Prison Peer Effects and the Public Safety Tradeoff

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Abstract

Penitentiary administrations pursue two goals: maintaining safety inside facilities and promoting rehabilitation after release. While often assumed to align, these objectives may conflict. We study this tradeoff by examining how cellmate assignment affects not only recidivism, but also misconduct and violence in jail. Using detailed administrative data covering the universe of incarceration spells in France and quasi-random cell assignments, we show that exposure to peers convicted of property or drug offenses increases reoffending after release, especially when peers are similar in age and origin, and provide evidence that network formation begins during incarceration. Yet the same similarities that increase recidivism also reduce within-cell conflict, revealing a policy tension. We formalize this tradeoff and simulate alternative assignment rules: keeping the carceral population constant, prioritizing safety reduces conflict by up to 5.2 percent, while prioritizing rehabilitation cuts reoffending by up to 7.5 percent – though gains in one dimension come at the expense of the other. These results highlight how social proximity within institutions can have opposing short- and long-term effects.

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1 Introduction

Institutions responsible for producing public safety often face a tension between maintaining short-term security and promoting long-term rehabilitation. In corrections, prison systems must maintain order and safety within, while also promoting rehabilitation after release. Some interventions, such as cognitive-behavioral therapy or job training, could advance both goals simultaneously, reducing violence within and building skills useful in the community (Heller et al., 2017; Zanella, 2020; Alsan et al., 2025; Galbiati et al., 2025). Others, such as solitary confinement, may strengthen short-run control but inflict lasting psychological harm (Gendreau and Goggin, 2019). We study this possible tradeoff in the context of an important operational decision: how individuals are grouped within correctional facilities. We provide new evidence that peer exposure generates tradeoffs in the production of public safety, between short-term institutional safety and long-term criminal trajectories.

Empirically isolating tradeoffs between short-term institutional outcomes and long-term criminal behavior is nontrivial. Studies of peer effects in correctional facilities face three challenges: measuring both in-prison behavior and post-release outcomes, capturing peer interactions at sufficiently granular levels, and identifying plausibly exogenous variation in peer exposure unrelated to misconduct or recidivism. We address these issues by using novel administrative data covering the universe of incarceration spells in France between June 2016 and December 2022, which record in-prison misconduct and conflicts and allow us to construct measures of recidivism after release. We have data on exact cell assignment, allowing us to conduct analyses at the level where peer interactions are most intense: shared cells. People spend 18 to 22 hours per day with a small and well-defined set of peers (8, on average, over their incarceration), enabling us to measure intensive peer exposure rather than relying on facility-wide or unit-level variation. Moreover, logistical constraints and high turnover generate quasi-random variation in cellmate composition, conditional on observable assignment criteria (Sacerdote, 2001; Zimmerman, 2003). In particular, we observe the intake survey information used by the committee to assign individuals to their initial cells. Taken together, these features allow us to isolate the effects of specific cellmate characteristics on in-prison and post-release behaviors.

Our empirical strategy exploits this quasi-random variation in peer exposure, arising from

institutional capacity constraints. Given high facility occupancy, cellmates are largely assigned based on availability conditional on explicit allocation criteria, leaving little room for discretionary matching. Initial cell assignments are made by an interdisciplinary committee that bases its decisions on responses to a detailed behavioral intake survey, which is the only source of information available before staff have had the opportunity to observe individuals' behavior in prison (Gomez and Pineau, 2024). So, in our main specification, we focus on peers encountered during the first month of incarceration. This addresses the concern that later in an incarceration spell, administrators may reassign people based on behaviors they observe but that are not present in the data, and that may be correlated with our outcomes, generating endogenous peer matches. However, this type of sorting appears limited in practice: our results are very similar when we consider all peers.

We find that exposure to peers convicted of income-generating offenses (drug distribution and property) increases the likelihood of future such offenses. These effects scale linearly with the number of peers. In addition, individuals are more likely to reoffend in the geographic areas where their former cellmates lived prior to incarceration. Taken together, these patterns suggest that peer effects may arise in part through the formation of connections that facilitate access to co-offenders or criminal opportunities in specific local markets. Lastly, we find that peer effects are most pronounced among cellmates who are similar in age or geographic backgrounds, suggesting that affinities may help foster these networks.

We next examine in-prison behavior, a dimension that has received limited empirical attention, despite its importance for institutional operations and inmate welfare. We find that the same peer characteristics correlated with higher recidivism also increase facility-wide misconduct. In particular, exposure to peers convicted of property or drug crimes increases contraband trafficking, as does sharing similar age or geographic origin. We also find evidence that these similarities make co-offending in jail more likely (measured as people being charged on the same day for the same offense), suggesting that proximity amplifies coordinated illicit activities within jails. Together, these patterns are consistent with criminal networks forming and operating during incarceration, not merely after release.

However, we show that the social proximity driving post-release offending and facility-wide misconduct is associated with lower rates of within-cell conflict, creating institutional tradeoffs.

Within-cell conflicts are important to consider, since they represent the most common form of interpersonal incidents in French prisons, and the margin administrators control most directly through cell assignment. When individuals are assigned to cellmates who are similar in age, geographic origin, or offense type, they are significantly less likely to have conflicts within their cells. This creates a tradeoff: assignment strategies that reduce within-cell conflicts in the short run increase both facility-wide misconduct and recidivism in the long run. In the final part of the paper, we use policy simulations to quantify this tension. We show that, keeping the incarcerated population size constant, alternative assignment rules could reduce recidivism by up to 7.5 percent or reduce within-cell conflict by up to 5.2 percent, but not both simultaneously.

Our paper makes three main contributions. First, we show that prison policies designed to improve long-run public safety can come with costs for short-run institutional security, highlighting an important tradeoff. A common finding in the peer effects literature, across crime, education, and other settings, is that resorting policies generate benefits for a particular outcome (Carrell et al., 2009; Bayer et al., 2009; Stevenson, 2017; Johnsen and Khoury, 2025). These analyses typically focus on one objective at a time, leaving unanswered the question of whether the recommended policy produces costs elsewhere. We find that the peer configurations that reduce reoffending have costs in terms of increased within-cell conflicts, suggesting that policies aimed at disrupting criminal network formation (Dell, 2015; Carvalho and Soares, 2016; Melnikov et al., 2020; Bruhn, 2021; Sviatschi, 2022a,b; Pyrooz, 2022; Castro et al., 2024; Cunha Bystrom, 2025) may be more difficult to sustain in practice than single-outcome analyses imply. This echoes insights from multitask principal-agent models (Holmstrom and Milgrom, 1991), where focusing incentives on one task can distort performance on others, thus generating unintended harms. Beyond the crime setting, peer effect estimates based on narrow objectives may be insufficient to guide policy in settings where peer influence operates across competing goals, for example schools balancing academic and behavioral outcomes (Carrell et al., 2009), or workplaces weighing the benefits of social cohesion against individual productivity incentives (Bandiera et al., 2005; Mas and Moretti, 2009).

Second, we introduce a new empirical setting and source of variation for studying peer

effects in prison. Prior work used data from juvenile facilities or Scandanavian prisons, where peer assignments are measured at the housing-unit or facility level (Bayer et al., 2009; Stevenson, 2017; Damm and Gorinas, 2020; Johnsen and Khoury, 2025). In larger facilities, however, variation in peer exposure at the this level is limited: average exposure to any given peer type will be similar across individuals, leaving little identifying variation, and smaller settings do not capture the most common incarceration experiences. We study large, high-turnover adult facilities in France and observe exact cell assignments, enabling us to analyze peer effects at the level where interactions are most intense. This granuarity allows us to examine outcomes that would be impossible to study in settings using facility-wide variation, including within-cell conflict. It also allow us to make progress on a broader challenge in the peer effects literature: isolating the causal effect of similarity from the tendency of individuals with similar traits to sort together (Hoxby, 2000; McPherson et al., 2001; Currarini et al., 2009; Bifulco et al., 2011; Fletcher and Ross, 2018; Lavy and Sand, 2019; Chetty et al., 2022). Because cell assignments are quasi-random, we can hold sorting constant and show that similarity causally reduces conflict while also facilitating learning. These results would not be recoverable from facility-level variation, and contribute to our understanding of how social proximity shapes behavior.

