NBER WORKING PAPER SERIES

BUILDING CRIMINAL CAPITAL BEHIND BARS: PEER EFFECTS IN JUVENILE CORRECTIONS

Patrick Bayer
Randi Hjalmarsson
David Pozen

Working Paper 12932
http://www.nber.org/papers/w12932

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2007

The authors wish to thank the Florida Department of Juvenile Justice (DJJ) and the Justice Research Center (JRC), Inc. for providing the data used in this study. In particular, we wish to thank Sherry Jackson, Dr. Steven Chapman, and Ted Tollett from the Florida DJJ and Julia Blankenship and Dr. Kristin Winokur from the JRC for many helpful conversations concerning the data and, more generally, the operation of the DJJ. We are also grateful to Joe Altonji, Dan Black, Tracy Falba, Erik Hjalmarsson, Caroline Hoxby, Mireia Jofre-Bonet, Thomas Kane, Jeffrey Kling, Steve Levitt, Carolyn Moehling, Robert Moffitt, Steve Rivkin, Paul Schultz, Doug Staiger, Ann Stevens, Chris Timmins, Chris Udry, and seminar participants at APPAM, BU, Duke, IRP, Maryland, NBER, Syracuse, UCLA, UCSC, and Yale for their valuable comments and suggestions. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

Building Criminal Capital behind Bars: Peer Effects in Juvenile Corrections
Patrick Bayer, Randi Hjalmarsson, and David Pozen
NBER Working Paper No. 12932
February 2007
JEL No. H0,H23,J0,J24,K0

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 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.

Patrick Bayer
Department of Economics
Duke University
213 Social Sciences
Durham, NC 27708
and NBER
patrick.bayer@duke.edu

Randi Hjalmarsson
School of Public Policy
2101 Van Munching Hall
University of Maryland
College Park, MD 20742
rhjalmar@umd.edu

David Pozen
Yale Law School
127 Wall Street
New Haven, CT 06511
david.pozen@yale.edu

"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

In his seminal paper, Becker (1968) examined crime from the perspective of microeconomic theory, considering the impact of private incentives such as the probability of arrest, expected punishment, and the relative return to criminal versus legal economic activity on behavior.[1] More recently, researchers have drawn on the theories of the firm and labor economics to provide insights into additional aspects of criminal careers and organizations. Levitt and Venkatash (2000), for example, use the theory of the firm to explain the financial structure of drug-selling street gangs, while Lochner (2004) uses a model of human capital formation to account for the relationships between age, education, and crime.

While many aspects of criminal behavior can be better understood by drawing analogies with the legitimate labor market, the criminal sector of the economy lacks many of the formal institutions of the legitimate labor market. Thus, while the acquisition of criminal human capital of the type postulated by Lochner is certainly important in criminal careers, formal "schools" for gaining such skills and knowledge do not exist. Likewise, the "hiring" practices of criminal gangs and networks must of necessity operate outside the formal recruiting and open application processes used in the legitimate labor market. The absence of these formal institutions suggests that social interactions are likely to have an extensive role in the criminal sector of the economy.[2] That is, due to the illicit nature of crime, learning and organizational formation must of necessity depend more heavily on informal social networks and peer interactions.

In addition to this theoretical motivation, prior empirical research has documented other robust features of crime that are also 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

[1] A great deal of recent empirical research seeks to measure the impact of the private incentives analyzed in Becker model on crime. To give just a few examples, Levitt (1998) considers the deterrence effects of harsher punishments; Grogger (1998) studies the impact of market wages; and Mocan and Rees (2005) study the impact of the probability of arrest, unemployment, and family structure on criminal behavior.

[2] 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 in the models of Sah (1991) and Calvo-Armengol and Zenou (2004). Ethnographic studies by Anderson (1990, 1999) and the theoretical model of Silverman (2004) describe social interactions that arise through reputational effects. Criminal gangs and other crime networks may have productive and learning effects (Sarnecki, 2001; Warr, 2002).

be explained by detailed measures of fundamental economic and social conditions.[3] Moreover, starting with Glueck and Glueck (1950), a longstanding literature in criminology documents a strong positive correlation between individual and peer criminal (delinquent) behavior.[4]

Understanding the importance and nature of social interactions in criminal behavior does not only inform our insight into crime as an economic and social phenomenon; it is also especially important from the perspective of policy. 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 are formed can also be used to shape decisions throughout the criminal justice system, such as when to aggregate individuals convicted of various crimes together in correctional facilities and how to optimally group these individuals within the facilities so as to reduce future recidivism.

Despite the importance and widespread interest in the nature of social interactions in crime, very few papers have been able to convincingly document causal effects of peers on one another. The aforementioned criminology literature, for example, establishes only correlations in delinquency. Jacob and Lefgren (2003) find that school attendance increases the amount of violent crimes but decreases the amount of 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.[5]

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 serving time in 169 juvenile correctional facilities

---

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

[4] Numerous studies since have replicated this relationship (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.

[5] For instance, Case and Katz (1991) find that residence in a neighborhood in which many other youth are involved in crime increases a juvenile's propensity to participate in criminal behavior himself. Ludwig, Duncan, and Hirschfield (2001) and Kling, Ludwig, and Katz (2005) have used the Moving to Opportunity (MTO) experiment to study the effects of neighborhoods on criminal behavior finding significant effects.

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.[6] 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 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

[6] 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 randomization derived from social experiments such as the MTO experiment in Boston (Katz, Kling, and Leibman, 2001) or the STAR experiment 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. Our goal in this paper is to provide new evidence on peer effects in criminal behavior using a research design that improves considerably on the existing literature in a setting where a series of diagnostic tests suggest that the variation in peer exposure isolated in the analysis is quasi-random.

