Prison, Peers, and Recidivism: Does Severity Matter?

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Abstract

I exploit variation in prison facility peer composition over time to identify heterogeneous peer effects on recidivism rates based on criminal severity. I do this using data from the Illinois Department of Corrections covering the entire prison population from 2014 to 2024. I use two proxies for individual criminal severity being sentence length and felony crime class. In total, I measure the effect of more severe criminal peers on total recidivism, recidivism by crime type, and recidivism into more severe crimes. I contribute to the quickly growing literature on peer effects within prisons on recidivism.

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I Introduction

The United States incarcerates individuals at a rate unmatched by any other similarly-developed nation (Travis, Western, and Redburn 2014). High recidivism rates, such as 55% in three years in Illinois, suggest a problem in the rehabilitation and reintegration process (Olson 2024). One concern is that prisons themselves are criminogenic, i.e. encourage criminal behavior, because of peer effects. Peer effects are especially strong in the illegal labor market due to its secrecy and lack of formal training or learning institutions. To this end, there exists a substantial body of literature aimed at discovering the potential existence and strength of peer effects that lead to criminal behavior. However, the literature on peers in prison is smaller but growing in recent years.

Stephen Billings and his coauthors have done much work on this front with data from North Carolina. Billings and Hoekstra (2024) exploits within-school and within-neighborhood variation in the proportion of peers arrested. They find that attending school with crime-prone peers, defined as peers with a criminal parent, increases arrest rates by as much as 6.5 percent. In addition, Billings and Schnepel (2022) looks at how the absence of pre-incarceration social networks affect an individual's recidivism rate. They find one fewer neighborhood peer deceases the one-year recidivism rate by 2.4 percentage points, roughly a 5 percent decrease. This effect was over four times as strong for peers who had committed the same crime.

Rivera (2022) takes a different approach to peer effects on criminal activity. This paper identifies peer effects of minority officers on arrest rates of minorities by non-minority officers in Chicago. The author exploits a lottery system which creates exogenous variation in the racial makeup of police academy cohorts. He finds that higher proportions of minorities in the police force reduces the likelihood that officers arrest minorities specifically for low-level crimes. He finds no effect on higher level crimes which threaten public safety.

Philippe (2024) finds evidence of criminals learning from each other in France. He uses a natural experiment which increased sentences for recidivism of the same crime in 2007. This decreased recidivism of only the same crime. Interestingly, co-defendants of those who recidivated in the same crime after the increased penalty recidivate less themselves in the same crime. This suggests learning of criminal law by personal experience when at their peer's expense.

While not about criminals, Lyle (2009) explores the effects of peer heterogeneity at West Point. He focuses on how the average and variance in ability of an individuals' peers can affect their own outcomes. This paper gives motivation for my work on peer severity where I use sentence length rather than SAT scores, both of which are determined before the peer interaction of interest. However, since exposure to peers is not uniform I use the weighted average of exposure. I go into further detail on this in section III.

Most similar to my paper are Bayer, Hjalmarsson, and Pozen (2009) and Tan and Zapryanova (2021) which look at how peers in prison can affect an individual's criminal behavior once released. Bayer, Hjalmarsson, and Pozen (2009) laid the groundwork and presented much of the identification strategy I use in this paper. They use juvenile data in Florida to see how exposure to peers who committed specific crimes affect the juvenile within a year of release. They use the timing of assignment to juvenile corrections as an exogenous source of variation. They find that the exposure to peers in corrections, previously convicted in a given crime category, increased the likelihood to recidivate in that crime category only when the juvenile had already been convicted in that same category. This suggests peers reinforce the behavior that got them into juvenile corrections. However, they did not find any converting effect of peers on a juvenile who had not previously been convicted in that crime category.

Tan and Zapryanova (2021) follows a similar model to Bayer, Hjalmarsson, and Pozen (2009) and looks at prisoners in Georgia. Similarly, they use exogenous variation in peer exposure created by the as-good-as random flow of prisoners through a given prison to identify peer effects. They add an additional qualifier to peers in that they must be of the same race and similar age as the individual[1]. They argue that peers of the same race and similar age have the greatest impact on individuals so only those fitting this should count as peers. They find similar results as Bayer, Hjalmarsson, and Pozen (2009) of a strong reinforcing effect and no evidence of a converting effect for prisoners who had not previously been convicted in the same crime category as their peers.

A recent working paper, Johnsen and Khoury (2024), uses Norwegian register data to identify peer effects which vary by experience of the peer. They use the number of previous convictions to proxy for experience and find that having more experienced peers in prison increases recidivism. In

[1] Prisoners must be within a year of age of each other to be considered peers.

addition, they find that peers at the top of the distribution have the greatest impact on shaping criminal behavior. The authors also found peer effects to be more pronounced when they share demographic characteristics and backgrounds, further supporting the peer measure used in Tan and Zapryanova (2021).