Third, we provide new causal evidence on the determinants of in-prison conflict. In Becker (1968)'s seminal model, the social planner's problem is to balance costs of crime and enforcement; incarceration raises the cost of crime, but it is not itself treated as a place for crime to occur. Since then, the economic study of the safety production function has likewise not considered crime inside of prison as an outcome. While there is a long tradition of theoretical and ethnographic research on prison violence (Sykes, 1958; Wooldredge, 2020), causal evidence is scarce. Existing studies highlight policy-relevant levers such as security classification (Camp and Gaes, 2005; Gaes and Camp, 2009), parole incentives (Kuziemko, 2013; Macdonald, 2024), and ambient conditions or programming (Tahamont, 2019; Mukherjee and Sanders, 2021; Arbour, 2021; Batistich et al., 2024; Abdul-Razzak et al., 2024; Alsan et al., 2025; Alsan and Yang, 2025). We build on these by showing that conflict is also shaped by peer composition at the cell level. Complementary work in law and economics models violence as a tool of informal governance by prison gangs (Skarbek, 2010, 2012; Kurzfeld, 2024). Within the liter-

ature on social interactions and criminal behavior, our rich geographic and socio-demographic data allows us to provide direct evidence of the role of network formation (Glaeser et al., 1996; Ballester et al., 2006; Patacchini and Zenou, 2008; Lindquist and Zenou, 2019; Lindquist et al., 2024). These findings complement a broader literature documenting peer effects across family (Lochner, 2007; Hjalmarsson and Lindquist, 2012; Bhuller et al., 2018; Dobbie et al., 2018), neighborhood (Billings et al., 2019; Billings and Schnepel, 2022), co-offending network (Drago and Galbiati, 2012; Philippe, 2017, 2024b), and school settings (Deming, 2011; Billings et al., 2014; Billings and Hoekstra, 2023; Bibler et al., 2025).[1]

The remainder of the paper is organized as follows. Section 2 provides background on the institutional setting and describes the data. Sections 3 - 5 present our main findings, focusing on recidivism, facility-wide misconduct, and within-cell conflicts, respectively. Finally, Section 6 provides policy simulations, considering counterfactual in-prison incidents and recidivism for different policies.

2 Institutional context and data

2.1 Incarceration in France

In January 2019, there were around 70,000 people in prison. France has an incarceration rate of 102 per 100,000 inhabitants, close to the average in the European Union (see Appendix Figure C.1).[2] There are 185 prisons, divided into three main types of facilities.

Short-term facilities ("maison d'arrêts") function much like jails in the United States: they hold individuals in pretrial detention (30% of the incarcerated population) as well as those serving sentences shorter than two years. These facilities account for 68% of the prison population, and have high rates of overcrowding, with an average occupation rate close to 140%. Cells are typically small; less than 3% of cells house more than four people. People can participate in activities (education, work, sports) and receive visits from family and friends. The rest of the time, between 18 and 22 hours a day, individuals are in their cells with the door locked. Defendants are typically held in jails within the county where their alleged offense

[1] A related literature has considered peer effects in policing harms (Quispe-Torreblanca and Stewart, 2019; Holz et al., 2023; Zhao and Papachristos, 2024).

[2] Since our study period, the prison population has increased in France, with 83,000 people incarcerated on January 1st, 2025, for an incarceration rate of 120 per 100,000.

occurred, since court jurisdiction determines detention location.

Individuals sentenced to more than two years should be incarcerated in "centres de détention", which are similar to low-security prisons in the United States.[3] They represent around 26% of the prison population during our study period. In these facilities, people have more work opportunities, and their cell doors are generally open during the day.

Because we focus on shorter sentences, nearly all individuals in our sample were incarcerated in "maison d'arrêts," the French equivalent of US jails: 85% exclusively, and most of the remaining 15% partly in a "centres de détention" but also in a jail.

2.2 Cell allocation

Admissions to and releases from jail are determined by independent magistrates; the penitentiary administration has no authority to influence or delay these flows. The law requires the separation of males and females; juveniles and adults; and people held on remand or those who are sentenced. In addition to these official criteria, institutions also rely on other characteristics – age, religiosity, tobacco consumption, and nationality – as documented in ethnographic research (El Magrouti, 2014; Bouagga, 2015; Fassin, 2015; Veaudor, 2020).

Once individuals are admitted, the administration is responsible for assigning them to specific cells. They are first attributed a place in the "arrival" department for a few days. They are usually alone in a call, and during this time, they are administered several intake surveys to collect information about their behavior and to assess their needs. These surveys include detailed information about their mental health, addiction, past carceral experiences, family and work trajectories. The survey responses are then transferred to the "commission pluridisciplinaire unique" (CPU), a committee chaired by the facility director and composed of staff from custody, rehabilitation, work, and education services, which assesses each person's situation and determines what unit to place a person in. The head of the unit then determines the cell in the unit.

Most subsequent cell changes (70%) come from moving to a different *type* of cell. Individuals may be transferred to "worker" cells, medical cells, disciplinary cells, or cells associated

[3]People convicted of very serious crimes and serving more than 10-year sentences are incarcerated in "maison centrales" (2.5% of the population), which are similar to maximum security prisons in the United States. Since these are only for long sentences, they are excluded from our analyses.

with specific programs. Such cell changes are decided by the CPU for work, medical reasons, or specific programs, and by the disciplinary commission for disciplinary cells. In addition, people may be transferred for prison management (13% of changes), or if there are conflicts (15% of changes).

Based on these institutional features, the number and composition of cellmates an individual encounters reflects several factors. First, cell size (typically two to three occupants) determines how many people a person can be housed with at a given time. Second, the timing and length of cellmates' sentences shape both how many peers a person meets, and how long they overlap, since it is rare for two people to start and finish their sentences simultaneously; instead, sentences are usually staggered. Third, people may change cells for administrative reasons (for example, they are sentenced so must leave a pretrial cell, or they get a job so get moved to a worker cell). Lastly, people may change cells because of conflicts with cellmates.

2.3 Victimization and conflicts in jail

Prison administrations must ensure inmate security, yet violence behind bars is common. Using the Survey of Prison Inmates and the National Crime Victimization Survey, Western (2021) estimates that violent victimization rates in custody are five times higher than in the community. Wolff et al. (2007) estimate that 20% of incarcerated people experienced violence in the last six months. In France, a 2023 Ministry of Justice initiative recorded 11,669 inmate-on-inmate violent incidents in 2022 (Ministère de la Justice, 2023). Benchmarked against typical average daily populations around 70,000, this implies on the order of 150-170 incidents per year per 1,000 incarcerated people. For comparison, there are 10.4 incidents of violence per 1,000 inhabitants per year in France – so victimization rates in prison are more than 10 times higher.

In the French prison system, when a correctional officer witnesses an incident, it is recorded in the prison information system. Prison administrators can then decide to investigate the incident, whether to charge the case, and whether to implement preventive confinement. Prison courts ("commission de discipline") are composed of three members: the director or deputy director of the facility, a corrections officer, and a volunteer layperson from outside the prison. Everyone is entitled to legal assistance during disciplinary proceedings. The procedure, the

classification of infractions, and the associated punishments are defined in a dedicated code ("code pénitentiaire"), which applies uniformly across all French prisons. The most common penalty is solitary confinement, which may be imposed immediately or be suspended, and can last for up to 30 days. Other sanctions are warnings, or restricting access to work or other activities.

2.4 Prison data

Data construction. We obtained data from the French penitentiary administration for the universe of incarceration spells in France between June 2016 and December 2022. A key advantage of this dataset is that it records the exact cell occupied by each person at every point in their incarceration spell. This allows us to reconstruct, day by day, precise sets of cellmates. Because most observations come from short-term stays in jail, where individuals spend the majority of each day confined to a single cell with a small number of peers, we can identify groups of people whose daily interactions are unavoidable and not subject to selective peer choice.

In addition to information about cell number, we also have data on the type of cell – regular, arrival, medical, disciplinary, work – and on the reason that people change cells, which we use to construct our measure of in-cell conflicts. The dataset includes person-level identifiers, which allow us to construct measures of reincarceration. The dataset also records socio-demographic characteristics (age, sex, nationality, city of residence, literacy), detailed offense codes with over 1,500 categories, and information from psychological evaluations conducted at the start of incarceration.[4]

A second dataset covers information on reports of facility-wide misconduct ("compte rendu d'incident", or CRI)[5]. For each individual, it records whether a CRI was filed and on what date, whether disciplinary charges were pursued, and what sanctions – if any – were imposed. When charges are pursued, the dataset also includes information on the underlying incident types that triggered the CRI.

We structure the data at the individual level, except when studying conflicts in cells, as

[4]We capture prior suicide attempts, self-harm, psychiatric hospitalization, aggressiveness, depression, and substance use disorder.