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, 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. Section III outlines our basic empirical methodology, identification strategy, and measurement issues. Section IV presents the main results. Section V presents a number of diagnostic tests of our identifying assumption as well as other robustness checks. Section VI extends the main results to consider whether the estimated peer effects are heterogeneous across facility characteristics as well as whether they are sensitive to the definition of the peer group. Section VII 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,[7] 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 full 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 restrict the sample to individuals age seventeen and younger at the time of release.[8]

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

[8] 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

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 emphasize, however, that 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.

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.[9] 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. Because individuals can be charged and adjudicated simultaneously for multiple offenses (i.e. 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.

Throughout the paper we focus 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. We chose these categories 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

---

inability to do so should not influence the results regarding relatively minor crimes such as misdemeanor drugs, petty larceny, and burglary.

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

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 assignment of juveniles to facilities in Florida typically occurs in two steps.[10] A judge first determines the level of treatment that is appropriate, assigning individuals to one of 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. 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. Only a handful of individuals (those in the maximum risk category) are assigned jails, where individuals are confined to locked cells.[11] 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 slightly more than 20 individuals, as a couple of facilities are particularly large.

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. The neighborhood characteristic variables are constructed using each individual's zip code of residence. With the 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 measures of peer characteristics; the list of peer characteristics parallels the list of individual characteristics (i.e. the demographic, criminal

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

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

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 means of the peer measures generally reflect the means of the individual criminal history variables although slight differences arise because the peer measures are averaged over days of exposure, 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 and peer characteristics. 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 when 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.[12]

The general specification that we take to the data can be written as:[13]

$$R_{ij}^h = \beta_0 \left(Offense_{ij}^h * Peer\_offense_{ij}^h \right) + \beta_1 \left(No\_Offense_{ij}^h * Peer\_offense_{ij}^h \right) + P_{ij}\alpha + X_{ij}\gamma + \lambda_j + Offense_{ij}^h * \mu_j + \varepsilon_{ij}^h \quad (1)$$

The dependent variable, R^h_{ij} indicates whether individual *i* in facility *j* recidivates with offense type *h*. $Peer\_offense^h_{ij}$ describes an individual's exposure to peers with a history of offense type

[12] 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.

[13] 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.

h. $Offense^h_{ij}$ equals one if individual i has a history of offense type h, while $No\_Offense^h_{ij}$ indicates no prior history of that offense. P_{ij} is a vector of additional peer characteristics including demographic variables as well as peer criminal histories in all other crime categories. Similarly, X_{ij} 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.[14]

Four features of our main specification merit further discussion. First, 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_{ij}.

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 of our study for two main reasons. First, the existing literature clearly demonstrates that juvenile offenders show strong tendencies to specialize – i.e., recidivate in a crime category in which they already have a criminal history. Within our dataset, Table 2 reports OLS estimates for the following simple specification:

$$(2) \qquad R^h_{ij} = \beta_2 Offense^h_{ij} + \varepsilon^h_{ij}$$

The first row of Table 2 demonstrates the strong tendency of those with experience in a crime category to recidivate in that category. 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.

In addition to this concern about the flexibility of the model, we are also directly interested in distinguishing between peer effects that reinforce existing criminal tendencies and those that cause individuals to branch out into new areas of criminal activity. This distinction is of first-order importance for (i) determining which theoretical explanations for the presence of peer

[14] 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 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.

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*, $Offense^h_{ij}$. 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 of the 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, 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. In Section V, we provide strong evidence, which is based on an examination of the correlation between individual and peer characteristics, that the within-facility variation in peer exposure is quasi-random.

A final important aspect of our main specification concerns the nature of the peer effect that is identified. In particular, given the variation in peer exposure that we exploit, the peer effect identified in our analysis captures the impact of changing peer composition within Florida's correctional facilities on recidivism behavior. Because we do not directly observe whether an individual interacts with all of his peers, this effect 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. Thus, while evidence of the existence of the type of peer effects identified in our analysis implies the existence of structural

[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.

peer effects, it is important to keep in mind the proper interpretation of the nature of the identified effect when interpreting the magnitudes of the estimates reported 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.[16] 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. As stated above, 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.[17] 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. We also provide evidence below based on a specification that uses

[16] 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.

[17] 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.

data from the middle of the sample period that the remaining measurement error is likely to have a reasonably small effect on the results.

IV. Main Results

Table 3 reports the coefficients β_0 and β_1 for a specification of the type shown in equation (1) for each crime category.[18] 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 is

The first row of Table 3 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 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 0.4404.[19] 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.[20] 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

[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 presents the full specification associated with the results reported in Table 3, generally revealing broad specialization across drug crimes as well all forms of theft. Particular crimes associated with each of these categories are shown in Appendix Table 1.

[19] One possible explanation for the evidence of negative peer effects is that individuals learn that the risk-return tradeoff for robbery, for instance, is less favorable to the criminal than the tradeoff for other types of property crimes (auto theft and burglary). 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 length (conditional on arrest and a punishment that involves assignment to a correctional facility).

[20] 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.

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 18.5 percent of the time. Thus, the estimated reinforcing peer effect of 0.21 for burglary implies that a standard deviation increase in exposure to peers that have committed burglaries (0.16) increases the likelihood of recidivism from 18.5 to 21.9 percent for these individuals at the mean. Similarly, the estimated reinforcing peer effect for felony drug crimes of 0.32 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 32.6 to 35.8 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.[21]

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 3 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 (particularly for misdemeanor drug crimes) is that peers may 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.[22] Conversely, access to peers that increase returns in *another* category may be much less valuable,

---

[21] 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.

