Peer Effects and Recidivism: The Role of Race and Age

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Abstract

Recidivism rates are a growing concern due to the high cost of imprisonment and the high rate of ex-prisoners returning back to prison. The factors leading to recidivism are multifaceted, but one policy-relevant and potentially important contributor is the composition of peer inmates. In this paper, we study the role of peer effects within a correctional facility using data on almost 80,000 individuals serving time in Georgia. We exploit randomness in peer-composition over time within prisons to identify effects of peers on recidivism rates. We find no evidence of peer effects for property and drug-related crimes in the general prison population. However, we find strong peer effects when we define peer groups by race and age. Our findings indicate that homophily plays a large part in determining the strength of peer exposure among prisoners in the same facility. Our findings suggest that prison assignments can be a way to reduce recidivism for particular groups of prisoners.

JEL codes: H76, K40.

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1 INTRODUCTION

The rate of incarceration and recidivism in the United States is high and costly. Keeping a prisoner incarcerated costs the state prison system approximately $26,000, more than a full time minimum wage earner in many states (Schmitt and Warner, 2010). Importantly, many members of the prison population are repeat offenders, cycling in and out of the prison system. This paper investigates a potentially key determinant of recidivism, namely peer effects in prisons. If, in fact, elements of the prison experience such as peer exposure results in higher rates of recidivism, this would create a vicious circle trapping offenders into the prison system. This not only could lead to increased prison costs, it also raises crime-related social costs.

Our study contributes to the literature by analyzing prison peer effects for a sample of adult prisoners in the US. Previous studies suggest that social interactions are particularly important in the criminal sector, where informal networks could compensate for the lack of formal institutions for gaining knowledge and criminal skills.[1] Our study adds to the peer effects literature in general by providing new evidence that peers in prison can impact recidivism of adults whereas prior studies using data from the US and elsewhere have focused on adolescents. While previous studies establish the existence of peer effects among fellow inmates in a prison and juvenile facilities, more is needed to formulate policies of prison assignments to reduce recidivism (Doleac, 2019). In particular, we need to understand which are the key characteristics of peers

[1] The concept of learning in criminal behavior has been emphasized, among others, by Glaeser et al. (1996), Case and Katz (1991), Calvó-Armengol and Zenou (2004), Ludwig et al. (2007), Bayer et al. (2009), Drago et al. (2011).

that drive the peer effect, and our paper shows that both race and age are important. Further, we show that the network effects are present conditional on defining peers as fellow inmates of the same race. This suggests that individuals sort into networks that exhibit racial homophily and that it is same-race and same-age peers that matter.

The composition of prisoners in a correctional facility is an important prison characteristic that is part of the role that prisons play in determining recidivism, and there is a small but growing literature examining these peer effects. A few papers study peer effects among juveniles (Bayer et al., 2009; Stevenson, 2017; Patacchini and Zenou, 2009) and young adults (Damm and Gorinas, 2013) in juvenile centers in the US and in prisons in Denmark, respectively. Stevenson (2017) argues that social contagion is the most likely channel through which such peer effects operate, but does not explore whether race plays a role. (Damm and Gorinas, 2013) show that peers similar in age have a larger effect in the context of Denmark's young adults prisoner population. However, their sample is more homogenous in terms of race which may explain a lack of precision on their race-specific peer effects estimates. More broadly, this paper contributes to the literature that links peer influences within schools and neighborhoods with criminal behavior (Deming, 2011; Billings et al., 2013; Steinberg et al., 2019; Case and Katz, 1991; Kling et al., 2005; Ludwig et al., 2001, 2007; Corno, 2016; Kirk, 2015; Kim and Fletcher, 2018).

This paper builds on the existing literature by investigating peer effects in a more general context. We examine adult prisoners who make up the vast majority of the prison population. While Bayer et al. (2009) study juveniles in the US and Damm and Gorinas (2013) study young adults in Denmark, we study a rich dataset from the state of Georgia containing the universe of prisoners in the state prison system from 1995 to 2005. We focus on male prisoners and estimate peer effects within prison on recidivism for violent, drug-related, property, and sex crimes. A complementary recent paper by Billings and Schnepel (2017) also studies peer effects and recidivism among adult former inmates in North Carolina. However, the peer group analyzed is that of the residential neighborhood rather than fellow prison inmates. This is a considerably broader definition of a peer group and perhaps less easily manipulated by policy makers. Nevertheless, they estimate the effect of neighborhood criminal peers on recidivism. They find that the more residential peers are incarecerated at the time of release from prison, the less likely it is for the released prisoner to reoffend, with the effect being larger for more similar peers in terms of demographics.

Our data therefore allows us the distinct opportunity to study adult prisoners in the US within the prison system setting, facing a well defined set of potential peers (their fellow inmates). However, there remains the challenge of endogenous sorting in the assignment of prisoners to facilities, likely generating a positive correlation between the types of fellow inmates a prisoner faces and the probability of recidivating. Our key identification assumption to address this challenge is that the changes in prison composition over time for a given prison is random, so that at any particular month, one's prison mates are randomly determined relative to other months in the same facility. Conditional on observable individual characteristics and criminal history, two inmates at the same prison may be exposed to considerably different peers depending on the timing of their stay. Similar to Bayer et al. (2009), we argue that this variation is quasi-random after dealing with non-random prison assignment rules by including facility-by-prior-offense fixed effects.[2]

A prison, however, can be a large place. Unfortunately we do not have direct data on the peer networks within prisons. In this paper, peers are therefore defined as all other inmates in the same prison at the same time. One way to improve resolution on peers is to rely on the principle of homophily. The networks literature has long noted a propensity for people with similar demographics to form ties more frequently (see McPherson et al. (2001) for an overview). We thus expect prisoners to have more social interactions with inmates from the same race, and we expect the share of inmates of the same race to have a larger effect on the individual's probability of recidivism than the share of inmates in general. If that is the case, a potentially fruitful policy would avoid segregation within prisons by race or crime. Alternatively, policies that assign prisoners by both their demographics and crime type may have the unintended effect of increasing exposure to peers who can facilitate a criminal career. We therefore construct peer measures irrespective of demographics, as well as taking into account both race and age. This approach is in a similar spirit to a number of papers in the literature suggesting that social interactions are strong conditional on socio-economic demographics (Billings et al., 2019; Bayer et al., 2008; Cohen-Cole and Fletcher, 2008).

We find that exposure to peers with a history in violent crimes has a

[2]See section 3.2 for further details.

deterrent effect on future violent crime if the prisoner has a history of violent crime, while it is linked to higher violent crime recidivism for prisoners with no history of violent crime. This effect is persistent both when peer effects are estimated within race and not. On the other hand, we find strong reinforcing effects for criminals convicted with property, drug sale, or drug possession crimes only when peer groups are defined by prisoners of the same age-and-race and convicted of the same crime. We do not find these effects if we look at general peer exposure. A standard deviation increase of 0.12 (0.10) [0.11] in the number of prison peers with a property (drug sale)[drug possession] history increases the probability of recidivism with a property (drug sale)[drug possession] offense for individuals with a criminal background in these crimes from 11.5% (2.8%)[7.5%] to 12.6% (4.1%)[8.8%]. Finally, we also document important heterogeneity in the peer effects and find that younger prisoners are particularly susceptible to peer influence for recidivism in drug related crimes.

We note that our main results should be interpreted broadly as "peer effects" and our identification strategy is unable to decompose these effects into more specific mechanisms such as direct social interactions or social learning. That said, the difference in the estimated peer effects when peer measures are defined by demographic characteristics are strongly suggestive that the internal dynamics of social interactions in the prison system are important. In our view, we interpret our findings of stronger reinforcing results among peers who have similar demographics to indicate that self-segregation plays a key role in determining exposure rates to other inmates within a prison. This, in turn, opens up interesting possibilities for policy makers to influence recidivism through the assignment of prisoners to prisons, as well as enforced segregation (or de-segregation) within prisons.

