO in Boston (Katz et. al., 2001) or STAR in Tennessee schools (Boozer and Cacciola, 2001). While the explicit randomization present in these events or experiments is ideal, relying exclusively on such events severely limits the settings where peer effects can be studied and the generalizability of the findings.

aggravated assault, and felony sex offenses. In contrast, there is no evidence of such peer effects for individuals with no prior experience in a given crime category. We demonstrate the robustness of these results to a variety of alternative specifications and explore heterogeneity in the magnitude and nature of peer effects across individuals, peers, and facilities. Taken as a whole, these results help to distinguish among alternative explanations for the existence of crime-specific peer effects, a matter we take up later in the paper.

The remainder of the paper is organized as follows. Section II describes the data and provides some background on the Florida juvenile justice system. Section III outlines our basic empirical methodology and presents a number of diagnostic tests of our identifying assumption. Section IV presents the results and Section V concludes.

II. Data and Juvenile Corrections in Florida

Assignment to Juvenile Corrections in Florida

The assignment of juveniles to facilities in Florida typically occurs in two steps with the judge first deciding the appropriate risk level of the youth and the Department of Juvenile Justice then assigning the youth to a particular program. More specifically, upon the finding by the courts that a juvenile has committed a delinquent act, Department of Juvenile Justice probation officers must prepare a predisposition report and assessment. Under Florida statutes, this predisposition report must include a classification of the risk level of the youth, which captures the degree to which the youths represent a risk to themselves and the public. There are five risk levels: minimum-, low-, moderate-, high-, and maximum-risk. During the period of our study, decisions were primarily made on the basis of current and past offense characteristics.[4] In addition, individuals whose current offense is a first-degree felony, a sex offense, or a firearm-related offense are automatically excluded from the minimum and low risk categories. Based on the probation officer's recommendation and assessment of the youth, the judge makes the final decision about the appropriate risk level.[5]

[4] More recently, the probation officer's report is largely based on the results of an assessment tool that was put in place in 2005; in addition to information about current and past offenses, PACT (Positive Achievement Change Tool) includes a series of questions about schooling, free time, employment, relationships, family history, living arrangements, alcohol and drugs, mental health problems, attitudes, aggression and skills. The recommended risk level is largely based on the youth's PACT score.

[5] Significant efforts were made to identify an algorithm that is used to assign the risk level. Such an algorithm is not written into Florida statutes nor readily available.

These risk levels are also used to classify facilities.[6] One of the primary differences across facilities within these different risk levels is the level of access that youths have to the community. Minimum risk facilities are non-residential; youths in these facilities live at home and participate at least five days a week in a day treatment program. Low risk facilities are residential but the youth are allowed to have unsupervised access to the community. Only supervised access to the community is allowed in moderate risk facilities and rare access in high and maximum risk facilities. The level of security also increases with facility level.

Given this judge-assigned risk level, the Florida Department of Juvenile Justice places the juvenile in a particular program. These programs 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, jails, etc.[7] The decision as to the appropriate program within a given risk level for a particular youth is based on a number of factors, including: the recommendation of the probation officer, any special needs of the youth that were determined in the assessment, and the availability of beds.

Data Description

The primary data source is the internal database maintained by the Florida Department of Juvenile Justice (DJJ) for juvenile offenders under its care. We were granted access to the DJJ's records on all youths (16,164 individuals) released from a Florida-based juvenile correctional facility between July 1, 1997 and June 30, 1999.[8] For each of these individuals, the data detail whether or not the individual recidivates within the first year following release. Because the type of crime committed upon recidivating is only available if the individual is younger than age eighteen at the date of re-arrest (i.e. still a juvenile in the Florida system), we restrict the sample to individuals age seventeen and younger at the time of release.[9] Of the 9,382 individuals younger than seventeen at release, the data are missing facility assignment in 982 cases and admit/release date information in an additional 184 cases. Thus, the primary sample used in our analysis contains 8,216 juveniles aged seventeen and younger at the time of release. It is important to

[6] See the Florida Department of Juvenile Justice website, http://www.djj.state.fl.us/Residential/index.html, for more details.

[7] A detailed description of the different types of facilities can be found in Bayer and Pozen (2005).

[8] 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.

[9] Individuals who are 14 and older and who commit sufficiently serious crimes may be processed in the adult criminal system. Though we cannot observe such recidivism offenses, this should not influence the results regarding relatively minor crimes such as misdemeanor drugs, petty larceny, and burglary.

emphasize, however, that all individuals for whom facility assignment and admit/release date information is available are used in constructing the measures of peer characteristics.

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 and 67 percent by the latter. We use a subsequent criminal charge as our definition of recidivism because 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.[10] Using this measure of recidivism, Table 1 shows that 14 percent of the sample recidivates with a burglary offense, 12 percent with a petty larceny offense, and 9 percent with a felony drug offense, misdemeanor drug offense, auto theft, and a grand larceny offense, respectively. Note that because the different possible outcome variables are not mutually exclusive, the sum of the recidivism rates in all possible crime categories is greater than the overall recidivism rate of 67 percent.

The paper focuses on ten main crime categories: auto theft, burglary, grand larceny, petty larceny, robbery, felony drug crimes, misdemeanor drug crimes, aggravated assault and/or battery, felony weapons crimes, and felony sex crimes. Appendix Table 1 contains descriptions of particular crimes associated with each of these categories. These categories were chosen on the basis of three criteria: (i) the offense is serious enough to contribute to the FBI crime index; (ii) the offense is defined well enough to interpret the results; and (iii) recidivism rates are great enough so that the estimation is reasonably precise. Disorderly conduct is not included, for example, because the exact nature of the offense varies greatly across crimes, and misdemeanor sex offense is not included because only 27 of the 8,216 individuals recidivate with this crime.

The individual characteristics listed in Table 1 provide basic information on the youths' age, gender, race, and sentence length. The criminal history variables encompass all charges formally brought against the youth within the Florida system prior to placement in a correctional facility; the variables used in our analysis indicate whether an individual has *any* history of committing a particular type of offense, regardless of the number of times the individual has committed the offense. Neighborhood characteristic variables are constructed using each youth's

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

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

Constructing the Peer Measures

Table 1 also presents descriptive statistics for measures of peer characteristics; the list of peer characteristics parallels the list of individual characteristics (i.e. the demographic, criminal history, and neighborhood characteristics). The peer measures are essentially weighted averages of a particular characteristic, where the weights are the number of days an individual is exposed to each peer. In constructing these peer measures, however, one must account for the fact that we only observe individuals who are *released* in the two-year period from July 1, 1997 to June 30, 1999. Thus, for individuals who are released towards the beginning (end) of the sample period, any peers who are released before (after) the sample period begins will not be observed; we classify these individuals as pre and post-censoring cases. However, while we cannot identify each youth's exact set of peers, we can calculate an unbiased estimate of their 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 is the central identifying assumption of the paper and we provide direct evidence to support this assumption below.

In particular, 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. 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 construct the peer measure, dealing with four separate cases of censoring, in Appendix 1.