[5]This information is only available from January 2017 to December 2022

explained in Section 5. Our main analyses focus on three dimensions of peer similarity: offense type (property, drug distribution, violent, and other), pre-incarceration place of residence (city, county, and region), and age. For each person, we then record both the number of cellmates by type along these dimensions and the total time spent together.

We consider three main outcomes in our paper: recidivism, facility-wide misconduct, and within-cell conflicts. Our main measures of recidivism are indicators for whether a person was reincarcerated within one year of release, for different crime types and in different places.[6] For facility-wide misconduct, we consider the number of CRI overall, and the type of CRI for cases that ended in a conviction. For within-cell conflicts, we consider indicators for cell changes due to a conflict. The main sample is restricted to people incarcerated between June 2016 and December 2019 for prison spells of two years or less, so that we can measure new incarcerations within one year after release.

Descriptive statistics. After excluding cases with missing information on prison or crime type, the final dataset includes 189,842 individuals. Table 1 reports summary statistics for this sample. On average, individuals are incarcerated for 7.1 months, and spend 5.4 months sharing a cell with at least one other person. Property crimes are the most common (30%), followed by violent crimes (25%) and drug distribution offenses (21%).[7] People had on average 8.3 cellmates over the course of incarceration—2.5 convicted of property crimes, 1.7 of drug offenses, and 2.2 of violent crimes.

The average age at incarceration is 32. The sample is overwhelmingly male (95%) and predominantly French, although foreign nationals are overrepresented: they account for 25% of the sample, compared to 7.7% of the general population. The population also faces significant social challenges: 29% are illiterate, 58% suffer from addiction, and 19% have a psychiatric history. Within one year of release, 18% were reincarcerated—6% for a property crime, 3% for a drug-related offense, and 5% for a violent crime. On average, 1.79 misconduct reports are initiated per person, and 0.5 are sanctioned. The most common sanctioned offenses are

[6] In France, almost all new convictions within one year lead to a new incarceration spell (Kensey and Benaouda, 2011).

[7] In France, most people who are incarcerated for drug crimes are convicted of drug distribution crimes, and not drug possession. For example, in 2024 only 4% of prison sentences for drug crimes were for drug possession (Ministère de la Justice, 2024); because possession carries shorter sentences, such cases make up an even smaller share of those incarcerated.

contraband trafficking (drugs or cellphones, most frequently) or disorder (insults, refusing to comply). There are on average 0.05 incidents of violence against corrections officers and 0.06 incidents of violence against other inmates. Within cells, 40% of people have a conflict at some point in time. They have an average of 1.28 reported conflicts.

2.5 Empirical evidence on quasi-random assignment of cells

As discussed in Section 2.2, there are explicit criteria for cell allocation, which we observe in our data. Beyond these criteria, however, space constraints make it unlikely that administrators can exercise much discretion in matching. In practice, replacement is quick: in roughly one-third of cases a new cellmate arrives the same day another departs, in one-half by the following day, and in nearly three-quarters within a week. This rapid turnover suggests that logistical constraints, rather than fine-tuned choices, drive much of cell allocation and thus peer exposure.[8]

However, one could worry that there is further matching, based on observable and unobservable characteristics, which could be correlated with our outcomes of interest – recidivism, misconduct and conflicts in jail. We provide empirical evidence that, in practice, considering the official allocation rules accounts for most of the variation in cellmate characteristics.

To assess whether peers are quasi-randomly assigned, we look at the correlation between predicted recidivism and peer characteristics. To do so, we first regress recidivism on a rich set of individual-level observable characteristics (current offense, criminal history, and socio-demographic characteristics). Using the coefficients from this regression, we compute a predicted probability of recidivism for every individual in our sample. We then test whether these predicted probabilities are correlated to peer characteristics, varying the controls that we include.

We begin by controlling only for current offense and sentence length. We then add prison fixed effects and controls for sex, age, pretrial detention status, nationality and smoking status – two attributes explicitly considered by correctional facilities in allocating cellmates, as discussed in Section 2.2. We present results in Table 2. When controlling only for crime type and sentence length, we find that peer characteristics are significantly correlated with predicted

[8]These figures refer to standard housing cells and exclude specialized placements, such as medical or disciplinary cells.

recidivism. This likely reflects geographic or institutional sorting across prisons. However, once we add prison fixed effects and individual-level covariates, the correlation disappears.

A potential concern is that our conflict measure – cell changes due to conflicts – could make peer exposure partly endogenous if administrators reassign cellmates in response to unobservables. Three facts and design choices mitigate this. First, most cell changes are unrelated to conflict: only about 15% are coded as conflict-driven. Second, even when conflicts trigger moves, this would primarily raise the number of distinct peers rather than systematically shifting the composition of peers by crime type, age, or geographic origin conditional on assignment criteria and fixed effects. Indeed, the above-mentioned institutional constraints (turnover, overcrowding, and the formal criteria we control for) make targeted composition-by-type moves less feasible than incremental exposure increases. Any remaining bias would tend to generate level shifts across all peer types. As described in Section 3.2 and in Appendix B, we provide tests for within-crime type to across-crime type effects; we argue that our findings are inconsistent with such a pattern. Third, we run a series of robustness tests that confirm that sorting does not explain our main results, such as dropping any person who changed cells because of a conflict, measuring the effect of the first cellmates, or focusing on jails with high overcrowding rates; magnitudes are generally similar.

Taken together, these findings support the identifying assumption that, conditional on observable characteristics used in the assignment process, peer exposure is as-good-as-random.

3 Peer composition and recidivism

In this section, we present empirical evidence on how people encountered in jail influence future offending trajectories.

3.1 Estimating peer effects

We consider four main crime types: property, drug, violence, other.[9] We define C as a focal person's crime; CP is peer offense; and CR is offense upon recidivism. In our baseline models, we use OLS to estimate the following equation:

[9]This category mostly contains road related offenses (45% of the category), rebellion (17%), vandalism (10%), immigration crimes (6%), and gun traffic (4%).

$$Y_i^{CR} = \sum_{CP=1}^{g} \alpha_{CP}^{CR} NbPeer_i^{CP} + \beta^{CR} X_i + \psi_C + \gamma_p + \delta_t + \varepsilon_i \quad (1)$$

Y_i^{CR} is an indicator equal to one if individual i, incarcerated in prison p for t days, is reincarcerated for a new crime of type CR — among g different categories — in the year following their release. $NbPeer_i^{CP}$ is the number of cellmates who were convicted of crime CP, whom individual i met during their prison spell. X_i is a set of person-level observables, including socio-demographic characteristics (such as age, sex, and nationality), literacy, substance use disorders, psychological conditions, sentence (decided at trial), past incarceration and month of incarceration.[10] ψ_C, γ_p and δ_t are offense type, prison and incarceration length fixed effects. Controlling for δ_t allows us to account for variations in exposure simply due to one's time incarcerated. Controlling for crime type ψ_C allows us to account for sorting based on crime type. This is important, since both incarceration length and crime type are plausibly correlated with future offending, especially if people tend to specialize in one crime type (Sullivan et al., 2009).

A key concern in the peer effects literature is that observed peer effects may reflect selection or simultaneity – particularly if correctional administrators systematically group individuals based on unobserved traits correlated with outcomes. Existing studies of peer effects in prison address this concern by exploiting variation in the pool of potential peers within a facility, showing that peer composition is as-good-as-random conditional on time and location (Bayer et al., 2009; Stevenson, 2017; Tan and Zapryanova, 2022; Johnsen and Khoury, 2025). The advantage of this approach is that inflows are typically not determined by prison administrators; but the downside is that peer groups are defined at the facility level, even though smaller peer groups may form within correctional settings (Carrell et al., 2013). While this empirical approach works for smaller settings – juvenile facilities, or smaller prisons in Scandanavia – the variation at the facility level is less pronounced in other populations, so this approach does not work for the vast majority of the incarcerated population.

Our approach complements and extends this strategy in several ways. First, we define peers at the cell level, a much more tightly defined unit of interaction than the housing units or facilities used in prior work. Given the structure of French prisons, we can be confident that

[10] We provide more details on how these are measured in Appendix A.

individuals assigned to the same cell interacted regularly and intensively. Second, our data allow us to separately identify the effects of the number of peer exposures and the duration of exposure, dimensions that are conflated in existing designs. Finally, because cell assignment is orthogonal to sentencing timing and not driven by institutional control over admissions, our estimates are directly informative for policy interventions that modify cell allocation rules.