These papers span peer effects on recidivism which differ with the size of peer networks and peers' past crime category and experience. To my knowledge, there is no work on how peer effects vary based on a peer's severity of crime. This is how my paper contributes to the literature. I look at this question of peers' severity in three ways. First, I measure how criminal severity among peers effect recidivism where sentence length is a proxy for criminal severity. Next, I see how exposure to more severe criminals influences recidivism into worse offenses where severity is measured by felony class. Here felony class serves as another proxy for criminal severity which is not perfectly collinear to prison sentence. Finally, I measure heterogeneous peer effects, based on criminal severity, on recidivism in different crime categories.

II Data

In order to look at peer effects in prison I use prisoner data maintained by the Illinois Department of Corrections (IDOC). These are public data which are reported either quarterly, semiannually, or annually depending on the dataset and year. I combine seventy-three total datasets which each fall under one of three subsets being: prison admissions, prison exits, and prison population. Together these give me a total of over 580,000 prison stays comprised of roughly 250,000 unique individuals. Crucially these datasets each contain the offender's IDOC number, an internally kept identification number, so that I can link them across datasets and sentences. This gives me key information on prisoners spanning as much as January 1, 2005 to September 30, 2024[2]. I present demographic and criminal summary statistics for the entire Illinois prison population from 2005 to 2024 in table 1.

The most expansive of these are the current prison population datasets. These are reported semiannually from 2006 to 2017 and quarterly from 2018 to the present[3]. These datasets include many important variables which I use to track the prisoner throughout their current stay as well

[2] I will continue to add data each quarter to include past this date.

[3] There is one dataset in June 2005 which I include, making for a total of fifty-one prison population datasets.

Table 1: Summary Statistics of Illinois Prisoners from 2005 to 2024

Variable	Mean	Std. Dev.	Min	Max
Year of Birth	1979.26	11.87	1918	2006
Female	0.08	0.28	0	1
White	0.32	0.47	0	1
Black	0.56	0.49	0	1
Hispanic	0.11	0.32	0	1
Asian	0.00	0.05	0	1
Native	0.00	0.04	0	1
Bi-racial	0.00	0.04	0	1
Veteran	0.01	0.13	0	1
Sentence (Years)	5.97	13.05	0	2500
Murderer	0.02	0.15	0	1
Class X Felon	0.12	0.32	0	1
Class 1 Felon	0.15	0.36	0	1
Class 2 Felon	0.27	0.44	0	1
Class 3 Felon	0.17	0.38	0	1
Class 4 Felon	0.27	0.44	0	1
Released to Parole	0.25	0.43	0	1

Note: The table is based on a total of 580,348 observations. Deceased prisoners or those with life sentences are excluded.

as controls. Variables used to identify a prison stay throughout the many datasets are their IDOC number, date of birth, custody date, felony class, holding offense, and sentence length. There are six felony classes which, ordered from most to least severe, are: murder, X, one, two, three, and four. These classes are a way to measure the severity of an individual's conviction as well as determine the number of grouped peers an individual is exposed to at a given time. Variables used as controls include gender, race, veteran status, year of custody, and sentencing county.

Admissions and exits data are reported on either, but recently both, a calendar year or fiscal year basis. Exits data are reported every calendar year since 2014 with fiscal year data since 2020. The admissions data coupled with the prison population data allows me to see the reception center and date for any offender who entered prison since January 1, 2005. The exits data gives the releasing institution and exact date for anyone released after December 31, 2013. This includes those discharged or released under mandatory supervised release (MSR) which replaced parole in Illinois in 1978 (Gruschow 2022).

In addition IDOC includes data on the parolee population beginning in 2016[4]. It is reported

[4]Parole was replaced with mandatory supervised release in Illinois in 1978, but the public IDOC data refers to

semiannually in 2016 and 2017 then quarterly beginning in 2018. This allows me to get more detailed data on how the prisoner was released. Although it does not give me any additional information on their actual release date, even if the individual was released to mandatory supervised release. This is because all release dates are included in the prison exits data.

Due to the frequency of reporting these datasets, I restrict my sample to individuals released from prison in 2014 through 2021 in my main specifications. This allows me to have accurate release dates, to the day, for all individuals in this time horizon as well as give the necessary full three years to calculate three year recidivism. This restriction is also required to calculate my peer exposure variables which I go into more detail about in section III. This restriction reduces my sample size to roughly 140,000 separate prison stays.

I include summary statistics of the restricted sample in table 2. This table includes both demographic and crime statistics for these prisoners. Twenty-one percent of prisoners released from 2014 to 2021 return to prison and thus recidivate at any point after their release. This number reduces to thirteen percent when looking only within three years of release. The most stark difference after reducing my sample is the rate at which people are released to parole. This is an effect of Illinois moving from parole to MSR in 1978 as well as adopting truth-in-sentencing laws in 1995 (Gruschow 2022 and Olson et al. 2009). I also include a table of the prison population by facility in table 4 in the appendix.

One important limitation of these data are they do not track transfers. However, I can determine these once the data is merged. Transferred prisoners show in a different facility on the following prison population dataset. This allows me to track if the prisoner was transferred, from which facility and to which other facility, but not what date this occurred. The frequency of my data allows me to get as close as within a quarter of a year to this date. Due to this limitation I assume all transfers occur in the middle of the quarter of transfer[5]. This results in an attenuation error of my final results. In addition to this, I have a term in my measurement of peers and their average sentence which allows me to adjust for this[6].

this section of the data as parole data (Gruschow 2022). Technically individuals in these datasets are on MSR, not parole. I use the terms interchangeably throughout this paper.