III. Empirical Methodology and Identification

Empirical Specification

The primary analysis presented in this paper relates recidivism to vectors of individual and peer characteristics.[11] The general specification that we take to the data can be written as:[12]

$$R^h_{ijt} = \beta_0 \left(Offense^h_{ijt} * Peer\_offense^h_{ijt}\right) + \beta_1 \left(No\_Offense^h_{ijt} * Peer\_offense^h_{ijt}\right) + P_{ijt}\alpha + X_{ijt}\gamma + \lambda_j + Offense^h_{ijt} * \mu_j + \eta_t + \varepsilon^h_{ijt} \quad (1)$$

The dependent variable, R^h_{ijt} indicates whether individual *i* in facility *j,* who is released in period *t*, recidivates with offense type *h*. $Peer\_offense^h_{ijt}$ describes an individual's exposure to peers with a history of offense type *h*. $Offense^h_{ijt}$ equals one if individual *i* has a history of offense type *h*, while $No\_Offense^h_{ijt}$ indicates no prior history of that offense. P_{ijt} is a vector of additional peer characteristics including demographic variables as well as peer criminal histories in all other crime categories. Similarly, X_{ijt} is a vector of individual demographic and criminal history variables, including prior histories in all other crime categories. We estimate equation (1) for ten crime categories simultaneously using a seemingly unrelated regression (SUR) framework.[13]

Following the theoretical motivation laid out in the introduction, we focus our analysis on crime-specific peer effects: e.g., does the increased exposure to peers with a history of auto theft make an individual more likely to commit auto theft upon release? These crime-specific peer effects are captured by the parameters β_0 and β_1 in equation (1). It is important to emphasize that the *total number* of prior felonies along with controls for the prior histories of peers in *each* of the ten crime categories are included in each regression in the vector P_{ijt}.

A second important feature of equation (1) is that it allows crime-specific peer effects to vary with an individual's own criminal experience, as reflected in the parameters β_0 and β_1. We chose this specification at the outset for two main reasons. First, the distinction between peer

[11]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, our analysis will understate the overall level of increased criminal activity that follows exposure to peers with more experience at a given crime. On the other hand, it is possible that exposure to peers in prison makes an individual bolder or less cautious when committing crimes upon release; this type of "machismo" effect could increase arrest rates even if the underlying level of criminal activity has not changed.

[12] 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.

[13] 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.

effects that reinforce existing criminal tendencies and those that cause individuals to branch out into new areas of criminal activity is of first-order importance for (i) determining which theoretical explanations for the presence of peer effects are consistent with the data and (ii) policymakers concerned with optimal assignment, as knowledge of the nature of crime-specific peer effects helps to determine the best way to group individuals on the basis of prior criminal records. Second, the existing literature demonstrates that juvenile offenders show tendencies to specialize – i.e., recidivate in a crime category in which they already have a criminal history (Wolfgang et. al., 1972; Bursik, 1980; Rojek and Erickson, 1982; Cohen, 1986; Farrington et. al., 1988). Within our dataset, Table 2 reports OLS estimates of regressions of recidivism in each crime category on whether the individuals had any history of each of the ten crimes. The first row presents the diagonal coefficients (e.g. the relationship between having a history of auto theft and recidivating with auto theft) while the second row presents the average of the off-diagonal coefficients. In every case but felony weapons, experience in a particular crime is a significant predictor of recidivating with that crime; in addition, the magnitudes of these specialization coefficients are greater than those for all other types of criminal experience (as reflected in the average of the off-diagonal coefficients). Thus, allowing an individual's prior criminal experience to have both a level and slope effect in equation (1) permits the estimated peer effects to take a flexible form with respect to the baseline propensity to recidivate in a crime category.[14]

A third important feature of our main specification, and the main innovation of our analysis vis a vis the existing literature, is the inclusion of facility-by-prior offense fixed effects. As written, λ_j applies to all individuals in the facility, while μ_j is an additional facility fixed effect that applies to individuals with a history of offense type *h*, $Offense^h_{ijt}$. The inclusion of these fixed effects controls for: (i) the non-random assignment of individuals to facilities and (ii) any unobserved differences correlated across all individuals in a facility. In both cases, separate fixed effects are estimated for those with and without a prior history in a given crime category. This ensures that the impact of peers on recidivism is identified using only within-facility variation in peer exposure.[15] In order for this methodology to yield consistent estimates of causal peer effects,

[14] It is important to note that both individual and peer criminal history measures are based on whether an individual has *any* history of the particular offense rather than whether it is the most recent offense. The results of additional regressions (not included in the paper) that include distinct variables characterizing an individual's past versus most recent crimes indicate that prior offenses have a remarkably similar impact on recidivism no matter when they occurred. This may reflect the short criminal histories of juveniles, which typically impy that even the most distant crimes have occurred in the not so distant past.

[15] 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. Table 1 reports both overall and within-facility standard deviations for each peer measure, showing that a substantial amount of variation in peer measures remains when the variation is restricted to within-facility.

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.[16]

Therefore, an important concern, which could invalidate this identifying assumption, is the possibility of trends in criminal activity. If, for example, there is a general upward trend in felony drug crimes over the course of our sample, then individuals observed later in the sample will both (i) likely be exposed to a higher proportion of peers with a history of felony drug crimes and (ii) be more likely to recidivate with a felony drug crime upon release; this would bias estimated peer effects upwards. To assess the extent to which peer composition (and therefore crime itself) has changed over the course of our sample period, we regress peer exposure in each of the ten crime categories on quarter of release dummies. Relative to the first quarter, we find that there is some evidence of downward trends in crime; this pattern is strongest for property crimes. However, just 29 of the 70 estimated coefficients are significant and the magnitudes of the coefficients are consistently quite small, especially when compared to the average peer measure; the average coefficient on the quarter of release dummies is just -.009.

To account for these slight trends in crime, we include quarter of release dummies η_t in our baseline specification - equation (1), although it is worth noting that these have a negligible effect on the estimated coefficients. We also provide additional evidence below that these minimal trends in crime are not a significant concern. In particular, we show that our main results are not sensitive to controlling for crime trends in a number of ways, including: month dummies, judicial circuit by quarter dummies, and judicial circuit specific monthly time trends.

Diagnostic Tests of Identifying Assumption and Other Threats to Identification

As mentioned above, our ability to identify causal peer effects rests on the assumption that the timing of the assignment of individuals to facilities is as good as random within the two-year study period. This assumption gives rise to a clear implication that is testable on observable characteristics: within-facility variation in peer characteristics should be uncorrelated with individual characteristics. In Tables 3a and 3b, we provide a test that individual observable characteristics are essentially orthogonal to the within-facility variation in peer measures. In

[16] It is important to note that because we do not directly observe whether an individual interacts with all of his peers, the peer effect identified in our analysis combines the true impact of each peer interaction within the facility with the likelihood (or intensity) with which that interaction occurs. In this way, it is important to recognize that the effect captured here is context-specific. While this would be the effect of interest for policymakers concerned with optimal assignment in Florida's juvenile facilities, because this effect depends in part on the nature of the interactions that occur within Florida's juvenile correctional facilities, it is impossible to ascertain the more structural effect associated with each distinct peer interaction.

particular, we construct an index of individual characteristics for each crime category using a measure of predicted recidivism derived from a regression of recidivism on individual characteristics and facility fixed effects; the predicted recidivism measure is the fitted value for the individual characteristics in this regression. This measure 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 3a reports the results of regressing this predicted recidivism measure on just the two peer measures of primary interest for each crime category; i.e. the two interaction terms. Table 3b repeats these regressions adding facility-by-prior offense fixed effects. In Table 3a, the estimated coefficients are statistically significant in almost every instance. Thus, peer exposure is strongly correlated with pre-determined individual attributes that likely affect facility assignment. In Table 3b, on the other hand, where only within-facility variation in peers is used in both measures, there is almost no evidence of correlation between peer characteristics and predicted recidivism. Almost all of the coefficients decrease in size by one to two orders of magnitude. In fact, for individuals without a prior history in the crime category, the coefficients, β_1, are never significant and in all cases are quite small. For individuals with a prior history in a crime category, only the felony weapons coefficient is significant, although it is still quite small in size.