[22] 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).

as this may not raise the returns in that category enough to change the individual's optimal behavior.[23]

Although each regression presented in Table 3 (and used throughout the remainder of the paper) 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 reported here would be eliminated if an individual's own offense history was fully interacted with the complete set of peer characteristics. To explore this possibility, we estimated versions of equation (1) that fully interacted an individual's own offense history in a category with all of the included peer measures. This analysis resulted in little change in the overall pattern and significance of the reinforcing peer effects. In fact, most of the coefficients on the off-diagonal interactions (i.e. between an individual's history of offense *h* and peer offenses different from *h*) are not significant. Thus, the reinforcing peer effect reported here is driven by crime-specific peer exposure.[24]

To gauge the impact of controlling for the potentially non-random assignment of juveniles to facilities, we compared the coefficients reported in Table 3 with those for an analogous specification that does not include facility-by-prior offense fixed effects.[25] In this case, positive and significant peer effects exist for those with and *without* prior experience in multiple categories and a joint test rejects the hypothesis that β_1 equals zero in each of the ten crime categories (with a p-value of 0.0262). This implies that the non-random assignment of individuals to facilities or the presence of correlated unobservables at the facility level gives rise to the appearance of peer effects when across-facility variation is included in the analysis. This is not surprising; the appearance of positive peer effects could result, for example, from the assignment of individuals to facilities based in part on unobserved aspects of their propensity to recidivate.

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

[24] 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.

[25] To save space, we do not report the full set of results in a table but instead summarize them here.

V. Diagnostic Tests of Identifying Assumptions and Other Robustness Checks

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 this section, we perform two diagnostic tests of this implication.[26]

We begin by comparing our main results to those from an analogous specification that does not include controls for individual characteristics; these are reported in Table 4. If individual characteristics are uncorrelated with peer measures, their inclusion should have no effect on the estimated peer effects. A comparison of Table 3 and Table 4 shows that many of the parameters are identical to two digits and that none of the parameters change significantly.

In Tables 5a and 5b, we provide a second test that individual observable characteristics are essentially orthogonal to the within-facility variation in peer measures. In 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 5a 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 5b repeats these regressions adding facility-by-prior offense fixed effects. In Table 5a, 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 5b, 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

[26] In previous versions of this paper, we also included a table that reported a matrix of correlation coefficients between a wide set of individual and peer measures. These correlation coefficients are strongly statistically and economically significant in the full sample when capturing variation both within and across facilities. However, they are typically more than an order of magnitude smaller, negative almost as often as positive, and rarely statistically significant when only within-facility variation is isolated. We omit this table in the current version of the paper for space considerations and because it is fairly redundant with the evidence reported here.

significant and in all cases are quite small. For individuals with a prior history in a crime category, only the coefficient for felony weapons offenses 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.[27]

Trends in Crime and the Clustering of Assignment

A potential alternative explanation for the evidence of peer effects described in Table 3 relates to 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. Clustering of individuals with particular criminal histories might also arise over time within facilities due to deliberate actions on the part of judges and other DJJ officials.

To address this possibility, we report the results of an additional diagnostic test here. At the outset, it is important to 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. We supplement this evidence by reporting the results of a specification that includes a vector of 160 interactions between eight quarter of release dummies and twenty dummies indicating each of the judicial circuits in Florida. A comparison of these specifications (reported in Table 6) to those in Table 3 reveals that, as expected, adding these judicial circuit-by-quarter dummies has no impact on the results. Thus, 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 of our main findings 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 in correctional

[27] Many additional alternative tests of randomness in the timing of entry and exit of individuals with particular criminal histories within facilities strongly fail to reject randomness.

facilities. 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 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 7 tests whether there is any undue clustering of release or admit dates for individuals from the same zip code; the first set of columns describes the release date while the last three columns describe the admit date. 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. 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.[28] We also consider individuals released (admitted) within 14 and 21 days of each other. None of the six differences are statistically significant at the 5 percent level. More importantly, even if these differences were statistically significant, the magnitudes of these differences, which are only between 0.2 and 0.3 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 3.

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 (i.e. the fact that we do not observe peers released before the beginning or after the end of our sample period), 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

[28] 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.

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 3, continuing to reveal a positive and significant peer effect for those with a history of the offense for the cases of burglary, petty larceny, misdemeanor drug, aggravated assault, and felony sex offenses and minimal evidence of any peer effects for individuals without a history of having committed a particular crime. As expected, the magnitudes of the effect sizes in Table 8 are generally greater than those reported in Table 3. This 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 appears to have an attenuating effect on the estimated peer effects.

VI. Extending the Main Results

We now turn to an examination of the heterogeneity in such effects across facility characteristics; in particular, we consider facility size and whether facilities are residential or non-residential. 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. While this exercise is therefore somewhat limited in what it tells us about the true nature of interactions, it is informative to policy makers concerned about the optimal assignment of different sets of peers in different size facilities.[29]

Peer Effects in Small Facilities

To explore how peer effects vary with size, we present a specification analogous to that shown in Table 3 that restricts the sample to only facilities with an average of 20 or fewer individuals concurrently serving sentences. Specifically, the upper-most panel of Table 9 presents the results from estimating equation (1) for the resulting sample of 3,998 individuals in the 115 smallest facilities. The results of this specification replicate 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

[29] 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.

experience with an offense and the intensity of exposure to peers with experience in that crime category (i.e. β_0) are positive in eight out of ten crime categories and statistically significant for burglary, petty larceny, felony drug offenses, misdemeanor drug offenses, and felony sex offenses. In comparison to the results presented in Table 3, 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 0.32 when using the entire sample to 0.61 when using the sample of small facilities.[30] As in Table 3, there is minimal evidence of peer effects for individuals who *do not have* any prior experience in that crime category when restricting the analysis to relatively small facilities. For this sample, β_1 is negative as often as it is positive; there is weak statistical evidence of a decrease in activity for the case of petty larceny.

Heterogeneity in Peer Effects - 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 (e.g., group homes, boot camps), we can estimate the model separately for residential versus non-residential facilities. 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). 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 others in the same facility. Secondly, the nature of peer effects may vary with the amount of criminal experience an individual and his peers have, 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.

