The First and the Worst: Evidence of Peer Effects in a Large U.S. Jail

Angelo Diaz[1], JJ Naddeo[2] and Neel U. Sukhatme[3]

[1]Georgetown University, Department of Economics
[2]U.S. Census Bureau
[3]Georgetown University Law Center

Abstract

Do brief social interactions shape long-term behavior? We causally examine this question in the context of short-term incarceration, using daily cell-level data from a large U.S. jail where individuals are quasi-randomly assigned to cells within housing blocks. We measure peer exposure through a novel standardized index that captures both the frequency and severity of each peer's prior criminal history. Beyond traditional linear-in-mean models, we explore different specifications for peer effects, finding that exposure to high-severity peers and one's first cellmate disproportionately influence post-release recidivism.

We show that a one standard deviation increase in exposure to peers with serious criminal histories raises the likelihood of rearrest within one year by up to 0.72 percentage points (1.64%). This effect is primarily driven by the first cellmate of an individual and the most severe peer in their network, rather than just cumulative or final exposure. We further validate these findings using a new structural estimation approach (Boucher et al. 2024), applied for the first time to an exogenously assigned peer network.

Beyond direct peer effects, we document indirect influence, where an individual's behavior is shaped not only by their immediate peers but also by the prior networks of those peers. These findings underscore the path dependence of social interaction in jail, reinforcing that early exposure in peer networks can be particularly influential.

Our results have important policy and economic implications. Our showing that even brief exposure to criminogenic peers can increase recidivism is especially troubling given that most individuals in jail are legally innocent and awaiting trial. Policies that restructure initial jail assignments or reduce unnecessary pretrial detention could lower future crime rates and correctional costs. More broadly, our findings contribute to the economics of social spillovers and peer networks in constrained environments, with potential relevance for labor markets, schools, and other institutional settings.

Keywords

Jails, Peer Effects, Reinforcing Peer Effects, Converting Peer Effects, Recidivism, Quasi-Random Assignment, Social Learning, Cell-level Assignment, Criminogenic Effect of Incarceration

Disclaimer: Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. This paper does not use any confidential Census Bureau data. The authors received no external funding for this research and are not aware of any potential conflicts of interest or conflicting financial interests.

ad1629@georgetown.edu (A. Diaz); joseph.naddeo@census.gov (J. Naddeo); neel.sukhatme@law.georgetown.edu (N. U. Sukhatme)

1. Introduction

> "You know, the funny thing is, on the outside, I was an honest man, straight as an arrow. I had to come to prison to be a crook." Andy Dufresne, The Shawshank Redemption

How do short-term social interactions shape long-term economic behavior? This question is central to economics, with implications for labor markets, education, financial decision-making, and crime. While social spillovers have been studied in schools (Sacerdote 2001; Pratschke and Abbiati 2020; Han and Li 2009), labor markets (Cornelissen, Dustmann, and Schönberg 2017; Mas and Moretti 2009), and neighborhoods (Glaeser, Sacerdote, and Scheinkman 1996; Ludwig, Duncan, and Hirschfield 2001; Damm and Dustmann 2014), one of the most socially and economically consequential environments—jails—remains largely unexplored.

This paper provides new evidence on peer effects in short-term incarceration settings, using daily cell-level data from a large U.S. jail, where individuals are quasi-randomly assigned to cellmates. Unlike prior studies that focus on prisons (Ouss 2011; Damm and Gorinas 2020; Harris, Nakamura, and Bucklen 2017; Tan and Zapryanova 2022; Marchand 2020; Johnsen and Khoury 2024; Arnaud 2024; Diaz 2024) or juvenile facilities (Bayer, Hjalmarsson, and Pozen 2009; Stevenson 2017), we examine jails, where most individuals are held pre-trial, for short durations. These features allow for a cleaner test of the effects of peer exposure, independent of long-term institutionalization.

The absence of research on peer effects in jails is particularly striking given their growing importance in the U.S. criminal legal system. Over the past 30 years, the U.S. jail population has tripled, with 8.7 million individuals admitted in 2020 alone (Minton and Zeng 2021). Unlike prisons, jails primarily house individuals for short stays—on average, 27.8 days in 2020.[1] This growth is largely driven by rising pretrial detention and monetary bail, which confine individuals before they are convicted (Aiken 2017; Zhen 2022). The trend is accelerating, with pretrial detainees accounting for 81% of the increase in jail populations from 2020 to 2021.

Even though most jail stints last less than a month, peer effects from those stints might extend far into the future.[2] This might occur, for example, if jails build criminal skills and networks that would otherwise not exist ("crime school"). This possibility should alarm policymakers: since most jailed individuals have not been convicted of the crimes for which they are charged, negative peer effects may push those presumed to be innocent toward criminal behavior.

The current paper fills this gap in the peer effects literature and makes at least four

[1] Minton and Zeng (2021).

[2] See, e.g., Alsan and Yang (2025) (effects of health care in jails); see also Agan, Doleac, and Harvey (2023) (positive impact of not prosecuting nonviolent misdemeanor offenses).

significant contributions. First, we use detailed corrections data to provide the first causal estimates of peer effects in the American jail system. Our rich dataset contains detailed daily information about the specific section, block, and cell to which each individual was assigned, as well as any transfers within the jail.

Importantly, and as we document below, individuals are quasi-randomly assigned to cells within blocks, which facilitates our identification strategy. In contrast to many earlier works, which often estimate peer effects based on variation over time in peers at the correctional facility level, our approach can more precisely and credibly capture social interactions inside the jail by leveraging quasi-random variation in specific cell assignments. This allows us to shed the unattractive assumption that all individuals in a correctional facility at a given time interact in some way.

Second, we expand beyond the traditional linear-in-mean model, where the reported effect is merely the average impact across all relevant peer groups. Such an approach might mask significant variation in influence across different peers. Motivated by the prior literature, we instead explore how different peer groups might differentially impact future criminal behavior. For example, perhaps it's an individual's early interactions in jail (first cellmates) or final impressions (last cellmates) that have the most profound impact on their future behavior. Maybe instead it's their peer with the most serious prior criminal history that most influences them. We explore all of these possibilities, in addition to the more traditional approaches of measuring the cumulative or average effects across all peers.

To accomplish this, we first create a severity index that captures the number and severity of prior convictions. Rather than relying on statutory sentencing ranges, which obscure significant practical differences across crime types, this index classifies individuals' criminal histories based on actual sentences served by other individuals convicted of the same crimes. Independent of our other results, this methodological contribution can serve as a valuable tool in other settings for policymakers and researchers.

We then use our unique severity index to create several exposure measures of peer interaction. We show that a one-standard-deviation increase in exposure raises the likelihood of rearrest within one year of release by up to 0.72 percentage points, a 1.64% increase. This effect is primarily driven by the first peers that individuals interact with inside jail; their peers with the highest severity scores; and the average severity across all their cellmates.

Though modest, these causal effects are noteworthy given the brief duration of most jail interactions. Who you happen to be paired with in jail, even for just a few days, can have a significant effect on your future. And traditional linear-in-mean models largely miss these peer effects, as an individual's most criminally severe peer and their first jail interactions turn out to be disproportionately important in shaping future criminal behavior.

Third, we examine indirect (endogenous) peer effects (Marchand (2020)), exploring how an individuals behavior is influenced not only by their immediate peers in jail but also by those peers prior peer networks. Put differently, we can test whether in-jail social interactions affect not only the immediate participants in those interactions, but also

others who later interact with those participants while still in jail. While evidence of indirect peer effects is weak overall, we find that an individual's first jail interactions have a modest but statistically significant downstream impact on future cellmates. These findings further highlight path dependence in peer networks, as an individual's first interactions in jail can have a disproportionate influence on future behavior.

Finally, we employ the methodological framework proposed by Boucher et al. (2024) to estimate peer effects using a structural approach. This theoretical model challenges the widely used linear-in-means specification and provides a framework to identify, among others things, the most appropriate functional form (i.e., minimum, mean, or maximum). While the model assumes that peers are chosen exogenously, their empirical analysis estimates peer effects using an endogenous network (AddHealth data), where individuals select their own peers.

By contrast, the present paper applies this structural model in its intended setting: an exogenously determined network, where peers are selected and quasi-randomly assigned by an external process. Once again, we find that interactions with peers with particularly severe criminal backgrounds most impact future criminal behavior. This result provides further independent confirmation of our reduced-form results discussed above. As a more general contribution to the peer effects literature, our results also validate for the first time the general structural approach of Boucher et al. (2024) in an exogenous setting. Our findings align with our reduced-form results, indicating that initial interactions exert a greater influence than final interactions.

Overall, these contributions offer insights into the dynamics of peer effects within jails, which can inform policy decisions aimed at reducing recidivism and promoting successful reintegration of jailed individuals back into society. Moreover, because jailed individuals are typically on the margins of the criminal legal system, our results are likely to be particularly relevant to decision makers seeking to operate on that policy-relevant margin.[3]

2. Literature review

Substantial evidence from many fields indicates that peer influence significantly affects human behavior. In education, criminology, and economics, research has predominantly focused on the adverse effects of peer interactions on individual outcomes. For example, Gaviria and Raphael (1997) demonstrate the prominent role of social interaction in various behaviors, including drug use, alcohol consumption, cigarette smoking, church attendance, and school dropout rates. More recently, Kim and Fletcher (2018) examine how classmates influence adolescent criminal activities. They find that escalating the proportion of peers involved in criminal behavior increases the likelihood of an individual's involvement in criminal activities. Other studies have also contributed to the body of evidence regarding the impact of peers on behavior. Notable examples of negative

[3]Agan, Doleac, and Harvey 2023 demonstrate that the effect of criminal justice interactions for marginal individuals can be criminogenic.

influence include Borsari and Carey (2006), Wilson (2007), Quinn and Fromme (2011), and C. Engel (2023), among other relevant studies.

Limited research has been conducted on estimating peer effects within correctional facilities, with the large majority of these studies predominantly focusing on peer effects in juvenile facilities or adult prisons. Using a novel methodology to account for non-random assignment to facilities and focusing on within-facility variation over time, Bayer, Hjalmarsson, and Pozen (2009) examine crime-specific peer effects in juvenile correctional facilities in Florida. Their findings indicate that individuals with prior involvement in specific categories of criminal activity, when exposed to peers with similar criminal backgrounds, exhibit a heightened propensity to recidivate in the same category of crime upon release. This phenomenon is particularly pronounced in cases of theft, burglary, felony drug offenses, and weapon-related crimes.

Damm and Gorinas (2020) employ a similar identification strategy to Bayer, Hjalmarsson, and Pozen (2009) to investigate the peer effects among young individuals incarcerated within the Danish prison population. Their study reveals that those with shared criminal expertise in specific types of offenses, such as drug offenses, threats, vandalism, and arson, demonstrate reinforcing peer effects. However, their research does not find any indication of individuals gaining new criminal capital while in prison. Intriguingly, they identify a deterrent peer effect for violent or sexual assault and robbery when individuals are exposed to peers with specialization in these crimes.

Tan and Zapryanova (2022) employ a similar identification strategy as previous studies and utilize data from the state of Georgia to examine the heterogeneous peer effects by race and age in the context of incarceration. They find no evidence of general crime-specific peer effects for property and drug-related crimes in the overall prison population. However, analyzing age and race, they observe stronger peer effects, indicating that homophily may play a crucial role in shaping peer interactions.

Ouss (2011) employs cell-level data from French prisons to establish measures of peer influence. By utilizing the number of overlapping days as an indicator of interaction intensity, the study reveals compelling evidence of peer effects on recidivism, particularly for skill-intensive offenses such as theft and drug offenses. Harris, Nakamura, and Bucklen (2017)'s study of the Pennsylvania Department of Corrections utilizes peer sentence length of the cellmate as an instrument to address endogeneity problems, and their findings do not support the hypothesis of peer effects within the prison system.

Stevenson (2017) examines the impact of peer effects in juvenile facilities using natural variation in small cohorts within the same facility. She finds evidence of social contagion and suggests that criminal skill transfer, criminal networks, and social contagion of negative attitudes and non-cognitive factors could be possible channels for these effects.

Usman (2022) conducts a study to examine the impact of gang members in prison on other inmates within correctional facilities. Her findings indicate that exposure to peers affiliated with gangs increases the likelihood of re-incarceration.

Most studies on peer effects rely on the linear-in-mean model. However, some researchers have investigated alternative functional forms and nonlinear approaches to studying peer effects. For instance, some studies have examined the influence of peers with dominant

traits, such as higher academic ability or greater criminal tendencies. For example, Tao and Lee (2014) use a model based on extreme order statistics to estimate peer effects. In their empirical analysis of basketball, they find that a college players performance (measured by assists, rebounds, steals, and blocks) is negatively related to both the average and maximum performance of their peers. Similarly, Díaz et al. (2021) use a structural model to show that removing all criminal leaders (i.e., those with higher criminal tendencies) reduces overall criminal activity. This finding aligns with key player theory (Ballester, Calvó-Armengol, and Zenou 2006), which emphasizes the leader's central role in influencing network dynamics. Additionally, Zenou (2021) demonstrate that central students, who typically have higher academic ability and stronger social skills, exert a greater influence on their peers' performance after receiving an academic intervention.