3.2 Evidence of network formation

Crime type. We begin by breaking out our results by crime type, estimating how the number of cellmates convicted of offense CP affects the likelihood of reincarceration for crime CR, as captured by the coefficients α_{CP}^{CR} from Equation 1. Figure 1 reports these estimates for recidivism overall, and separately for reincarceration for property, drug distribution, violent, and other offenses within one year.[11] Each of the five panels corresponds to a different crime type and shows the estimated coefficients (in percentage points) for exposure to cellmates convicted of property, drug distribution, violent and other crimes. All regressions control for sentence length, own crime type, criminal history, and socio-demographic characteristics.

The red triangles show the relationship between predicted outcomes and peer characteristics. This provides additional evidence of quasi-random assignment: if assignment is indeed quasi-random, predicted outcomes should be uncorrelated with peer exposure. The estimated coefficients are all very small in magnitude and mostly insignificant, confirming that cellmates appear to be assigned quasi-randomly.

We next examine outcomes, captured in black circles in all panels. In Panel A, we show that exposure to additional peers convicted of property or drug crimes increases overall recidivism. When we disaggregate results by offense type, the effects are strongest for income-generating offenses: an additional cellmate convicted of a drug offense increases the probability of reincarceration for that offense by 0.20 percentage points (7.3%), and an additional cellmate convicted of a property offense raises it by 0.21 percentage points (3.8%). Exposure to peers convicted of violent crimes also increases the likelihood of violent recidivism, though the effect is smaller in magnitude and less precisely estimated. We note also that several other coefficients are also positive and significant, raising the question of whether these patterns reflect peer influence

[11] Table 3 presents point estimates.

or also partially capture sorting. To further isolate crime-specific peer effects, we consider an alternative, stricter test for identifying peer influence on post-release behaviors, that requires weaker assumptions, presented in more details in Appendix B.

Under the stricter test, we say that peers convicted of crime type CP influence recidivism for crime CR only if the effect exceeds that of peers convicted of other crime types (condition ii) and it exceeds the effect of CP peers on other recidivism outcomes (condition iii), in addition to the coefficient being significant (condition i). These additional requirements rule out forms of correlated sorting that could generate positive coefficients without crime-type-specific peer influence. For example, if individuals with mental health challenges are both more likely to reoffend violently and also to interact with peers incarcerated for *multiple crime types* (because they change cell frequently), rather than predominantly with those convicted of CP, condition (ii) would be violated. Likewise, condition (iii) rules out cases where exposure to drug peers is correlated with violent recidivism only because it predicts higher recidivism across all crime categories.[12] With this stricter definition of peer effects, we find evidence of peer effects only for property and drug crimes on property and drug crimes, respectively, and not for violent crimes on violent crime. Indeed, while $\alpha^{violent}_{violent} > 0$, exposure to peers convicted of violent crimes fails to satisfy condition (iii), which requires outcome specificity: the effect of violent peers must be stronger for violent recidivism than for other outcomes. [13]

These findings may reflect two underlying mechanisms. First, individuals may be acquiring new skills: both drug distribution and property crimes often require specialized knowledge or techniques, which can be learned from cellmates with relevant experience. Second, increased exposure to peers convicted of specific crimes may expand individuals' access to criminal networks and opportunities in those domains – connections to people involved in drug (respectively, property) crimes may facilitate further involvement in drug (respectively, property) offenses, while other connections are less relevant. One way to disentangle skill transfer from network-based effects is through geography: while acquired skills are generally portable, criminal networks tend to be localized. We therefore next examine where individuals and their

[12]This test would hold for other contexts than prison. For example, one could define peer math ability as affecting individual math performance only if it predicts math scores more strongly than ability in other subjects, and more strongly for math than for non-math outcomes. This framework distinguishes subject-specific peer learning from general academic spillovers.

[13]We also note that the magnitude is smaller than for violent crime than property and drug crimes.

cellmates lived before incarceration and where they reoffend after release.

Crime location. To examine how peers shape the geographic pattern of post-release crime, we exploit variation in where cellmates lived prior to incarceration and where individuals are later reincarcerated.[14] We begin by distinguishing two places: the county where individuals lived before incarceration or where they have been incarcerated – home county – and the rest of France. In Figure 2, we measure the effect of the number of cellmates from one's home county versus the rest of France on reincarceration in home county (left panel) or elsewhere in France (right panel). Table 3 presents point estimates. We find that exposure to a peer from a given area increases the likelihood of reoffending in that area, but not in other areas. In other words, individuals are more likely to commit crimes in locations where their former cellmates lived, suggesting that geographic proximity is an important channel through which peer effects operate after release. Appendix Figure C.2 shows that this pattern also holds across regions, with the number of peers from a given region positively and significantly associated with the probability of being reincarcerated there.

With the exception of contemporaneous work by Johnsen and Khoury (2025), prior studies on peer effects in prison lack information on place of residence, limiting their ability to distinguish skill transfer from network formation. Our findings on skill-intensive crimes align with Bayer et al. (2009), who show that juveniles housed with peers convicted of similar offenses are more likely to reoffend in those categories. Stevenson (2017) documents social contagion effects in juvenile facilities, while Damm and Gorinas (2020) find evidence of learning-based peer effects among adults in Denmark. In contrast, we show that peer effects are highly localized: individuals are more likely to reoffend in areas where their former cellmates lived. This spatial pattern, which is consistent with some of the results in Johnsen and Khoury (2025), supports network-based mechanisms and underscores the role of geographic proximity in shaping post-release behavior.

[14]Place of residence prior to incarceration is recorded for 81% of inmates. Because crime locations are not directly observed, we use the location of first reincarceration as a proxy for where the offense occurred. In particular, according to Article D.53 of the French Code of Criminal Procedure, individuals held in pretrial detention are typically incarcerated in the jurisdiction where their case is being investigated – which generally corresponds to the location of the alleged offense.

Number of peers vs. length of exposure. A complementary way to distinguish between networks and learning is to look separately at the effects of number of peers and of length of exposure. In principle, broader networks may expand with the number of peers encountered, whereas longer overlaps could facilitate deeper learning or skill transfer. Our results are more consistent with the former. As shown in Appendix Figure C.3, the effects of exposure to cellmates convicted of property or drug offenses rise roughly linearly with the number of such peers. By contrast, we find little evidence that the duration of overlap matters, once we control for number of peers (Appendix Table C.1). For each outcome, while this pattern supports the network interpretation, we note that duration effects may be difficult to detect if learning occurs rapidly.

Using citizenship to distinguish network from skill transmission

3.3 Social proximity increases network formations

The remainder of Figure 3 shows how peer effects vary by age, prior incarceration, and geographic proximity. Two clear patterns emerge. First, peer effects are strongest when individuals are housed with cellmates of similar age – especially for drug distribution and property crimes (see Appendix Figure C.4). Second, they are more pronounced when cellmates come from the same city. Prior incarceration also matters: individuals with previous convictions are more influential than first-time offenders, consistent with a mechanism in which experience contributes to peer effects; but there are no match-specific effects, as with age or geography.

Taken together, these results highlight the role of social proximity in shaping peer effects. Similarity in age and place of origin likely reduce communication barriers and foster collaboration, both during incarceration and after release. These analyses also help unpack the notion of homophily. Because peers are quasi-randomly assigned in our setting, we can directly test whether similarity strengthens peer effects, helping to unpack the role of homophily. The evidence presented here indicates that it does: social affinity facilitates network formation.

3.4 Robustness

Exploiting constraints on the administration's cell allocation choices. We present analyses that focus on settings where the penitentiary administration has particularly limited

discretion over cell assignments. These contexts add an additional reason to think that peer exposure is exogenous. The first such setting arises when the overcrowding rate is high, since this likely constrains the administration's ability to match inmates based on behavioral assessments or administrative criteria – people are plausibly more likely to simply be assigned to cells where there is more space. In Appendix Figure C.5, we break out our analyses for prisons where overcrowding is above and below the median. Second, we limit our sample to people incarcerated in jails for the totality of their stay, in Appendix Figure C.6, which experience most overcrowding. Results are very similar for these. Another is at the very beginning of incarceration spells, when prison staff have limited information about individuals beyond what is recorded at intake and included in our dataset. In Appendix Figure C.7, we only consider cellmates encountered in the first four weeks of one's incarceration. These estimates are noisier, but in both analyses, the estimated effects of cellmate exposure remain similar in magnitude and direction to those reported in our main specifications. This further confirms that our results are not driven by endogenous sorting or administrative manipulation of cellmate assignment.