[5]More work is being done to address this issue. Accurate reports of the frequency of transfers are not publicly reported. However, requests for transfers are only allowed after six months tenure at the current facility.

[6]This term is w_{in} which I detail in section III.A.

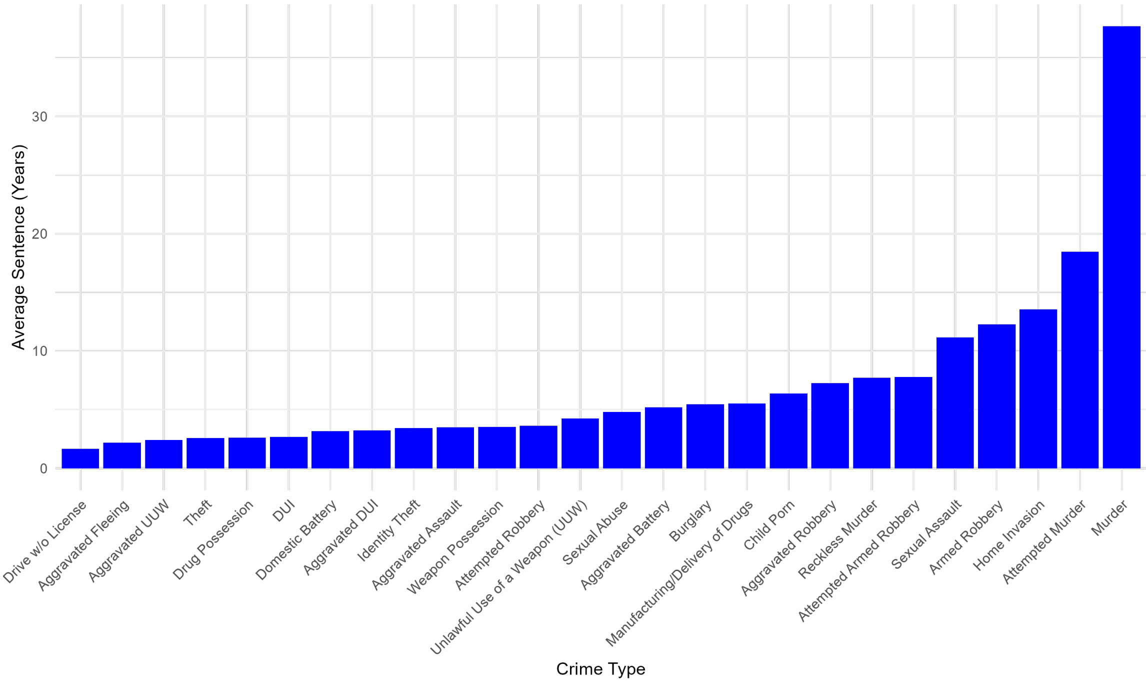
It is important to note that sentence length serves as a proxy for criminal severity. I provide motivation for its use in Figure 1, where I display the average sentence lengths for prisoners in my sample based on their crimes. While the severity of crimes is inherently subjective, this figure aligns well with both legal classifications of severity and public opinion. For example, murder, which is considered the most severe crime under the law—so much so that it belongs to the harshest felony class—has the longest average sentence. In contrast, offenses like driving without a license, fleeing, and drug possession, which are relatively minor and often seen as victimless crimes, fall at the opposite end of the spectrum.

This comparison across different crimes becomes more intuitive when examining crimes of a similar nature. For instance, comparing various types of theft-related crimes highlights differences in severity. Home invasion, defined as knowingly entering another's dwelling while someone is present and threatening or causing harm, carries the longest average sentence among such crimes. Armed robbery, which may not occur in someone's home or result in harm, has a lower average sentence. This is followed by attempted armed robbery, aggravated robbery-which requires only a verbal indication of a weapon)-and burglary, which does not necessitate that anything be taken. Finally, theft—typically involving property valued at $300 or less, often from retail stores—has the shortest average sentence among these crimes.

It is worth noting that sentence length is not a perfect proxy for criminal severity, as evidenced by some discrepancies. For example, aggravated unlawful use of a weapon carries a lower average sentence than unlawful use of a weapon, despite the aggravated nature of the former offense.

The Illinois Department of Corrections data are of particular interest as they include the Chicago and Cook County area which has one of the highest crime rates in the United States (Skogan 2022). This area is also known for its prominence of organized crime which makes peer effects particularly interesting to measure because of the higher benefit of networks in this context (Bruhn 2021).

Figure 1: Average Sentences of Crimes



Note: All crimes with fewer than 1,000 observations are not included. This table is based on 723,356 observations from IDOC which includes all prisoners from January 1, 2005 to September 30, 2024.