2 DATA

2.1 Sources and descriptive statistics

We take advantage of an administrative dataset provided by the Georgia Department of Corrections (GDC) to examine the effect of prison characteristics and composition on recidivism. We observe the universe of people released from the Georgia prison system from 1995 to 2008. These data provide rich socio-demographic, criminal history, facility assignment, prisoner's diagnostic evaluation, and recidivism information for each inmate. We focus on Georgia because of two main reasons. First, the richness of the data allows us to pin down all inmates housed in each prison facility over time, which is crucial in identifying any peer effects that might occur within an institution. Second, at least on key observable characteristics, the prison population in Georgia seems to be representative of that nationwide.[3]

We restrict our analysis to male inmates who are not housed in bootcamps, local jails, out-of-state or unknown facilities.[4] We further drop individuals who are missing security assignment or any other demographic or criminal

[3]Zapryanova (forthcoming) shows evidence that sentence length, average age at sentencing, and type of crime committed are similar across the prison populations of Georgia and the US in general.

[4]For these types of institutions, we do not have any information about the accommodation and programs offered. The profiles of the GDC residential facilities do not contain any details about these types of facilities.

characteristics that are crucial for our analysis. Our data provides information about the last institution in which the inmate was housed as well as his most recent three previous institutions. In addition to that, we have information on how many days he spent in each institution and the reason for transfer (if any). For the analysis in this paper, we use only one of the four institutions we observe. We define this institution to be the one in which the inmate spends at least fifty percent of the total time he serves in the Georgia state prison system.[5] In the data, we observe that 86% of all inmates in Georgia spent at least fifty percent of the total time they spent in the prison system in a single institution.[6] Figure A1 lists all the institutions used in the analysis along with the number of observations per institution. On average, we observe around 1,000 inmates released from each one of the 67 institutions in our analysis. Further more, in Table 2 we observe that the average inmate spends 394 days in this institution.

The GDC has two main ways to measure recidivism—as the rate of return to prison rates (RTP) or as the rate of felony reconviction (FR). The RTP classifies an inmate as a recidivist if he returns to a Georgia prison for any reason, including technical violations of parole or probation. On the other hand, FR classifies an inmate as recidivist if he is subsequently convicted in Georgia of a new felony offense for which he receives either probation, prison or a split sentence. We use the FR rate, measured within three years of release, as a proxy for recidivism because of two main reasons. First, we want to

[5]Note that we are restricting only to the state prison system and we are abstracting from any time an inmate might have spent in local jails.

[6]If we calculate this percentage out of the total time a prisoner spend in *both* prison and jail, we observe 55% of all prisoners spending more than fifty percent in a single facility.

Table 1: Individual descriptive statistics

	mean	sd	sd_w
White	0.336	0.472	0.465
Age at release	33.369	9.586	8.966
Age at first contact	24.279	7.673	7.440
Employed	0.542	0.498	0.496
Years of schooling	10.623	2.027	2.017
IQ score	98.569	14.999	14.888
Married	0.130	0.336	0.336
Number of children	1.486	1.613	1.607
No alcohol problem	0.549	0.498	0.497
Alcoholic	0.063	0.242	0.242
Alcohol abuser	0.283	0.451	0.450
Alcohol eval missing	0.105	0.306	0.305
No drug problem	0.190	0.393	0.391
Drug experimenter	0.286	0.452	0.450
Drug abuser	0.403	0.491	0.487
Narcotic addict	0.016	0.126	0.125
Drug eval missing	0.104	0.306	0.304
Any convictions with violent crime	0.258	0.438	0.429
Any convictions with non-violent crime	0.026	0.159	0.158
Any convictions with property crime	0.549	0.498	0.496
Any convictions with drug sale crime	0.204	0.403	0.400
Any convictions with drug possession crime	0.428	0.495	0.492
Any convictions with alcohol/DUI crime	0.128	0.334	0.332
Any convictions with sex crime	0.053	0.225	0.220
Any convictions with other crime	0.348	0.476	0.475
Num of total violent convictions	0.857	1.960	1.931
Num of total non-violent convictions	0.051	0.420	0.420
Num of total property convictions	2.434	3.284	3.273
Num of total drug sale convictions	0.529	1.269	1.264
Num of total drug possession convictions	1.299	1.921	1.912
Num of total alcohol/DUI convictions	0.499	1.637	1.631
Num of total sex convictions	0.153	0.773	0.763
Num of total other crime convictions	1.082	1.978	1.971
N	82012.000		

All variables labeled as "Any convictions ..." are indicator variables that are equal to 1 if there are any charges of the specific crime on the individual's criminal history record, and 0 otherwise. All variables labeled as "Num of total ..." are continous variables defined as the number of felony convictions charges in the individual's record. We report both the overall (Col. "sd") and the within (Col. "sd_w") standard deviation.

Table 2: Individual descriptive statistics: Recidivism and Facility

	mean	sd	sd_w
Reconvicted with any crime	0.304	0.460	0.459
Reconvicted with violent crime	0.036	0.187	0.186
Reconvicted with property crime	0.115	0.320	0.319
Reconvicted with drug sale	0.028	0.166	0.165
Reconvicted with drug possession	0.075	0.263	0.263
Reconvicted with sex crime	0.011	0.104	0.104
Days in institution	392.703	368.801	341.590
Sentence length in days	1500.510	1473.015	1445.349
N	82012.000		

The recidivism variables are defined to be equal to 1 if an inmate is reconvicted with a felony within 3 years of release from prison. Refer to Section 2.1 for more detail.

examine whether one's peers have any affect on one's decision to recidivate with a crime that he has already committed or with a crime that he has not committed but his peers have.[7] Second, parole (probation) are revoked based on the judgement of the parole (probation) officer, and therefore people who return to prison because of revocation might be different from those returning because of a new conviction. Since we observe all releases in Georgia through 2008 and we want each released prisoner to have a well-defined three year window period to potentially recidivate, we restrict our estimation sample to prisoners who were released before 2005. Table 2 presents summary statistics for our recidivism measure. Within three years of release, 30% of the sample is reconvicted of a new crime. Property crimes are the most frequent types of recidivating crimes accounting for 11.5%, followed by drug possession with 7.5%. We focus our main analysis on five of eight crime categories listed in

[7] Although it will be interesting to explore peer effects for parole violators, it is difficult to see through what channels the peers can influence one's decision to violate parole.

Table 2 violent personal, property, drug sale, drug possession, and sex crime. We exclude non-violent personal, habitual DUI, and alcohol crime for two reasons. First, the recidivism rates for these crimes are not high enough for a precise estimation. For instance, recidivism rates for these crimes are less 1%. Second, due to the low severity of these crimes, there are very few people incarcerated for them. Specifically, only 12.8% and 2.6% of the inmates we observe have a history of either DUI or alcohol crime and non-violent crime, respectively.[8]

Table 3: Race-age distribution

	Percent
Black	
Born before 1960	21.70
Born between 1960 and 1970	34.14
Born after 1970	44.17
White	
Born before 1960	25.37
Born between 1960 and 1970	36.05
Born after 1970	38.58
Total	
Born before 1960	22.93
Born between 1960 and 1970	34.78
Born after 1970	42.29

This table shows the distribution of percent black and white within each age bin.

Finally, to motivate our detailed analysis of peer composition in this paper, we report the race and age composition of prisoners in our sample (see Table 3). We see that the prisoners are fairly heterogeneous in age, and that both blacks and whites are well represented across the age distribution. There are

[8]We also do not analyze people recidivating with "other crime" as the crimes in this category are very miscellaneous and it is hard to interpret the effect of peers on reoffending within this category.

slightly more black prisoners in the younger age category. This heterogeneity suggests that it is important to account for age and race in constructing peer measures.

2.2 Facility assignment

Upon prison admission in Georgia, offenders are put through a series of evaluations, including medical and mental health screenings on one of the GDC evaluation prisons. In Georgia, there are four such prisons for male convicts (Georgia Diagnostic and Classification Center, Arrendale, Scott, and Bostick) and one for female convicts (Metro Women's State Prison).