The bottom two panels of Table 9 present the results of estimating equation (1) when the sample is restricted to the 6,990 and 1,226 individuals in residential and non-residential facilities, respectively. Not surprisingly given the size of the sample, the pattern of results for residential

[30] One may expect the reinforcing peer effects estimated for drug offenses to be especially large since a number of potential mechanisms are particularly applicable to drug offenses. For instance, 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.

facilities generally mirrors the results presented in Table 3. However, the bottom panel shows that peer effects in non-residential facilities differ dramatically from those in residential facilities. In non-residential facilities, there are significant positive reinforcing peer effects for 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.[31] Non-residential facilities may inadvertently increase the formation and expansion of criminal networks by bringing together young offenders from surrounding neighborhoods.

Definition of the Peer Group

To this point in our analysis, peer measures have been constructed as weighted averages of the characteristics of an individual's peers in a facility, where an individual's peer group is defined to include *all* others in the facility at the same time as the individual. Because interactions may be more intense among some types of individuals and the magnitude of the effects of some peers may be greater than the effects of others, Table 10 presents results for alternative peer group definitions.[32,33] Again it is important to keep in mind that these results might differ from our main specification due to either the nature of interactions among different types of peers or heterogeneity in the effects of those interactions.

The upper-most panel of Table 10 re-estimates equation (1) defining the peer group as all older individuals. With this specification, we seek to examine whether older individuals have a more intense effect on their younger peers such as might be expected if they serve as role models. As in our main specification, there is no evidence of peer effects for individuals who do not have a history in a given crime category. Significant reinforcing peer effects exist for individuals who have histories of burglary, robbery, misdemeanor drugs, and aggravated assault. Though older peers are certainly not driving the full peer effects observed in Table 3, they do appear to exert a significant influence over younger individuals with the same offense history.

[31] 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.

[32] Alternative specifications not reported in the paper imply 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 are most important. In other words, the peer effects associated with the peers' first offense in a crime category appear to be much more important than those associated with the third or fourth offense in that category.

[33] In addition to the peer group definitions presented in the paper, we also considered peer groups based on timing of entry, i.e. whether individuals entered a facility within a specified time period of one another, finding these to be unimportant.

The middle panel defines the peer group as individuals of the same age, where two individuals are considered to be the same age if their ages are within one year of each other. Evidence of peer effects is generally weaker when defining the peer group to be peers of the same approximate age rather than as older peers. For same age peers, significant reinforcing peer effects exist for misdemeanor drug crimes and felony sex offenses. In addition, for the first time, there is some evidence of a non-reinforcing peer effect; the exposure of an individual with no history of felony drug offenses to same-age peers with a history of felony drug offenses increases the likelihood that he recidivates with a felony drug offense.

Lastly, the bottom panel defines the peer group to be individuals of the same race. Once again, there is no evidence of peer effects for individuals without a prior history in a category. But, for individuals with a history of the particular offense, strong reinforcing peer effects exist for petty larceny, felony and misdemeanor drug offenses, and aggravated assault. This effect is particularly large and precise for felony drug offenses, with a t-statistic greater than seven.

VII. Conclusion

This paper analyzes the influence that juvenile offenders serving time in the same correctional facility have on each other's subsequent criminal behavior. This analysis is based on data that provide a complete record of past crimes, facility assignments, and arrests and adjudications in the year following release for over 8,000 juveniles released from 169 juvenile correctional facilities over a two-year period in Florida. Our main analysis consists of a series of regressions relating recidivism in a crime category to individual, peer, and neighborhood characteristics. To control for the non-random assignment to facilities, we include facility-by-prior offense fixed effects, thereby estimating peer effects using only within-facility variation over time. We conduct a number of diagnostic tests that demonstrate that (in as much as it is testable on observables) the within-facility variation in peer characteristics is as good as randomly assigned, i.e., it is orthogonal to all relevant observable individual characteristics. Moreover, we show that our results are robust to concerns about broad or localized trends 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 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, we find evidence of peer effects for different crimes in non-residential versus residential facilities. In non-residential facilities, there is a strong reinforcing peer effect for the more serious crimes of auto theft, robbery, and felony drug offenses while there is such an effect for the more minor crimes of burglary and misdemeanor drugs in residential facilities. We conjecture that the grouping of juveniles from nearby neighborhood in non-residential facilities may inadvertently foster the formation and expansion of criminal networks. Lastly, we find that older peers tend to exert more influence than peers of the same age and that the reinforcing peer effects for petty larceny and felony drug offenses are primarily driven by interactions among peers of the same race.

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 most robust feature of our findings regarding peer effects: that they tend to reinforce existing criminal behavior. One such 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.

References

Akers, RL, MD Krohn, L. Lanza-Kaduce, and M. Radosevich. "Social Learning and Deviant Behavior: a Specific Test of a General Theory" *Am. Sociol. Rev.* 44 (1979) 636-655.

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.

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." *J. Law and Econ.*, 2005, 48(2): 549-90.

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

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.

Calvo-Armengol, Antoni, and Zenou, Yves. "Social Networks and Crime Decisions: The Role of Social Structure in Facilitating Delinquent Behavior." *International Economic Review*. 45 (2004): 939-958.

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.

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.

Elliott, DS., D. Huizinga, and SS. Ageton. *Explaining Delinquency and Drug Use*. Beverly Hills: Sage. 1985.

Erickson, ML. and LT. Empey. "Class Position, Peers, and Delinquency" *Sociol. Soc. Res*. 49 (1965): 268-282.

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.

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

Glueck, S. and E. Glueck. *Unraveling Juvenile Delinquency*. Cambridge, MA: Harvard University Press. 1950.

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

Jacob, Brian A., and Lefgren, Lars. "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration and Juvenile Crime." *A.E.R.* 93(5), 2003.

Jensen, G.F. "Parents, Peers, and Delinquent Action: A Test of the Differential Association Perspective" *Am. J. Sociol.* 78 (1972): 562-75.

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.

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

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.

Levitt, Steven D. and Venkatesh, Sudhir. "An Economic Analysis of a Drug-Selling Gang's Finances." *Q.J.E.* 115 (August 2000): 755-789.

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.

Lochner, Lance. "Education, Work, and Crime: A Human Capital Approach," I*nternational Economic Review*, 45 (August 2004): 811-43.