III Methodology

III.A Peer Measures

Every individual i in my sample was in prison in Illinois from 2015 to 2021 and has a corresponding measure of peer exposure for each felony class[7]. This measure of peer exposure is the weighted average of characteristics of all other inmates n in prison facility j which is the same as individual i. The weights are determined by the number of days i's sentence in prison overlaps with prisoner n's. I follow Bayer, Hjalmarsson, and Pozen (2009) to create peer measures. I define peer exposure to only include peers of the same race and relative age as in Tan and Zapryanova (2021). This measure

[7]I restrict my sample in most regressions to not include years 2022-2024 so that I can get three-year recidivism measures.

Table 2: Summary Statistics of Prisoners Released from 2014 to 2021

Variable	Mean	Std. Dev.	Min	Max
Recidivism	0.21	0.41	0	1
3-Year Recidivism	0.13	0.33	0	1
Year of Release	2017.12	2.21	2014	2021
Year of Birth	1981.20	11.50	1920	2004
Female	0.08	0.27	0	1
White	0.31	0.46	0	1
Black	0.58	0.49	0	1
Hispanic	0.12	0.32	0	1
Asian	0.00	0.06	0	1
Native	0.00	0.04	0	1
Bi-racial	0.00	0.03	0	1
Veteran	0.01	0.12	0	1
Sentence (Years)	5.20	13.55	0	2500
Murderer	0.01	0.12	0	1
Class X Felon	0.10	0.30	0	1
Class 1 Felon	0.15	0.36	0	1
Class 2 Felon	0.27	0.44	0	1
Class 3 Felon	0.16	0.37	0	1
Class 4 Felon	0.30	0.46	0	1
Released to Parole	0.91	0.29	0	1

Note: The table is based on a total of 140,083 observations. Deceased prisoners or those with life sentences are excluded. Recidivism rates do not include mandatory supervised release violations.

is given in equation 1 and will be a control variable used in all estimates unless otherwise stated.

$$\text{Peer}_{ijt} = \frac{\sum_{n \neq i}(d_{in} + w_{in}) * c_n}{\sum_{n \neq i}(d_{in} + w_{in})} \tag{1}$$

$$\text{where race}_i = \text{race}_n \text{ and age}_n \in [\text{age}_i - 1, \text{age}_i + 1]$$

d_{in} is the exact number of days i's sentence overlaps with n's sentence and w_{in} is the expected additional number of days overlap that is censored[8]. c_n is a demographics vector of prisoner n which includes age, race, and release date. While I do not observe exact direct interactions within prison, this measure proxies for peer exposure. This proxy holds under the assumption that peer characteristics, with respect to individual i's characteristics, are as good as random within the prison.

[8]Due to censoring the peer measure would be calculated incorrectly at the beginning and end of the sample period without this term. To account for measurement error, I follow Bayer, Hjalmarsson, and Pozen (2009) and construct w_{in} as the expected number of censored days i's sentence would overlap with peer n. This process is described in Data Appendix II of their paper.

III.B Average Sentence Exposure

My first specification is similar to Lyle (2009). This allows me to assess how exposure to more severe criminals affects a prisoner's recidivism rate. I use the peers' sentence as a proxy for the severity of their criminal behavior. My approach is different from his in that prisoners are not exposed to each other uniformly. Staggered admissions and releases make a weighted average of sentence more appropriate. I use the following measure of peers' average sentence as my key identifying variable.

$$\text{AvgSentence}_{ijt} = \frac{\sum_{n \neq i}(d_{in} + w_{in}) * \text{Sentence}_n}{\sum_{n \neq i}(d_{in} + w_{in})} \tag{2}$$

$$\text{where race}_i = \text{race}_n \text{ and age}_n \in [\text{age}_i - 1, \text{age}_i + 1]$$

I use ordinary least squares (OLS) to estimate the following model[9]. The outcome of interest Recidivate_{ijt}, the three year recidivism status of individual i, is regressed on the average sentence of individual i's peers and other controls.

$$\text{Recidivate}_{ijt} = \alpha_0 + \alpha_1 \text{AvgSentence}_{ijt} + \alpha_2 X_i + \alpha_3 \text{Peer}_{ijt} + \nu_j + \nu_j * \text{Off}_i^c + \tau_t + \epsilon_{ijt} \tag{3}$$

Recidivate_{ijt} is an indicator equal to one if prisoner i, who is released in period t from prison j is convicted of a felony crime within three years of their release[10]. AvgSentence_{ijt} is the weighted average of prisoner i's peers' sentences while in prison as described previously. X_i is a vector of individual i's criminal and personal characteristics and Peer_{ijt} is a vector of individual i's peers' criminal and personal characteristics as described in section III.A. ν_j is a prison facility fixed effect required since prison assignment is not random. τ_t is a vector of quarter-of-release-by-year fixed effects to account for any trends over time. Lastly, ϵ_{ijt} is the error term which includes everything not specified in the model including other unobservables.

The coefficient of interest is α_1. This is the average effect of an increase of one year in the weighted average of peers' sentence on recidivism. If positive then exposure to peers with longer

[9] I use the same model as a logit in case of nonlinearity. There is more on this in section IV.C.