Other scholars have examined peer effects among both low- and high-ability individuals. (Hoxby and Weingarth, n.d.), in the context of education, explore various peer effect models to identify the best fit for the data. They reject the linear-in-mean model and find that individuals benefit from interacting with higher-ability peers, while high-ability individuals also gain from engaging with peers slightly below their own level. Tatsi (2015) also analyze the effects of peers with the highest and lowest scores, as well as different functional forms, such as the sum and average of peers' performance, on student outcomes, identifying heterogeneous effects based on individual student characteristics.

Similarly, Marchand (2020) employs prison cell-level data in Canada to estimate both endogenous and contextual peer effects separately. Rather than employing a linear-in-mean model, he adopts a linear-in-sum approach. His findings indicate qualitatively large and statistically significant contextual peer effects, while evidence for endogenous peer effects remains weak.

Given the challenges in selecting the appropriate model to estimate peer effects, Boucher et al. (2024) introduce a flexible theoretical model designed to estimate peer effects, questioning the suitability of linear-in-mean specifications in every context. Their approach provides an estimation strategy that identifies the optimal functional form—whether it follows a min, mean, or max structure—based on the data. However, they do not address the temporal dimension of social interactions, leaving this important aspect unaddressed.

In contrast, some studies have explored the role of timing in peer influence. Rees and Zimmerman (2016) employ a nonlinear model to show that the impact of peer delinquency on an individual's delinquency diminishes as the number of delinquent peers increases. This pattern, consistent with a satiation effect, suggests that early exposure to delinquent peers has the strongest influence.

Unlike other peer effects contexts, existing studies on peer influence within prisons predominantly rely on linear-in-mean models, with little attention given to alternative functional forms. While research in other domains has explored nonlinear specifications, such as the influence of dominant peers or extreme order statistics, these approaches have not been applied to incarcerated populations. Additionally, the temporal dimension of peer interactions in correctional settings remains largely unexamined.

As discussed below, this paper addresses these gaps by investigating both the functional form and timing of peer effects in prison environments. Understanding how the duration and sequencing of exposure to certain peers influence recidivism and behavioral outcomes can offer valuable insights for policy and rehabilitation strategies.

3. Conceptual Framework

Here we provide a simple conceptual framework to assess whether an individuals interactions with peers in jail might impact their future criminal activity. Among other things, such peer effects might vary based on the type of interaction between inmates (e.g., whether the two share the same cell or merely share the same cell block), the timing of the interaction (e.g., whether the two interact early or later during a jail stint), the characteristics of the individual (e.g., the length and severity of ones criminal history), or the duration of the interaction (e.g., the number of days of overlap in the jail). Our approach enables us to capture these different measures of peer effects flexibly.

3.1. Severity Index

For each individual i in jail, we define $C(c_i)$ as that individual's propensity to commit crime, which in turn might be a function of their past criminal history, (c_i). A simple mapping $C(c_i)$ would merely tally the number of previous criminal convictions (or arrests). A slightly more advanced mapping might differentiate these sums by type of crime (e.g., felony/misdemeanor) or crime characteristic (e.g., violent/non-violent). However, even with such differentiation, simple sums imply that each criminal conviction within a category contributes equally to future criminal activity, an assumption that seems implausible given the wide range of criminal activity encompassed within these broad classifications.

To better capture propensity, we propose a function S(crime type) that produces a separate severity score for each individual crime type. After determining the severity of each crime type we can then aggregate an individuals severity scores to distill an individual's past criminal history—and the seriousness of their offense—into a single index. In doing so, it captures the frequency of past criminal activity; prior crime types and severity.

To calculate the severity index, we first calculate the median sentence imposed for each type of crime, standardize this median to be mean 0 with a standard deviation of 1, and then rescale this index so that the minimum (lowest severity crime) is 1 and the maximum (most severe crime) is 10.[4] For reference, Table 1 presents the severity index (after standardization and rescaling) for the five most and five least severe crime types considered.

Having defined the severity of each specific crime, we then aggregate all past criminal activity for individual i into a single index using two simple methods: the sum and the

[4]We do this for each crime type as defined by whether the crime was considered violent or non-violent, a misdemeanor or felony, as well as fine grained crime type (e.g., drug sales versus drug possession).

Most Severe Crimes			
Crime Type	Crime Level	Violent	Severity Index
Person - Murder	Other	Violent	10.00
Sex - Rape	Felony	Violent	7.21
Person - Murder	Felony	Violent	7.21
Person - Robbery	Felony	Violent	5.97
Person - Kidnapping	Felony	Non-Violent	5.97
Least Severe Crimes			
Crime Type	Crime Level	Violent	Severity Index
Traffic - Other	Ordinance	Non-Violent	1.00
Ordinance - Animals	Ordinance	Non-Violent	1.00
Ordinance - Other	Other	Non-Violent	1.00
Person - Assault	Other	Non-Violent	1.00
Weapon - Other	Other	Non-Violent	1.00

Table 1
The most and least severe crime types using the median sentence length to create a severity index

maximum. The former (our preferred specification[5]) provides a total summary statistic of the severity of an individual's criminal history, while the latter distills a person's criminal history into the most severe crime ever committed.

As we show, our approach of using a severity index is more predictive of future criminal behavior than other approaches. This function can then be used to label each prior criminal event in an individual's criminal history for a severity score. Accordingly, we use our severity index function ($C(c_i) \equiv \sum S(c_i)$) to calculate one's estimated propensity to commit future crime, an important input into peer effects measures.

3.2. Peer effects: Functional form and timing

Given the complexity of peer effects, different functional forms may capture distinct mechanisms through which exposure to peers in jail influences future behavior. As noted above, the prior literature in criminology has largely relied on the linear-in-mean or linear-in-sum models. Yet research in other contexts suggests that peer effects may also depend on the magnitude and timing of exposure.

To account for these possibilities, we consider multiple ways to summarize an individuals interactions with peers while incarcerated. Specifically, we distinguish between measures that capture the distribution of exposures—for example, the average, maximum, or sum peer exposures—and measures that capture the timing of those exposures, such as when they occur during incarceration. These distinctions allow us to assess whether peer effects are driven by the peer with the most severe criminal history, cumulative exposure, or critical moments during incarceration.

[5]Appendix 12.4 show that severity index sum exhibits a clear relationship with future arrest

In our context, we define relevant exposure using the following measures:

Magnitude

Maximum exposure: Individual i's future criminal behavior is influenced by their exposure to the peer with the most severe criminal history, $\max S(c_{j\neq i})$.

Mean exposure: Individual i's future criminal behavior is influenced by a central measure of the distribution of exposures, $\sum_{j\neq i} \delta_j S(c_j) / \sum_{j\neq i} \delta_j$, where δ_j is the number of days that individual i and j overlap.

Sum of exposure: Individual i's future criminal behavior is influenced by the total exposure they receive, $\sum_{t=1}^{T} \delta_j S(c_{i,t})$.[6]

Timing

First exposure: Individual i's future criminal behavior is influenced by the first exposure they experience, $S(c_{i,1})$

Last exposure: Individual i's future criminal behavior is influenced by the last exposure they experience before release, $S(c_{i,T})$

4. Data

Our study investigates social interactions and peer effects occurring within the primary jail in a large city in a southern U.S. state. The data, which begin in June 2019 and continue until October 2024, consist of daily measurements of incarcerated individuals in the jail. This includes detailed information on where individuals were housed on a daily basis within the jail (including the specific floor, block, and cell to which they were assigned) as well as any changes in assignment across these units. These granular location data allow us to precisely identify all incarcerated individuals to whom a given person was exposed during their time in jail, making our data more comprehensive than those of previous studies. In addition, the data are rich on demographic information about the incarcerated individuals, as well their criminal histories and detailed case and charge information, allowing us to categorize offenses into various subtypes of crime.

The detailed data were created by web-scraping individual information from multiple publicly available sources and cleaning and merging them into a large database. This process required expertise in database management and web-scraping, resulting in a novel and rich source of data previously unavailable to researchers. Figure 1 displays the schema of sub-datasets used to construct the final database. This information includes details on the sentence, charge, cases, and location within the jail, as well as individual characteristics, such as name, home address, and date of birth.

Our data also provide a comprehensive portrait of the criminal background of jailed individuals, including their number of prior convictions and arrests, as well as their experience in different types of criminal activities. Additionally, we can monitor their subsequent arrests and convictions upon release. Together with location data, this

[6]Note that because the length of time spent in jail is endogenous one should control for length of time in jail when using cumulative measures.

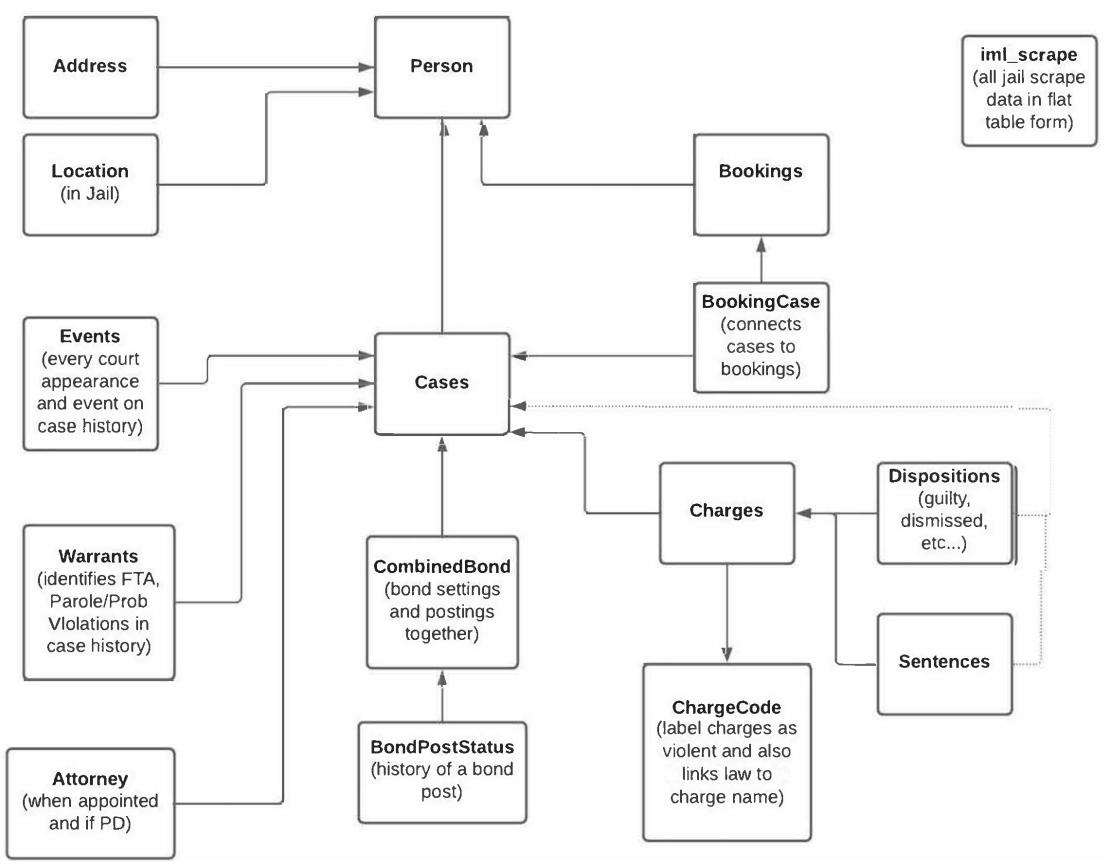


Figure 1: Schema of data used to construct final database

information allows us to observe with whom incarcerated individuals interact while in jail and investigate how the characteristics of their peers may be linked to their future behavior.

Because the vast majority of individuals in the jail are classified as male, and because individuals who are classified as female are housed in a separate facility for which we currently lack sufficient institutional background, our analysis here focuses solely on incarcerated men. In the future, however, we plan to expand our focus to include incarcerated women as well.

The detention facility comprises seven distinct levels, with each level accommodating individuals of varying security classifications and needs. The facility features 64 blocks and 1,070 cells distributed among the seven floors. These floors include designated areas for solitary confinement, specialized units for individuals experiencing mental health concerns, and high, medium-high, and low-security sections to cater to the different security requirements of detainees. Importantly, incarcerated individuals are assigned randomly to cells within the block to which they were non-randomly assigned. For more information on the structure of the jail, see Appendix 12.2.

Our dataset to date contains over 73,000 observations across more than 40,000 individuals. Given our observation of the aggregate populace, our analysis is predicated on examining those individuals who are integrated into the dataset subsequent to our initial observation period. This methodology enables us to comprehensively monitor their interactions within their peer groups. Furthermore, our analysis omits individuals diagnosed with mental health conditions and those from floors with insufficient sample sizes.[7]

Our final dataset includes over 43,000 observations across more than 25,000 individuals. Some key demographic characteristics are important to note. First, the incarcerated individuals in our sample are overwhelmingly Black (83%) and unmarried (89%) men. The mean age is 34.9 years, with an average stint in jail of 33.4 days. This population is highly likely to recidivate; 44% will have another future arrest in our data set within one year after being released. For more detailed information, see Appendix 12.1.