Additional specifications. We test for the robustness of the results in several ways. First, we re-estimate the effects of peer exposure on recidivism using Cox competitive duration models (Appendix Figure C.8) to account for time-to-event dynamics and competing risks. Second, we extend the follow-up period to two and three years (Appendix Figure C.9), adjusting the sample accordingly to have sufficient post-release data. In both cases, the results are consistent with our main estimates.

One potential concern is that conflict-driven reassignments could make peer exposure endogenous, for example if people who have conflicts are systematically reassigned to different peer types. First, we note that if this mechanism were important, it would generate shifts in peer composition across all crime categories rather than in a single dimension, but as noted in our discussion of Table B.1, this pattern does not emerge. In Appendix Figure C.10, we present results from a permutation exercise in which individuals are randomly assigned placebo cellmates from others who began a new cohabitation in the same week in the same prison. The effects of property- and drug-related peer exposure are markedly different from the per-

mutations, while those for violent crime are statistically indistinguishable from the placebo distribution. Lastly, in Appendix Figure C.11, we drop people who changed cells because of a conflict. Our results for income-generating crimes are very similar, suggesting that sorting did not explain the patterns in the data.

4 Peer composition and facility-wide misconduct

In the first part of our analysis, we showed that peer effects on reoffending are strongest for income-generating crimes; that people tend to reoffend where their cellmates previously lived; and that effects are most pronounced among similar-age peers. A natural policy response would avoid pairing similar individuals, but this may entail offsetting costs. We now turn to how peer composition affects institutional safety. This section examines facility-wide misconduct, which provides evidence that networks begin to form in jail; Section 5 then considers within-cell conflict, and we show that similarity increases facility-wide misconduct but reduces within-cell violence – highlighting a fundamental tradeoff between short- and long-run safety objectives.

4.1 Empirical approach

First, we consider misconduct and violence that occurs in communal areas, outside of jail cells: courtyards, workplaces, hallways, and other shared spaces. Interactions in these settings involve some autonomy, since people can choose whom to engage or confront. However, who they share a cell with could influence how people interact in common areas – the first topic that we investigate.

Facility-wide incidents are formally recorded in incident reports (*compte rendu d'incident*, CRI) and can include violence against other inmates or correctional officers, contraband trafficking, insults, vandalism, disturbance, or resistance to staff directives. Because CRIs require direct observation by correctional officers, incidents inside cells are rarely documented – doors are locked and in-cell behaviors are typically unobservable. This means that our cell-level conflict measure (Section 5) and our facility-wide misconduct measure capture distinct, largely non-overlapping sets of behaviors.

To identify the causal effect of in-cell encounters on facility-wide misconduct, we estimate:

$$Y_i = \sum_{d=1}^{D} \alpha_d NbPeer_i^d + \beta X_i + \psi_C + \gamma_p + \delta_t + \varepsilon_i \quad (2)$$

where Y_i captures misconduct, defined as the number of disciplinary infraction during incarceration, and separately for having been convicted of violence (against another inmate or a corrections officer), for contraband trafficking, or for disorder.[15] Because we can only observe the type of misconduct for incidents that result in formal disciplinary proceedings, our breakdown by incident type focuses on sentenced infractions. $NbPeer_i^d$ is the number of peers one encounters during incarceration with characteristics d (among D). As in previous analyses, we focus primarily on proximity in crime types, age and place of residence.

4.2 Evidence of network formation in jail

Figures 4 to 6 present our main results regarding disciplinary incidents that occur in common areas. In both figures, we consider different dimensions of peer characteristics, as they relate to the focal person's characteristics: crime type, city of origin, age, nationality, and priors. The dynamics are similar to those that we found for recidivism, and consistent with network formation playing a key role even already in jail, especially for income-generating offenses.

Figure 4 presents results for all documented incidents (white circles) and incidents resulting in formal discipline (black circles). Similar to recidivism, we find that exposure to similar peers – particularly those close in age or from the same city – significantly increases the likelihood of having a disciplinary record. The effect is strongest for age proximity: each additional cellmate within five years of one's age increases the number of a disciplinary incident by approximately .16 (9% of the mean). In terms of percent change, results are similar for reported and sentenced incidents.

In Figure 5, we separately examine misconduct committed jointly with cellmates and misconduct committed alone. We classify an incident as "joint" if two individuals who shared a cell receive misconduct reports on the same day in the same facility. Effects are consistently larger for joint incidents, suggesting that similarity matters most for misconduct carried out with people encountered in cells. This pattern provides direct evidence of co-offending within facilities among cellmates.

[15] The disorder category includes insults, vandalism, disturbance, or resistance to staff directives.

Figure 6 decomposes sentenced incidents by type: Panel a reports contraband trafficking (hollow circles) and disorder (full circles), and Panel b reports violence against corrections officers (hollow circles) and violence against other inmates (full circles). Contraband trafficking – the most common facility-wide infraction – increases with exposure to peers close in age. Age proximity similarly predicts violations for disorder. Interacting with people who are close in age increases the likelihood of committing income-generating offenses even while incarcerated.

Geographic proximity follows patterns consistent with network formation, though effects are more muted than for recidivism. Exposure to peers from the same city increases facility-wide misconduct, but the magnitudes are smaller than for post-release offending. This difference is consistent with the distinct roles of geographic networks inside versus outside prison. On the outside, geographic proximity can play two roles: (1) it can foster social proximity; and (2) it can generate location-specific criminal opportunities: there is no variation in geographic opportunities during incarceration.

Next, we turn to heterogeneity across the crimes for which peers were initially convicted. We find that exposure to peers convicted of property and drug distribution crimes – the same peer types that increased post-release recidivism – also raises disciplinary records for contraband trafficking during incarceration (Appendix Figure D.1). The same peer characteristics predict both in-prison and post-release offending, suggesting that network formation starts during incarceration.

We now turn to interpersonal violence – a primary concern for prison administrators, and an important dimension of institutional safety that has received limited empirical attention. Violence against both inmates and correctional officers increases with age proximity; geographic proximity exhibits similar though somewhat weaker patterns for violence against inmates (not against correctional officers). These results show that peer composition has immediate consequences for safety and well-being during incarceration. Our findings are consistent with criminal networks operating during incarceration itself, potentially generating violence through competition over criminal opportunities or enforcement of informal agreements.

Those results are robust to alterations of the main specification. In Appendix Figure D.2, we consider whether a person is charged with misconduct, instead of convicted. In Appendix Figure D.3, the outcomes are indicators for ever being sanctioned for misconduct, instead

of the number of sanctionned misconduct incidents. In Appendix Figure D.4 we restrict the sample to individuals who did not change cell because of conflicts. Appendix Figure D.5 shows the results for overcrowded facilities, when the administration arguably has less room for optimizing cell allocation. Lastly, in Appendix Figure D.6 we restrict the sample to individuals who served their whole sentence in jail. In all those analyses, the results remain similar to our main estimates.

Considering facility-wide outcomes alone, short-run and long-run institutional objectives appear aligned: peer similarity increases both misconduct and recidivism, suggesting administrators should avoid matching on observable characteristics like age and geography. These facility-wide analyses, however, do not account for within-cell interactions – cells being the margin administrators control most directly, and the setting where conflicts are most common. As we show in the following section, peer similarity operates differently within cells than in the rest of the facility.

5 Peer composition and within-cell conflicts

5.1 Empirical approach

To study in-cell conflicts, we restructure the data to have one observation per interaction and we use a duration model to identify the importance of peer characteristics. Conflicts, unlike recidivism or facility-wide incidents, are inherently dyadic: we observe whether a pair of cellmates was separated because of a conflict, not which individual was at fault. In theory, one could rely on two different sources of information to measure conflict in cells. First, the time inmates spend together signals how well they get along. Second, the penitentiary administration documents whether people were separated because of conflicts.[16] However, those two dimensions interact in a non-trivial way. Indeed, conditional on a certain probability of fighting, the longer individuals stay together, the more likely we are to observe a conflict. This tension makes analysis based on OLS regressions hard to interpret.

Duration models allow us to study cases where we observe a situation over a certain amount of time until an event eventually happens. In this setting, movements driven by latent tensions

[16] In practice, for our main measure of peer conflicts, we identify words like "fight", "dissension", "aggression" as well as requests to move which, in practice, are most often motivated by interpersonal conflicts (Bony, 2015).

are our events of interest; transfers for other reasons – such as carceral sentence ending or medical necessity – are treated as right-censored observations. We can then examine how the characteristics of the cellmates drive conflicts. In practice, we estimate a Cox proportional hazard model of the form:

$$h_{ijp}(t) = h_0(t) * exp(\beta X_{i,j} + \gamma_p) \tag{3}$$

where $h_{ijp}(t)$ is the hazard rate at time t – i.e. the probability of observing a conflict between individuals i and j incarcerated in prison p at time t –; $h_0(t)$ the baseline hazard rate; $X_{i,j}$ the joint characteristics of i and j; and γ_p prison fixed effects. As in our recidivism and facility-wide analyses (Sections 3 and 4), we measure the effect of similarity in crime, in age, in geography (same city, cities within 30 km, or distant cities), in prior incarcerations, and in nationality. We also control for the age of each cellmate. In supplementary analyses, we explore variation across additional health, social, and educational dimensions.