[10] I exclude any violations of mandatory supervised release (MSR), also known as parole, so that recidivism only captures new crimes committed after release.

sentences and thus more severe criminals increases an individual's recidivism rate on average. This may help to explain some of the purported criminogenic behavior promoted by prisons.

III.C Exposure to More Severe Criminals

Next, I aim to model if the exposure to worse peers impacts recidivism in felonies of a worse class than individual i's current conviction. My key variable is PeerOff_{ijt}^{z} is the weighted average of peer exposure to prisoners who are currently held for a felony class z. z is defined as any felony of a worse class than the individual i's current conviction. For example, if an individual i is convicted and sentenced to prison j for a felony of class three, then only prisoners n in prison j who have committed a felony which is worse than a class three will count as peers. In this example those classes would be murder, X, one, and two. In order to count as a peer, a prisoner n must also be of the same race and relative age as individual i, as in all other specifications. This is shown in equation 4.

$$\begin{gathered}\text{PeerOff}_{ijt}^{z} = \frac{\sum_{n \neq i}(d_{in} + w_{in}) * c_n}{\sum_{n \neq i}(d_{in} + w_{in})} \\ \text{where } \text{race}_i = \text{race}_n,\ \text{age}_n \in [\text{age}_i - 1, \text{age}_i + 1]\,,\ \text{and} \\ z \in \{\text{Felonies with worse class than } i\text{'s current conviction}\}\end{gathered} \tag{4}$$

I use ordinary least squares (OLS) to estimate the following model[11].

$$\text{Recidivate}_{ijt}^{z} = \gamma_0 + \gamma_1 \text{PeerOff}_{ijt}^{z} + \gamma_2 X_i + \gamma_3 \text{Peer}_{ijt} + \nu_j + \nu_j * \text{Off}_i^c + \tau_t + \epsilon_{ijt} \tag{5}$$

The outcome variable is $\text{Recidivate}_{ijt}^{z}$ which is a dummy variable equal to one if the individual i recidivates in a felony class z which is any of those worse than the class of their most previous conviction. Many of the same controls from previous specifications are included as well. These are X_i which is a vector of individual i's criminal and personal characteristics, ν_j and $\nu_j * \text{Off}_i^c$ are prison facility and facility-by-felony-class history fixed effects, respectively, and τ_t is a vector of quarter-of-release-by-year fixed effects.

[11] I use the same model as a logit in case of nonlinearity. There is more on this in section IV.C.

The coefficient of interest is γ_1. If positive, this captures the "worsening" effect. Thus the effect of being exposed to more peers, which are more severe criminals than prisoner i, on recidivism of a more severe crime. If this effect is negative, then it serves as a "deterring" effect. This model again relies on the identification assumption that the exposure to more severe criminals is independent of the individual i's observables. This allows for an unbiased estimate using OLS even with the assignment of individuals to each facility being non-random.

III.D Severity Exposure by Crime Type

I follow the identification strategy of Bayer, Hjalmarsson, and Pozen (2009), Tan and Zapryanova (2021), and Johnsen and Khoury (2024) to measure peer effect heterogeneity on recidivism based on sentence and crime category.

$$\begin{aligned}\text{Recidivate}^c_{ijt} &= \beta_0 + \beta_1\,\text{AvgSentence}^c_{ijt} + \beta_2\,\text{AvgSentence}^c_{ijt} * \text{Off}^c_i \\ &\quad + \beta_3\,X_i + \beta_4\,\text{Peer}_{ijt} + \nu_j + \nu_j * \text{Off}^c_i + \tau_t + \epsilon_{ijt}\end{aligned} \tag{6}$$

Here $\text{Recidivate}^c_{ijt}$ is an indicator equal to one if prisoner i, who is released in period t from prison j, is convicted of a felony in crime category c within three years of release. There are five crime categories being personal, property, drugs, sex, and other. Similar to equation 2, $\text{AvgSentence}^c_{ijt}$ is the weighted average of sentence length of peers who have previously been convicted of a felony crime in category c.

Off^c_i is equal to one if prisoner i has previously been convicted of a felony in category c. As in my previous models, X_i is a vector of individual i's criminal and personal characteristics and Peer_{ijt} is a vector of individual i's peers' criminal and personal characteristics. ν_j and $\nu_j * \text{Off}^c_i$ are prison facility and facility-by-felony-class history fixed effects, respectively. τ_t is a vector of quarter-of-release-by-year fixed effects.

I include facility-by-crime $\nu_j * \text{Off}^c_i$ fixed effects to control for non-random assignment of prisoners to facilities based on observables. In addition, they control for unobservable characteristics correlated across all individuals in the facility. I include quarter-of-release-by-year fixed effects, τ_t, to account for potential trends in peer group composition and overall crime rates. Prior to this I regressed my key measure of peers, $\text{AvgSentence}^c_{ijt}$, on quarter-of-release-by-year dummies to check for trends in peer composition[12].

I estimate this using a seemingly unrelated regressions (SUR) model where the specification is the same but the crime class c is different for each regression[13]. I do this since the error terms are plausibly correlated across crimes. Using SUR allows me to leverage this correlation for improved efficiency over running ordinary least squares (OLS) individually for each felony class.