In general, then, this 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 pre-determined individual attributes related to recidivism in each crime category and (ii) any analysis of peer effects that incorporates across-facility variation is likely to lead to sizeable biases in the estimated effects.

A separate issue related to facility assignment that might invalidate our identifying assumption is the concern that youths who have committed crimes together might be assigned to the same facility. 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 in correctional facilities. With regards to this potential concern, it is important to first point out that the lack of any systematic within-facility correlation between individual and peer characteristics described above already implies that there is not any undo clustering in the timing of assignment to correctional facilities for individuals with particular criminal histories. However, we further 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 many peers from the same zip code. In particular, of the 189 individuals released, on average, from a facility, an individual is exposed to only six individuals with the same residential 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 4 tests whether there is any undue clustering of release or admit dates for individuals from the same zip code. To test whether individuals from the same zip code are disproportionately 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. We consider individuals released within 7, 14, and 21 days of each other. Of the individuals released within seven days of one another, 2.8 percent share the same zip code, while 2.7 percent of all individuals released from the same facility share the same zip code. Similarly, 2.9 percent of those admitted within seven days of one another share the same zip code compared to 2.8 percent of those admitted during the first year of our sample period.[17] These differences, as well as those for the 14- and 21-day time periods, are not significant at the 5 percent level. More importantly, even if these differences were statistically significant, the magnitudes, which are only between 0.2 and 0.3 percent, would contribute so little to the variation in our peer measures that such neighborhood clustering cannot possibility explain even a small fraction of our results.

IV. Results

Main Results

Table 5 reports the coefficients β_0 and β_1 for a specification of the type shown in equation (1) for each crime category. The full specification is reported in Appendix Table 2 and includes facility-by-prior offense fixed effects as well as additional controls for peer and individual characteristics characterizing criminal history in each crime category, total number of past felonies, age at first offense, current age, sex, and characteristics of the residential zip code.[18]

The first row of Table 5 reports β_0, the estimated crime-specific peer effect for those *with* a history of having committed the relevant offense and the second row reports β_1, the estimated

[17] 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.

[18] 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 generally reveals broad specialization across drug crimes as well all forms of theft.

peer effect for individuals *without* a history of having committed this offense. The estimates of β_1 are negative as often as positive, with no statistically significant evidence of positive peer effects in any crime category. In addition, the hypothesis that β_1 equals zero in each category cannot be rejected; the p-value of the joint test is 0.3694. In contrast, the parameter estimates for β_0 are positive in almost every case and statistically significant for burglary, petty larceny, felony and misdemeanor drug crimes, aggravated assault, and felony sex offenses.[19] Thus, exposure to a greater percentage of peers with a history of having committed burglaries increases the likelihood that an individual with a prior adjudication for burglary commits another burglary upon release; no such effect exists for those without a prior history of burglary.

As shown in Table 2 above, the history of a prior offense in a category is a strong predictor of future recidivism. Thus, in order to get a sense of the magnitudes of the estimated reinforcing peer effects, it is helpful to compare them to the mean propensity of an individual with a prior offense to recidivate in that same crime category. On average, for example, as indicated in Table 2, individuals with a prior history of burglary recidivate with a burglary 13.6 percent of the time. Thus, the estimated reinforcing peer effect of 0.19 for burglary implies that a standard deviation increase in exposure to peers that have committed burglaries (0.16) increases the likelihood of recidivism from 13.6 to 16.6 percent for these individuals at the mean. Similarly, the estimated reinforcing peer effect for felony drug crimes of 0.31 implies that a one standard deviation increase in exposure to peers with a history of a felony drug crime (0.10) increases the likelihood of recidivating with a felony drug crime at the mean from 28.5 to 31.6 percent. In this way, the estimated magnitudes of these peer effects are sizeable, but also appear to be reasonable given the relatively high baseline propensities of individuals to recidivate in a crime category in which they have prior experience.[20]

While the nature of our analysis limits our ability to distinguish specific mechanisms through which peer effects operate, the general pattern of results presented in Table 5 does fit better with some mechanisms. One explanation that fits well with the existence of strong reinforcing peer effects and limited effects on those without prior experience in a crime category

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

[20] The magnitudes of the peer effects estimated here are also reasonable when compared to other setting where peers are randomly assigned. In a study of the effect of college roommate drinking on GPA, for example, Kremer and Levy (2003) find evidence of a large reinforcing peer effect. 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 reports evidence that the interaction between own and roommate background characteristics has a strong influence on an individual's own freshman year GPA in college.

(particularly for misdemeanor drug crimes) is that peers reinforce addictive behavior. Another explanation that fits well with economic theory is that individuals may experience different returns from participation in different types of crimes related to natural abilities, opportunities, human capital accumulation, involvement in crime networks, or other factors (as in the legitimate sector of the economy). In this case, individuals with a history in a crime category have already revealed themselves to have high returns and, likely, substantial human capital in this category. Consequently, access to peers that increase the individual's returns to this type of crime through, for example, social learning, may lead to increased activity in this category.[21] Conversely, access to peers that increase returns in *another* category may be much less valuable, as this may not raise the returns in that category enough to change the individual's optimal behavior.[22]

Robustness and Heterogeneity of Main Results

As discussed previously, one concern is that our findings are driven by trends in criminal activity. We therefore controlled for quarter of release in our main specification, as presented in Table 5. To further assess the validity of this concern, we first test the joint significance of the quarter of release dummies in each crime category presented in Table 5 and present the resulting p-values. They are jointly significant at the five percent level only for auto theft and at the ten percent level for petty larceny. Thus, not only is there a low correlation between quarter of release and our peer measures, quarter of release also predicts little of recidivism. Table 6 further shows the robustness of our results across crime categories to time trends and presents the results of estimating equation (1) with (i) no controls for time, (ii) quarter of release dummies (i.e. our baseline specification), and (iii) interactions between dummies for the 20 judicial circuits and each quarter of release. The point estimates are remarkably similar across each of these specifications and evidence of a reinforcing peer effect is consistently seen for burglary, felony drugs, misdemeanor drugs, aggravated assault, and felony sex offenses; the reinforcing peer effect for petty larceny loses its significance when quarter by judicial circuit interactions are included, but is still very close in magnitude.