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

Matsueda, R.L. and K. Heimer. "Race, Family Structure, and Delinquency: A Test of Differential Association and Social Control Theories" *Am. Sociol. Rev.* 52 (1987): 826-840.

Mocan, H. Naci, and Rees, Daniel I. "Economic Conditions, Deterrence and Juvenile Crime: Evidence from Micro Data." *American Law and Economics Review*. 7:2 (2005): 319-49.

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

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 (2001): 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.

Silverman, Dan. "Street Crime and Street Culture." *International Economic Review*. 45:3 (2004): 761-786.

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

Tittle, C.R., M.J. Burke, and E.F. Jackson. “Modeling Sutherland’s Theory of Differential Association: Toward and Empirical Clarification.” *Social Forces* 65 (1986): 405-432.

Voss, H.L. “Differential Association and Reported Delinquency Behavior: A Replication” *Soc. Problems*. 12 (1964) 78-85.

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.

Warr, M. and M. Stafford. “The Influence of Delinquent Peers: What They Think or What They Do?” *Criminology* 29 (1991): 851-865.

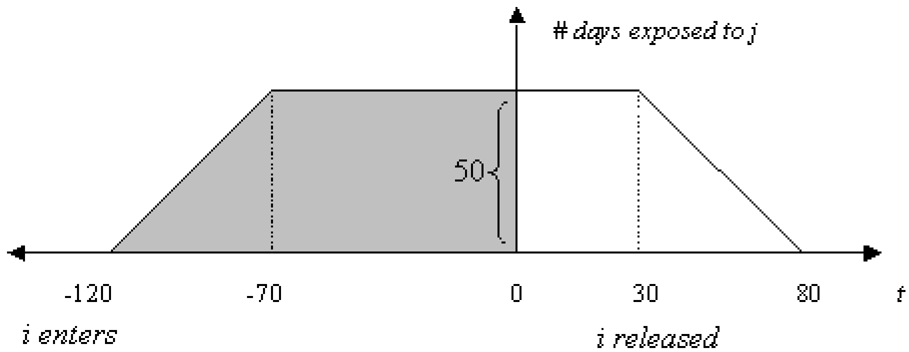
Appendix 1

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*.

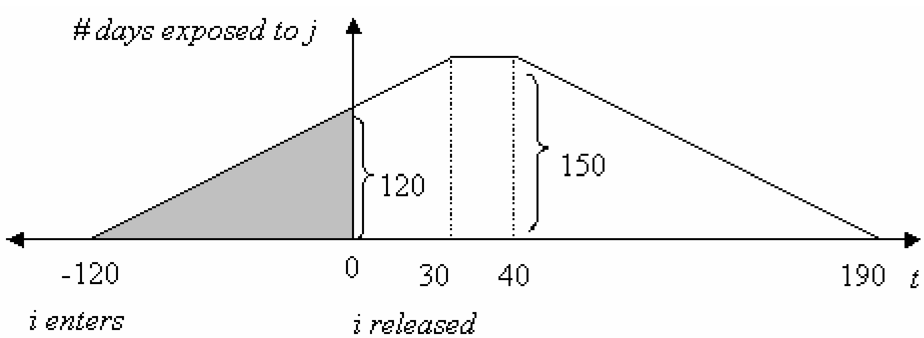
Scenario 1: *date_release[i] <= days_in[i] - days_in[j]*
Example: date_release[i] = 30; days_in[i] = 150; days_in[j] = 50



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.

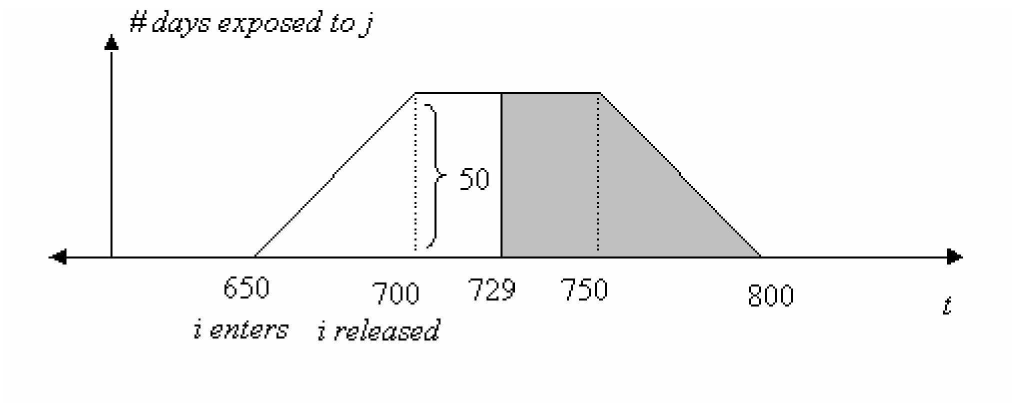
This example depicts the correction made for just one case of pre-censoring. For peers with very long sentences, pre-censoring can occur such that the unobserved region is just the shaded triangular portion of the diagram above. Similarly, there are two cases of post-censoring that parallel those of 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