When assigning individuals to prisons, the GDC develops an individual comprehensive profile that includes the offender's crime, social background, education, job skills and work history, health, addiction problems, and criminal record. Primarily based on the current and past criminal history, the offenders are also assigned to the most appropriate security level classification—trusty, minimum, medium, close, maximum. The classification levels are in ascending order of perceived public safety risks of the inmate. Our estimation sample consist of predominantly people housed in minimum or medium security institutions. In particular, 59% of observations in Figure A1 are in minimum security prisons, while 29% are in medium security ones. Since we observe most of the elements from the evaluation process, we can account for the non-random prison assignment to some extent by controlling for observable individual characteristics that are likely to influence prison assignment.

From conversations with the Director of Offender Administration at the

GDC, security classification and program needs of the inmate are the two main factors the GDC takes into account in determining prison assignment. We control for all individual characteristics which are essential in determining security classification such as offender's sentence, nature of the crime, criminal history, and history of violence. We also include indicators for drug or alcohol problem along with education attainment and the IQ score of the inmate in order to account for selection based on inmate's prison program needs.

2.3 Peer measures

For each individual i in our sample, we construct a measure of peer exposure as a weighted average of the characteristics of all other inmates j serving in the same institution, where the weights are the number of days i's sentence overlaps with j's. We follow Bayer et al. (2009) and create the peer measures using the following formula

$$Peer_{ij} = \frac{\sum_{j \neq i}(d_{ij} + w_{ij}) \cdot Char_j}{\sum_{j \neq i}(d_{ij} + w_{ij})} \tag{1}$$

where d_{ij} is the exact number of days inmate i's sentence overlaps with j's while w_{ij} is the additional number of days overlap that is due to censoring.[9] $Char_j$ is vector with demographic characteristics (e.g. race, age at release

[9] Refer to Appendix II of Bayer et al. (2009) for more details on the construction of w_{ij}. The basic idea is that the peer measure will be incorrectly calculated for individuals released towards the beginning or the end of the sample period, 1995-2005, since the data does not cover their peers who were released before the sample period begins or after it ends. To correct for this potential measurement bias, we follow Bayer et al. (2009) to construct w_{ij} as the expected number of days individual's i's time spend in prison would overlap with his peer j.

and first contact, education, IQ) and criminal history of prisoner j. Table A1 summarizes the demographic and crime peer characteristics. Even though we do not observe the exact set of peers each inmate directly interacts in prison, the above constructed measure proxies for peer exposure under the assumption that peer characteristics are as good as random within the prison. In other words, the timing of assignment of inmates with respect to their peers is as close to random as possible. Since the validity of our analysis hinges upon this assumption, we test it empirically later in Section 3.2.

Table A1 presents a summary description of the demographic and criminal peer measures. We note that 51% of inmates peers have had a property crime conviction. The other two crime categories that most of one's peers have been convicted are violent (47%), drug possession (32%), and drug sale (19%). Most inmates have higher peer exposure to property and drug offenders as the spread of the distribution is much bigger, while less exposure to sex and violent criminals. This is not surprising given that violent (and to some extent, sex) offenders are usually assigned to close or maximum security prisons.

We also construct race, age, and race-and-age-specific peer measures by computing Equation 2 for each race and age group separately. That is to say, only inmates in the same age and/or race group would contribute to the peer measure:

$$Peer_{ij} = \frac{\sum_{j \neq i}(d_{ij} + w_{ij}) \cdot Char_j}{\sum_{j \neq i}(d_{ij} + w_{ij})}, \text{ if } race_i = race_j \tag{2}$$

Table A2–Table A4 present summary descriptions of the demographic and criminal peer measures by race, age, and race-and-age.

3 PEER EFFECTS

Peer effects in prison can operate through multiple, not necessarily mutually exclusive, channels. Prisons may facilitate the transmission of information and skills and make individuals better criminals. They can likewise decrease the frictions of meeting potential co-offenders in order to build informal social networks (eg. prison gangs). Prisons may also serve as catalysts for increasing or even adopting antisocial behavior. This paper, however, will not speak to what the exact mechanism peers affect individual reoffending decisions. Rather we are more interested in establishing the existence (or lack thereof) of peer effects in the US adult prison population.

3.1 Empirical Methodology

We follow the empirical methodology of (Bayer et al., 2009) and for each crime type c we estimate the following specification:

$$\begin{aligned} Y^c_{ijt} =& \beta_1 PeerOff^c_{ijt} * NoOff^c_i + \beta_2 PeerOff^c_{ijt} * Off^c_i \\ &+ \beta_3 X_i + \beta_4 Peer_{jt} + \nu_j + (\mu_j * Off^c_i) + \tau_t + \epsilon_{ijt} \end{aligned} \tag{3}$$

Here, Y^c_{ijt} is an indicator equal to 1 if inmate i, who is released in period t from prison facility j, is reconvicted of crime c within three years of release. As describe in Section 2.3, $PeerOff^c_{ijt}$ is the weighted average of exposure to peers who have a history of committing a crime type c. The indicator Off^c_i is equal to one if inmate i has committed crime of type c before and 0 otherwise. Similarly, the indicator $NoOff^c_i$ is equal to one if inmate i has not committed crime of type c before and 0 otherwise. X_i is a vector of individual criminal and personal characteristics, while $Peer_{jt}$ are the counterpart vector containing the same characteristics but for inmate's i's peers. ν_j and $\mu_j * Off_i^c$ are facility and facility-by-crime history fixed effects, respectively; τ_t is a vector of indicators with quarter of release.

The interactions terms, $PeerOff_{ijt}^c * NoOff_i^c$ and $PeerOff_{ijt}^c * Off_i^c$ capture the differential impact peers can have on individuals who do and do not have any previous history of crime type c. On one hand, the influence of peers could affect individuals who already have some experience in a particular crime category, and this effect would be captured by β_2. We refer to this specific peer effect as "reinforcing." On the other hand, the peer effect can be "converting" if peers influence individuals who have no history in a particular crime category. The converting peer effect will be captured by the coefficient β_1. If the estimates are negative, we refer to the peer effect as "deterring".

Table 4: Crime Specialization

	(1) Violent	(2) Property	(3) Drug sale	(4) Drug poss.	(5) Sex
Any history	0.054***	0.140***	0.052***	0.082***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
Avg off-diag coeff	-0.03922	-0.00053	-0.02876	-0.01569	-0.06262
Observations	87223	87223	87223	87223	87223
R^2	0.019	0.064	0.024	0.028	0.057

Robust standard errors clustered by facility in parentheses. Each column is estimated by a separate OLS. The dependant variable is individual's probability to recidivate with the crime type indicated with the title of the column. "Any history" is an indicator whether the individual has a history committing the crime type indicated with the title of the column. Each regression controls for whether the individual has a history of all other seven crime categories. The average of these seven coefficients is listed under "Avg off-diag coeff."
*** p<0.01, ** p<0.05, * p<0.1

Table 4 shows evidence for why it is important to distinguish between the two possible type of peer effects. In this table, we regress the individual's probability to recidivate with one of the eight crime categories on having a history of committing this particular crime or any of the other seven crimes. The first row reports the coefficient estimate on the indicator whether an individual has ever been convicted with the crime he is recidivating with. For brevity, the second row report the average of the off-diagonal coefficients for the crimes with which the individual is not recedivating with. The results show a clear pattern: having a history of a particular crime statistically significantly increases the odds of reoffending with the same crime.[10] The effect is the biggest for property criminals—having had a property offense on one's criminal history record increases one's chance to commit a property offense after being released from prison by almost 14 percentage points.

Note that the average of the off-diagonal coefficients in all crime categories is more than ten times smaller than that on the diagonal coefficients. This implies that the correlation between recidivating with a particular crime having a history in the same crime is much higher than of having a history in any other crime type. This results present suggestive evidence that it is important to separate the effect of peers by individual's criminal history.