5. Empirical Framework

To empirically test for peer effects, we construct peer exposure measures using three variables that reflect an individual's criminal history: the total number of previous convictions, the value of the severity index for their most severe crime, and the sum of the severity index value for each crime in their criminal history. As noted in Section 3, the last one is our preferred measure, as it has the attractive properties of putting more weight on more severe crimes and takes into account the number of convictions. However, our results are qualitatively similar if we use either of the alternative definitions, as detailed in the Appendix 12.7.

First, we compute the sum of severity indexes for each individual by summing the severity index values across their entire criminal history. Second, we develop five distinct peer exposure measures: 1) Maximum exposure: We rank the severity of all the peers with whom individual i overlaps in cell and select the highest severity among them; 2) Mean exposure: we calculate a weighted average of the severity of all peers with whom individual i overlaps in jail. The severity of each peer is weighted by the number of days they shared the same cell; 3) Sum of exposure: we compute the weighted sum of the severity of all peers with whom individual i overlaps in jail, with each peer's severity weighted by the number of days they were housed in the same cell; 4) First peer(s) exposure: this measure considers the severity of all peers who overlap with individual i in the same cell on their first day of incarceration. If multiple peers are present, the measure is calculated as the simple average of their severities; 5) Last peer(s) exposure: This measure captures the severity of peers who share the same cell with the individual i on their last day of incarceration. If multiple peers are present, the measure is computed as the simple average of their severities.

To ensure comprehensive coverage of all overlaps, we include only individuals whose

[7]Specifically, our examination includes the first, third, fourth, fifth, and sixth levels of the jail, as well as those at lower levels, but excludes individuals who have been allocated to the mental health floor at least once.

entire incarceration period is observed. Consequently, our sample is restricted to individuals whose full jail term falls within the observation period, specifically those who entered on or after June 13, 2019. Based on this restricted sample, we construct our exposure variables.

To empirically test the effect of peer exposure on recidivism, we estimate the following ordinary least squares (OLS) model:

$$R_{ijt} = \beta_0 + \beta_1 \text{Exposure variable}_{ijt} + X_{ijt}\gamma + \lambda_j + \eta_t + \epsilon_{ijt}, \tag{1}$$

where R_{ijt} is our dependent variable—an indicator equal to 1 if individual i in section-block j commits a re-offense within 365 days of release. The term Exposure variable$_{ijt}$ represents one of the standardized peer exposure measures (maximum, mean, sum, first peer(s), or last peer(s)), while X_{ijt} captures relevant individual-level characteristics, including age, race, marital status, and prior criminal history. We incorporate block fixed effects, λ_j, to control for time-invariant unobserved heterogeneity, and quarter-of-incarceration fixed effects, η_t, to account for temporal fluctuations in recidivism risk. Finally, ϵ_{ijt} is the disturbance term that captures unobserved factors not accounted for by the included covariates and fixed effects. Our coefficient of interest, β_1, reflects the extent to which exposure to more criminally experienced peers shapes the likelihood of re-offending.

Our fixed effect structure also accounts for movement of inmates across blocks. Figure 4 shows that 64% of individuals remain in the same cell, 68% remain in the same block, and 75% remain on the same floor throughout their incarceration. Notably, using ten block fixed effects captures approximately 99% of the incarceration spells across blocks. As a robustness check, we re-estimate the model exclusively for individuals who do not change blocks and find that our results remain consistent. Our identification hinges on within-block variation in peer composition among individuals who share similar demographic backgrounds and criminal histories, allowing us to isolate the causal effect of peer exposure on recidivism.

5.1. Randomization

Our identification relies on random variation in exposure after accounting for non-random block assignment. Based on discussions with personnel previously employed within the correctional facility, we learned that the process of allocating individuals to specific cells within a block—once the floor and block have been determined—is conducted in a non-systematic quasi-random manner. This randomization in cell allocation within blocks serves as a critical assumption in our analysis, allowing for the mitigation of potential selection biases that could otherwise influence the estimation of peer effects on re-offending rates.

While we are confident in jail officials' assertions that the jail conducts quasi-random cell assignment within blocks, we take multiple steps to independently verify this. As is standard practice, we implement randomization tests to rigorously examine the potential impact of observable individual characteristics on the composition of peer groups within cells, as measured by the exposure variable. This statistical procedure is designed

to assess whether the distribution of observable traits among incarcerated individuals systematically influences the criminal history profile of their immediate peer group after removing block-level fixed effects, thereby testing for any selection bias in cell assignment that could confound our analysis of peer effects. Specifically, we test whether individual characteristics and criminal history predict our variables of interest—the exposure variables among peers at the cell level.

The results of the randomization analysis are presented in Appendix 12.5. Figure 2 shows all the adjusted p-values for all these randomization tests. The figure shows that most individual characteristics and criminal history variables do not exhibit statistically significant relationships with our exposure variables. In contrast, these same characteristics exhibit strong predictive power of our outcome variable (future arrests) evidenced by a marked increase in the F-statistics.

Moreover, the results in Appendix 12.5 reveal that even among the relatively few variables that achieve statistical significance, their effects are economically insignificant with no discernible pattern. This suggests that individual characteristics have at most a weak association with our key exposure variables but are more strongly correlated with the outcome variable, future arrests. These patterns are consistent with jail officials' assertion of non-systematic allocation at the cell level.[8]

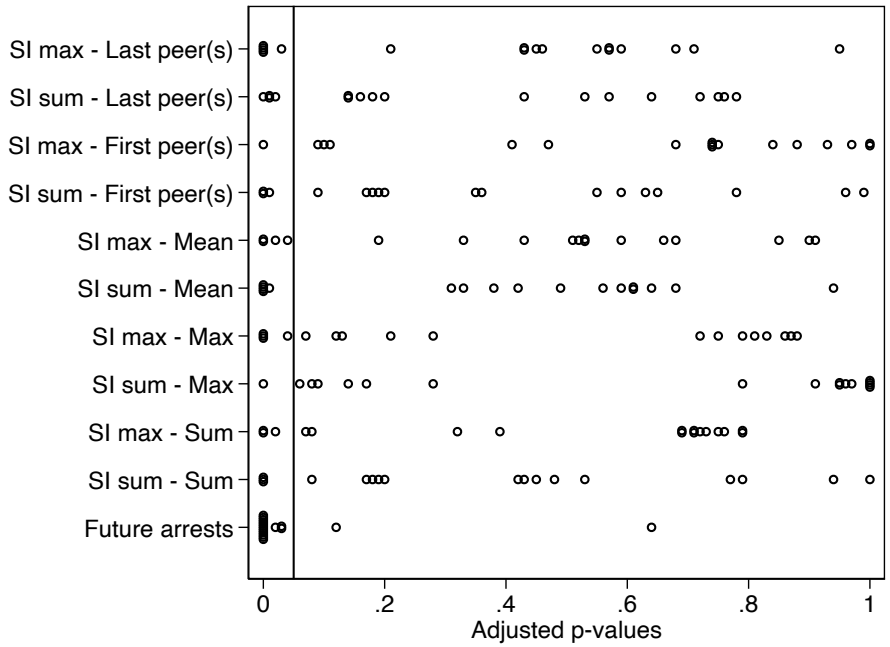


Figure 2: Adjusted p-values for the randomization tests

[8]Later we detail a placebo analysis that further supports our identifying assumption of quasi-random cell assignment.

6. Results

Table 2 presents the results of Equation (1) for the exposure variable constructed using our preferred measure of exposure. The analysis considers three functional forms— the sum, max, and mean of exposures—along with two timing aspects: first peer(s) (First) and last peer(s) (Last). For interpretation, we standardize our exposure variable so that a one unit increase in exposure represents a one standard deviation increase in exposure.

We find a modest, yet significant effect for the maximum and mean functional forms, as well as for the first peer(s) interactions. Overall, a one-standard deviation increase in our exposure variables raises the probability of re-arrest by approximately 0.5 to 0.7 percentage points, corresponding to an increase of about 1.6% in the likelihood of re-arrest. However, the effects observed for our other exposure variables are smaller and are not statistically significant at conventional levels. Our results in Appendix 12.7 show similar results for our other specifications (severity index max, and number of prior convictions). Moreover, Appendix 12.6 demonstrates that the results remain largely consistent even when demographic and criminal history controls are omitted, highlighting the robustness of the findings.

Our findings suggest that focusing solely on the mean, a commonly used measure in the peer effects literature, may overlook important and policy relevant dynamics. Specifically, the most severe individual within a peer group can have a significant influence on the future behavior of their peers. Furthermore, our results indicate that initial interactions have a greater impact than later ones. This insight is particularly relevant for policymakers, as optimizing the allocation of incarcerated individuals at the time of entry into jail could serve as an effective strategy to reduce recidivism.

Table 2
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity Index	0.0028	0.0072**	0.0048**	0.0063***	0.0035
	(0.363)	(0.048)	(0.029)	(0.003)	(0.122)
	[0.4194]	[0.1200]	[0.0855]	[0.0249]	[0.2284]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	71.06	70.33	70.18	79.74	72.62
R^2	0.0804	0.0805	0.0805	0.0805	0.0804
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation (1). Observations are at the individual level. Each peer who interacts with an individual is a cellmate who is represented by the sum of severity of their previous convictions ("severity index sum"). Each column applies a distinct functional or temporal form to combine severity index sums across peers. These forms are: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

7. Heterogeneous effects

We previously examined how different measures of peer exposure—cumulative (sum), maximum, mean, and first and last peer interactions—capture the multifaceted nature of social influences in the incarceration environment. We might expect that different subgroups of incarcerated individuals might have varying reactions to peer exposure. In this section, we explore this possibility, specifically focusing on heterogeneity by prior criminal history and age.

Our results reveal a striking pattern: significant heterogeneity across these subgroups emerges only when exposure is measured cumulatively. For individuals without prior convictions, cumulative exposure to high-risk peers is associated with an effect size of approximately 3% (see first column in Table 3). Similarly, for younger individuals (those under 25 years old), the effect is around 1.7% (see the first column in Table 4). By contrast, the non-cumulative measures—namely, maximum, mean, and first peer exposure—affect all individuals relatively uniformly, yielding coefficients of approximately 0.7%, 0.5%, and 0.6%, respectively (see Table 2). This finding suggests that while the non-cumulative measures affect all individuals similarly, the homogeneous analysis masks meaningful variation in the cumulative exposure effect that emerge only once we account for differences by age and prior criminal history.

Our results show that individuals without prior convictions and younger individuals

exhibit similar patterns. Namely, these groups require sustained, cumulative exposure to high-risk peers before their behavior is significantly altered—a phenomenon perhaps attributable to their lower initial levels of criminal human capital. The larger effect observed for prior criminal history (3%) compared to age (1.7%) may reflect that prior criminal history is a more precise proxy of criminal human capital.

Note that the cumulative measure, by aggregating exposure over an individuals entire stint in jail, is inherently less sensitive to transient interactions. For example, a brief encounter with a peer who has a severe criminal history might heavily influence the maximum, mean, or initial/final exposure measures, but its effect is diluted in the cumulative measure. As a result, the cumulative measure captures the gradual accumulation of criminogenic influence rather than isolated peaks that do not reflect sustained exposure.

Theoretical explanations such as differential social learning (Pratt et al. 2010), threshold effects (Christoph Engel 2023), criminal identity and self-labeling (Restivo and Lanier 2015), cognitive and psychological sensitization (Albert, Chein, and Steinberg 2013), and network integration (Calvó-Armengol, Patacchini, and Zenou 2005; Lindquist and Zenou 2014) all provide plausible mechanisms for these observations. For example, under differential social learning, individuals who are not yet embedded in criminal networks may only gradually acquire criminal techniques and norms through continuous interaction, whereas threshold effects imply that a certain "dose" of exposure is necessary before any behavioral change occurs.

Similarly, in terms of criminal identity and self-labeling, repeated exposure may be required for individuals to start identifying with a criminal role, while cognitive and psychological sensitization suggests that only sustained interactions heighten responsiveness to criminal cues. Finally, network integration indicates that the gradual accumulation of peer influence is the key to deepening the embeddedness of individuals in a criminal subculture. Although these mechanisms are not mutually exclusive, each provides a potential explanation for why repeated, sustained interactions—rather than isolated encounters—are critical in triggering behavioral change among these more vulnerable subgroups.

In summary, our exploration of heterogeneous effects underscores how both the particular measure of peer exposure and individual characteristics—such as age and criminal history—matter when assessing the impact of peers on future criminal behavior. Recognizing that cumulative exposure is particularly impactful for those with limited criminal experience has significant implications for policy. Tailored interventions, such as restructuring initial placements or providing targeted support to these more susceptible groups, could prove crucial in reducing recidivism and promoting successful reintegration.