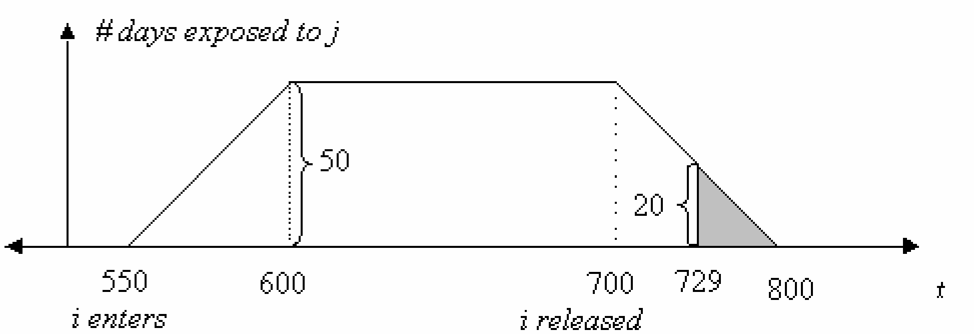


Table 1. Descriptive Statistics and Variable Definitions

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

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 (β_2)	.106**	.117**	.077**	.055**	.073**	.267**	.138**	.020**	.120**	.050**
	10.77	*15.07*	*10.06*	*7.97*	*6.42*	*16.77*	*12.13*	*2.03*	*7.43*	*5.91*
Constant	.065**	.068**	.067**	.082**	.036**	.059**	.067**	.030**	.103**	.010**
	13.48	*14.80*	*17.32*	*18.09*	*10.47*	*11.57*	*18.67*	*11.14*	*16.74*	*6.48*
Facility-by-Prior Offense Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Peer Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Individual Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0258	.0285	.0157	.0071	.0136	.0945	.0317	.0008	.0118	.0120

NOTE.—Each column represents a different specification; Offense varies across specifications e.g., in the first column, Offense is "Auto Theft" (individuals 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. All standard errors are corrected for clustering at the facility level.

Table 3. 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)	-.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*
Facility-by-Prior Offense Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peer Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
# recidivate with offense	760	1116	770	954	369	762	738	221	813	108
% 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	.0953	.0930	.0700	.0520	.0937	.1961	.0990	.0463	.0715	.0709
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$	p = 0.0003									
H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$	p = 0.4404									

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. All specifications are simultaneously estimated as a seemingly unrelated regression (SUR). The joint hypotheses that the coefficients are equal to zero are evaluated using a Wald test.

Table 4. Robustness of Main Results to Exclusion of Individual Controls

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)	-.0068	.21**	-.038	.10*	.091	.36**	.26**	-.12	.28*	.35**
	0.07	*3.17*	*0.53*	*1.74*	*0.78*	*2.22*	*2.37*	*0.76*	*1.91*	*2.33*
No_Offense*Peer_offense (β_1)	.031	.00031	-.011	-.12	-.067	.074	-.042	.050	.10	.039
	0.54	*0.00*	*0.21*	*1.60*	*1.35*	*1.15*	*0.77*	*0.90*	*1.01*	*1.15*
Facility-by-Prior Offense Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peer Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual Characteristics	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0849	.0791	.0582	.0430	.0798	.1696	.0914	.0401	.0595	.0695
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$	p =.0002									
H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$	p = .4616									

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. All specifications are simultaneously estimated as a seemingly unrelated regression (SUR). The joint hypotheses that the coefficients are equal to zero are evaluated using a Wald test.

Table 5a. 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 on just the variables presented in these tables.

Table 5b. 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 6. Robustness: Peer Effects 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_Felony Weapon	R_Agg. Assault	R_Felony Sex
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*
# observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.1240	.1178	.0897	.0738	.1146	.2204	.1194	.0625	.1004	.1001

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. All specifications include facility-by-prior offense 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

	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 8. Robustness: Individuals Released during the Middle Sixteen Months (two-thirds) 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_Felony Weapon	R_Agg. Assault	R_Felony Sex
Offense*Peer_offense (β_0)	.028	.27**	-.013	.16**	.20	-.046	.35**	-.12	.40**	.57**
	0.24	*3.29*	*0.13*	*2.18*	*1.13*	*0.21*	*2.64*	*0.51*	*2.12*	*2.75*
No_Offense*Peer_offense (β_1)	.066	-.022	.0027	-.067	-.10	.10	-.084	.022	.061	.078*
	0.91	*0.23*	*0.04*	*0.70*	*1.60*	*1.25*	*1.25*	*0.28*	*0.48*	*1.77*
# observations	5448	5448	5448	5448	5448	5448	5448	5448	5448	5448
R^2	.1123	.1155	.0910	.0653	.1196	.2228	.1272	.0551	.0939	.1030
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$	p = .0001									
H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$	p = .4040									

NOTE.—The regressions above use just those 5,448 individuals who were released between October 31, 1997 and February 28, 1999 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). The absolute values of t-statistics are in italics. ** represents significance at 5% level and * represents significance at 10% level. All specifications include facility-by-prior offense 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. The joint hypotheses that the coefficients are equal to zero are evaluated using a Wald test.

Table 9. Heterogeneity in Peer Effects Across Facility Characteristics

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
Small Facilities										
Offense*Peer_offense (β_0)	-.17	.19**	.061	.11*	.17	.61**	.21*	-.072	.19	.49**
	1.60	*2.63*	*0.72*	*1.71*	*1.44*	*3.40*	*1.77*	*0.46*	*1.30*	*2.64*
No_Offense*Peer_offense (β_1)	-.057	-.055	-.019	-.14*	-.070	.067	-.068	.083	.089	.068
	0.90	*0.66*	*0.29*	*1.68*	*1.38*	*0.99*	*1.15*	*1.44*	*0.91*	*1.63*
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$ p =.0000		H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$ p = .1797								
Residential Facilities										
Offense*Peer_offense (β_0)	-.081	.24**	-.034	.083	.033	.22	.29**	-.15	.19	.35**
	0.78	*3.25*	*0.44*	*1.30*	*0.26*	*1.21*	*2.38*	*0.86*	*1.21*	*2.31*
No_Offense*Peer_offense (β_1)	.074	-.053	.0059	-.16*	-.079	.088	-.083	.046	.054	.057
	1.17	*0.64*	*0.10*	*1.90*	*1.47*	*1.21*	*1.34*	*0.73*	*0.50*	*1.58*
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$ p = .0018		H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$ p = .1737								
Non-residential Facilities										
Offense*Peer_offense (β_0)	.40*	.035	-.071	.16	.39*	.95**	.0091	-.12	.89**	-.29
	1.84	*.15*	*0.37*	*1.10*	*1.67*	*2.54*	*0.03*	*0.28*	*2.35*	*0.34*
No_Offense*Peer_offense (β_1)	-.11	.20	-.11	.055	.0059	.056	.13	-.043	.33	-.22*
	0.81	*1.30*	*0.89*	*0.33*	*0.05*	*0.45*	*1.12*	*0.36*	*1.38*	*1.94*
H_0: $\beta_0^{auto} = \ldots = \beta_0^{sex} = 0$ p = .0303;		H_0: $\beta_1^{auto} = \ldots = \beta_1^{sex} = 0$ p = .3944								

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. All specifications include facility-by-prior offense 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. Non-residential facilities included 1226 individuals and residential facilities include 6990 individuals. 3,988 are considered to be in small facilities; 115 facilities are defined to be small and have an average of 20 or fewer individuals concurrently serving sentences. The joint hypotheses that the coefficients are equal to zero are evaluated using a Wald test.