[10]The only exception to this pattern are people who have committed "other" crime type. This is most probably due to the fact that this crime category includes very different types of crime—from possession of a weapon to obstruction of a law enforcement officer.

3.2 Identification

The main identifying assumption of both the "converting" and "reinforcing" peer effect is that exposure to peers within a given prison is as good as random. To guarantee that this assumption holds, we need the timing of the assignment of individuals to facilities with respect to the already existing composition of the prison to be as good as random. This argument relies on the intuition that while the stock composition of each prison is clearly not random with respect to the type of offense committed by prisoners, the flow is. We check that the identifying assumption holds in two ways.

First, we include quarter of release indicators to account for any criminal trends. Further, we test the existence of time trends by regressing the peer crime indicators on quarter of release dummies. We present our results in Figure A2. We find some weak evidence that peer crime characteristics (with exception of property crimes) increase over time, providing some evidence for an upward trend in criminality. However, almost all of the coefficients on the quarter dummies are not statistically significant suggesting that any trend in criminality is very weak. If crime trends were significantly changing over our study period, the prison compositions would be less comparable over time, and threaten the assumption that variation in composition over time is random. Additionally, we perform a robustness check by exploiting only within-facility variation over a 3-year span (instead of the entire 10-year period) by interacting the facility fixed effects with 3-year dummies. We find that the trends are small and do not affect the estimated coefficients significantly (Table A6).

Second, if the variation in peer composition within a facility is strongly correlated with individual characteristics, that would undermine our identification strategy for peer effects. To test if such a correlation exists in the data, we employ the two-step test discussed by Bayer et al. (2009). Overall, we find no evidence that this is the case.

In the first step, we run an OLS of the individual's probability to recidivate with one of the five crimes (violent, property, drug sale, drug possession, and sex) on the individual's demographic characteristics, drug and alcohol addiction, and any crime history characteristics listed in Table 1.[11] Then, we estimate the predicted probability of recidivism based on these observable characteristics. The estimated predicted recidivism thus encapsulates the role of observable individual characteristics in predicting recidivism.

In the second stage, we test whether the "converting" peer effect ($PeerOff^c_{ijt} * NoOff^c_i$) and "reinforcing" ($PeerOff^c_{ijt} * Off^c_i$) have any predictive power to explain the predicted recidivism probability from the first stage. In particular, we regress the predicted recidivism on the two interaction terms via a seemingly unrelated regressions (SUR) model and present our results in Table 5, Panel A. We observe that the coefficients on the two interaction terms are large and statistically significant for all five crime categories. These results suggest that there exist a strong relationship between peer exposure and observable individual characteristics that are very likely to determine both facility assignment and individual's propensity to recidivate.

In Table 5, Panel B, we exploit only the *within* prison variation in peer exposure by adding facility-by-prior-offense fixed effects. We find almost no

[11]We also include facility fixed effects and cluster our standard errors on the facility level.

Table 5: Specification test

	(1) Violent	(2) Property	(3) Drug sale	(4) Drug poss.	(5) Sex
	Peer Effects				
	Panel A: Without facility-by-offense fixed effects				
$PeerOff_{ijt}^c * Off_i^c$	0.094***	0.180***	0.238***	0.176***	0.007***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$PeerOff_{ijt}^c * NoOff_i^c$	-0.027***	-0.125***	-0.053***	-0.089***	0.006***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
R^2	0.517	0.806	0.674	0.749	0.000
	Panel B: With facility-by-offense fixed effects				
$PeerOff_{ijt}^c * Off_i^c$	-0.015***	-0.005	0.006	0.013***	-0.030**
	(0.004)	(0.005)	(0.004)	(0.003)	(0.015)
$PeerOff_{ijt}^c * NoOff_i^c$	0.001	-0.002	0.009***	0.011***	-0.040***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.004)
R^2	0.550	0.814	0.746	0.798	0.006
	Race-Age-Specific Peer Effects				
	Panel C: Without facility-by-offense fixed effects				
$PeerOff_{ijt}^c * Off_i^c$	0.089***	0.133***	0.219***	0.173***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$PeerOff_{ijt}^c * NoOff_i^c$	-0.030***	-0.158***	-0.020***	-0.070***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.437	0.768	0.575	0.675	0.008
	Panel D: With facility-by-offense fixed effects				
$PeerOff_{ijt}^c * Off_i^c$	-0.017***	0.014***	0.002*	-0.002	-0.049***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
$PeerOff_{ijt}^c * NoOff_i^c$	-0.000	0.016***	0.003***	0.001	-0.007***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R^2	0.568	0.830	0.823	0.825	0.067

Robust standard errors clustered by facility in parentheses. All specifications in Panels A and C are estimated with OLS while those in Panels B and D are estimated as a SUR. The dependent variable is the predicted individual's probability to recidivate with the crime type indicated with the title of the column. This prediction is obtained through an OLS regression on all individual demographic and crime indicators listed in Table 1 along with facility fixed effects, and quarter of release dummies. We also include peer demographic and criminal characteristics listed in Table A1 and A4 in Panels A-B and C-D, respectively. $PeerOff_{ijt}^c$ is the weighted average of exposure to peers who have committed the crime type indicated with the title of the column. Off_i^c and $NoOff_i^c$ are indicators whether individual i has committed or has never committed the crime type indicated with the title of the column, respectively.
*** p<0.01, ** p<0.05, * p<0.1

evidence of the strong relationship between peer exposure and observable individual characteristics that we showed in Panel A. Most coefficients are more than ten times smaller than those in Panel A and most of them are not statistically significant.[12] From the results presented in Table 5 we can draw two main conclusions. First, if we estimate the peer effects across prisons, our estimates are likely to be biased (as evident from Panel A). Second, Panel B provides little evidence that the variation in peer composition within an institution is correlated with observable personal and criminal characteristics that are very likely to influence recidivism rates, and thus lends support to the conclusion that our data is consistent with our identifying assumption. When we run the same specification test for race-specific and age-specific peer effects in Table A5, we draw qualitatively similar conclusions—namely, we find almost no evidence of the strong relationship between peer exposure and observable individual characteristics when we include facility-by-offense fixed effects.

3.3 Main Results

Table 6 presents the estimation of Equation 3 as a SUR. For brevity we report only the coefficients of interest, β_1 and β_2, but we also include all individual demographic and criminal characteristics from Table 1, all peer characteristics from Table A1, quarter of release dummies, and facility fixed effects. Note that we are exploring only the within facility variation in peers

[12]In contrast to Bayer et al. (2009) and Damm and Gorinas (2013), we obtain more coefficients that are statistically significant, although similar in that they are small in magnitude. We attribute this to the fact that we have ten times more observations compared to Bayer et al. (2009) and 40 times compared to Damm and Gorinas (2013). It is worth emphasizing that our coefficients are very small in magnitude and close to zero in most instances.

as we are also including facility-by-offense fixed effects in all specifications.

The estimated reinforcing peer effect (β_1) is statistically significant for individuals who have already committed and re-offend with a violent crime, while we find no evidence of it for all the other types of crime. Greater exposure to peers with violent criminal experience decreases the probability that an individual with a violent criminal record commits another violent crime within three years after prison release. This result can be rationalized if the prison experience of interacting with other violent crime offenders acts as a deterrent, or causes the individual to become better at committing such crimes, or alternatively better at avoiding being caught with another violent crime.[13] The opposite is true if the individual's has never committed a violent crime—namely, greater peer exposure to violent crime offenders results in a higher probability that the individual recidivates with a violent crime.

However, once we examine race-specific, age-specific, and race-and-age specific peer effects, the results are quite different. In addition to the patterns seen for violent crime, we find that there are significant reinforcing effects for property and drug-related crimes. Accounting for race similarities gives rise to "reinforcing" effects for property and drug possession, accounting for age similarities gives rise to effects for property, and accounting for the combination gives rise to property, drug possession, and drug sale effects.