Table 3
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity Index (SI)	0.0302***	0.0079	0.0010	0.0036	-0.0010
	(0.000)	(0.160)	(0.815)	(0.440)	(0.813)
SI x PC	-0.0311***	-0.0009	0.0051	0.0035	0.0062
	(0.000)	(0.863)	(0.334)	(0.517)	(0.245)
Total effect: SI + SI x PC	-0.0008	0.0070*	0.0062**	0.0072**	0.0051*
	(0.865)	(0.094)	(0.027)	(0.010)	(0.066)
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.43	0.43	0.43	0.43	0.43
F	99.32	98.66	98.72	98.82	98.66
R^2	0.0808	0.0805	0.0805	0.0806	0.0805
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression for heterogeneous effects. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (severity index sum). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). We introduce an interaction term between the main independent variable and a binary indicator equal to 1 if the individual has at least one prior conviction. All regressions include the following control variables: days incarcerated, age, race, marital status (single), and number of peers. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Table 4
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity Index (SI)	0.0166**	0.0066	0.0043	0.0030	0.0020
	(0.030)	(0.266)	(0.374)	(0.538)	(0.670)
Age > 25 (A)	0.0162*	0.0164*	0.0163*	0.0161*	0.0163
	(0.058)	(0.054)	(0.056)	(0.059)	(0.056)
SI x A	-0.0153**	0.0006	0.0004	0.0041	0.0017
	(0.023)	(0.906)	(0.929)	(0.464)	(0.757)
Total effect: SI + SI x A	0.0013	0.0073*	0.0048*	0.0072***	0.0038
	(0.770)	(0.076)	(0.077)	(0.009)	(0.166)
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.43	0.43	0.43	0.43	0.43
F	95.10	95.01	95.04	95.17	94.96
R^2	0.0688	0.0688	0.0806	0.0806	0.0805
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression for heterogeneous effects. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (severity index sum). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). We introduce an interaction term between the main independent variable and a binary indicator equal to 1 if the individual is older than 25 years old. All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

8. Indirect peer effects

According to Manski (1993), three distinct factors influence the relationship between an individuals behavior and that of their peers: (1) endogenous peer effects, where an individual's behavior is directly influenced by their peers' actions; (2) contextual peer effects, where an individual's behavior is shaped by their peers' characteristics; and (3) correlated effects, which capture similarities driven by shared group characteristics. While correlated effects can often be addressed using techniques such as group fixed effects, distinguishing between endogenous and contextual peer effects remains a significant challenge.

Marchand (2020) introduces a social interaction model for prisons that allows the simultaneous estimation of contextual peer effects—analogous to direct peer effects—and endogenous peer effects—analogous to indirect peer effects. In this framework, endogenous peer effects capture the influence of peers' negative behaviors during incarceration, which he defines as criminal tendencies. According to Marchand (2020), indirect peer effects can stem exclusively from endogenous peer influences. Endogenous peer effects create a social multiplier, potentially leading to the long-term spread of criminal behavior.

A simple example can help illustrate this more clearly. Consider the dynamic nature of jails, where inmates frequently overlap at various points in time. Our jail data provides an opportunity to simultaneously estimate both direct (contextual) peer effects and indirect (endogenous) peer effects. Figure 3 illustrates a simplified example of such overlap taken from Marchand (2020). For instance, Individual 3 may influence the behavior of Individual 2 through their shared time in the same cell, and in turn, Individual 2 could impact the future criminal behavior of Individual 1. Similarly, Individual 5 might indirectly affect Individual 1 through their interaction with Individual 4.

Using this model, we construct various measures that capture the accumulated influence of peers by leveraging our comprehensive observation of all inmate movements and interactions within the facility. The theoretical model proposed by Marchand (2020) can be estimated using a reduced form model. In Equation (2), y_{ijt} represents the outcome variable of the individual i, from section-block j who was incarcerated at time t. The vector x'_{ijt} represents a set of control variables, including demographic characteristics and criminal history. $Exposure\ var_{(ijt,-1)}$ captures the characteristics of an individuals direct peers, what Marchand (2020) calls distance 1. $Exposure\ var_{(ijt,-2)}$ captures the characteristics of peers-of-peers, what the author calls distance 2, continuing similarly for higher order distances. We include block fixed effects (λ_j) and entry quarter fixed effect (η_t). Finally, μ_i denotes the error term.

$$y_{ijt} = x'_{ijt}\beta + Exposure\ var_{(ijt,-1)}\pi_1 + Exposure\ var_{(ijt,-2)}\pi_2 + Exposure\ var_{(ijt,-3)}\pi_3 + ... + \lambda_j + \eta_t + \mu_{ijt}, \tag{2}$$

We use the same exposure measures introduced in Section 5 to represent direct peer influence, denoted as distance 1 ($D1$). Additionally, we construct new exposure variables that capture endogenous peer effects by incorporating information from the peers of an individual's peers, using metrics such as the severity index sum, severity index max, and prior convictions; we call it distance 2 ($D2$). For example, in Figure 3, we examine how

the sum of the severity index of Individual 3, mediated through Individual 2, influences the behavior of Individual 1. Similarly to the previous section, we construct five measures for $Exposure\ var_{(i,-2)}$, including sum, max, mean, first peer(s), and last peer(s).

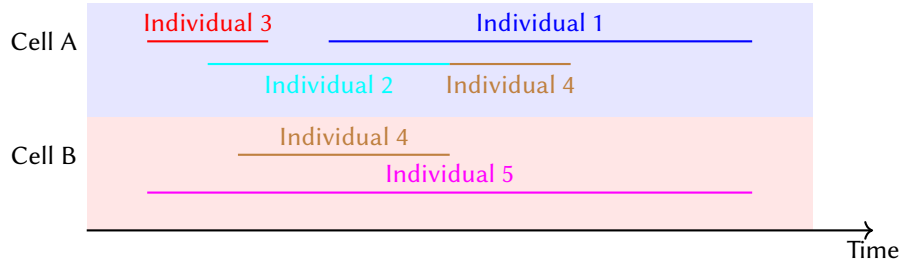


Figure 3: Dynamic overlaps of incarcerated individuals across different cells over time. Source: Marchand (2020)

Accordingly, we can now run a reduced form regression similar to Equation (2), where y_{ijt} is an indicator variable equal to 1 if individual i in section-block j commits a re-offense within 365 days of release. The variable $Exposure\ var_{(ijt,-1)}$ represents the standardized exposure measure based on peer information, while $Exposure\ var_{(ijt,-2)}$ captures the standardized exposure measure incorporating information from peers of peers. The model controls for a variety of demographic characteristics and criminal history variables, denoted by x_{ijt}, as well as section-block fixed effects and quarter-of-entry fixed effects.

8.1. Indirect peer effects: Results

Table 5 presents the results for Equation (2). First, we observe that the coefficients for the $D1$ variables remain consistent with those reported in Section 6, even when accounting for the inclusion of the $D2$ variable. This consistency further supports jail officials' claim that individuals are not assigned to cells through a systematic process. If cell assignment by jail officials were systematic within blocks—meaning officials deliberately placed individuals in cells based upon their observable characteristics—this would potentially introduce correlation between D_1 and D_2, as both would contain unobserved selection. This correlation would then cause instability in the estimated coefficient in front of D_1, when including D_2 in the model. The absence of such instability in the estimated effect of D_1 suggests that there is no correlation between D_1 and D_2. This result further supports the claim that the assignment of individuals to cells is quasi-random.

Secondly, consistent with the findings of Marchand (2020), we observe weak evidence of endogenous peer effects. The strongest effects are found in the case of first peer(s) exposure, suggesting that both direct and indirect initial interactions play a significant role. It is noteworthy that the estimated effect of $D1$ for first peer(s) exposure is 0.6 percentage points, which is closely comparable to the estimated effect of $D2$ at 0.56 percentage points. Appendix 12.8 shows similar results for our other specifications. This result has policy-relevant implications, as it suggests that the first exposure of individuals influences their criminality in a way that transmits to their future interactions.

Table 5
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity Index D1	0.0036	0.0073**	0.0048**	0.0062***	0.0034
	(0.304)	(0.046)	(0.028)	(0.003)	(0.122)
	[0.4805]	[0.1550]	[0.1179]	[0.0472]	[0.3044]
Severity Index D2	-0.0028	-0.0002	0.0039*	0.0056**	0.0024
	(0.546)	(0.936)	(0.099)	(0.018)	(0.377)
	[0.6551]	[0.9357]	[0.2694]	[0.1055]	[0.5390]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	68.81	68.57	67.87	77.68	71.38
R^2	0.0804	0.0805	0.0805	0.0807	0.0805
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation (2), adding the same variable but with distance 2 D_2. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (severity index sum). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

8.2. Indirect peer effects: Placebo

The peers-of-peers measurement also suggests a placebo test grounded in the logic of Directed Acyclic Graphs (DAGs), where future events cannot causally affect past outcomes. To illustrate, consider Figure 3. We examine whether the future peers of an individual's peers could influence that individual's prior criminal behavior. Specifically, we test if Individual 1's criminal characteristics might indirectly affect Individual 3 through Individual 2, even though Individual 2 meets Individual 1 only after overlapping with Individual 3. Because such a path would violate the acyclicity principle, we label this variable the $D2$ placebo.

Table 21 presents the results of these placebo regressions. Consistent with the restriction that future events cannot alter past behavior, the coefficients are all statistically insignificant, reinforcing the validity of our findings in Table 5. This result also supports the notion that selection biases in cell or block assignment do not drive our estimates. Furthermore, the exposure estimates for $D1$ remain consistent with the primary results reported in Section 6, highlighting the robustness of our analysis. Similar findings for other specifications are provided in Appendix 12.9.

Table 6
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Dependent Variable	**Future arrests**	**Future arrests**	**Future arrests**	**Future arrests**	**Future arrests**
Severity Index D1	0.0044	0.0076**	0.0048**	0.0063***	0.0034
	(0.234)	(0.043)	(0.030)	(0.003)	(0.126)
	[0.4690]	[0.2138]	[0.1779]	[0.0491]	[0.3787]
Severity Index D2 placebo	-0.0048	-0.0083	0.0029	0.0013	0.0025
	(0.403)	(0.125)	(0.164)	(0.585)	(0.248)
	[0.5259]	[0.4179]	[0.4105]	[0.6505]	[0.4136]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	68.74	68.78	67.65	77.09	69.86
R^2	0.0804	0.0805	0.0805	0.0806	0.0805
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation (2), including the placebo version for D_2. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (severity index sum). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

9. Structural estimation

In the previous sections, we have presented evidence underscoring the importance of employing alternative models to the traditional linear-in-mean specifications. However, selecting the appropriate empirical econometric model remains challenging. In this context, Boucher et al. (2024) offers valuable insights into identifying a suitable empirical approach. While their methodological framework assumes a conditionally exogenous network, their empirical analysis relies on an endogenous network, where individuals select their own peers. The present paper contributes to the peer effects literature by implementing their methodology for the first time using an exogenously determined network, where peers are quasi-randomly and exogenously determined.

Consider a standard linear-in-means model like Equation (3), where y_i represents the outcome variable, $\bar{y}_{-i} = \sum_{j=1}^{n} \tilde{g}_{ij} y_j$ denotes the average outcome of the peers of the individual i', and $\mathbf{x}_i$ is a vector of control variables.

$$y_i = \mathbf{x}_i \gamma + \lambda \bar{y}_{-i} + \epsilon_i \tag{3}$$

They introduce a flexible Constant Elasticity of Substitution (CES) social norm, which allows for different degrees of substitutability between peers, as specified in Equation (4):

$$\tilde{y}_{-i}(\beta) = \Big(\sum_{j=1}^{n} \tilde{g}_{ij} y_j^{\beta}\Big)^{\frac{1}{\beta}} \tag{4}$$

This formulation generalizes the standard linear-in-means model by enabling peer influences to be aggregated in a more flexible manner, depending on the value of β.

Note that when $\beta = 1$, Equation (4) simplifies to

$$\bar{y}_{-i}(1) = \sum_{j=1}^{n} \tilde{g}_{ij} y_j$$

which corresponds to the standard linear-in-means model.

However, as $\beta \to +\infty$, Equation (4) approaches

$$\tilde{y}_{-i}(\beta) = max_{j \in N_i}\{y_j\}$$

This occurs because, when one of the y_j values is significantly larger than the others, raising all values to a large β amplifies differences, making the largest term dominate the sum.

Conversely, as $\beta \to -\infty$, Equation (4) converges to

$$\tilde{y}_{-i}(\beta) = min_{j \in N_i}\{y_j\}$$

since raising values to a large negative exponent disproportionately shrinks larger values relative to smaller ones, causing the smallest term to dominate the sum.

Boucher et al. (2024) introduce two structural methodologies to estimate β. The first identifies parameters that distinguish between a spillover and a conformism framework for assessing peer effects. That model relies on the critical assumption that individual characteristics for both isolated and non-isolated individuals similarly affect the private benefit associated with the outcome variable (reoffense in our context). That assumption is plainly implausible in our setting, given that selection into solitary confinement is non-random, and that individual characteristics (e.g., criminal history or risk aversion) might interact differently depending on the type of incarceration environment.

Fortunately, the authors also propose a second methodology to estimate peer effects that does not rely on the isolation assumption and that we use to estimate peer effects in our context. Although this approach does not allow for distinguishing between spillover and conformism models, it still enables the estimation of β. Equation (5) presents this model, where, in our context, y_{ib} represents the recidivism of individual i from section-block b, $\mathbf{x}_i$ is a vector of individual characteristics and our severity index variable, and ξ_b denotes section-block fixed effects[9]. The parameter λ captures the peer effect, while

[9]For this estimation, we employ a fixed effects specification, using the block in which individuals spent the most time in incarceration as the identifying fixed effect.