Table 10. Sensitivity of Peer Effects to Definition of the Peer Group

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
Peer Group: Older Peers										
Offense*Peer_offense (β_0)	-0.084	0.14**	-0.031	0.035	0.12*	0.13	0.12*	-0.023	0.19*	0.087
	1.56	*3.60*	*0.72*	*0.97*	*1.93*	*1.50*	*1.77*	*0.31*	*1.73*	*1.36*
No_Offense*Peer_offense (β_1)	-0.013	-0.0056	-0.040	-0.014	0.00067	0.026	0.019	-0.010	0.0013	-0.0054
	0.41	*0.14*	*1.24*	*0.34*	*0.02*	*0.71*	*0.60*	*0.31*	*0.01*	*0.26*
Peer Group: Same Age Peers										
Offense*Peer_offense (β_0)	-.071	.068	-.0054	.029	.038	-.056	.18**	-.074	.090	.19**
	1.10	*1.57*	*0.11*	*0.75*	*0.50*	*0.47*	*2.24*	*0.97*	*0.81*	*3.04*
No_Offense*Peer_offense (β_1)	.038	.0019	-.027	-.071	-.023	.089**	-.023	-.024	.035	.013
	1.03	*0.04*	*0.77*	*1.53*	*0.72*	*1.98*	*0.59*	*0.71*	*0.40*	*0.60*
Peer Group: Same Race Peers										
Offense*Peer_offense (β_0)	-.032	.033	-.032	.10**	.080	.46**	.24**	.022	.22**	-.066
	0.65	*0.94*	*0.88*	*3.29*	*1.44*	*7.22*	*3.66*	*0.26*	*2.84*	*0.85*
No_Offense*Peer_offense (β_1)	-.012	.013	.0075	-.047	.012	.047	.019	-.0048	.034	.0051
	0.41	*0.34*	*0.26*	*1.17*	*0.44*	*1.50*	*0.60*	*0.15*	*0.65*	*0.26*

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. All specifications include facility-by-prior offense 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. 8,099 individuals were used when the peer group was constrained to include older peers. 8,201 individuals were included when the peer group was defined as individuals of the same age and 8,147 when the peer group was defined as individuals of the same race. An individual is considered to be the same age if their ages are within one year of each other.

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 Results for the Main Specification