This specification captures two different effects. The first comes from $\text{AvgSentence}^c_{ijt}$ which gives the "converting" effect, β_1, of individual i's peers. This is the peers' influence on an individual who has not committed a felony in the category c prior to their current conviction. $\text{AvgSentence}^c_{ijt} * \text{Off}^c_i$ gives the "reinforcing" effect, β_2, of peers. This is the peers' influence on an individual who has previously committed a felony in category c. If either of these effects β_1 or β_2 are negative then they serve as a "deterring" effect.

I use a more restricted sample for this model as I do not have the offense type for all individuals[14]. This restricts my sample to roughly 33,000 prison visits among 30,000 unique prisoners. The summary statistics for this subsample are included in table 5 of the appendix.

While the assignment of prisoners to facilities is non-random and determined by systematic factors, this does not prevent identification. Rather my identification assumption is that the exposure to peers within a facility at a given time is as good as random. This variation arises from the staggered admission and release of other prisoners and parolees which is independent of individual characteristics and unobserved traits.

IV Robustness Checks

I check many alternatives to my specification and present these results in this section. These robustness checks are modifications to my peer definition, time to recidivate, and linearity. I also check for heterogeneous effects across demographics such as gender and race.

[12]Due to the current state of my data I have not done this, but I will once my data is cleaned so I include this here.

[13]I use the same model with a multivariate in case of nonlinearity.

[14]I have yet to determine why this is not available for all prisoners in my sample. This will be key to determining if there is a selection problem in this reduced sample.

IV.A Peer Definition

In my main specification I follow Tan and Zapryanova (2021) and Johnsen and Khoury (2024) which require prisoners be of the same race and similar age to be considered peers. I first drop these qualifiers to measure the overall impact on peers, not just those who are the most similar to the individual. This creates peer measurements which are more similar to those of Bayer, Hjalmarsson, and Pozen 2009. Since those of similar age and and race are likely to be the strongest and most accurate measure of peers, removing this requirement is likely to attenuate my results.

IV.B Time to Recidivate

Next, I use specifications with different timelines of recidivism. This is common in the literature and allows me to use more data under some measures. I include one, two, four, and five-year recidivism using the same specifications as before. The one and two-year measures allow for many new observations which were not in the previous three-year dataset. These being observations between 2022 and 2023. The four and five-year timelines reduce my observations and presumably the significance of my results. However, these provide insight to long-term peer effects as I have defined them. The recidivism rates by window length as well as number of observations for each are shown in table 3.

Table 3: Varying Recidivism Rates by Window

Years to Recidivate	Recidivism Rate (%)	Observations
1	5.36	156,844
2	9.44	149,835
3	12.86	140,083
4	15.78	129,072
5	18.71	113,778

IV.C Nonlinearity

Previously, I have displayed all model specifications, equations 3, 6, and 5, in a linear form. There is no reason that the peer effects cannot take a non-linear form. I check all models with that of a non-linear form. That is equations 3 and 5 are run again as a logit model and equation 6 is run again as a multivariate probit model due to correlation of the error terms.

IV.D Demographic Heterogeneity

In all previous identification strategies I include both male and female individuals in my sample as well as all races. In this section, I follow the convention in labor economics and run separate regressions for each gender and race separately. This allows me to check for heterogeneous effects of each variable across every subgroup which I did not do previously. One concern of this restriction is I may lose much of the statistical power of my sample. I display summary statistics by race in table 6 and sex in table 7 of the appendix.

V Mechanisms

The mechanisms of peer effects are difficult to dissect in this literature due to endogeneity concerns and data limitations. In this section I focus on three mechanisms which I believe could impact the peer effects I aim to measure in Illinois. These mechanisms are prisons being schools of crime, criminal networks, and social contagion. Each of these effects are multifaceted, but the first two can be thought of as direct effects and the last an indirect effect.

The idea of prison being a "school of crime" is not new[15]. Prisons are believed to have adverse effects on the imprisoned through knowledge spillovers similar to those outside of prison. This mechanism is rooted in Mincer (1974) which predicts that labor returns increase as knowledge does. Unlike the legal labor market however, there are no formal schools or job trainings for criminals. This makes knowledge spillovers the primary way of gaining criminal knowledge and increases the chances of criminal behavior, recidivism in my case, in the presence of prisoners.

The second of these is the effect of creating a rolodex of criminals while in prison. An expansion of a criminal network can increase opportunities in the illegal labor market (Stevenson 2017). Again, in comparing this to the legal market there are no job postings. This makes networking the primary way to hear about potential work. This mechanism should be strongest when a gang member or

[15] See Bentham (1791) and Howard (1777).

leader is your peer. This is the most likely scenario to lead to many connections post-release and opens the door for prisoners to engage in gang activity when they get out of prison, which they may not have done otherwise (Philippe 2017). This is of particular interest in my context as Chicago is well known for their organized crime with over seventy gangs and 150,000 members[16]. Lastly, increasing your network increases your choice set of crimes available to commit. It allows for crimes which are rarely committed by a sole individual such as human trafficking and counterfeiting. These crimes may have been infeasible previous to the individual's network expansion in prison. Together each of these components would increase crime and recidivism.