β determines the functional form. Note that the superscript niso refers specifically to non-isolated individuals.

$$y_{ib} = \mathbf{x}_i \gamma^{niso} + \lambda \tilde{y}_{-ib}(\beta) + \xi_b + \epsilon \tag{5}$$

We modified the publicly available code[10] to estimate Equation (5). One of the most significant differences in our implementation is the assignment of fixed effects. The original code is designed for a school setting, where individuals rarely transfer between institutions. In contrast, our context allows us to observe movements across different blocks. For our general estimation, we define the section-block fixed effect based on the block in which individuals spend the majority of their incarceration period. However, this approach inherently disregards interactions occurring in other blocks.

Table 7, panel A, presents the estimation results for Equation (5). We identify a peer effect of 0.059, which is statistically significant at the 10% level. Furthermore, the estimated parameter $\beta = 754.728$ suggests that individuals exhibit peer preferences skewed toward the right-hand side of the distribution. Specifically, this implies that the relevant social norm is more closely associated with $\tilde{y}_{-i}(\beta) = \max_{j \in N_i}\{y_j\}$.

These results are important for at least two reasons. First, although we apply an entirely different structural approach than our previous conceptual framework, λ aligns with our previous reduced-form findings in Section 6. That is, once again, we show that short stints in jail can cause a modest but significant increase in future recidivism. Furthermore, the estimated β reinforces the idea that, in this context, the worst peer in jail might have the most impact on future criminal behavior.

Second, our application of Boucher et al. (2024) is the first use of this structural model in its actual intended setting, where the underlying peer network is exogenously determined. Our results thus help validate this general structural approach and provide some comfort and guidance to other researchers seeking to apply this model in other peer effects contexts.

Although Boucher et al. (2024) provide a rich theoretical and empirical framework for identifying the most appropriate functional form, they do not explicitly account for the temporal dimension. However, this aspect could be incorporated by assigning different weights to early versus later peer interactions.

First, we sort the vector $y_{-i} = (y_1, \ldots, y_{i-1}, y_{i+1}, \ldots, y_n)^T$ by the time of interaction, such that y_1 corresponds to the first interaction and y_n to the last. We then apply two distinct weighting schemes. In the first approach, we assign a weight of 1 to the initial interactions and 0 otherwise. In the second approach, we assign a weight of 1 to the final interaction and 0 otherwise. In the first approach, we use as a fixed effect the block to which individuals were assigned upon entering jail. In the second approach, we instead use the block to which they were assigned prior to release.

Table 7, Panel B, presents the results when assigning greater weight to the earliest peer interactions. The estimated coefficient λ is higher than in the general specification

[10] Boucher, V., Rendall, M., Ushchev, P., & Zenou, Y. (2024). Toward a general theory of peer effects. Econometrica, 92(2), 543565. https://doi.org/10.3982/ECTA21048

that considers all interactions and is statistically significant. Additionally, the parameter β remains relatively high, consistent with the initial findings.

Table 7, Panel C, reports the results when assigning greater weight to the most recent peer interactions. In this case, the coefficient λ is not statistically significant; however, β remains both large and statistically significant.

These results are consistent with our reduced-form approach, where we find that initial interactions have a greater impact on future criminal behavior than later interactions in the context of incarceration.

Table 7
Dependent Variable: **Recidivism**

	λ	β
A: Total number of peers		
Recidivism	0.059*	754.728***
	(0.031)	(0.002)
B: First		
Recidivism	0.109***	789.853***
	(0.026)	(0.002)
C: Last		
Recidivism	0.067	905.924***
	(0.059)	(0.001)

Notes: We report the results from Equation (5). All the results control for section-block fixed effects. Standard errors are reported in parentheses. Statistical significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01.

10. Conclusion

Our findings contribute to the growing literature on peer effects in correctional facilities by demonstrating the critical importance of the timing and nature of interactions among jailed individuals in shaping future criminal behavior. The results highlight that early peer interactions, and the influence of the most severe individuals within a peer group, play a significant role in determining recidivism. This underscores the need for policymakers to consider the initial conditions of incarceration, as they may have long-lasting effects on an individual's post-release behavior.

One key takeaway from our analysis is the robustness of direct peer effects ($D1$) even when accounting for indirect peer influences ($D2$). The consistency of the $D1$ coefficients across specifications suggests that the jail's quasi-random allocation process effectively mitigates selection biases, lending credibility to our estimates. This supports the notion that the direct exposure to peers in the same cell has a modest but significant impact on an individuals likelihood of re-offending.

Our study also finds weaker evidence for the influence of peers of peers (endogenous peer effects), contrasting with the findings of Marchand (2020) who do not find these higher order effects. Interestingly, the strongest effects are observed in the first peer(s) exposure measure, reinforcing the idea that initial social interactions during incarceration are particularly influential.

The results of our placebo tests further validate the robustness of our approach. As expected, future peer interactions did not have a statistically or economically significant impact on current behaviors, providing additional evidence that our estimates are not driven by selection biases or omitted variable bias. This strengthens the credibility of our identification strategy and supports the conclusion that peer effects within jail settings operate through direct, contemporaneous exposure.

Furthermore, we contribute to the literature on peer effects by estimating them using the structural approach proposed by Boucher et al. (2024). Our findings are significant for two reasons. First, this study is the first to estimate peer effects in an empirical setting with an exogenous network. Second, the results reinforce our reduced-form estimation, highlighting the influence of the worst peer and initial interactions.

From a policy perspective, our study highlights the potential benefits of refining placement strategies in jails to optimize social interactions and minimize negative peer influences. Allocating individuals to cells in ways that reduce exposure to high-risk peers, especially in the early stages of incarceration, could yield significant benefits in terms of reducing recidivism rates. Additionally, our findings suggest that efforts to intervene at later stages may have limited effectiveness, further emphasizing the importance of early-stage interventions.

Overall, our research provides novel insights into the mechanisms through which peer effects operate in jails. By demonstrating that both direct and indirect peer interactions matter—albeit to varying degrees—our findings offer guidance for policymakers seeking to improve rehabilitation strategies and reduce recidivism. Future research could explore additional factors such as the role of social networks among the incarcerated, the impact

of longer incarceration durations, and the potential heterogeneity of peer effects across different demographic and offense-related characteristics.

11. References

References

Agan, Amanda, Jennifer L Doleac, and Anna Harvey. 2023. "Misdemeanor Prosecution*." The Quarterly Journal of Economics 138, no. 3 (August): 1453–1505. ISSN: 0033-5533, accessed January 31, 2025. https://doi.org/10.1093/qje/qjad005. https://doi.org/10.1093/qje/qjad005.

Aiken, J. 2017. Era of Mass Expansion: Why State Officials Should Fight Jail Growth. Prison Policy Initiative Report. Retrieved April 1, 2023. https://www.prisonpolicy.org/reports/jailsovertime.html.

Albert, Dustin, Jason M. Chein, and Laurence Steinberg. 2013. "Peer Influences on Adolescent Decision Making." Current directions in psychological science 22 2:114–120. https://api.semanticscholar.org/CorpusID:276080607.

Alsan, Marcella, and Crystal Yang. 2025. The Hidden Health Care Crisis Behind Bars: A Randomized Trial to Accredit U.S. Jails. Working Paper, Working Paper Series 33357. National Bureau of Economic Research, January. https://doi.org/10.3386/w33357. http://www.nber.org/papers/w33357.

Arnaud, Phillippe. 2024. "Building Criminal Network in Prison." Accessed: 2025-01-31, Working paper, https://www.dropbox.com/scl/fi/dgj1b8wasp29j25vqgv2y/peer_in_prison-6.pdf?rlkey=7j2vfge15i9bimennfmk1z1rr&e=2&st=fgcun9il&dl=0.

Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou. 2006. "Who's Who in Networks. Wanted: The Key Player." Econometrica 74 (5): 1403–1417. ISSN: 00129682, 14680262, accessed January 30, 2025. http://www.jstor.org/stable/3805930.

Bayer, P., R. Hjalmarsson, and D. Pozen. 2009. "Building Criminal Capital behind Bars: Peer Effects in Juvenile Corrections." The Quarterly Journal of Economics 124 (1): 105–147. http://www.jstor.org/stable/40506225.

Borsari, B., and K.B. Carey. 2006. "How the quality of peer relationships influences college alcohol use." Drug and Alcohol Review 25 (4): 361–370.

Boucher, Vincent, Michelle Rendall, Philip Ushchev, and Yves Zenou. 2024. "Toward a General Theory of Peer Effects." Econometrica 92 (2): 543–565. https://doi.org/https://doi.org/10.3982/ECTA21048. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA21048. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA21048.

Calvó-Armengol, Antoni, Eleonora Patacchini, and Yves Zenou. 2005. "Peer Effects and Social Networks in Education and Crime." Labor: Demographics & Economics of the Family, https://api.semanticscholar.org/CorpusID:55528602.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2017. "Peer Effects in the Workplace." American Economic Review 107 (2): 425–456.

Damm, Anna Piil, and Christian Dustmann. 2014. "Does Growing Up in a High Crime Neighborhood Affect Youth Criminal Behavior?" Publisher: American Economic Association, The American Economic Review 104 (6): 1806–1832. ISSN: 0002-8282, accessed February 4, 2024. https://www.jstor.org/stable/42920867.

Damm, Anna Piil, and Cédric Gorinas. 2020. "Prison as a Criminal School: Peer Effects and Criminal Learning behind Bars." Journal of Law and Economics 63 (1): 149–180.

Diaz, Angelo. 2024. "Who You Serve Time With: Peer Effects and Recidivism." Unpublished manuscript. Accessed: March 13, 2025.

Díaz, Carlos, Eleonora Patacchini, Thierry Verdier, and Yves Zenou. 2021. "Leaders in Juvenile Crime." SSRN Electronic Journal (October). https://doi.org/10.2139/ssrn.3233317. https://ssrn.com/abstract=3233317.

Engel, C. 2023. "How Little Does It Take to Trigger a Peer Effect? An Experiment on Crime as Conditional Rule Violation." Journal of Research in Crime and Delinquency.

Engel, Christoph. 2023. "How Little Does It Take to Trigger a Peer Effect? An Experiment on Crime as Conditional Rule Violation." Journal of Research in Crime and Delinquency 60 (4): 455–492. https://doi.org/10.1177/00224278231152625. eprint: https://doi.org/10.1177/00224278231152625. https://doi.org/10.1177/00224278231152625.

Gaviria, A., and S. Raphael. 1997. "School-Based Peer Effects and Juvenile Behavior." Review of Economics and Statistics 83:257–268.

Glaeser, Edward L., Bruce Sacerdote, and José A. Scheinkman. 1996. "Crime and Social Interactions*." The Quarterly Journal of Economics 111, no. 2 (May 1, 1996): 507–548. ISSN: 0033-5533, accessed February 4, 2024. https://doi.org/10.2307/2946686. https://doi.org/10.2307/2946686.

Han, Li, and Tao Li. 2009. "The gender difference of peer influence in higher education." Economics of Education Review 28, no. 1 (February): 129–134. ISSN: 0272-7757, accessed January 31, 2025. https://doi.org/10.1016/j.econedurev.2007.12.002. https://www.sciencedirect.com/science/article/pii/S0272775708000575.

Harris, H., K. Nakamura, and K. Bucklen. 2017. "Do cellmates matter? A causal test of the schools of crime hypothesis with implications for differential association and deterrence theories." Criminology 56 (4): 671–706. https://doi.org/10.1111/1745-9125.12155.

Hoxby, Caroline M., and Gretchen Weingarth. n.d. "Taking Race Out of the Equation: School Reassignment and the Structure of Peer Effects." Accessed: 2025-01-30, SSRN Electronic Journal, https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=386de4e83235738ec333387e23abf71a4c1f1e4d.

Johnsen, Julian, and Laura Khoury. 2024. "Peer Effects in Prison" [in en]. SSRN Electronic Journal, ISSN: 1556-5068, accessed January 31, 2025. https://doi.org/10.2139/ssrn.4885845. https://www.ssrn.com/abstract=4885845.

Kim, Jinho, and Jason M. Fletcher. 2018. "The Influence of Classmates on Adolescent Criminal Activities in the United States." Publisher: Routledge _eprint: https://doi.org/10.1080/01639625.2016.1269563, Deviant Behavior 39, no. 3 (March 4, 2018): 275–292. ISSN: 0163-9625, accessed February 4, 2024. https://doi.org/10.1080/01639625.2016.1269563. https://doi.org/10.1080/01639625.2016.1269563.

Lindquist, Matthew J., and Yves Zenou. 2014. "Key Players in Co-Offending Networks." IZA Discussion Paper 8012. https://doi.org/10.2139/ssrn.2409534. https://ssrn.com/abstract=2409534.

Ludwig, Jens, Greg J. Duncan, and Paul Hirschfield. 2001. "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing-Mobility Experiment." Publisher: Oxford University Press, The Quarterly Journal of Economics 116 (2): 655–679. ISSN: 0033-5533, accessed February 4, 2024. https://www.jstor.org/stable/2696475.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." The Review of Economic Studies 60 (3): 531–542. ISSN: 00346527, 1467937X, accessed January 29, 2025. http://www.jstor.org/stable/2298123.

Marchand, Steeve. 2020. Peer Effects in Prison and Recidivism. Accessed May 28, 2024. https://drive.google.com/file/u/2/d/1B23IcVFCWcHEzy7U-caPkewoimt7G3iY/view?usp=drive_open&usp=embed_facebook.