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)	-.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*
Peer Characteristics										
Peer_auto		.016	.052	.048	-.014	.037	.055	-.084**	.13	-.032
		0.26	*1.01*	*0.83*	*0.38*	*0.78*	*1.10*	*2.23*	*1.51*	*1.59*
Peer_burg	.0030		.035	.029	.020	.030	-.012	.0059	.060	-.0079
	0.07		*0.75*	*0.57*	*0.63*	*0.69*	*0.26*	*0.17*	*0.75*	*0.44*
Peer_glrcn	-.056	.029		-.017	-.0072	.037	.052	.028	.10	.031*
	1.21	*0.54*		*0.33*	*0.22*	*0.84*	*1.15*	*0.82*	*1.24*	*1.69*
Peer_plrcn	.016	-.079	-.015		.023	.014	.0097	-.017	-.00047	-.00046
	0.39	*1.63*	*0.36*		*0.78*	*0.35*	*0.24*	*0.56*	*0.01*	*0.03*
Peer_rob	.055	-.045	-.11*	-.012		.072	.039	-.039	-.060	-.018
	0.88	*0.62*	*1.77*	*0.17*		*1.23*	*0.64*	*0.84*	*0.55*	*0.74*
Peer_fel_drg	-.0060	-.090	-.0046	.11	-.044		.040	-.0018	.26**	-.018
	0.09	*1.19*	*0.07*	*1.45*	*0.96*		*0.64*	*0.04*	*2.31*	*0.73*
Peer_mis_drg	-.043	-.091	-.042	-.025	.057	.020		.0025	-.063	.032
	0.03	*1.54*	*0.82*	*0.43*	*1.58*	*0.43*		*0.07*	*0.72*	*1.60*
Peer_fwpn	-.0021	-.0088	.087	.019	-.045	.087	.0027		.27**	.018
	0.03	*0.11*	*1.22*	*0.24*	*0.90*	*1.31*	*0.04*		*2.19*	*0.63*
Peer_aggass	.053	.025	.0058	.029	.046	-.055	.025	.0092		.034*
	1.11	*0.44*	*0.12*	*0.54*	*1.36*	*1.23*	*0.54*	*0.26*		*1.82*
Peer_fel_sex	.040	.19**	.073	-.059	0.51	-.021	.026	.021	.11	
	0.49	*1.96*	*0.87*	*0.63*	*0.87*	*0.27*	*0.32*	*0.35*	*0.78*	
Peer_black	-.069*	.067	-.027	-.0078	.0043	.068*	-.014	.016	.043	.0077
	1.71	*1.41*	*0.66*	*0.17*	*0.15*	*1.80*	*0.35*	*0.54*	*0.61*	*0.48*
Peer_age_exit	.013	.033*	.046**	.015	.014	.0023	.0068	.010	-.012	-.00029
	0.84	*1.80*	*2.87*	*0.86*	*1.28*	*0.16*	*0.44*	*0.86*	*0.45*	*0.05*
Peer_age1st	.0087	.0023	-.0051	-.0062	-.012	-.0016	-.014	.011	.0058	.00045
	0.80	*0.18*	*0.46*	*0.49*	*1.54*	*0.16*	*1.32*	*1.39*	*0.30*	*0.10*
Peer_Percapi	-.000004	.000007	.000006	.000001	.000004	-.000007*	-.000007*	.000001	.000001	.000001
	1.08	*1.44*	*1.59*	*0.29*	*1.54*	*1.95*	*1.82*	*0.43*	*0.15*	*0.67*
Peer_Percorin	-.000068	.000086	.000007	.000022	.000064	.00007	.000059	.000050	-.000038	.000018
	0.91	*0.97*	*0.10*	*0.26*	*1.19*	*0.95*	*0.79*	*0.90*	*0.29*	*0.60*
Peer_Felonies	.0066	-.014*	-.0059	-.00083	-.0016	-.0046	-.0082	.0016	-.012	.00049
	1.02	*1.81*	*0.90*	*0.11*	*0.34*	*0.75*	*1.29*	*0.33*	*1.04*	*0.19*
Individual Characteristics										
Auto theft		.019**	.0027	.0096	.025**	.019**	.021**	.0021	.013	.0015
		2.08	*0.34*	*1.09*	*4.54*	*2.55*	*2.74*	*0.36*	*0.93*	*0.48*
Burglary	.015**		.023**	.021**	.0030	.0052	.0035	.0067	-.0049	.0026
	1.98		*2.95*	*2.40*	*0.55*	*0.73*	*0.47*	*1.19*	*0.37*	*0.86*
Grlrcn	.0019	.018**		.0054	.0044	-.0075	-.0066	-.0046	-.018	-.0014
	0.25	*2.04*		*0.63*	*0.80*	*1.04*	*0.88*	*0.82*	*1.37*	*0.47*
Plrcn	.011*	.022**	.026**		.0036	-.0023	.0068	-.0046	-.011	-.00061
	1.69	*2.70*	*3.69*		*0.73*	*0.35*	*1.01*	*0.93*	*0.91*	*0.23*
Robbery	-.0020	-.0085	-.034**	.0018		.022**	.0064	.011	.026	-.0043
	0.20	*0.73*	*3.32*	*0.16*		*2.36*	*0.66*	*1.45*	*1.51*	*1.09*
Fel drug	-.022**	-.042**	-.031**	-.032**	.0039		.041**	.0043	-.015	.0018
	2.18	*3.51*	*3.01*	*2.82*	*0.54*		*4.05*	*0.56*	*0.83*	*0.44*
Mis drug	-.0025	-.0070	-.011	-.025**	.0045	.0061		.011*	.018	-.0016
	0.29	*0.67*	*1.28*	*2.51*	*0.72*	*0.73*		*1.68*	*1.16*	*0.47*
Fel_wpn	-.0096	.028**	.014	.038**	.013*	.0054	.0044		.044**	.0029
	0.88	*2.18*	*1.30*	*3.04*	*1.68*	*0.52*	*0.40*		*2.27*	*0.66*
AggAss	.0032	-.0046	-.0068	.0042	.011**	.00048	.0039	.020**		.00037
	0.44	*0.53*	*0.91*	*0.50*	*2.06*	*0.07*	*0.54*	*3.64*		*0.14*

Fel sex	.0014	-.021	-.029**	-.0072	-.0046	-.029**	-.028**	-.014	.021	
	0.11	*1.31*	*2.16*	*0.47*	*0.48*	*2.32*	*2.17*	*1.42*	*0.90*	
Black	.035**	-.0053	-.018**	.00026	.029**	.085**	.012*	.015**	.080**	.00028
	5.13	*0.66*	*2.61*	*0.03*	*5.99*	*13.16*	*1.73*	*2.88*	*6.69*	*0.10*
Female	-.018	-.094**	-.031*	-.014	-.018	-.045**	-.052**	-.021*	.029	-.017**
	1.13	*4.82*	*1.89*	*0.78*	*1.61*	*3.00*	*3.27*	*1.75*	*1.02*	*2.59*
Age Exit	-.015**	-.013**	-.0058	-.017**	-.0041	.011**	.0037	-.0026	-.015**	-.00085
	3.81	*2.86*	*1.50*	*3.86*	*1.50*	*3.17*	*0.98*	*0.91*	*2.21*	*0.56*
Age First Offense	-.00053	-.0011	-.0021	.0017	-.0025*	-.00062**	-.0050**	-.0019	-.0068**	.00072
	0.28	*0.51*	*1.08*	*0.82*	*1.86*	*3.45*	*2.66*	*1.33*	*2.03*	*0.96*
Incarcerated in Zip	.0017	.0018	.0014	.0015	.0010	-.0012	-.00040	.0011	-.000016	.00026
	1.58	*1.39*	*0.13*	*1.21*	*1.28*	*1.14*	*0.37*	*1.30*	*0.01*	*0.58*
Per Capita Income in Zip	.0000004	-.0000003	-.0000002	-.000001	-.000001**	-.0000008	.0000006	.00000004	-.0000009	-.00000006
	0.63	*0.45*	*0.34*	*1.49*	*3.20*	*1.39*	*1.05*	*0.09*	*0.83*	*0.26*
Felonies	.0032**	.0046**	.0022**	.0015	.00020	-.00055	-.00090	.00023	.0043**	.000075
	3.38	*4.17*	*2.30*	*1.43*	*0.31*	*0.63*	*0.98*	*0.33*	*2.68*	*0.20*
# Observations	8216	8216	8216	8216	8216	8216	8216	8216	8216	8216
R^2	.0849	.0791	.0582	.0430	.0798	.1696	.0914	.0401	.0595	.0695

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-by-prior fixed effects. The results presented above correspond to the main results presented in Table 3.