5.2 Proximity in cellmates characteristics reduces conflicts in cells

In Figure 7 and Appendix Figure E.1, we plot estimates from a Cox proportional hazard model of the effect of peer encounters on in-cell conflicts (Equation 3). These figures show that conflict arises not only because of individual characteristics, but also from mismatches between cellmate characteristics.

For some characteristics, the likelihood of conflict rises with the number of inmates who share them. This is true for behavioral and health-related risks (e.g., addiction, smoking, mental-health problems), for indicators of crime propensity (e.g., prior convictions), and for socio-economic vulnerabilities (e.g., indigence, low educational attainment). Dyads in which both people have this characteristic have the highest risk of conflict, mixed dyads occupy the middle ground, and dyads in which neither person has this characteristic have the lowest risk (see Appendix Figure E.1). The administration does not control who enters jail or prison. Because aggregate conflict in this case depends mainly on the prevalence of a given characteristic, rather than the specific assignment of inmates, reshuffling alone offers limited scope for reducing in-prison conflicts.

However, on other dimensions, the *pairing* matters: risk of conflict depends on the com-

bination rather than the prevalence of characteristics. We see this to be the case for crime type, age, city of origin, and nationality. Indeed, hazard rates are systematically higher when dyads do not share the same characteristics. To help interpret the magnitude, we can use our estimates to calculate the differences in the probability of conflict within 15 days for cellmates not separated for another reason.[17] For example, within dyads that committed the same crime, the probability of conflict within 15 days is 11.8%, compared to 13.6% for dyads with different crime types – a 15% difference. Analogous gaps appear for age (12.5% versus 13.4%), geographic proximity (11.6% when peers come from the same city vs 12.9% when they are from close cities and 13.2% from distant cities), and nationality (14.8% when only one is not French vs 12.4% when both are French and 11.7% when neither are French). These results imply that among those dimensions, the pairing – not the overall composition – drives conflicts, so simple assignment rules (e.g., avoid very young-older matches) can reduce conflict even when the distribution of ages, crimes, or nationalities is fixed. These results in the prison context align with a broader literature showing that similarity fosters cooperation and lowers conflict (Alesina and La Ferrara, 2000; Miguel and Gugerty, 2005; Currarini et al., 2009). Note that in that literature, networks are typically formed voluntarily; by contrast, at the jail cell level, people do not get to choose whom they interact with explicitly, yet affinity patterns arise, underscoring that matching rules alone can have sizable behavioral consequences.

5.3 Robustness

First, we examine whether our findings on cellmate conflicts are similar in settings where the administration has particularly limited discretion over cell assignments, which provide an additional reason to view peer exposure as plausibly exogenous. The first such setting arises in prisons operating above the median overcrowding level, where limited cell capacity reduces the scope for matching based on behavioral assessments or other criteria. Appendix Figure E.2 shows that our estimates are similar in magnitude and direction to those obtained in the full sample. Likewise, at the beginning of incarceration spells, staff have little information about individuals beyond the administrative records we observe. Appendix Figure E.3 restricts the analysis to pairs in which at least one cellmate is in the first four weeks of his incarceration.

[17] These estimates combine the baseline hazard function from the Cox model with the coefficient estimates presented in Figure 7.

While these estimates are noisier, given the smaller samples, the pattern of results is again consistent with our main findings. Together, these exercises suggest that our conflict results are not driven by endogenous sorting or manipulation of cellmate assignment. Lastly, Appendix Figure E.4 shows that our estimates are similar when we restrict the sample to groups of people who served their entire spell in jails. Overall, results are very similar across these different specifications.

6 Misaligned incentives: policy simulations

Our results highlight a key tradeoff: peer configurations that reduce within-cell conflict increase both facility-wide misconduct and post-release recidivism. Social similarity – whether in age, background, or place of origin – fosters compatibility and reduces friction in cells. But the same characteristics that make peers compatible in cells also make them effective collaborators inside jail and outside, implying that reducing conflict and minimizing long-run harm may require distinct assignment strategies.

Appendix Table F.1, which outlines theories of peer effects and empirical predictions, shows that these tradeoffs arise because of mechanisms of peer influence. If peer effects operated through skill transfer or social contagion, grouping similar people would improve both short- and long-run safety; for example, clustering by place of residence could reduce conflict without raising recidivism. Under network-formation mechanisms, however, social similarity fosters both cohesion and criminal collaboration, generating opposing policy objectives: matching on similarity lowers conflict but increases future offending. In our setting, network mechanisms dominate, meaning that practices that stabilize daily prison life can simultaneously reinforce criminal ties. In the final part of the paper, we use counterfactual cell-assignment simulations to quantify these tensions.

6.1 Procedure

Our simulation proceeds in several steps:

1. We define "randomization units": cellmates incarcerated in the same prison, starting and ending their cohabitation the same week. For example, if A and B share a cell from week 1 to 3 in prison X, and C and D also share a cell between weeks 1 and 3 in prison X,

they belong to the same "randomization unit". E and F who share a cell from week 1 to 5 in the same prison do not. Neither do G and H who share a cell between week 1 and 3 but in prison Y.

2. We reshuffle individuals within those groups. In the preceding example that means we could create the pairs A-C or A-D but not the pairs A-E or A-G.

3. We predict conflicts in prison, misbehavior, and recidivism post-release. In the previous sections, we identified three dimensions leading to conflicting incentive structures: crime types, age differences, and geographical distance. Therefore, we estimate the effect of all the combinations of those parameters and base our predictions on the coefficients we obtained.[18]

We repeat this procedure 100 times.[19] Averaging the predictions of each reshuffle and then averaging among reshuffles gives the reincarceration rate, the number of behavioral incidents, and the number of conflicts per inmate if prisoners were randomly allocated to cells.

To obtain optimal allocations, we add an additional step:

4. For each "randomization unit" we identify the permutation, among the 100 created, for which the average recidivism (or conflict, or misbehavior, or a weighted average of them) is the smallest. The cell allocation composed of all the optimized allocations per "randomization unit" is the optimal allocation along one dimension.

We conduct this permutation exercise in three ways. First, we reshuffle individuals while holding fixed any periods in which someone was housed alone. In the earlier example, if individual I was alone in a cell in prison X between week 1 and 3, I would not be reassigned with A, B, C, and D during that period, even though they all belong to the same "randomization unit." The intuition is that the administration may have private information explaining why they decided to leave an individual alone at some point.

Second, we reshuffle everyone, including those who were in cells alone. Using the same example, a reshuffle could place B alone, A and C together, and D and I together.

[18]The coefficients of all the interactions are presented on Appendix Figure F.1, Figure F.2, and Figure F.3

[19]Repeating the procedure only 50 times produces nearly identical results, suggesting that the objective function converges rapidly and additional random draws do not materially affect the estimates.

Third, we model an increase in prison capacity – that is, in the total number of beds available. Capacity can grow either by expanding infrastructure (adding beds to existing jails or building new facilities), or by reducing the carceral population (for example, by diverting people with short sentences, reforming pretrial detention, or shortening time served). To operationalize this, we add 2,000 beds – roughly the number that would be freed if individuals serving less than two months were not incarcerated but instead placed on probation or electronic monitoring – and then reassign the same population into this larger stock of beds.[20] For simplicity, we assume that the new beds are evenly distributed across all facilities.[21]

Before presenting the simulation results, we note an important caveat: we are assuming that the point estimates that we obtain are policy-invariant, which may not necessarily be the case. In particular, our simulations hold the duration of each cell assignment fixed (e.g. three weeks with one peer, seven weeks with another), regardless of whether a conflict would have shortened – or a harmonious match would have extended – the actual cohabitation spell. Because we do not adjust spell lengths based on match quality, the conflict-minimization simulations likely overestimate both recidivism and conflict: in reality, good matches likely prolong overlap. Conversely, the recidivism-minimization simulations likely underestimate both outcomes, since bad matches would shorten overlap and force more rapid reshuffling among peers.