Mas, Alexandre, and Enrico Moretti. 2009. "Peers at Work." American Economic Review 99, no. 1 (March): 112–45. https://doi.org/10.1257/aer.99.1.112. https://www.aeaweb.org/articles?id=10.1257/aer.99.1.112.

Minton, T.D., and Z. Zeng. 2021. Jail Inmates in 2020 - Statistical Tables. U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics. Retrieved from Bureau of Justice Statistics. https://bjs.ojp.gov/content/pub/pdf/ji20st.pdf.

Ouss, A. 2011. "Prison as a School of Crime: Evidence from Cell-Level Interactions" (December). https://ssrn.com/abstract=1989803.

Pratschke, Jonathan, and Giovanni Abbiati. 2020. "Peer Effects in Education" (February). https://doi.org/10.1093/acrefore/9780190264093.013.849. https://oxfordre.com/education/view/10.1093/acrefore/9780190264093.001.0001/acrefore-9780190264093-e-849.

Pratt, Travis C., Francis T. Cullen, Christine S. Sellers, L. Thomas Winfree, Tamara D. Madensen, Leah E. Daigle, Noelle E. Fearn, and Jacinta M. Gau. 2010. "The Empirical Status of Social Learning Theory: A MetaAnalysis." Justice Quarterly 27:765–802. https://api.semanticscholar.org/CorpusID:56424856.

Quinn, P.D., and K. Fromme. 2011. "Alcohol use and related problems among college students and their noncollege peers: the competing roles of personality and peer influence." Journal of Studies on Alcohol and Drugs 72 (4): 622–632.

Rees, Carter, and Gregory M. Zimmerman. 2016. "The First Delinquent Peers Are the Most Important: Examining Nonlinearity in the Peer Effect." Justice Quarterly 33 (3): 427–454. https://doi.org/10.1080/07418825.2014.915978. eprint: https://doi.org/10.1080/07418825.2014.915978. https://doi.org/10.1080/07418825.2014.915978.

Restivo, Emily, and Mark M. Lanier. 2015. "Measuring the Contextual Effects and Mitigating Factors of Labeling Theory." Justice Quarterly 32:116–141. https://api.semanticscholar.org/CorpusID:143357360.

Sacerdote, B. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." The Quarterly Journal of Economics 116 (2): 681–704. http://www.jstor.org/stable/2696476.

Stevenson, M. 2017. "Breaking Bad: Mechanisms of Social Influence and the Path to Criminality in Juvenile Jails." The Review of Economics and Statistics 99 (5): 824–838. https://doi.org/10.1162/REST_a_00685. https://doi.org/10.1162/REST_a_00685.

Tan, Kegon Teng Kok, and Mariyana Zapryanova. 2022. "Peer Effects and Recidivism: The Role of Race and Age [Building Criminal Capital behind Bars: Peer Effects in Juvenile Corrections]." The Journal of Law, Economics, and Organization 38 (3): 721–740.

Tao, Ji, and Lung-fei Lee. 2014. "A social interaction model with an extreme order statistic." The Econometrics Journal 17 (3): 197–240. ISSN: 13684221, 1368423X, accessed January 30, 2025. http://www.jstor.org/stable/43697672.

Tatsi, Eirini. 2015. "Endogenous Social Interactions: Which Peers Matter?" [In eng]. Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung - Theorie und Politik - Session: Understanding the nature of peer effects, E02-V1. ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft. https://hdl.handle.net/10419/113168.

Usman, Hina. 2022. Do Gang Members in Prison Impact Others to Recidivate? Working paper.

Wilson, J.J. 2007. "Peer Effects and Cigarette Use Among College Students." Atlantic Economic Journal 35:233–247.

Zenou, Yves. 2021. "Centrality-Based Spillover Effects." SSRN Electronic Journal (July). https://doi.org/10.2139/ssrn.3880728. https://ssrn.com/abstract=3880728.

Zhen, Zeng. 2022. Jail Inmates in 2021 Statistical Tables. U.S. Department of Justice Office of Justice Programs Bureau of Justice Statistics. Retrieved from Bureau of Justice Statistics. https://bjs.ojp.gov/library/publications/jail-inmates-2021-statistical-tables.

12. Appendix

12.1. Summary Statistics

Table 8: Descriptive Statistics

Variable	Mean	Sd
Age entry	34.84	11.81
Black	0.83	0.38
Single	0.89	0.32
Days	33.36	95.67
Prior convictions (cases)	6.78	10.10
Prior weapon other	0.13	0.41
Prior traffic other	1.59	3.24
Prior sex rape	0.01	0.10
Prior property theft	0.99	3.28
Prior property other	0.03	0.22
Prior property burglary	0.75	2.87
Prior person robbery	0.08	0.50
Prior person other	0.02	0.15
Prior person murder	0.01	0.10
Prior person domestic assault	0.32	0.83
Prior person aggravated assault	0.03	0.22
Prior person assault	0.22	0.67
Prior drug possession	0.22	0.63
Prior drug man dist sell	0.44	1.10
Future arrests	0.44	0.49
Future weapon other	0.04	0.20
Future traffic other	0.03	0.16
Future sex rape	0.00	0.03
Future property theft	0.11	0.31
Future property other	0.00	0.06
Future property burglary	0.07	0.25
Future person robbery	0.01	0.11
Future person other	0.01	0.09
Future person murder	0.00	0.06
Future person domestic assault	0.02	0.14
Future person aggravated assault	0.03	0.17
Future person assault	0.03	0.17
Future drug possession	0.06	0.23
Future drug man dist sell	0.03	0.16

Continued on next page

Table 8: Descriptive Statistics (continued)

Variable	Mean	Sd
Exp. Var. prior convictions (sum)	2361.53	8896.68
Exp. Var. severity index sum (sum)	4298.74	16451.26
Exp. Var. severity index max (sum)	647.52	2380.39
Exp. Var. prior convictions (max)	30.31	27.81
Exp. Var. severity index sum (max)	47.02	38.51
Exp. Var. severity index max (max)	4.32	2.42
Exp. Var. prior convictions (mean)	6.79	6.67
Exp. Var. severity index sum (mean)	12.44	11.08
Exp. Var. severity index max (mean)	2.06	1.36
Exp. Var. prior convictions (first peer(s))	6.79	7.01
Exp. Var. severity index sum (first peer(s))	12.43	11.71
Exp. Var. severity index max (first peer(s))	2.06	1.44
Exp. Var. prior convictions (last peer(s))	6.79	7.04
Exp. Var. severity index sum (last peer(s))	12.47	11.73
Exp. Var. severity index max (last peer(s))	2.06	1.44
Exp. Var. D2 prior convictions (sum)	128889.89	367329.50
Exp. Var. D2 severity index sum (sum)	229202.28	674969.31
Exp. Var. D2 severity index max (sum)	33635.57	97193.10
Exp. Var. D2 prior convictions (max)	31.73	34.48
Exp. Var. D2 severity index sum (max)	46.36	46.76
Exp. Var. D2 severity index max (max)	3.86	3.02
Exp. Var. D2 prior convictions (mean)	5.17	6.01
Exp. Var. D2 severity index sum (mean)	9.42	10.38
Exp. Var. D2 severity index max (mean)	1.55	1.42
Exp. Var. D2 prior convictions (first peer(s))	5.01	6.29
Exp. Var. D2 severity index sum (first peer(s))	9.14	10.93
Exp. Var. D2 severity index max (first peer(s))	1.49	1.49
Exp. Var. D2 prior convictions (last peer(s))	4.35	5.98
Exp. Var. D2 severity index sum (last peer(s))	7.84	10.25
Exp. Var. D2 severity index max (last peer(s))	1.25	1.39
Exp. Var. D2 placebo prior convictions (sum)	150178.29	416923.69
Exp. Var. D2 placebo severity index sum (sum)	270673.18	781842.21
Exp. Var. D2 placebo severity index max (sum)	39351.46	111985.37
Exp. Var. D2 placebo prior convictions (max)	31.24	34.56
Exp. Var. D2 placebo severity index sum (max)	45.81	46.56
Exp. Var. D2 placebo severity index max (max)	3.86	2.92
Exp. Var. D2 placebo prior convictions (mean)	5.44	6.04
Exp. Var. D2 placebo severity index sum (mean)	10.02	10.45

Continued on next page

Table 8: Descriptive Statistics (continued)

Variable	Mean	Sd
Exp. Var. D2 placebo severity index max (mean)	1.65	1.42
Exp. Var. D2 placebo prior convictions (first peer(s))	4.53	6.06
Exp. Var. D2 placebo severity index sum (first peer(s))	8.18	10.37
Exp. Var. D2 placebo severity index max (first peer(s))	1.31	1.40
Exp. Var. D2 placebo prior convictions (last peer(s))	5.27	6.42
Exp. Var. D2 placebo severity index sum (last peer(s))	9.71	11.10
Exp. Var. D2 placebo severity index max (last peer(s))	1.59	1.50
Observations	43695	

12.2. Jail Floor Classifications

Table 9
Prison Floor Allocation

Floor	Type	Blocks	Individuals
Lower level	Short term inmates	11	30,793
First	Some blocks of isolation	9	1,229
Second	Mental health	15	2,312
Third	Medium security	16	1,365
Fourth	High security	17	952
Fifth	Low security	3	15,743
Sixth	Low security	3	5,898