Both Bayer et al. (2009) and Damm and Gorinas (2013) find reinforcing peer effects for drug offenders. Our results are consistent with their findings,

[13] Note that robbery, which is a crime that is motivated by trying to steal something from a victim, is classified as a violent crime. Thus, criminals could learn new skills of how to avoid being caught with such a crime.

Table 6: Main results

	(1) Violent	(2) Property	(3) Drug sale	(4) Drug poss.	(5) Sex
			A: Peer Effects		
$PeerOff^c_{ijt} * Off^c_i$	-0.135***	0.072	0.027	0.054	-0.012
	(0.040)	(0.063)	(0.063)	(0.062)	(0.068)
$PeerOff^c_{ijt} * NoOff^c_i$	0.036	-0.124*	0.025	0.006	0.016
	(0.026)	(0.067)	(0.039)	(0.059)	(0.025)
R^2	0.033	0.080	0.043	0.044	0.069
			B: Race-Specific Peer Effects		
$PeerOff^c_{ijt} * Off^c_i$	-0.047**	0.092**	0.159***	0.136***	-0.026
	(0.021)	(0.039)	(0.027)	(0.049)	(0.054)
$PeerOff^c_{ijt} * NoOff^c_i$	0.015	0.016	0.010	0.051	-0.017
	(0.016)	(0.041)	(0.020)	(0.043)	(0.028)
R^2	0.033	0.080	0.044	0.044	0.069
			C: Age-Specific Peer Effects		
$PeerOff^c_{ijt} * Off^c_i$	-0.111***	0.126***	0.026	0.018	-0.007
	(0.024)	(0.031)	(0.039)	(0.036)	(0.027)
$PeerOff^c_{ijt} * NoOff^c_i$	0.044***	-0.072**	0.011	0.010	-0.001
	(0.014)	(0.032)	(0.025)	(0.033)	(0.011)
R^2	0.033	0.080	0.043	0.044	0.069
			D: Race-Age-Specific Peer Effects		
$PeerOff^c_{ijt} * Off^c_i$	-0.053***	0.133***	0.130***	0.041	-0.013
	(0.016)	(0.016)	(0.020)	(0.025)	(0.023)
$PeerOff^c_{ijt} * NoOff^c_i$	0.026***	-0.003	0.015	0.042**	-0.011
	(0.010)	(0.017)	(0.014)	(0.021)	(0.009)
R^2	0.033	0.081	0.044	0.044	0.069

Robust standard errors clustered by facility in parentheses. All specifications are estimated as a SUR. The dependent variable is the individual's probability to recidivate with the crime type indicated with the title of the column. Each specification controls for all individual demographic and crime indicators listed in Table 1, facility-by-crime history fixed effects, sentence length fixed effects, and quarter of release dummies. We also include peer demographic and criminal characteristics listed in Table A1, A2, A3, and A4 in Panel A, B, C, and D, respectively. $PeerOff^c_{ijt}$ is the weighted average of exposure to peers who have committed the crime type indicated with the title of the column. Off^c_i and $NoOff^c_i$ are indicators whether individual i has committed or has never committed the crime type indicated with the title of the column, respectively.
*** p<0.01, ** p<0.05, * p<0.1

although in our data the peer effects only appear when race (drug possession) and race-and-age (drug sale) are accounted for. The need to account for homophily in our data is similar to Billings et al. (2019), where the authors only find peer effects on youth crime outcomes only when race, gender, and school grade are factored into the analysis. We find that prisoners with or without prior conviction of drug possession, when exposed to peers who have already committed a drug possession crime, will be more likely to recidivate with that crime.

The estimate on the reinforcing effect of 0.13 in Panel B of Table 6, Col.(4). Thus, for a one standard deviation increase in the exposure to peers with a history of a drug possession crime (0.10 as seen from Table A2) increases the individual's probability to recidivate with a drug possession crime at the mean from 7.5% to 8.8%. To put this into context, recall from Table 4 that inmates with prior drug possession history have a 8.2% higher chance to recidivate with another drug possession crime. Having drug-possession offenders as peers can therefore increase the probability of recidivating with a drug possession crime significantly.

Similarly, from Panel D, we see that the estimated reinforcing effect for drug sales is 0.13. Given a standard deviation increase in exposure to peers with a drug sale history (0.10, see Table A4), the mean probability of recidivating with a drug sale crime increases from 2.8% to 4.1%. Again, for context, inmates with prior drug sale history have a 5.2% higher chance to recidivate with another drug sale crime.

These peer effects are large, especially for drug sales, where the size of the peer effect is roughly 25% of the effect of having an own-history with a crime-type. However, they are consistent with other papers in the peer effects literature. For instance, Bayer et al. (2009) find that for felony drug offenses among juveniles, the reinforcing effect is 0.25. With a peer-exposure standard deviation of 0.1, the mean probability of recidiviating with a felony drug offense increases by 2.5 p.p., about double our effect. The broader peer effects literature also find large effects. Kremer and Levy (2008), for example, study the peer effects of college students who frequently consumed alcohol prior to college on the GPA of their roommates, and estimate peer effects that quite large. Carrell et al. (2008) argue that each high school cheater admitted to a U.S. military service academy spread academic dishonesty to as many as 0.47 more students during their college years.

3.4 Heterogeneous Effects

In addition to the main results, we explore heterogeneity in the peer effect by ex-ante prisoner characteristics. We focus on the age of the prisoner, the presence of mental health problems, and sentence length. All regressions in this section focus on race-by-age specific peer measures. The results are reported in Table 7.

We find that our race-by-age peer effects for drug sales and drug possession are driven by young prisoners (less than 30 years of age). Building on the findings from Bayer et al. (2009), it appears that not only juveniles are susceptible to peer influences in the prison system, but also young adults. It also suggests that the policy implications for drug sales and possession from

Table 7: Heterogeneous effects

	(1) Violent	(2) Property	(3) Drug sale	(4) Drug poss.	(5) Sex
			A: Young adults		
$Young * PeerOff^c_{ijt} * Off^c_i$	0.025**	0.019	0.082***	0.063***	0.012
	(0.010)	(0.025)	(0.015)	(0.018)	(0.020)
$Young * PeerOff^c_{ijt} * NoOff^c_i$	0.010	0.040	0.031**	0.002	0.022**
	(0.010)	(0.026)	(0.013)	(0.018)	(0.009)
R^2	0.033	0.078	0.039	0.040	0.068
			B: Mental health problems		
$Mental * PeerOff^c_{ijt} * Off^c_i$	0.051***	0.017	-0.013	0.077***	-0.042**
	(0.013)	(0.027)	(0.023)	(0.025)	(0.017)
$Mental * PeerOff^c_{ijt} * NoOff^c_i$	-0.003	-0.057**	-0.011	0.048*	-0.032***
	(0.013)	(0.029)	(0.019)	(0.025)	(0.009)
R^2	0.035	0.080	0.039	0.040	0.068
			C: Sentence length		
$Sent * PeerOff^c_{ijt} * Off^c_i$	0.003*	0.015***	0.025***	0.019***	-0.000
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
$Sent * PeerOff^c_{ijt} * NoOff^c_i$	-0.016***	-0.003	-0.022***	-0.016***	-0.000
	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
R^2	0.035	0.078	0.043	0.043	0.066
			D: Small Prisons		
$Small * PeerOff^c_{ijt} * Off^c_i$	0.045	0.041	-0.069	0.005	-0.015
	(0.039)	(0.030)	(0.055)	(0.048)	(0.045)
$Small * PeerOff^c_{ijt} * NoOff^c_i$	0.011	-0.005	0.003	-0.077**	0.007
	(0.021)	(0.032)	(0.029)	(0.039)	(0.014)
R^2	0.033	0.078	0.039	0.040	0.068