6.2 Results

We present our simulation results in Figure 8. On the X axis, we present the reincarceration rate, and on the Y axis, the number of conflicts in cell per individual. The red dot presents the current average number of incidents (1.22) and average recidivism rates (17.4%).[22] We then consider different permutations, relative to the existing allocation of peers. First, we

[20] We note that this comparison is imperfect. For computational reasons, the simulation holds the incarcerated population fixed and does not incorporate the fact that eliminating short stays would change who is incarcerated under this policy counterfactual.

[21] We need to allocate those cells to certain "randomization units". To do that we allocate to each new cell the structure of an existing one randomly selected (i.e. the number of beds and the moment at which individuals enter or leave the cell). We conduct this allocation exercise 5 times and the results present the average of those 5 procedures.

[22] The simulation procedures being computationally demanding, we restrict the sample to the individuals (and their peers) incarcerated between July 2016 and December 2017 for a period of less than two years; averages are therefore slightly different from those in Table 1.

keep the number of peers constant for each individual (orange). Second, we keep the total number of people incarcerated constant, but we allow the number of cellmates to change by including inmates incarcerated alone to be reshuffled (green). Third, we consider adding 2,000 extra cells (blue). Within each of these scenarios, we consider different simulations: randomly allocate cellmates (full circle); reduce the number of conflicts (triangles); reduce reincarceration (diamonds). In addition to the two optimums, we explore the frontier of possibilities by considering simulations where we minimize the weighted average of the two outcomes going from $.9*reincarceration+.1*conflicts$ to $.1*reincarceration+.9*conflicts$ Relative to a random shuffling of people, when number of interactions are kept constant, there are slightly fewer conflicts in prison, but more recidivism. This should not be interpreted as evidence against quasi-random assignment. Rather, our simulation does not incorporate the full set of formal and informal constraints that shape how administrators assign people to cells, beyond basic rules such as sex and age-based separation. Characteristics like smoking status or nationality, which we control for in the main analyses, are not modeled as constraints here. As a result, the comparison simply shows that the actual assignment process slightly reduces conflicts relative to a fully random benchmark, but at the cost of somewhat higher recidivism under this stylized exercise. We find that, even without reducing the number of cellmates, some allocations would dominate the current allocations. When we consider the optimums, we find that reincarceration rate could be reduced by up to 6.9% (but conflicts increase by .9%) while conflicts could be reduced by up to 3% (and reincarceration would drop by only .3%) relative to the current allocation.

However, gains are bigger once we add in other dimensions of optimization. In green, we estimate instead changes in the number of cellmates that a person interacts with. This means that individuals who spend some time alone could be placed with a cellmate while others could have a period alone instead of being incarcerated with somebody else. In this case we do not consider that the administration has private information on who should be left alone. Even without optimizing the composition of cellmates, just limiting exposure to different people would reduce the number of conflicts. Optimizing allocation would mainly reduce recidivism (by up to 7.7%), with little cost in terms of conflicts in prison (+.1% when minimizing reincarceration). Conversely, it would be possible to reduce conflicts by up to

5.2%; recidivism would virtually stay the same.

Lastly, we consider the effects of adding more cells, and therefore limiting cell size (in blue). Interestingly, there are fewer gains in terms of lower recidivism (8%) from adding more cells when we consider optimal allocation; instead, most of the gains there are in reduced conflicts (up to 11.1%). At the same time, these results indicate an overlooked cost of prison overcrowding: beyond conflicts, overcrowding increases the number of people one interacts with, and in turn, the opportunity to build networks. Even when only considering gains in terms of fewer peer interactions, and ignoring other scarring effects of overcrowding on people's well-being and recidivism, these policies would reduce recidivism.

In Appendix Figure F.4, we consider an alternative analysis where we define the short-term objectives of the prison administration to include not only within-cell conflicts, but also violence against correctional officers and other inmates. The patterns are similar in several respects to our analyses focusing on conflicts in cells. Most notably, there are again clear trade-offs between reducing recidivism and reducing in-prison violence, broadly defined. A difference, however, is that the counterfactual allocations in this exercise do not increase either in-prison violence or recidivism. Yet even with this in-prison objective, administrators still face trade-offs regarding which objective to prioritize.

Table 4 indicates the proportion of different types of groups in the main case of interest. The main takeaway is that conflict-minimizing rules systematically increase homogeneity along key dimensions (age, crime type, geography), whereas recidivism-minimizing rules do the opposite. This is most notable for age and for crime type: conflict minimization would change the same-crime composition, and recidivism minimization would change the same-age composition. Under the current allocation, 44.1 percent of pairs are close in age (within five years); proximity in age is barely changed under conflict minimization, but recidivism minimization reduces it to 30.7 percent, thus avoiding the age proximity that we found amplified criminal peer influence. For crime type, same-crime pairings would stay similar in recidivism minimization (32.3 percent compared to 33.1 percent currently), but it would increase to 46.2 percent under the conflict-minimization rule, consistent with our finding that crime similarity reduces within-cell friction. Overall, these patterns illustrate the underlying tension: optimizing for one objective systematically moves composition along those dimensions in opposite

directions for the other objective.

Finally, prior work cautions that peer allocation policies can backfire if individuals can re-sort into smaller friendship groups: Carrell et al. (2013) show that a theoretically optimal classroom allocation worsened outcomes because students self-selected their actual peers. This concern is far less relevant in the context of prisons, where inmates spend nearly all day confined with a small, fixed set of peers. The rigidity of these assignments makes them more consequential, and it increases the likelihood that our simulations capture persistent differences in exposure rather than assignments that can be easily undermined in practice.

7 Conclusion

Our paper demonstrates that peer effects in prison create tradeoffs for institutional design between short-term goals within facilities and long-term goals related to reentry. Using detailed administrative data from French prisons and exploiting quasi-random cell assignments, we show that exposure to cellmates convicted of property or drug crimes increases recidivism in those same categories. We also provide evidence that these networks start to operate during incarceration. These network effects are most pronounced when people come from similar areas and are close in age. However, we show that the same peer characteristics that increase long-run recidivism – similarity in age, geographic origin, and offense type – also reduce short-run conflict within prison, which creates tensions in policy objectives. Our policy simulations quantify this tension: without capacity expansion, alternative assignment rules could reduce recidivism by up to 7.5 percent or reduce in-prison conflict by up to 5.2 percent, but not both simultaneously.

These findings contribute to several literatures. First, we advance understanding of peer effects in criminal contexts by documenting how social proximity can amplify both prosocial and antisocial effects. Second, our high-resolution data on cell-level interactions allows us to move beyond facility-wide analyses used in all prior papers on peer effects in prisons. By observing the specific peer groups with whom individuals spend 18-22 hours daily, we can identify mechanisms and policy-relevant parameters that are hard to recover in broader institutional comparisons. Third, by focusing on violence and victimization behind bars, we revisit the notion of incapacitation. Beyond community-level replacement effects noted in prior

work (Ehrlich, 1996; Miles and Ludwig, 2007) – that is, the idea that others would step into the criminal activities of those who are incarcerated – our findings suggest that incarceration may displace crime from communities to within prisons themselves.

More broadly, this research speaks to institutional design challenges wherever peer effects operate across multiple organizational goals. For example, schools balancing academic achievement and behavioral outcomes, or workplaces balancing productivity and retention, plausibly face similar tensions. Our framework for analyzing these tradeoffs – identifying peer characteristics that affect multiple outcomes, quantifying the magnitudes through policy simulation, and recognizing that optimization along one dimension may come at costs on other dimensions – provides a template useful in other contexts as well.