The last of these mechanisms is social contagion which has an ambiguous effect. This mechanism is based on the effect of criminal role models. Exposure to criminals can change criminal salience, social norms, and crime-oriented attitudes (Billings, Deming, and Ross 2019, Posner 1997, and Stevenson 2017). It is reasonable for these effects to be largest amongst younger individuals which has been studied previously[17]. This effect may differ by individual with exposure to hardened criminals inside prison serving as a crime deterrent or a catalyst. Overall this creates an ambiguous effect of the social contagion mechanism.

[16]See NBC 2012.

[17]See Stevenson (2017) and Bayer, Hjalmarsson, and Pozen (2009) for work on juveniles

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VI Appendix

Table 4: Prison Facility Distribution of Reduced Sample

Prison Facility	Observations	Percent of Sample
Big Muddy River	2,888	2.06
Centralia	3,561	2.54
Danville	3,874	2.77
Decatur	3,645	2.60
Dixon	4,535	3.24
Dwight	56	0.04
East Moline	5,666	4.04
Graham	5,132	3.66
Hill	2,803	2.00
Illinois River	5,702	4.07
Jacksonville	4,903	3.50
Joliet Treatment Center	141	0.10
Kewanee Reentry Center	448	0.32
Lawrence	4,097	2.92
Lincoln	3,025	2.16
Logan	7,728	5.52
Menard	2,871	2.05
Pinckneyville	7,039	5.02
Pontiac	1,701	1.21
Robinson	4,015	2.87
Shawnee	5,415	3.87
Sheridan	6,751	4.82
Southwestern Illinois	2,697	1.93
Stateville	30,789	21.98
Tamms	7	0.00
Taylorville	2,884	2.06
Vandalia	7,368	5.26
Vienna	6,153	4.39
Western Illinois	4,189	2.99
Total	140,083	100.00

Table 5: Summary Statistics of Prisoners with Offense Types

Variable	Mean	Std. Dev.	Min	Max
Recidivate	0.22	0.41	0	1
3-Year Recidivism	0.13	0.34	0	1
Year of Release	2017.00	1.35	2014	2021
Year of Birth	1981.49	11.48	1925	2004
Female	0.08	0.27	0	1
White	0.30	0.46	0	1
Black	0.59	0.49	0	1
Hispanic	0.39	0.49	0	1
Asian	0.00	0.05	0	1
Native	0.00	0.04	0	1
Biracial	0.00	0.04	0	1
Veteran	0.01	0.12	0	1
Sentence (Years)	5.29	23.96	0	2500
Murder	0.02	0.13	0	1
Class X Felon	0.09	0.28	0	1
Class 1 Felon	0.14	0.34	0	1
Class 2 Felon	0.24	0.43	0	1
Class 3 Felon	0.16	0.37	0	1
Class 4 Felon	0.43	0.48	0	1
Released to Parole	0.88	0.32	0	1

Note: This table is based on 33,462 observations which each have their offense type included in the IDOC data. These are only prisoners released from 2014 through 2021. Deceased prisoners or those with life sentences are excluded. Recidivism rates do not include mandatory supervised release violations.

Table 6: Summary Statistics by Race

Variable	Black	White	Hispanic	Asian	All
Recidivism	0.23	0.18	0.17	0.14	0.20
	(0.42)	(0.39)	(0.37)	(0.35)	(0.40)
3-Year Recidivism	0.14	0.12	0.10	0.08	0.13
	(0.35)	(0.32)	(0.30)	(0.27)	(0.34)
Year of Release	2017.05	2017.25	2017.14	2017.15	2017.14
	(2.19)	(2.23)	(2.21)	(2.11)	(2.21)
Year of Birth	1981.59	1980.11	1982.12	1980.22	1981.25
	(11.78)	(11.11)	(10.68)	(10.36)	(11.48)
Female	0.05	0.14	0.05	0.09	0.08
	(0.23)	(0.35)	(0.22)	(0.28)	(0.29)
Veteran	0.01	0.03	0.01	0.01	0.02
	(0.10)	(0.16)	(0.07)	(0.11)	(0.13)
Sentence (Years)	5.45	4.65	5.38	5.18	5.06
	(9.04)	(8.93)	(6.70)	(5.63)	(8.53)
Murderer	0.02	0.01	0.02	0.01	0.02
	(0.13)	(0.08)	(0.13)	(0.09)	(0.11)
Class X Felon	0.11	0.07	0.17	0.15	0.11
	(0.31)	(0.26)	(0.37)	(0.36)	(0.31)
Class 1 Felon	0.15	0.14	0.17	0.19	0.15
	(0.36)	(0.35)	(0.37)	(0.40)	(0.36)
Class 2 Felon	0.26	0.29	0.24	0.25	0.27
	(0.44)	(0.46)	(0.43)	(0.44)	(0.45)
Class 3 Felon	0.14	0.21	0.11	0.16	0.16
	(0.35)	(0.41)	(0.32)	(0.37)	(0.39)
Class 4 Felon	0.32	0.28	0.29	0.24	0.30
	(0.47)	(0.45)	(0.46)	(0.42)	(0.46)
Released to Parole	0.90	0.91	0.94	0.94	0.91
	(0.30)	(0.28)	(0.24)	(0.24)	(0.28)
Observations	81,486	42,853	15,901	453	140,693
Percentage of Population	62.56	32.91	12.20	0.35	100.00