To simplify the comparison of our main results presented in Table 5 with alternative specifications (like those in Table 6), the rest of our analysis estimates equation (1) under the constraints that (i) the reinforcing peer effects are equal across crime categories and (ii) the non-

[21] A small but growing body of research in economics on social learning and network formation includes Besley and Case (1994), Foster and Rosenzweig (1995), Munshi (1999), and Conley and Udry (2002).

[22] Put another way, it is important to distinguish between learning from one's peers and how that learning translates into subsequent criminal activity. The results suggest that learning in a category in which the youth already has experience may be more valuable and therefore more likely to be translated into action.

reinforcing peer effects are equal across crime categories. This yields just two coefficients of interest from each specification rather than twenty. Row (1) of Table 7 displays the results of estimating our baseline specification, presented in Table 5, in this way. This yields a highly significant reinforcing peer coefficient of 0.111 and insignificant non-reinforcing peer coefficient of 0.006. These coefficients are virtually identical when controlling for quarter by judicial circuit interactions, month of release dummies, and judicial circuit specific time trends, as seen in rows (2) – (4) of Table 7.

Row (5) of Table 7 presents the constrained coefficients that result when estimating equation (1) without individual characteristics. The estimated reinforcing and non-reinforcing peer effects are virtually identical to our baseline results (0.114 and 0.007). This result is further evidence in support of our identifying assumption since the inclusion of individual characteristics should have no effect on the estimated peer effects if they are uncorrelated with peer measures.

Although each regression presented thus far includes separate fixed effects for individuals with and without a history of having committed that crime, it is important to note that an individual's own history of committing an offense is interacted with only a single peer measure – the propensity of peers to have previously committed crimes in that category. This naturally leads to the question of whether the evidence of reinforcing peer effects would be eliminated if an individual's own offense history was fully interacted with the complete set of peer offense characteristics. To explore this possibility, we estimated the following fully interacted specification.

$$
\begin{aligned}
R^h_{ijt} &= \beta_0 \left(Offense^h_{ijt} * Peer\_offense^h_{ijt}\right) + \beta_1 \left(No\_Offense^h_{ijt} * Peer\_offense^h_{ijt}\right) \\
&\quad + \left(Offense^h_{ijt} * Peer\_offense^{-h}_{ijt}\right)\varpi + \left(No\_Offense^h_{ijt} * Peer\_offense^{-h}_{ijt}\right)\sigma \\
&\quad + X_{ijt}\gamma + \lambda_j + Offense^h_{ijt} * \mu_j + \eta_t + \varepsilon^h_{ijt}
\end{aligned} \tag{2}
$$

Row (6) of Table 7 presents the results from estimating equation (2) when β_0 and β_1 are constrained to be constant across crime categories; the estimates are 0.117 and 0.006 respectively. These are virtually identical to our baseline specification. In addition, most of the coefficients on the off-diagonal interactions, ϖ and σ, are not significant. Tests of the joint significance of these off-diagonal terms for each crime category indicate that (i) none of the non-reinforcing off-diagonal coefficients, σ, are jointly significant and (ii) the reinforcing off-diagonal terms, ϖ, are jointly significant at the ten percent level for only burglary, aggravated assault, and felony sex offenses. In addition, none of the off-diagonal coefficients are consistently significant across the ten crime categories. For instance, exposure to peers with a history of felony drug offenses or sex offenses does not increase the recidivism of all individuals, just those individuals with histories of these offenses themselves. Thus, the reinforcing peer effect reported in our main specification is driven by crime-specific peer exposure.

To test the robustness of our measures of peer exposure to the measurement error associated with the censoring of the sample, we estimate equation (1) using only those individuals who are released during the middle two-thirds of our sample, October 31, 1997 through February 28, 1999. 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 constrained coefficients are presented in row (7) of Table 8 and are equal to 0.176 (β_0) and 0.014 (β_1). The magnitudes of these effects are somewhat greater than those reported in our baseline specification, which is consistent with the notion that the measurement error induced by the portion of the peer measure that needs to be estimated for some individuals due to censoring has an attenuating effect on the estimated peer effects.

Finally, we assess whether the estimated peer effects are heterogeneous across facility characteristics, beginning with facility size. As discussed above, the peer effect identified in our analysis combines the true impact of each peer interaction within the facility with the likelihood (or intensity) with which that interaction occurs. Thus, the estimated peer effect might differ by facility size for two reasons: (i) the true peer effect is different in small facilities or (ii) peers interact differently within large versus small facilities.[23] Row (8) of Table 7 presents the results of estimating the constrained version of equation (1) for the sample of 3,998 individuals in the 115 smallest facilities, i.e. those facilities with an average of 20 or fewer individuals concurrently serving sentences. The estimated reinforcing and non-reinforcing peer effects are equal to 0.134 and -0.002, which are again quite comparable to the results for the whole sample.

While we do not have enough data to examine peer effects separately for each type of programming used in the state (e.g., group homes, boot camps), we can estimate the model separately for the 6,990 individuals in residential facilities and 1,226 individuals in non-residential facilities. Rows (9) and (10) of Table 7 present the results for residential and non-residential facilities, respectively. The constrained reinforcing peer coefficient is equal to 0.100 in residential facilities, which is very similar to that seen for the entire sample. For non-residential facilities, this coefficient is equal to 0.171. Thus, reinforcing peer effects appear to be even larger

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[23] Also note, 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. 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.

in non-residential facilities. The constrained specification, however, masks the fact that this reinforcing peer effect is being driven by large coefficients for the crimes of auto theft, robbery, felony drug offenses, and aggravated assault. A potential explanation for these effects is that the crimes of auto theft and felony drugs are largely dependent on access to networks.[24] Non-residential facilities may inadvertently increase the formation and expansion of criminal networks by bringing together young offenders from surrounding neighborhoods.[25] This points to an obviously difficult issue for policymakers in how best to deal with first-time and other young juvenile offenders, as the evidence presented here implies that grouping them together in non-residential facilities may lead to the rapid expansion of criminal networks.[26]

V. 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 results provide strong evidence of the existence of peer effects in juvenile correctional facilities. In almost all 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. In our main analysis, this form of a reinforcing peer effect is positive and significant for the cases of burglary, petty larceny, felony drug offenses, misdemeanor drug offenses, aggravated assault, and felony sex offenses. In contrast, we find no evidence that exposure to peers with particular criminal histories significantly increases an individual's propensity to recidivate in a crime category in which the individual has no prior experience. In addition, there are large reinforcing peer effects for the crimes of auto theft and felony drug offenses in non-residential facilities; we, therefore, conjecture that the grouping of juveniles from nearby neighborhoods may inadvertently foster the formation and expansion of criminal networks.

A number of mechanisms are particularly capable of explaining the most robust feature of our findings: that peer effects tend to reinforce existing criminal behavior. One such

[24] 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.

[25] Individuals in the lowest risk category are typically assigned to non-residential facilities close to their homes (94 percent are in the same county of residence), while all others are assigned to residential facilities typically much further from home (only 27 percent are in the county of residence).