12.3. Movements

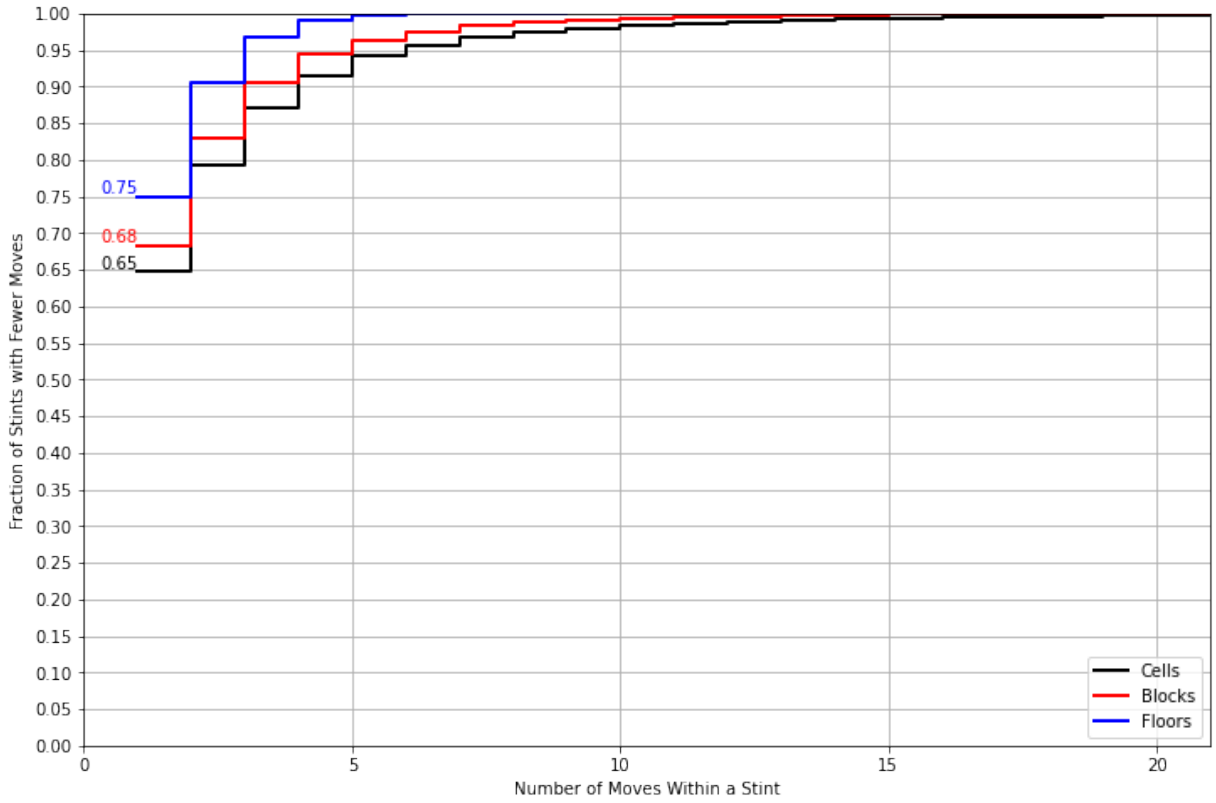


Figure 4: Moves within stint

12.4. Relation between future arrest and indexes

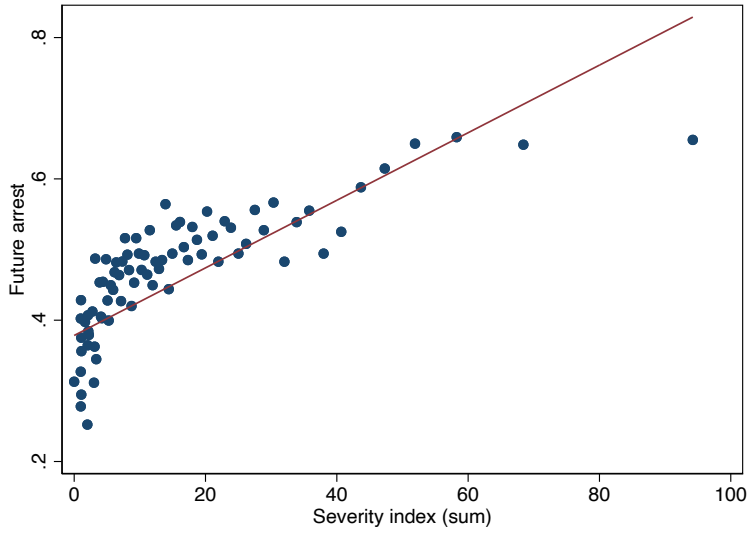


Figure 5: Severity index sum

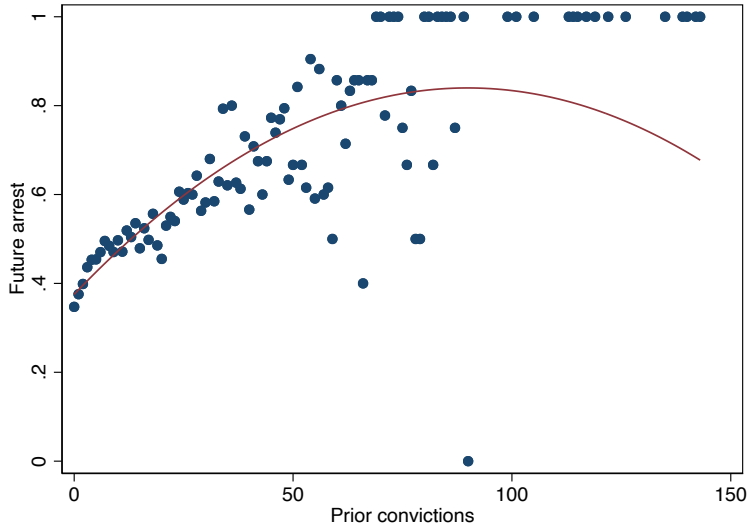


Figure 6: Prior convictions

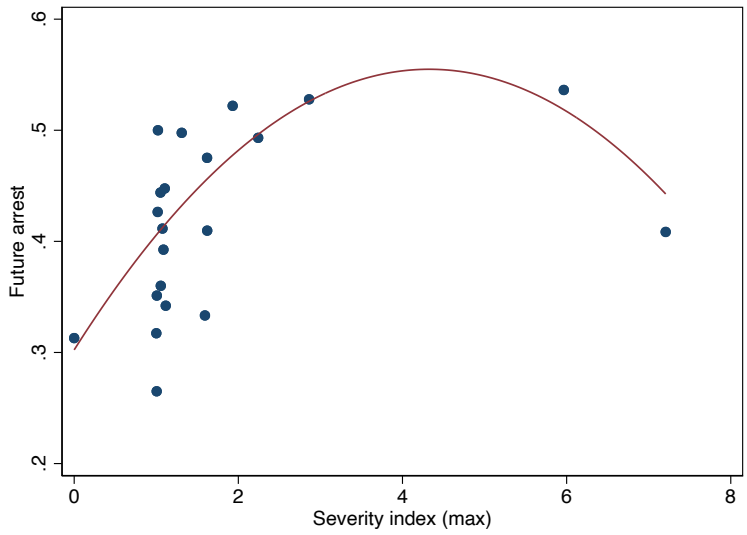


Figure 7: Severity index max

12.5. Randomization

Table 10
Randomization Sum

	Severity index sum (SUM)	Severity index max (SUM)	Future Arrests
Age	10.9948**	1.7234***	-0.0062***
	(0.007)	(0.003)	(0.000)
	[0.0253]	[0.0094]	[0.0000]
Black	88.5457	10.9918	0.0326***
	(0.435)	(0.490)	(0.000)
	[0.5691]	[0.6405]	[0.0000]
Single	-121.2524	-13.1309	0.0889***
	(0.358)	(0.478)	(0.000)
	[0.5531]	[0.6769]	[0.0000]
Weapon other	92.3274	16.0922	0.0169***
	(0.228)	(0.134)	(0.000)
	[0.4307]	[0.3257]	[0.0000]
Traffic other	14.2335	1.8735	0.0022***
	(0.255)	(0.286)	(0.001)
	[0.4338]	[0.4855]	[0.0014]
Sex rape	-1259.5586***	-172.8332***	0.0671***
	(0.000)	(0.000)	(0.000)
	[0.0010]	[0.0014]	[0.0000]
Property theft	-5.8712	-1.0570	0.0151***
	(0.599)	(0.500)	(0.000)
	[0.6790]	[0.6070]	[0.0000]
Property other	-44.9443	-9.4062	0.0127*
	(0.670)	(0.524)	(0.028)
	[0.7116]	[0.5572]	[0.0343]
Property burglary	-0.8710	0.1635	0.0121***
	(0.952)	(0.936)	(0.000)
	[0.9520]	[0.9359]	[0.0000]
Person robbery	-73.9725	-10.5956	0.0049
	(0.213)	(0.203)	(0.116)
	[0.4517]	[0.3835]	[0.1233]
Person other	-120.1174	-17.1677	0.0180**
	(0.400)	(0.392)	(0.017)
	[0.5674]	[0.6052]	[0.0223]
Person murder	-1252.4537***	-162.7821***	-0.0181*
	(0.000)	(0.000)	(0.029)
	[0.0000]	[0.0000]	[0.0328]
Person d assault	-205.9534***	-27.9766***	0.0331***
	(0.000)	(0.001)	(0.000)
	[0.0017]	[0.0026]	[0.0000]
Person a assault	-145.1368	-18.3824	0.0233***
	(0.075)	(0.108)	(0.000)
	[0.2128]	[0.3059]	[0.0000]
Person assault	-38.2746	-4.9822	0.0136***
	(0.487)	(0.519)	(0.000)
	[0.5914]	[0.5880]	[0.0000]
Drug possession	-43.7313	-6.0439	0.0130***
	(0.191)	(0.198)	(0.000)
	[0.4641]	[0.4200]	[0.0000]
Drug man-dist-sell	320.4395***	39.9652***	0.0013
	(0.000)	(0.000)	(0.642)
	[0.0000]	[0.0000]	[0.6415]
Constant	0.4123	0.0899	0.0000
	(0.992)	(0.988)	(1.000)
Mean dep. variable	4263.47	642.06	0.44
F	7.2515	6.4203	152.3177
r2	0.0030	0.0027	0.0561
Observations	40892	40892	43604

Notes: This table presents the results of testing for randomization using the SUM exposure variables. The analysis is conducted at the individual level, with demographic characteristics and criminal records included as independent variables. Column 1 uses the severity index sum (SUM) as the independent variable, while Column 2 uses the severity index max (SUM). P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01 based on adjusted p-values.

Table 11
Randomization Max

	Severity index sum (MAX)	Severity index max (MAX)	Future Arrests
Age	-0.1017***	-0.0020*	-0.0062***
	(0.000)	(0.016)	(0.000)
	[0.0000]	[0.0932]	[0.0000]
Black	-0.7404	0.0073	0.0326***
	(0.019)	(0.756)	(0.000)
	[0.1055]	[1.0000]	[0.0000]
Single	0.0812	-0.0158	0.0889***
	(0.824)	(0.562)	(0.000)
	[0.9341]	[0.9552]	[0.0000]
Weapon other	0.2159	0.0248	0.0169***
	(0.309)	(0.117)	(0.000)
	[0.7513]	[0.2840]	[0.0000]
Traffic other	-0.0504	-0.0051	0.0022***
	(0.146)	(0.049)	(0.001)
	[0.4144]	[0.1659]	[0.0014]
Sex rape	-1.3863	0.0140	0.0671***
	(0.137)	(0.840)	(0.000)
	[0.4668]	[1.0000]	[0.0000]
Property theft	0.0166	-0.0021	0.0151***
	(0.592)	(0.370)	(0.000)
	[0.8381]	[0.7872]	[0.0000]
Property other	-0.0641	0.0044	0.0127**
	(0.826)	(0.841)	(0.028)
	[0.8779]	[0.9534]	[0.0343]
Property burglary	-0.0902	0.0002	0.0121***
	(0.025)	(0.953)	(0.000)
	[0.1048]	[0.9531]	[0.0000]
Person robbery	0.0416	0.0240	0.0049
	(0.800)	(0.050)	(0.116)
	[1.0000]	[0.1416]	[0.1233]
Person other	-0.3072	0.0083	0.0180**
	(0.438)	(0.779)	(0.017)
	[0.7446]	[1.0000]	[0.0223]
Person murder	-0.1491	0.0347	-0.0181**
	(0.821)	(0.479)	(0.029)
	[0.9969]	[0.9052]	[0.0328]
Person d assault	0.4104*	0.0282*	0.0331***
	(0.011)	(0.019)	(0.000)
	[0.0935]	[0.0793]	[0.0000]
Person a assault	-0.0096	0.0789***	0.0233***
	(0.966)	(0.000)	(0.000)
	[0.9663]	[0.0000]	[0.0000]
Person assault	-0.1173	-0.0049	0.0136***
	(0.443)	(0.664)	(0.000)
	[0.6839]	[1.0000]	[0.0000]
Drug possession	0.0867	-0.0008	0.0130***
	(0.350)	(0.909)	(0.000)
	[0.7431]	[0.9655]	[0.0000]
Drug man-dist-sell	0.1154	-0.0269*	0.0013
	(0.393)	(0.008)	(0.642)
	[0.7430]	[0.0640]	[0.6415]
Constant	-0.0147	-0.0003	0.0000
	(0.898)	(0.974)	(1.000)
Mean dep. variable	46.95	4.32	0.44
F	8.0594	3.6959	152.3177
r2	0.0033	0.0015	0.0561
N	40892.0000	40892.0000	43604.0000

Notes: This table presents the results of testing for randomization using the MAX exposure variables. The analysis is conducted at the individual level, with demographic characteristics and criminal records included as independent variables. Column 1 uses the severity index sum (MAX) as the independent variable, while Column 2 uses the severity index max (MAX). P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01 based on adjusted p-values.

Table 12
Randomization Mean

	Severity index sum (MEAN)	Severity index max (MEAN)	Future Arrests
Age	-0.0609***	-0.0029***	-0.0062***
	(0.000)	(0.000)	(0.000)
	[0.0000]	[0.0000]	[0.0000]
Black	0.2547	0.0405*	0.0326***
	(0.084)	(0.020)	(0.000)
	[0.1581]	[0.0696]	[0.0000]
Single	-0.0854	-0.0097	0.0889***
	(0.618)	(0.634)	(0.000)
	[0.7502]	[0.8286]	[0.0000]
Weapon other	0.3057**	0.0310**	0.0169***
	(0.002)	(0.009)	(0.000)
	[0.0119]	[0.0366]	[0.0000]
Traffic other	-0.0281	-0.0038	0.0022***
	(0.083)	(0.050)	(0.001)
	[0.2017]	[0.1206]	[0.0014]
Sex rape	-0.3949	-0.0083	0.0671***
	(0.366)	(0.873)	(0.000)
	[0.5654]	[0.8733]	[0.0000]
Property theft	-0.0040	-0.0011	0.0151***
	(0.781)	(0.512)	(0.000)
	[0.7815]	[0.7914]	[0.0000]
Property other	-0.1563	0.0102	0.0127**
	(0.253)	(0.529)	(0.028)
	[0.4306]	[0.7493]	[0.0343]
Property burglary	-0.0079	0.0018	0.0121***
	(0.673)	(0.424)	(0.000)
	[0.7151]	[0.7206]	[0.0000]
Person robbery	0.2184**	0.0403***	0.0049
	(0.005)	(0.000)	(0.116)
	[0.0195]	[0.0001]	[0.1233]
Person other	-0.3637	-0.0079	0.0180**
	(0.050)	(0.719)	(0.017)
	[0.1413]	[0.8148]	[0.0223]
Person murder	0.2140	0.0735	-0.0181**
	(0.488)	(0.045)	(0.029)
	[0.6380]	[0.1264]	[0.0328]
Person d assault	0.0672	0.0034	0.0331***
	(0.374)	(0.708)	(0.000)
	[0.5296]	[0.8601]	[0.0000]
Person a assault	0.3445***	0.1052***	0.0233***
	(0.001)	(0.000)	(0.000)
	[0.0096]	[0.0000]	[0.0000]
Person assault	-0.1452	-0.0139	0.0136***
	(0.042)	(0.101)	(0.000)
	[0.1434]	[0.2139]	[0.0000]
Drug possession	0.0752	0.0011	0.0130***
	(0.083)	(0.825)	(0.000)
	[0.1773]	[0.8771]	[0.0000]
Drug man-dist-sell	-0.0269	-0.0109	0.0013
	(0.671)	(0.146)	(0.642)
	[0.7599]	[0.2759]	[0.6415]
Constant	-0.0087	-0.0004	0.0000
	(0.872)	(0.950)	(1.000)
Mean dep. Variable	12.44	2.06	0.44
F	14.2066	9.2629	152.3177
r2	0.0059	0.0038	0.0561
Observations	40892.0000	40892.0000	43604.0000

Notes: This table presents the results of testing for randomization using the MEAN exposure variables. The analysis is conducted at the individual level, with demographic characteristics and criminal records included as independent variables. Column 1 uses the severity index sum (MEAN) as the independent variable, while Column 2 uses the severity index max (MEAN). P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01 based on adjusted p-values.