Robust standard errors clustered by facility in parentheses. Each panel explores heterogeneous effect of the race-age specific peer effect by whether the prisoner is a young adults, whether the prisoner underwent mental health treatment in prison, and by sentence length in panel A, B, and C, respectively. All specifications are estimated as a SUR. The dependent variable is the individual's probability to recidivate with the crime type indicated with the title of the column. Each specification controls for all individual demographic and crime indicators listed in Table 1, facility-by-crime history fixed effects, sentence length fixed effects, and quarter of release dummies. We also include peer demographic and criminal characteristics listed in Table A2. $PeerOff^c_{ijt}$ is the weighted average of exposure to peers who have committed the crime type indicated with the title of the column. In this table, we consider only peer measures that are race-age specific. Off^c_i and $NoOff^c_i$ are indicators whether individual i has committed or has never committed the crime type indicated with the title of the column, respectively. $Young$ is an indicator that equals to 1 if a prisoner is less than 30 years old at the time of prison admission, and 0 otherwise. $Mental$ is an indicator that equals to 1 if a prisoner underwent any mental health treatment level in prison, and 0 otherwise. $Sent$ is a continuous variable that equals to prisoner's sentence length measured in years. $Small$ is an indicator that equals to 1 if a prisoner is housed in an institution with capacity below the median capacity in the sample, and 0 otherwise.
*** p<0.01, ** p<0.05, * p<0.1

our main results apply especially to younger prisoners. On the other hand, the results for property crimes appear to be driven by older prisoners.

We also considered mental health a potential moderator for peer effects in that prisoners with mental health problems may be more susceptible to peer influence. We find that for drug possession, prisoners with weaker mental health are indeed more susceptible to both the reinforcing and converting effects from peers.

It is also likely that prisoners who have committed more severe crimes may drive the peer effects if prisoners sort within prisons by crime severity, conditional on own sentence length. We find that to be the case, consistent with a number of potential mechanisms including homophily among prisoners by crime severity, as well as within-prison segregation by prison wardens by crime severity. Unfortunately we are unable to distinguish between the two in our data, due to a lack of detailed information regarding the prison facilities and their management. However, we believe our findings serve as motivation for future work.

Finally, we examine heterogeneity of our results based on prison capacity. We collected data on prison capacity from online profiles of the GDC residential facilities.[14] We created indicator that is equal to one if an inmate is housed at a prison with capacity below the median in the sample, and 0 otherwise. We interact this indicator with our peer measures and report the results in Table 7 Panel D. The effects are largely insignificant with exception of drug sale, for which the effect is negative, indicating a deterring effect instead.

[14] Refer to `http://www.dcor.state.ga.us/GDC/FacilityMap/jsp/FacQrybyFacility.jsp`.

4 CONCLUSIONS

The objective of this study is to investigate peer effects within a prison, and to highlight the importance of peer age and race. We leverage data on the universe of inmates serving time in the Georgia Department of Correction System between 1995 and 2005. Using only within-prison variation, we find evidence of peer effects for violent (deterrent), property (reinforcing), and drug possession (reinforcing) offenders, but only when peers are defined by their ethnic group.

Our findings have an important implication for the debate about the role prisons in recidivism rates. Our estimates suggest that prison composition is important and relevant to the prison experience, and in particular, can contribute to higher recidivism rates among same-race and same-age inmates convicted for property, drug possession, and drug sale crimes. Our results also highlight the importance of research aimed at determining which peers play a role in increasing or reducing recidivism, and have broad policy implications for prison assignment as well as group-specific post-release program assignments (Doleac, 2019). In addition, our results speak to rehabilitation programs, where prison social interaction ought to be a part of broader pushes toward lowering recidivism. For instance, the impact of sentence lengths on prisoner efforts to rehabilitate (Bernhardt et al., 2012) can potentially interact with the peer effects within prisons that this paper documents.

A richer understanding of the ways inmates respond to exposure with similar or different peers would likely allow policymakers to decrease socially costly recidivism by adjusting conditions and redesigning assignment systems, both between and within prisons. For instance, one potential implication is that prisons ought to restrict interactions between prisoners of the same race-and-age categories perhaps by introducing more race-and-age diversity within the prisons. Therefore, even if assignments are determined primarily by crime-type, we can still alleviate recidivism rates through adjusting prison allocations by race-and-age.

Additionally, to get a better grasp of the policy relevant effects, we could use this framework to calculate counterfactual recidivism rates given changes in prison composition. Combined with information on the cost of prisoner reassignments, this can yield valuable insights for prison assignment in a bid to reduce recidivism rates.

Finally, our heterogeneity analysis suggests further avenues of fruitful research for a better grasp of the social and institutional structures at play. This can improve the targeting of prison allocation policies to reduce recidivism.

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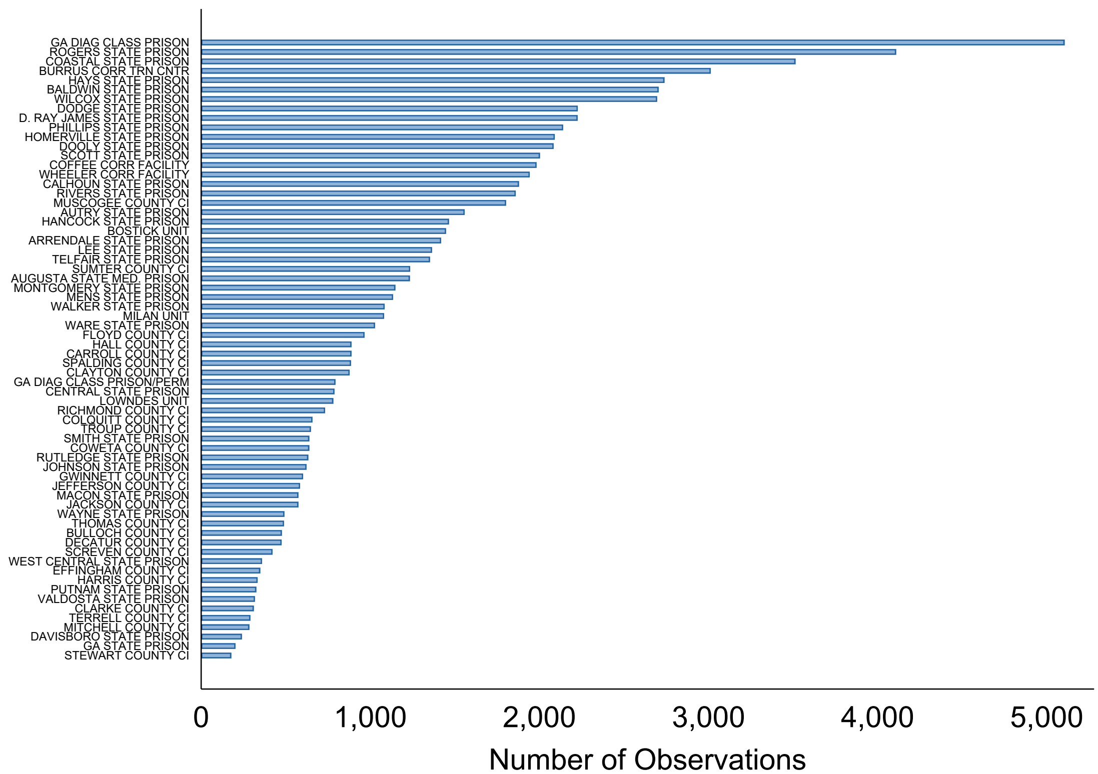
A APPENDIX