[26] Previous specifications also considered the role played by sentence length in more detail and, in particular, controlled for the number of days served by peers. The coefficient on this variable (both when other peer measures were included and excluded) varied in sign and was never significant.

explanation is that peers reinforce addictive behavior, which may explain part of the large reinforcing peer effect for misdemeanor drug crimes. Another important explanation is that the matching of peers with common histories may lead to the creation and expansion of criminal networks, which are important for crimes such as auto theft and felony drug crimes. A more general explanation for reinforcing peer effects that we advance in the paper is that peers may increase knowledge about specific crimes, thereby increasing returns to committing those crimes. While one might initially expect this to lead to increased criminal activity by all individuals, the importance of specialization in criminal activity suggests that increased returns to a criminal activity are likely to lead to the largest increase in criminal activity in a crime category in which an individual has already specialized, thereby leading to the existence of reinforcing peer effects.

The results of our analysis have several policy implications. First, while a policy of grouping offenders with others who have committed the same crimes may seem prudent to prevent the exposure of young offenders to peers with experience in other criminal activities, such a policy may inadvertently increase exposure to peers with experience precisely in those crime categories where it is likely to be of greatest use. Second, and more broadly speaking, the existence of peer effects in juvenile criminal behavior suggests that any reduction in crime leads, through reductions in the criminal histories of peers, to future reductions in crime. It is important to account for these dynamic benefits when considering the overall benefits of reducing crime. Our analysis suggests caution in pursuing strategies that incarcerate more juveniles, as the intense exposure of juvenile offenders to one another in correctional facilities may increase the amount of criminal behavior upon release.[27] However, our analysis also suggests that other programs that reduce juvenile crime might have dynamic benefits that greatly enhance the short-term benefits derived from the decreased criminal behavior of program participants, so long as they do not increase the intensity of juvenile offenders' exposure to one another or maintain a controlled social environment.

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[27] 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.

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Appendix 1

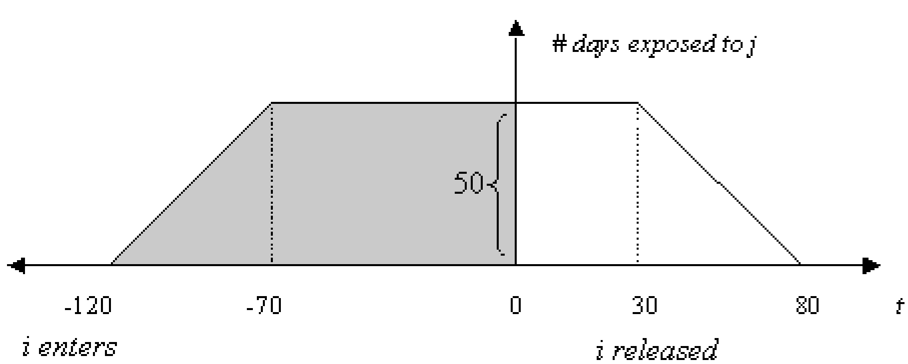
This appendix describes the exact procedure we use to calculate the peer characteristics used in the analysis. More specifically, when calculating an individual *i*'s peer exposure, we allow each observed potential peer, *j*, in the facility to contribute to this measure in two ways—directly and indirectly. 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

$$Exp_{ij} = \frac{\sum_j \left(d_{ij} + w_{ij}\right) \bullet c_j}{\sum_j \left(d_{ij} + w_{ij}\right)} \qquad \text{(A1)}$$

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

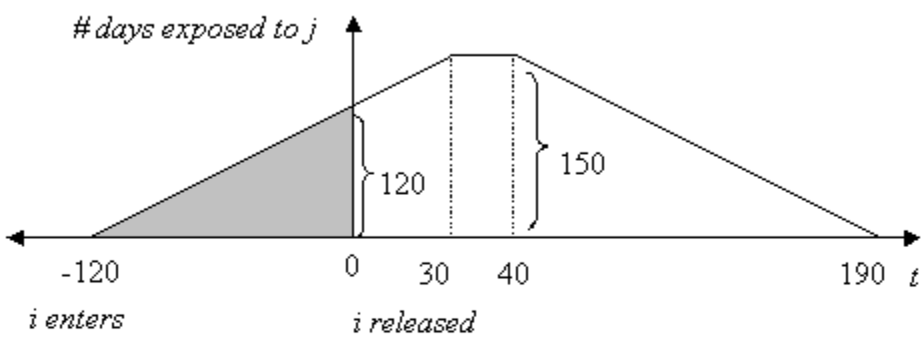


Any individuals who are released before $t = 0$ will be unobserved in the sample. To calculate the average number of days that individual i is expected to have been exposed to individual j, we simply divide the area of the shaded region by 729 (the number of days in the observed sample). To see this 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.

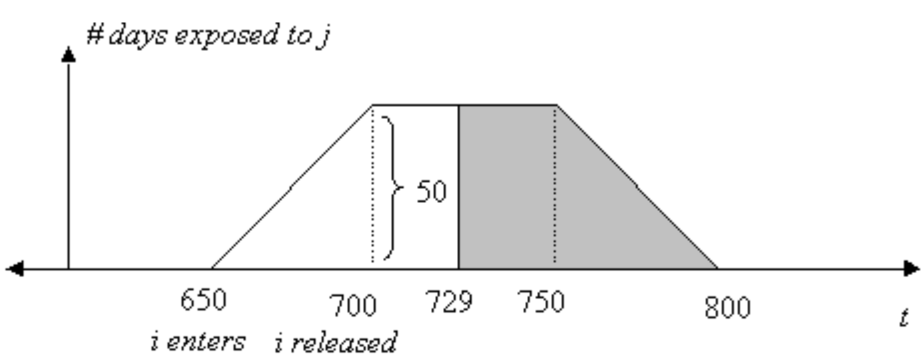
Scenario 2: *days_in[i] - days_in[j] < date_release[i] <= days_in[i]*

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

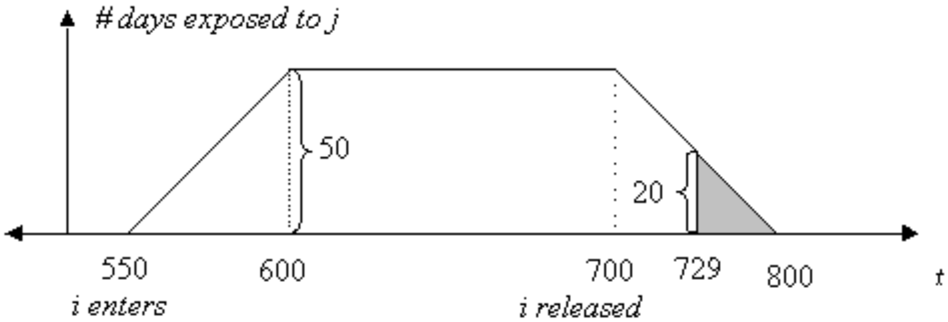


Table 1. Descriptive Statistics and Variable Definitions

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_Felony Weapon	8216	.027	.16	.16	1 if client committed felony weapon offense within one year of release, 0 otherwise
R_Agg. Assault	8216	.099	.30	.29	1 if client committed aggravated assault 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
Fel_wpn	8216	.095	.29	.29	1 if any felony weapon offense charges on client's record, 0 otherwise
Agg_Ass	8216	.29	.45	.44	1 if any aggravated assault 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_felwpn	8216	.092	.070	.046	Weighted average of whether an individual's peers have a record of any felony weapon offenses
Peer_aggass	8216	.28	.13	.070	Weighted average of whether an individual's peers have a record of any aggravated assault 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 2. Specialization in Crime