Table 13
Randomization First Peer(s)

	Severity index sum (First Peer(s))	Severity index max (First Peer(s))	Future Arrests
Age	-0.0552***	-0.0028***	-0.0062***
	(0.000)	(0.000)	(0.000)
	[0.0000]	[0.0002]	[0.0000]
Black	0.2445	0.0353	0.0326***
	(0.117)	(0.070)	(0.000)
	[0.3302]	[0.1752]	[0.0000]
Single	0.0206	-0.0001	0.0889***
	(0.910)	(0.997)	(0.000)
	[0.9095]	[0.9435]	[0.0000]
Weapon other	0.3051**	0.0278*	0.0169***
	(0.004)	(0.034)	(0.000)
	[0.0210]	[0.0790]	[0.0000]
Traffic other	-0.0199	-0.0037*	0.0022***
	(0.247)	(0.088)	(0.001)
	[0.5258]	[0.1666]	[0.0014]
Sex rape	-0.3754	0.0952	0.0671***
	(0.416)	(0.099)	(0.000)
	[0.5899]	[0.4298]	[0.0000]
Property theft	-0.0094	-0.0021	0.0151***
	(0.542)	(0.278)	(0.000)
	[0.6576]	[0.4528]	[0.0000]
Property other	-0.1489	0.0145	0.0127**
	(0.303)	(0.422)	(0.028)
	[0.5158]	[0.5306]	[0.0343]
Property burglary	-0.0128	0.0008	0.0121***
	(0.520)	(0.740)	(0.000)
	[0.6806]	[0.7653]	[0.0000]
Person robbery	0.2863***	0.0539***	0.0049
	(0.000)	(0.000)	(0.116)
	[0.0038]	[0.0000]	[0.1233]
Person other	-0.2112	0.0236	0.0180**
	(0.282)	(0.337)	(0.017)
	[0.5318]	[0.4216]	[0.0223]
Person murder	0.0639	0.0336	-0.0181**
	(0.845)	(0.410)	(0.029)
	[0.8975]	[0.1974]	[0.0328]
Person d assault	0.0782	-0.0042	0.0331***
	(0.327)	(0.674)	(0.000)
	[0.5061]	[0.7943]	[0.0000]
Person a assault	0.2866**	0.0913***	0.0233***
	(0.010)	(0.000)	(0.000)
	[0.0445]	[0.0000]	[0.0000]
Person assault	-0.1438	-0.0175	0.0136***
	(0.057)	(0.065)	(0.000)
	[0.1946]	[0.1886]	[0.0000]
Drug possession	0.0617	-0.0010	0.0130***
	(0.179)	(0.860)	(0.000)
	[0.4346]	[0.9963]	[0.0000]
Drug man-dist-sell	-0.0210	-0.0065	0.0013
	(0.754)	(0.435)	(0.642)
	[0.8548]	[0.4844]	[0.6415]
Constant	-0.0082	2.0615***	0.0000
	(0.885)	(0.000)	(1.000)
Mean dep. variable	12.43	2.06	0.44
F	10.8927	7.1901	152.3177
r2	0.0045	0.0030	0.0561
Observations	40892	40894	43604

Notes: This table presents the results of testing for randomization using the First Peer(s) exposure variables. The analysis is conducted at the individual level, with demographic characteristics and criminal records included as independent variables. Column 1 uses the severity index sum (First Peer(s)) as the independent variable, while Column 2 uses the severity index max (First Peer(s)). P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01 based on adjusted p-values.

Table 14
Randomization Last Peer(s)

	Severity index sum (Last Peer(s))	Severity index max (Last Peer(s))	Future Arrests
Age	-0.0624***	-0.0029***	-0.0062***
	(0.000)	(0.000)	(0.000)
	[0.0000]	[0.0001]	[0.0000]
Black	0.2041	0.0436*	0.0326***
	(0.191)	(0.025)	(0.000)
	[0.3607]	[0.0704]	[0.0000]
Single	-0.1467	-0.0138	0.0889***
	(0.419)	(0.541)	(0.000)
	[0.5931]	[0.7452]	[0.0000]
Weapon other	0.3177**	0.0279*	0.0169***
	(0.003)	(0.034)	(0.000)
	[0.0145]	[0.0844]	[0.0000]
Traffic other	-0.0288*	-0.0018	0.0022***
	(0.094)	(0.412)	(0.001)
	[0.1991]	[0.6892]	[0.0014]
Sex rape	-0.4297	-0.0139	0.0671***
	(0.353)	(0.810)	(0.000)
	[0.5457]	[0.7335]	[0.0000]
Property theft	0.0009	-0.0012	0.0151***
	(0.956)	(0.535)	(0.000)
	[0.9558]	[0.7579]	[0.0000]
Property other	-0.2546	-0.0077	0.0127**
	(0.079)	(0.670)	(0.028)
	[0.1918]	[0.6901]	[0.0343]
Property burglary	0.0018	0.0016	0.0121***
	(0.930)	(0.508)	(0.000)
	[0.9877]	[0.7062]	[0.0000]
Person robbery	0.1538	0.0279**	0.0049
	(0.060)	(0.006)	(0.116)
	[0.1689]	[0.0176]	[0.1233]
Person other	-0.4523*	-0.0190	0.0180**
	(0.021)	(0.439)	(0.017)
	[0.0908]	[0.7205]	[0.0223]
Person murder	0.2216	0.0236	-0.0181**
	(0.498)	(0.562)	(0.029)
	[0.6511]	[0.3910]	[0.0328]
Person d assault	0.0513	0.0048	0.0331***
	(0.522)	(0.632)	(0.000)
	[0.6339]	[0.7122]	[0.0000]
Person a assault	0.4024***	0.0946***	0.0233***
	(0.000)	(0.000)	(0.000)
	[0.0028]	[0.0000]	[0.0000]
Person assault	-0.0962	-0.0051	0.0136***
	(0.204)	(0.592)	(0.000)
	[0.3469]	[0.7868]	[0.0000]
Drug possession	0.0886	0.0009	0.0130***
	(0.054)	(0.873)	(0.000)
	[0.1839]	[0.7925]	[0.0000]
Drug man-dist-sell	-0.0265	-0.0117	0.0013
	(0.692)	(0.161)	(0.642)
	[0.7845]	[0.3230]	[0.6415]
Constant	-0.0084	2.0627***	0.0000
	(0.883)	(0.000)	(1.000)
Mean dep. variables	12.47	2.06	0.44
F	12.7643	5.6632	152.3177
r2	0.0053	0.0023	0.0561
Observations	40892.0000	40894.0000	43604.0000

Notes: This table presents the results of testing for randomization using the Last Peer(s) exposure variables. The analysis is conducted at the individual level, with demographic characteristics and criminal records included as independent variables. Column 1 uses the severity index sum (Last Peer(s)) as the independent variable, while Column 2 uses the severity index max (Last Peer(s)). P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01 based on adjusted p-values.

12.6. Main result without controls

Table 15
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity Index	-0.0002	0.0089**	0.0074***	0.0084***	0.0063**
	(0.923)	(0.027)	(0.000)	(0.000)	(0.002)
Demo. Char.	NO	NO	NO	NO	NO
Criminal history	NO	NO	NO	NO	NO
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	0.9235	5.13	14.29	16.99	10.81
R^2	0.0243	0.0244	0.0245	0.0246	0.0245
Observations	40896	40896	40896	40896	40896

Notes: This table reports the regression results derived from estimating Equation (1). Observations are at the individual level. Each peer who interacts with an individual is a cellmate who is represented by the sum of severity of their previous convictions ("severity index sum"). Each column applies a distinct functional or temporal form to combine severity index sums across peers. These forms are: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions do not include controls except block and quarter fixed effects. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

12.7. Main result: severity index max, and number of prior convictions

Table 16
Dependent Variable: Future arrests

Functional form	Sum	Max	Mean	First	Last
Severity index (max)	0.0025	0.0111***	0.0049	0.0076**	0.0029
	(0.377)	(0.001)	(0.143)	(0.010)	(0.351)
	[0.3771]	[0.0119]	[0.2383]	[0.0502]	[0.4382]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	70.51	73.30	74.82	70.33	78.43
R^2	0.0804	0.0806	0.0805	0.0806	0.0804
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation (1). Observations are at the individual level. Each peer who interacts with an individual is a cell-mate who is represented by the max of severity of their previous convictions ("severity index max"). Each column applies a distinct functional or temporal form to combine severity index sums across peers. These forms are: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Table 17
Dependent Variable: Future arrests

Functional form	Sum	Max	Mean	First	Last
Number of prior convictions	0.0029	0.0043	0.0046*	0.0056**	0.0029
	(0.364)	(0.209)	(0.064)	(0.023)	(0.238)
	[0.3904]	[0.3142]	[0.1375]	[0.0875]	[0.3245]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	70.95	70.30	70.34	75.86	71.28
R^2	0.0804	0.0804	0.0805	0.0805	0.0804
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation (1). Observations are at the individual level. Each peer who interacts with an individual is a cell-mate who is represented by the number of their previous convictions. Each column applies a distinct functional or temporal form to combine the number of previous convictions across peers. These forms are: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

12.8. Main result D2: severity index max, and number of prior convictions

Table 18
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity index (max) D1	0.0033	0.0114**	0.0049	0.0076**	0.0028
	(0.298)	(0.001)	(0.148)	(0.010)	(0.356)
	[0.4973]	[0.0359]	[0.3423]	[0.0753]	[0.5339]
Severity index (max) D2	-0.0032	-0.0031	0.0010	-0.0009	0.0013
	(0.477)	(0.417)	(0.686)	(0.621)	(0.569)
	[0.6224]	[0.5686]	[0.7094]	[0.6894]	[0.6561]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	68.23	72.37	76.58	75.09	75.31
R^2	0.0804	0.0807	0.0805	0.0806	0.0804
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation XXX, adding the same variable but with distance 2 D_2. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (severity index max). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Table 19
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Numb. Prior Convictions D1	0.0037	0.0041	0.0047*	0.0056**	0.0029
	(0.293)	(0.249)	(0.059)	(0.021)	(0.237)
	[0.5164]	[0.4673]	[0.1766]	[0.1041]	[0.4730]
Numb. Prior Convictions D2	-0.0032	0.0013	0.0054**	0.0069***	0.0036
	(0.500)	(0.630)	(0.034)	(0.006)	(0.213)
	[0.6249]	[0.6752]	[0.1270]	[0.0605]	[0.4564]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	68.84	70.48	68.58	73.85	71.99
R^2	0.0804	0.0804	0.0806	0.0807	0.0805
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation XXX, adding the same variable but with distance 2 D_2. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (number of previous convictions). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

12.9. Main result D2 placebo: severity index max, and number of prior convictions

Table 20
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Severity Index (max) D1	0.0041	0.0112**	0.0048	0.0076**	0.0028
	(0.235)	(0.001)	(0.148)	(0.010)	(0.365)
	[0.4413]	[0.0217]	[0.4040]	[0.1034]	[0.4974]
Severity Index (max). D2 placebo	-0.0050	-0.0011	0.0013	-0.0002	0.0008
	(0.362)	(0.742)	(0.487)	(0.911)	(0.489)
	[0.5172]	[0.7680]	[0.6092]	[0.9114]	[0.5873]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	68.11	70.37	71.91	68.83	254.13
R^2	0.0804	0.0806	0.0805	0.0806	0.0804
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation XXX, including the placebo version for D_2. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (severity index max). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Table 21
Dependent Variable: **Future arrests**

Functional form	Sum	Max	Mean	First	Last
Numb. Prior Convictions D1	0.0045	0.0046	0.0046	0.0056**	0.0029
	(0.221)	(0.209)	(0.062)	(0.023)	(0.236)
	[0.4738]	[0.4835]	[0.2662]	[0.1708]	[0.4173]
Numb. Prior Convictions D2 placebo	-0.0052	-0.0106*	0.0020	0.0016	0.0010
	(0.361)	(0.070)	(0.323)	(0.524)	(0.597)
	[0.5419]	[0.2620]	[0.5096]	[0.6046]	[0.6398]
Demo. Char.	YES	YES	YES	YES	YES
Criminal history	YES	YES	YES	YES	YES
Block fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Mean dep. variable	0.4389	0.4389	0.4389	0.4389	0.4389
F	68.63	68.72	69.48	77.24	254.13
R^2	0.0804	0.0805	0.0805	0.0805	0.0804
Observations	40892	40892	40892	40892	40892

Notes: This table reports the regression results derived from estimating Equation XXX, including the placebo version for D_2. Observations are at the individual level, with the primary independent variables being exposure measures of peer severity (number of previous convictions). These variables are defined with distinct functional forms and temporal dimensions: sum (Column 1), max (Column 2), mean (Column 3), first peer(s) exposure (Column 4), and last peer(s) exposure (Column 5). All regressions include the following control variables: days incarcerated, age, race, marital status (single), number of peers, and criminal history. The dependent variable is an indicator for whether the individual was rearrested within one year of release. P-values are presented in parentheses, and adjusted p-values are in brackets. Standard errors are clustered at both the individual and block levels. Statistical significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.