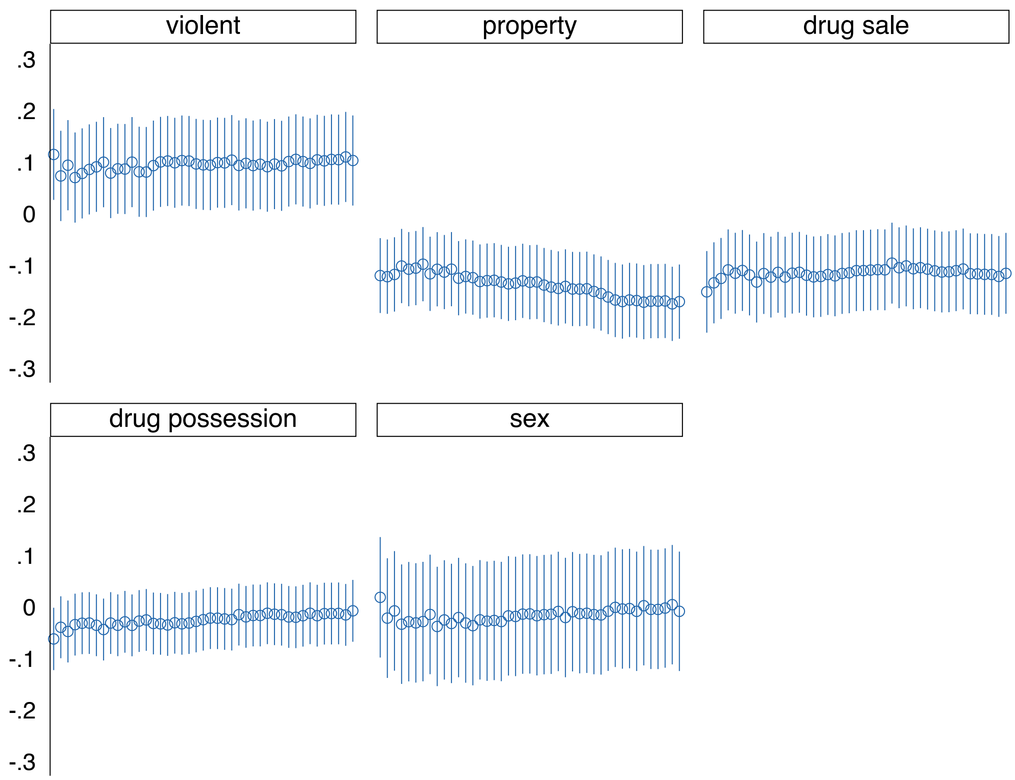
A.1 Supplementary Tables and Figures

Figure A1: Total number of inmates per prison facility for the period 1995-2005



Notes: On the y-axis we list all correctional facilities used in the main analysis. The x-axis presents the number of individuals we observe in each institution over our sample period, 1995-2005.

Figure A2: Peer crime effect time trends



Notes: The figure reports the coefficient estimates and their 95% confidence intervals on quarter of release indicators that result from a regression with dependent variable peer crime indicator specified in the title of each individual graph.

Table A1: Peer descriptive statistics

	mean	sd	sd_w
White	0.336	0.090	0.031
Age at release	30.483	4.386	2.004
Age at first contact	24.245	2.212	0.480
Years of schooling	10.353	0.265	0.105
IQ score	95.268	3.692	2.115
Married	0.135	0.028	0.015
Number of children	1.414	0.185	0.074
Employed	0.499	0.070	0.028
No alcohol problem	0.547	0.047	0.036
Alcoholic	0.061	0.018	0.013
Alcohol abuser	0.274	0.038	0.021
Alcohol eval missing	0.118	0.035	0.022
No drug problem	0.245	0.054	0.020
Drug experimenter	0.263	0.047	0.030
Drug abuser	0.354	0.070	0.031
Narcotic addict	0.019	0.011	0.008
Drug eval missing	0.118	0.035	0.022
Any convictions with violent crime	0.470	0.118	0.038
Any convictions with non-violent crime	0.049	0.019	0.009
Any convictions with property crime	0.511	0.054	0.027
Any convictions with drug sale crime	0.185	0.058	0.020
Any convictions with drug possession crime	0.321	0.081	0.026
Any convictions with alcohol/DUI crime	0.096	0.034	0.022
Any convictions with sex crime	0.123	0.085	0.019
Any convictions with other crime	0.331	0.033	0.020
Num of total violent convictions	1.582	0.504	0.157
Num of total non-violent convictions	0.073	0.026	0.018
Num of total property convictions	2.438	0.321	0.163
Num of total drug sale convictions	0.505	0.150	0.060
Num of total drug possession convictions	0.998	0.286	0.104
Num of total alcohol/DUI convictions	0.371	0.174	0.116
Num of total sex convictions	0.381	0.269	0.061
Num of total other crime convictions	1.045	0.138	0.078
N	82012.000		

For details on how the peer measures are calculated refer to Section 2.3. The crime variables are the peer counterparts of the crime variables as described in the notes of Table 1.

Table A2: Race-specific peer descriptive statistics

	mean	sd	sd_w
Age at release	30.498	4.501	2.368
Age at first contact	24.248	2.490	1.318
Years of schooling	10.351	0.365	0.268
IQ score	95.246	5.199	4.212
Married	0.135	0.049	0.044
Number of children	1.415	0.240	0.168
Employed	0.499	0.105	0.083
No alcohol problem	0.547	0.068	0.061
Alcoholic	0.060	0.032	0.030
Alcohol abuser	0.274	0.054	0.043
Alcohol eval missing	0.119	0.043	0.033
No drug problem	0.245	0.062	0.037
Drug experimenter	0.263	0.053	0.038
Drug abuser	0.354	0.079	0.049
Narcotic addict	0.019	0.014	0.011
Drug eval missing	0.118	0.043	0.033
Any convictions with violent crime	0.469	0.132	0.075
Any convictions with non-violent crime	0.048	0.023	0.016
Any convictions with property crime	0.511	0.069	0.051
Any convictions with drug sale crime	0.185	0.091	0.073
Any convictions with drug possession crime	0.322	0.102	0.066
Any convictions with alcohol/DUI crime	0.095	0.069	0.064
Any convictions with sex crime	0.123	0.104	0.063
Any convictions with other crime	0.331	0.048	0.040
Num of total violent convictions	1.577	0.551	0.291
Num of total non-violent convictions	0.073	0.034	0.029
Num of total property convictions	2.439	0.482	0.399
Num of total drug sale convictions	0.506	0.239	0.194
Num of total drug possession convictions	1.000	0.337	0.205
Num of total alcohol/DUI convictions	0.371	0.345	0.322
Num of total sex convictions	0.381	0.339	0.214
Num of total other crime convictions	1.047	0.216	0.184
N	82012.000		

For details on how the within race peer measures are calculated refer to Section 2.3. The crime variables are the peer counterparts of the crime variables as described in the notes of Table 1 and are all calculated within a specific race.

Table A3: Age-specific peer descriptive statistics

	mean	sd	sd_w
Age at release	30.053	8.369	7.292
Age at first contact	23.933	4.675	4.145
Years of schooling	10.346	0.382	0.303
IQ score	95.456	4.956	3.852
Married	0.131	0.055	0.049
Number of children	1.388	0.394	0.351
Employed	0.499	0.087	0.059
No alcohol problem	0.551	0.074	0.068
Alcoholic	0.059	0.031	0.028
Alcohol abuser	0.271	0.060	0.050
Alcohol eval missing	0.118	0.043	0.033
No drug problem	0.243	0.067	0.046
Drug experimenter	0.266	0.057	0.045
Drug abuser	0.354	0.084	0.056
Narcotic addict	0.019	0.016	0.014
Drug eval missing	0.118	0.043	0.033
Any convictions with violent crime	0.465	0.126	0.060
Any convictions with non-violent crime	0.049	0.025	0.018
Any convictions with property crime	0.511	0.084	0.071
Any convictions with drug sale crime	0.186	0.062	0.033
Any convictions with drug possession crime	0.325	0.087	0.044
Any convictions with alcohol/DUI crime	0.094	0.057	0.050
Any convictions with sex crime	0.117	0.093	0.050
Any convictions with other crime	0.330	0.050	0.042
Num of total violent convictions	1.548	0.543	0.287
Num of total non-violent convictions	0.073	0.039	0.034
Num of total property convictions	2.421	0.678	0.617
Num of total drug sale convictions	0.504	0.180	0.120
Num of total drug possession convictions	1.005	0.315	0.177
Num of total alcohol/DUI convictions	0.363	0.290	0.256
Num of total sex convictions	0.358	0.306	0.184
Num of total other crime convictions	1.043	0.210	0.177
N	82012.000		

For details on how the within race peer measures are calculated refer to Section 2.3. The crime variables are the peer counterparts of the crime variables as described in the notes of Table 1 and are all calculated within a specific age group.