	(1) R_Auto Theft	(2) R_Burglary	(3) R_Grand Larceny	(4) R_Petty Larceny	(5) R_Robbery	(6) R_Felony Drug	(7) R_Misd. Drug	(8) R_Felony Weapon	(9) R_Agg. Assault	(10) R_Felony Sex
Offense	0.096**	0.093**	0.055**	0.047**	0.065**	0.256**	0.125**	0.014	0.112**	0.050**
	(9.78)	(10.73)	(6.54)	(6.57)	(5.74)	(15.60)	(11.05)	(1.40)	(7.25)	(5.93)
Average of Off-Diagonal Coefficients	0.013	0.014	0.001	0.002	0.014	0.015	0.012	0.008	0.025	0.000
Constant	0.029**	0.043**	0.041**	0.072**	0.008	0.029**	0.042**	0.013**	0.074**	0.008**
	(4.68)	(5.83)	(6.43)	(9.62)	(1.50)	(3.66)	(6.40)	(3.12)	(5.84)	(3.27)
Observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R-squared	0.03	0.04	0.03	0.01	0.02	0.11	0.04	0.01	0.02	0.01

NOTE.—Each column represents a different specification which is estimated by OLS, where the dependent variable is recidivism in the crime category at the top of the column. Offense varies across specifications, according to the crime category listed at the top of the column. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft). Each specification also includes controls for whether the individual has any history of each of the other nine crime categories; for brevity, only the average of these off-diagonal coefficients is presented in the table. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All standard errors are corrected for clustering at the facility level.

Table 3a. Regressions of Predicted Recidivism on the Relevant Peer Measure without Facility-by-Prior Offense Fixed Effects

Dependent Variable =	Predicted Auto	Predicted Burglary	Predicted Grand Larceny	Predicted Petty Larceny	Predicted Robbery	Predicted Felony Drug	Predicted Misd. Drug	Predicted Felony Weapon	Predicted Agg. Ass.	Predicted Felony Sex
Offense*Peer_offense (β_0)	.131**	.137**	.041**	.084**	.143**	.522**	.215**	.092**	.176**	.068**
	13.34	*13.27*	*4.92*	*10.71*	*10.94*	*23.34*	*14.16*	*11.24*	*12.86*	*3.82*
No_Offense*Peer_offense (β_1)	-.055**	.022**	-.016*	-.028**	.022*	-.039**	-.038**	.031**	-.022*	-.008**
	5.49	*2.06*	*1.88*	*3.63*	*1.93*	*2.22*	*3.18*	*5.65*	*1.71*	*2.13*
Facility-by-Prior Offense Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.3427	.3236	.2227	.1263	.1550	.3522	.3060	.0387	.2043	.2450

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). The absolute values of t-statistics are in italics and are based standard errors that are clustered at the facility level. ** 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 with OLS on just the variables presented in these tables.

Table 3b. Regressions of Predicted Recidivism on the Relevant Peer Measure with Facility-by-Prior Offense Fixed Effects

Dependent Variable =	Predicted Auto	Predicted Burglary	Predicted Grand Larceny	Predicted Petty Larceny	Predicted Robbery	Predicted Felony Drug	Predicted Misd. Drug	Predicted Felony Weapon	Predicted Agg. Ass.	Predicted Felony Sex
Offense*Peer_offense (β_0)	-.000045	-.0011	-.0015	.00089	.0036	.0021	.0020	.0077*	-.00026	.00078
	0.01	*0.31*	*0.44*	*0.42*	*0.78*	*0.23*	*0.42*	*1.83*	*0.06*	*0.27*
No_Offense*Peer_offense (β_1)	.0018	.0051	-.0030	-.0018	.00061	-.00027	.00021	.00041	.0011	.00084
	0.92	*1.21*	*1.19*	*0.67*	*0.32*	*0.08*	*0.09*	*0.29*	*0.36*	*1.28*
Facility-by-Prior Offense Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.5552	.5486	.4262	.3812	.4353	.5751	.5844	.3055	.4130	.8432

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). 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; all specifications are simultaneously estimated as a seemingly unrelated regression (SUR).

Table 4. Test for Clustering of Individuals by Five Digit Zip Codes

	Release Date			Admit Date		
	Observations	Mean in 5-digit zip	Difference from Overall	Observations	Mean in 5-digit zip	Difference from Overall
Overall	8,216	0.0273		4,148	0.0278	
Within 7 days	7,185	0.0284	0.0022 *1.34*	3,553	0.0292	0.0027 *1.22*
Within 14 days	7,808	0.0290	0.0026 *1.91*	3,938	0.0291	0.0022 *1.36*
Within 21 days	8,102	0.0290	0.0022 *1.86*	4,096	0.0297	0.0023 *1.80*

NOTE.— The value in each 'Mean in 5-digit zip' 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. 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 t-statistic corresponding to each difference is presented in italics.

Table 5. Main Results: Crime-Specific Peer Effects in Florida Juvenile Correctional Facilities

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Felony Weapon	R_Agg. Assault	R_Felony Sex
Offense*Peer_offense (β_0)	-.029	.19**	-.027	.098*	.079	.31*	.25**	-.12	.26*	.34**
	0.31	*2.93*	*0.38*	*1.67*	*0.69*	*1.90*	*2.29*	*0.78*	*1.78*	*2.30*
No_Offense*Peer_offense (β_1)	.032	-.022	-.00044	-.11	-.084*	.075	-.045	.049	.090	.043
	0.56	*0.29*	*0.01*	*1.52*	*1.70*	*1.18*	*0.82*	*0.88*	*0.91*	*1.27*
% recidivate with offense	9.3%	13.6%	9.4%	11.6%	4.5%	9.3%	9.0%	2.7%	9.9%	1.3%
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0970	.0943	.0712	.0536	.0942	.1965	.1002	.0468	.0724	.0722
P-value on test of joint significance of quarter dummies	.0328	.1075	.1557	.0575	.7902	.7817	.1463	.7371	.3827	.1096
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$	p = 0.0008									
H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$	p = 0.3694									

NOTE.— This table presents the results of estimating equation (1) for the ten crime categories simultaneously via a seemingly unrelated regression (SUR). Offense and Peer_offense vary across columns according to the crime category listed at the top of each column. 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). Each specification controls for: facility-by-prior offense fixed effects, quarter of release dummies, peer demographic and criminal history characteristics, and individual demographic and criminal history characteristics. The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. The joint hypotheses that the coefficients are equal to zero are evaluated using a Wald test.