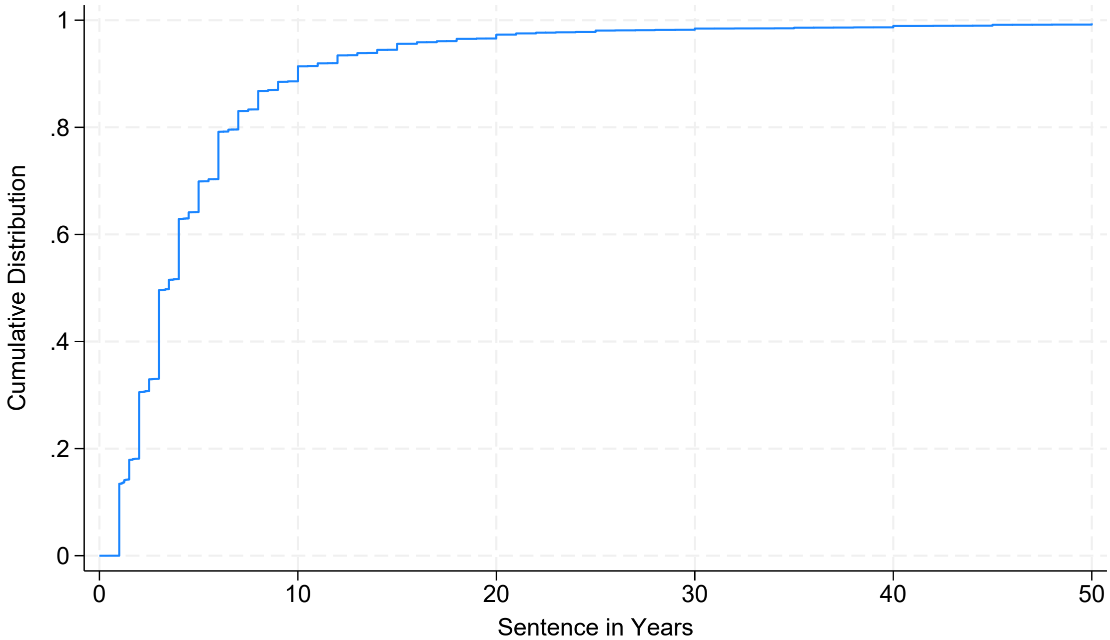
Note: Table includes only prisoners who were released from 2014 to 2021. Deceased prisoners or those with life sentences are excluded. Recidivism rates do not include mandatory supervised release violations.

Table 7: Summary Statistics by Sex

Variable	Male	Female	All
Recidivism	0.22	0.14	0.21
	(0.41)	(0.35)	(0.40)
3-Year Recidivism	0.13	0.09	0.13
	(0.34)	(0.27)	(0.33)
Year of Release	2017.12	2017.15	2017.13
	(2.21)	(2.17)	(2.21)
Year of Birth	1981.29	1980.18	1981.22
	(11.57)	(11.52)	(11.56)
White	0.28	0.53	0.30
	(0.45)	(0.50)	(0.46)
Black	0.60	0.38	0.58
	(0.49)	(0.49)	(0.49)
Hispanic	0.12	0.17	0.12
	(0.33)	(0.37)	(0.34)
Asian	0.00	0.00	0.00
	(0.03)	(0.03)	(0.03)
Native	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Bi-racial	0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)
Veteran	0.02	0.00	0.02
	(0.12)	(0.03)	(0.12)
Sentence (Years)	5.34	3.58	5.18
	(13.87)	(4.16)	(13.37)
Murderer	0.01	0.01	0.01
	(0.11)	(0.08)	(0.11)
Class X Felon	0.11	0.06	0.10
	(0.31)	(0.24)	(0.31)
Class 1 Felon	0.15	0.12	0.15
	(0.35)	(0.30)	(0.35)
Class 2 Felon	0.27	0.23	0.27
	(0.44)	(0.42)	(0.44)
Class 3 Felon	0.30	0.20	0.29
	(0.36)	(0.31)	(0.36)
Class 4 Felon	0.29	0.23	0.28
	(0.46)	(0.42)	(0.46)
Released to Parole	0.91	0.96	0.92
	(0.29)	(0.20)	(0.28)
Observations	129,474	11,566	141,040
Percentage of Population	91.79	8.21	100.00

Note: Table includes only prisoners who were released from 2014 to 2021. Deceased prisoners or those with life sentences are excluded. Recidivism rates do not include mandatory supervised release violations.

Figure 2: CDF of Prison Sentences



Note: This figure is based on 140,083 observations of prisoners released between 2014 and 2021. CDF does not equal one at 50 as there are an additional 926 observations with sentences greater than 50 years. There is no mass below 2 as only individuals sentenced to at least 2 years are sent to prison.