Table A4: Race-and-age-specific peer descriptive statistics

	mean	sd	sd_w
Age at release	30.088	8.410	7.372
Age at first contact	23.913	4.731	4.224
Years of schooling	10.337	0.520	0.462
IQ score	95.409	6.615	5.810
Married	0.131	0.069	0.065
Number of children	1.386	0.447	0.406
Employed	0.501	0.120	0.103
No alcohol problem	0.551	0.091	0.087
Alcoholic	0.059	0.043	0.041
Alcohol abuser	0.272	0.076	0.069
Alcohol eval missing	0.118	0.055	0.047
No drug problem	0.241	0.083	0.069
Drug experimenter	0.266	0.068	0.058
Drug abuser	0.356	0.103	0.083
Narcotic addict	0.019	0.020	0.018
Drug eval missing	0.118	0.055	0.047
Any convictions with violent crime	0.462	0.143	0.094
Any convictions with non-violent crime	0.048	0.031	0.027
Any convictions with property crime	0.513	0.116	0.107
Any convictions with drug sale crime	0.186	0.097	0.081
Any convictions with drug possession crime	0.325	0.113	0.083
Any convictions with alcohol/DUI crime	0.094	0.085	0.081
Any convictions with sex crime	0.117	0.109	0.076
Any convictions with other crime	0.331	0.068	0.063
Num of total violent convictions	1.540	0.613	0.419
Num of total non-violent convictions	0.072	0.052	0.049
Num of total property convictions	2.439	0.863	0.820
Num of total drug sale convictions	0.503	0.274	0.238
Num of total drug possession convictions	1.005	0.391	0.288
Num of total alcohol/DUI convictions	0.362	0.437	0.417
Num of total sex convictions	0.357	0.362	0.267
Num of total other crime convictions	1.045	0.299	0.278
N	82012.000		

For details on how the within race peer measures are calculated refer to Section 2.3. The crime variables are the peer counterparts of the crime variables as described in the notes of Table 1 and are all calculated within a specific race-and-age group.

Table A5: Specification test

	(1) Violent	(2) Property	(3) Drug sale	(4) Drug poss.	(5) Sex
	Race-Specific Peer Effects				
	Panel A: Without facility-by-offense fixed effects				
$PeerOff^c_{ijt} * Off^c_i$	0.086***	0.167***	0.211***	0.178***	0.022***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$PeerOff^c_{ijt} * NoOff^c_i$	-0.034***	-0.134***	-0.019***	-0.070***	0.032***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R^2	0.437	0.818	0.635	0.732	0.017
	Panel B: With facility-by-offense fixed effects				
$PeerOff^c_{ijt} * Off^c_i$	-0.012***	0.005	0.003	0.006***	-0.025**
	(0.004)	(0.004)	(0.003)	(0.002)	(0.011)
$PeerOff^c_{ijt} * NoOff^c_i$	-0.003	0.006	0.006***	0.008***	-0.032***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.004)
R^2	0.474	0.835	0.746	0.800	0.072
	Age-Specific Peer Effects				
	Panel C: Without facility-by-offense fixed effects				
$PeerOff^c_{ijt} * Off^c_i$	0.098***	0.113***	0.232***	0.171***	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$PeerOff^c_{ijt} * NoOff^c_i$	-0.022***	-0.185***	-0.058***	-0.085***	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R^2	0.445	0.782	0.617	0.695	0.000
	Panel D: With facility-by-offense fixed effects				
$PeerOff^c_{ijt} * Off^c_i$	-0.031***	0.012***	0.002	-0.001	-0.065***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.013)
$PeerOff^c_{ijt} * NoOff^c_i$	-0.010***	0.005	0.005***	0.000	-0.073***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.003)
R^2	0.569	0.832	0.814	0.824	0.014

Robust standard errors clustered by facility in parentheses. All specifications in Panels A and C are estimated with OLS while those in Panels B and D are estimated as a SUR. The dependent variable is the predicted individual's probability to recidivate with the crime type indicated with the title of the column. This prediction is obtained through an OLS regression on all individual demographic and crime indicators listed in Table 1 along with facility fixed effects, and quarter of release dummies. We also include peer demographic and criminal characteristics listed in Table A2 and A3 in Panels A-B and C-D, respectively. $PeerOff^c_{ijt}$ is the weighted average of exposure to peers who have committed the crime type indicated with the title of the column. Off^c_i and $NoOff^c_i$ are indicators whether individual i has committed or has never committed the crime type indicated with the title of the column, respectively.
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Robustness: Facility-by-Crime History-by-Time Period Fixed Effects

	(1) Violent	(2) Property	(3) Drug sale	(4) Drug poss.	(5) Sex
			A: Peer Effects		
$PeerOff_{ijt}^c * Off_i^c$	-0.138**	0.185**	-0.022	0.069	-0.009
	(0.061)	(0.093)	(0.088)	(0.090)	(0.097)
$PeerOff_{ijt}^c * NoOff_i^c$	0.058	-0.262***	0.029	-0.053	0.026
	(0.038)	(0.100)	(0.052)	(0.085)	(0.036)
R^2	0.040	0.085	0.050	0.053	0.074
			B: Race-Specific Peer Effects		
$PeerOff_{ijt}^c * Off_i^c$	-0.029	0.081**	0.175***	0.147**	-0.022
	(0.024)	(0.041)	(0.028)	(0.066)	(0.066)
$PeerOff_{ijt}^c * NoOff_i^c$	0.019	0.006	0.016	0.041	-0.020
	(0.018)	(0.044)	(0.021)	(0.055)	(0.034)
R^2	0.040	0.085	0.051	0.053	0.074
			C: Age-Specific Peer Effects		
$PeerOff_{ijt}^c * Off_i^c$	-0.113***	0.126***	0.002	0.011	-0.002
	(0.028)	(0.031)	(0.042)	(0.038)	(0.029)
$PeerOff_{ijt}^c * NoOff_i^c$	0.044***	-0.085***	0.006	0.002	0.000
	(0.016)	(0.033)	(0.025)	(0.034)	(0.012)
R^2	0.040	0.085	0.050	0.053	0.074
			D: Race-Age-Specific Peer Effects		
$PeerOff_{ijt}^c * Off_i^c$	-0.048***	0.132***	0.133***	0.034	-0.009
	(0.017)	(0.016)	(0.021)	(0.027)	(0.024)
$PeerOff_{ijt}^c * NoOff_i^c$	0.024**	-0.005	0.015	0.043*	-0.010
	(0.011)	(0.017)	(0.014)	(0.022)	(0.009)
R^2	0.040	0.086	0.051	0.053	0.074

Robust standard errors clustered by facility in parentheses. All specifications are estimated as a SUR. The dependent variable is the individual's probability to recidivate with the crime type indicated with the title of the column. Each specification controls for all individual demographic and crime indicators listed in Table 1, facility-by-crime history-by-time period fixed effects, sentence length fixed effects, and quarter of release dummies. We define time period in three-year bins based on inmate's prison admission year. We also include peer demographic and criminal characteristics listed in Table A1, A2, A3, and A4 in Panel A, B, C, and D, respectively. $PeerOff_{ijt}^c$ is the weighted average of exposure to peers who have committed the crime type indicated with the title of the column. Off_i^c and $NoOff_i^c$ are indicators whether individual i has committed or has never committed the crime type indicated with the title of the column, respectively.
*** p<0.01, ** p<0.05, * p<0.1