Table 6. Robustness of Main Results to Time Trends

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Felony Weapon	R_Agg. Assault	R_Felony Sex
Panel1: No Time Controls										
Offense*Peer_offense (β_0)	-.017	.21**	-.038	.10*	.091	.32*	.25**	-.13	.27*	.34**
	0.18	*3.19*	*0.53*	*1.75*	*0.79*	*1.95*	*2.23*	*0.80*	*1.88*	*2.30*
No_Offense*Peer_offense (β_1)	.037	-.0084	-.0091	-.11	-.074	.078	-.044	.050	.092	.037
	0.65	*0.12*	*0.17*	*1.50*	*1.52*	*1.24*	*0.81*	*0.90*	*0.93*	*1.09*
Panel2: Quarter Dummies (Baseline)										
Offense*Peer_offense (β_0)	-.029	.19**	-.027	.098*	.079	.31*	.25**	-.12	.26*	.34**
	0.31	*2.93*	*0.38*	*1.67*	*0.69*	*1.90*	*2.29*	*0.78*	*1.78*	*2.30*
No_Offense*Peer_offense (β_1)	.032	-.022	-.00044	-.11	-.084*	.075	-.045	.049	.090	.043
	0.56	*0.29*	*0.01*	*1.52*	*1.70*	*1.18*	*0.82*	*0.88*	*0.91*	*1.27*
Panel3: Quarter By Judicial Circuit Interactions										
Offense*Peer_offense (β_0)	.045	.20**	-.042	.081	.049	.34**	.24**	-.14	.24*	.30**
	0.48	*3.03*	*0.58*	*1.36*	*0.42*	*2.08*	*2.15*	*0.87*	*1.68*	*2.05*
No_Offense*Peer_offense (β_1)	.042	-.033	.019	-.11	-.097	.12*	-.052	.028	.065	.036
	0.73	*0.45*	*0.34*	*1.51*	*1.95**	*1.87*	*0.94*	*0.49*	*0.65*	*1.05*

NOTE.— Each of the above panels estimates equation (1) for the ten crime categories simultaneously via a seemingly unrelated regression. The results presented in each panel control for facility-by-prior fixed effects, peer demographic and criminal history characteristics, and individual demographic and criminal history characteristics. Controls for time trends differ across panels. The first panel has no controls for time trends, the second panel includes quarter of release dummies, and the third panel includes quarter of release dummies, judicial circuit dummies, and a complete set of interactions between quarter of release and judicial circuit. Offense and Peer_offense vary across columns, and correspond to the crime category noted at the top of the column. 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). The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level.

Table 7. Robustness and Heterogeneity with Peer Effects Constrained to Be Equal Across Crime Categories

Row	Specification/Subsample Description	Offense* Peer_offense (β_0)	No_Offense* Peer_offense (β_1)
(1)	Baseline Specification (see Table 5)	.111**	.006
		3.83	*0.34*
(2)	Quarter by Judicial Circuit Interactions	.109**	.004
		3.73	*0.22*
(3)	Monthly Dummies	.112**	.006
		3.85	*0.33*
(4)	Judicial Circuit Monthly Time Trends	.105**	.004
		3.60	*0.21*
(5)	Without Individual Characteristics	.114**	.007
		3.92	*0.38*
(6)	Fully Interacted Specification	.117**	.006
		3.95	*0.33*
(7)	Middle Two-Thirds of the Sample	.176**	.014
		4.61	*0.62*
(8)	Small Facilities	.134**	-.002
		4.14	*0.12*
(9)	Residential Facilities	.100**	.005
		3.12	*0.28*
(10)	Non-Residential Facilities	.171**	-.001
		2.38	*0.03*

NOTE.— Each row of this table presents the results of a separate specification. A brief description of the specification (i.e. the variables included/excluded or the sub-sample used) is presented in the second column. We estimate each specification for all ten crime categories using a seemingly unrelated regression (SUR) but constrain both the estimated reinforcing and non-reinforcing peer effects to be equal across crime categories. Thus, rather than 20 coefficients of interest, each of these specifications generate just two coefficients of interest and provide a way of summarizing the results presented, for instance, in the first two rows of Table 5. Unless otherwise indicated, ach specification also controls for: facility-by-prior offense fixed effects, quarter of release dummies, peer demographic and criminal history characteristics, and individual demographic and criminal history characteristics.

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	Aggravated assault and/or battery; Battery on elected or education official; Hit and run (failure to remain at scene) ; Aggravated assault with deadly weapon; Aggravated assault with intent to commit a felony.
Felony Weapon	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. Full Set of Table 5 Results: Crime-Specific Peer Effects in Florida Juvenile Correctional Facilities

Dependent Variable =	R_Auto Theft	R_Burglary	R_Grand Larceny	R_Petty Larceny	R_Robbery	R_Felony Drug	R_Misd. Drug	R_Felony Weapon	R_Agg. Assault	R_Felony Sex
Offense*Peer_offense (β_0)	-.029	.19**	-.027	.098*	.079	.31*	.25**	-.12	.26*	.34**
	0.31	*2.93*	*0.38*	*1.67*	*0.69*	*1.90*	*2.29*	*0.78*	*1.78*	*2.30*
No_Offense*Peer_offense (β_1)	.032	-.022	-.00044	-.11	-.084*	.075	-.045	.049	.090	.043
	0.56	*0.29*	*0.01*	*1.52*	*1.70*	*1.18*	*0.82*	*0.88*	*0.91*	*1.27*
Peer Characteristics										
Peer_auto		.0067	.045	.051	-.020	.036	.059	-.085**	.16*	-.027
		0.11	*0.87*	*0.88*	*0.55*	*0.75*	*1.18*	*2.24*	*1.79*	*1.34*
Peer_burg	-.0071		.031	.025	.013	.027	-.0093	.0053	.088	-.00094
	0.16		*0.66*	*0.48*	*0.38*	*0.62*	*0.21*	*0.15*	*1.09*	*0.05*
Peer_glrcn	-.049	.041		-.021	-.0026	.036	.049	.028	.091	.027
	1.06	*0.75*		*0.40*	*0.08*	*0.83*	*1.09*	*0.81*	*1.13*	*1.46*
Peer_plrcn	.0029	-.090*	-.019		.018	.0089	.011	-.019	.020	.0053
	0.07	*1.84*	*0.44*		*0.59*	*0.23*	*0.26*	*0.61*	*0.28*	*0.32*
Peer_rob	.033	-.068	-.12*	-.024		.071	.047	-.040	-.040	-.0098
	0.52	*0.92*	*1.87*	*0.33*		*1.19*	*0.76*	*0.85*	*0.36*	*0.39*
Peer_fel_drg	-.0053	-.086	-.0036	.11	-.043		.036	-.0020	.27**	-.018
	0.08	*1.14*	*0.06*	*1.53*	*0.94*		*0.57*	*0.04*	*2.39*	*0.69*
Peer_mis_drg	-.039	-.095	-.042	-.028	.058	.023		.0027	-.077	.030
	0.78	*1.59*	*0.82*	*0.49*	*1.60*	*0.49*		*0.07*	*0.87*	*1.52*
Peer_fwpn	-.0045	-.017	.085	.014	-.048	.089	.0045		.27**	.019
	0.06	*0.20*	*1.18*	*0.18*	*0.95*	*1.33*	*0.06*		*2.17*	*0.68*
Peer_aggass	.050	.021	.0091	.022	.046	-.057	.021	.0097		.036*
	1.05	*0.37*	*0.19*	*0.41*	*1.34*	*1.26*	*0.45*	*0.27*		*1.88*
Peer_fel_sex	.036	.18*	.070	-.054	.046	-.028	.017	.020	.14	
	0.44	*1.87*	*0.83*	*0.58*	*0.78*	*0.36*	*0.21*	*0.32*	*0.95*	
Peer_black	-.070*	.068	-.020	-.015	.0031	.066*	-.014	.017	.055	.0091
	1.74	*1.42*	*0.49*	*0.32*	*0.11*	*1.74*	*0.36*	*0.55*	*0.77*	*0.57*
Peer_age_exit	.020	.041**	.049**	.020	.018	.0021	.0033	.011	-.019	-.0031
	1.25	*2.18*	*3.01*	*1.09*	*1.57*	*0.14*	*0.21*	*0.89*	*0.69*	*0.49*
Peer_age1st	.0056	.00037	-.0058	-.0068	-.013*	-.0028	-.014	.011	.011	.0021
	0.51	*0.03*	*0.51*	*0.54*	*1.69*	*0.27*	*1.30*	*1.38*	*0.58*	*0.47*
Peer_Percapi	-.0000051	.0000055	.0000063	.00000075	.0000037	-.0000075**	-.0000071*	.0000012	.0000031	.0000016
	1.29	*1.18*	*1.57*	*0.17*	*1.33*	*2.03*	*1.82*	*0.40*	*0.44*	*0.99*
Peer_Percorin	-.000074	.000069	-.000012	.000021	.000057	.000078	.000076	.000047	-.000043	.000018
	0.98	*0.77*	*0.16*	*0.25*	*1.06*	*1.10*	*1.03*	*0.83*	*0.33*	*0.59*
Peer_Felonies	.0066	-.013*	-.0053	-.00063	-.0015	-.0050	-.0086	.0018	-.010	.00067
	1.01	*1.73*	*0.79*	*0.09*	*0.32*	*0.82*	*1.35*	*0.36*	*0.91*	*0.26*
Individual Characteristics										
Auto theft		.019**	.0028	.0091	.025**	.019**	.021**	.0020	.014	.0016
		2.02	*0.35*	*1.03*	*4.48*	*2.56*	*2.78*	*0.34*	*1.02*	*0.52*
Burglary	.014*		.022**	.020**	.0027	.0051	.0038	.0068	-.0040	.0029
	1.87		*2.90*	*2.38*	*0.50*	*0.71*	*0.51*	*1.19*	*0.30*	*0.98*
Grlrcn	.0024	.019**		.0052	.0044	-.0074	-.0067	-.0047	-.018	-.0016
	0.32	*2.07*		*0.60*	*0.82*	*1.03*	*0.90*	*0.83*	*1.37*	*0.52*
Plrcn	.011*	.021**	.025**		.0034	-.0025	.0066	-.0047	-.0099	-.00036
	1.63	*2.66*	*3.69*		*0.70*	*0.40*	*0.99*	*0.92*	*0.84*	*0.13*
Robbery	-.0034	-.010	-.034**	.0013		.022**	.0065	.011	.027	-.0037
	0.34	*0.85*	*3.39*	*0.12*		*2.33*	*0.66*	*1.45*	*1.56*	*0.95*
Fel drug	-.022**	-.042**	-.031**	-.032**	.0040		.041**	.0042	-.014	.0018
	2.19	*3.48*	*3.00*	*2.82*	*0.55*		*4.04*	*0.55*	*0.81*	*0.44*
Mis drug	-.0021	-.0070	-.012	-.025**	.0046	.0062		.011*	.017	-.0017
	0.24	*0.67*	*1.29*	*2.47*	*0.73*	*0.74*		*1.70*	*1.11*	*0.50*
Fel_wpn	-.0090	.028**	.015	.037**	.013*	.0055	.0039		.043**	.0029
	0.83	*2.20*	*1.35*	*3.00*	*1.68*	*0.53*	*0.36*		*2.24*	*0.68*
AggAss	.0027	-.0052	-.0071	.0041	.011**	.00027	.0037	.020**		.00062
	0.37	*0.60*	*0.94*	*0.49*	*2.03*	*0.04*	*0.51*	*3.62*		*0.21*

Fel sex	.0023	-.020	-.029**	-.0067	-.0043	-.030**	-.029**	-.014	.022	
	0.17	*1.25*	*2.12*	*0.44*	*0.45*	*2.35*	*2.24*	*1.40*	*0.92*	
Black	.035**	-.0054	-.018**	-.000073	.029**	.085**	.012*	.015**	.080**	.00024
	5.14	*0.67*	*2.56*	*0.01*	*5.98*	*13.17*	*1.76*	*2.88*	*6.68*	*0.09*
Female	-.017	-.093**	-.031*	-.014	-.018	-.046**	-.052**	-.021*	.029	-.017**
	1.08	*4.79*	*1.88*	*0.75*	*1.60*	*3.00*	*3.31*	*1.75*	*1.03*	*2.61*
Age Exit	-.014**	-.012**	-.0056	-.017**	-.0039	.011**	.0036	-.0026	-.015**	-.00093
	3.79	*2.77*	*1.44*	*3.84*	*1.45*	*3.14*	*0.95*	*0.92*	*2.23*	*0.61*
Age First Offense	-.00072	-.0013	-.0021	.0017	-.0026*	-.0062**	-.0049**	-.0019	-.0066**	.00079
	0.38	*0.59*	*1.11*	*0.77*	*1.91*	*3.47*	*2.64*	*1.34*	*1.99*	*1.05*
Incarcerated in Zip	.0017	.0018	.000051	.0016	.0010	-.0012	-.000039	.0011	-.0000054	.00025
	1.58	*1.37*	*0.05*	*1.26*	*1.28*	*1.12*	*0.36*	*1.30*	*0.03*	*0.57*
Per Capita Income in Zip	.00000034	-.00000039	-.00000024	-.0000011	-.0000014**	-.0000008	.00000065	.000000060	-.00000083	-.00000037
	0.56	*0.54*	*0.38*	*1.51*	*3.25*	*1.38*	*1.08*	*0.13*	*0.77*	*0.15*
Felonies	.0031**	.0046**	.0022**	.0015	.00020	-.00055	-.00088	.00024	.0043**	.000077
	3.36	*4.17*	*2.33*	*1.41*	*0.31*	*0.63*	*0.96*	*0.35*	*2.68*	*0.21*
# Observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0970	.0943	.0712	.0536	.0942	.1965	.1002	.0468	.0724	.0722

NOTE.— This table presents the results of estimating equation (1) for the ten crime categories simultaneously via a seemingly unrelated regression (SUR) and correspond to the main results presented in Table 5. All specifications include facility-by-prior fixed effects and quarter of release dummies. Offense and Peer_offense vary across columns according to the crime category listed at the top of each column. 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). The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level.