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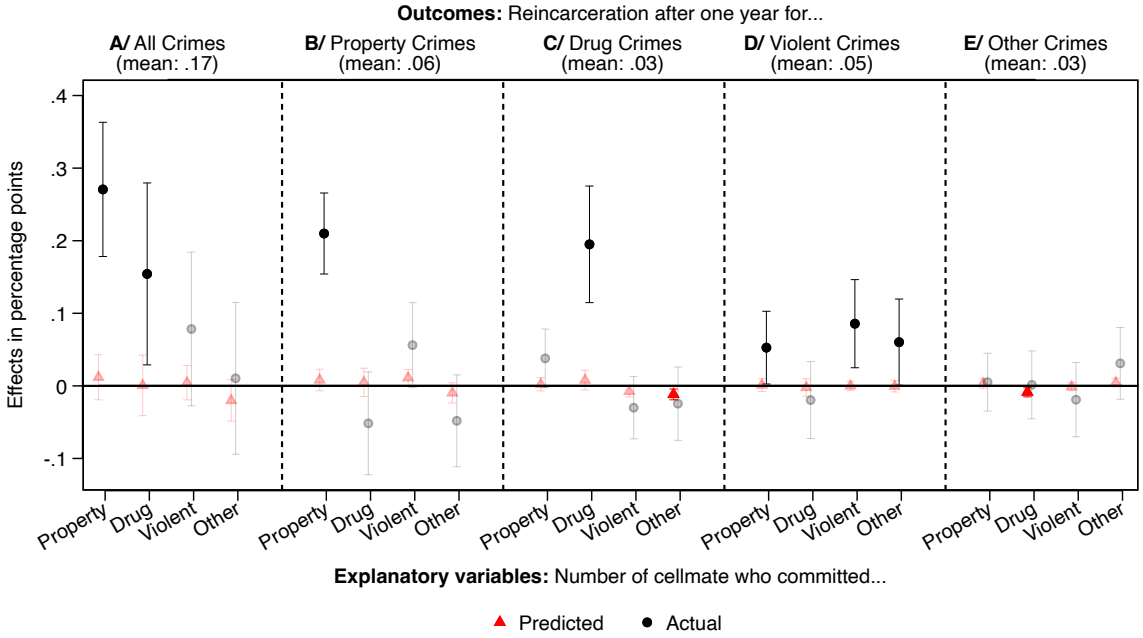
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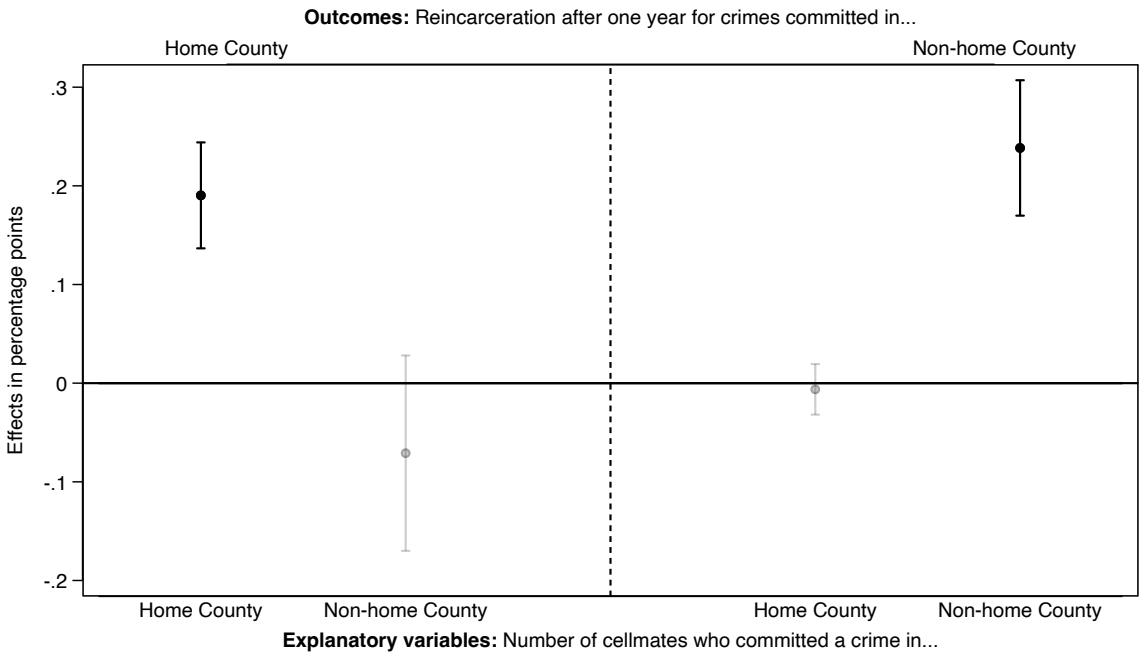
TABLES AND FIGURES

Figure 1: *Peer composition and recidivism, by crime type*



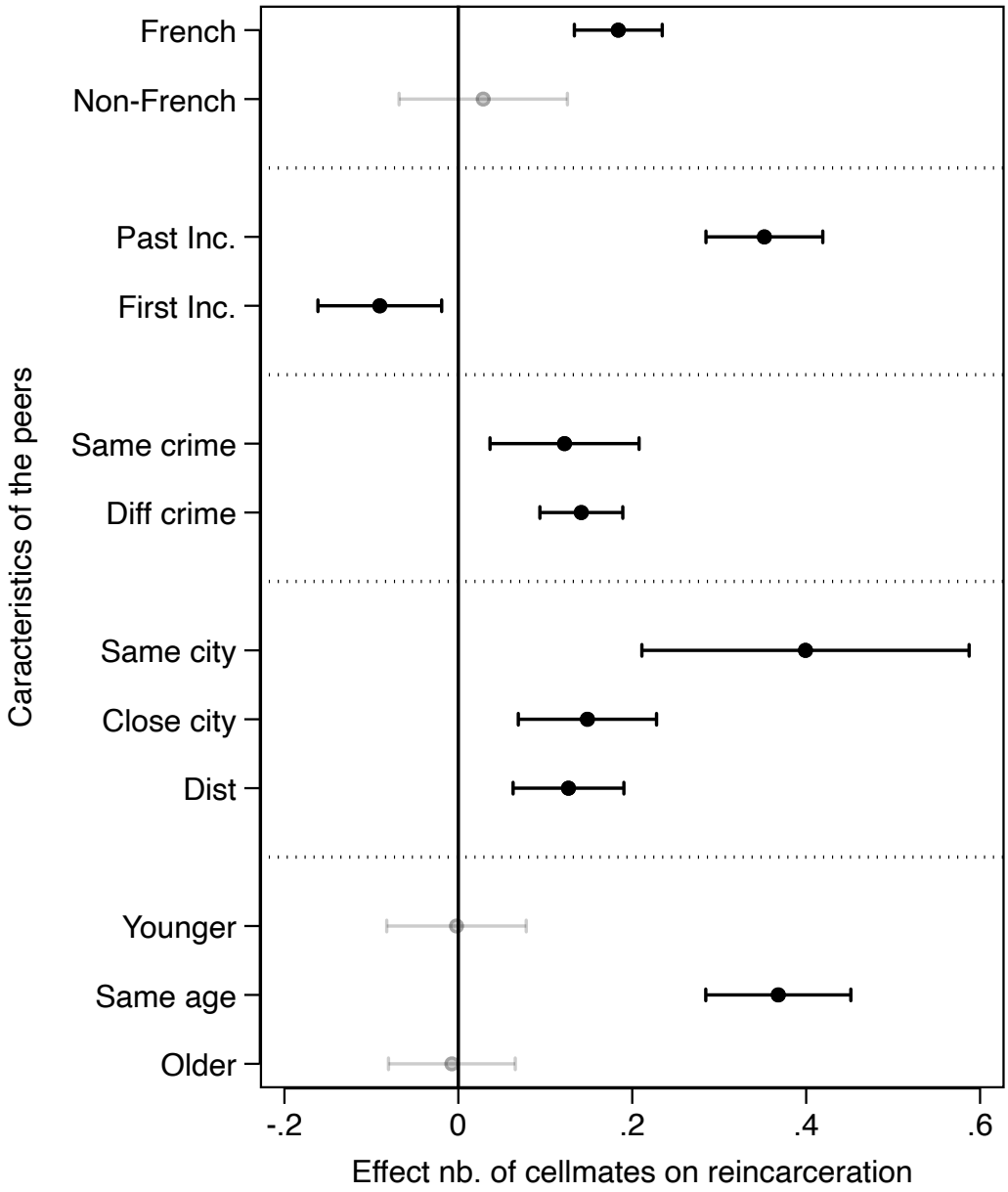
Notes: This Figure presents estimates of the effects of the number of cellmates convicted of different crime types on reincarceration by crime type. Estimates come from Equation 1. Peer crime types appear on the x-axis, and the crime type of reincarceration after one year is indicated in the panel headers. Black circles plot the estimated effects of peer crime type on reincarceration. Red triangles present estimates from regressions with predicted recidivism as the outcome, allowing us to assess whether peer characteristics are correlated with unobserved determinants of recidivism. All models control for prison, time-in-prison, crime type, age at entry, calendar month of incarceration, nationality (French vs. non-French), gender, pretrial incarceration, and smoking. In addition, regressions on reincarceration (black circles) control for qualification, literacy, past incarceration, mental health, and children. Those dimensions are used to construct the prediction and, therefore, not included in regressions with predicted recidivism as the outcome (red triangles). Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure 2: Peer composition and recidivism, by place of residence



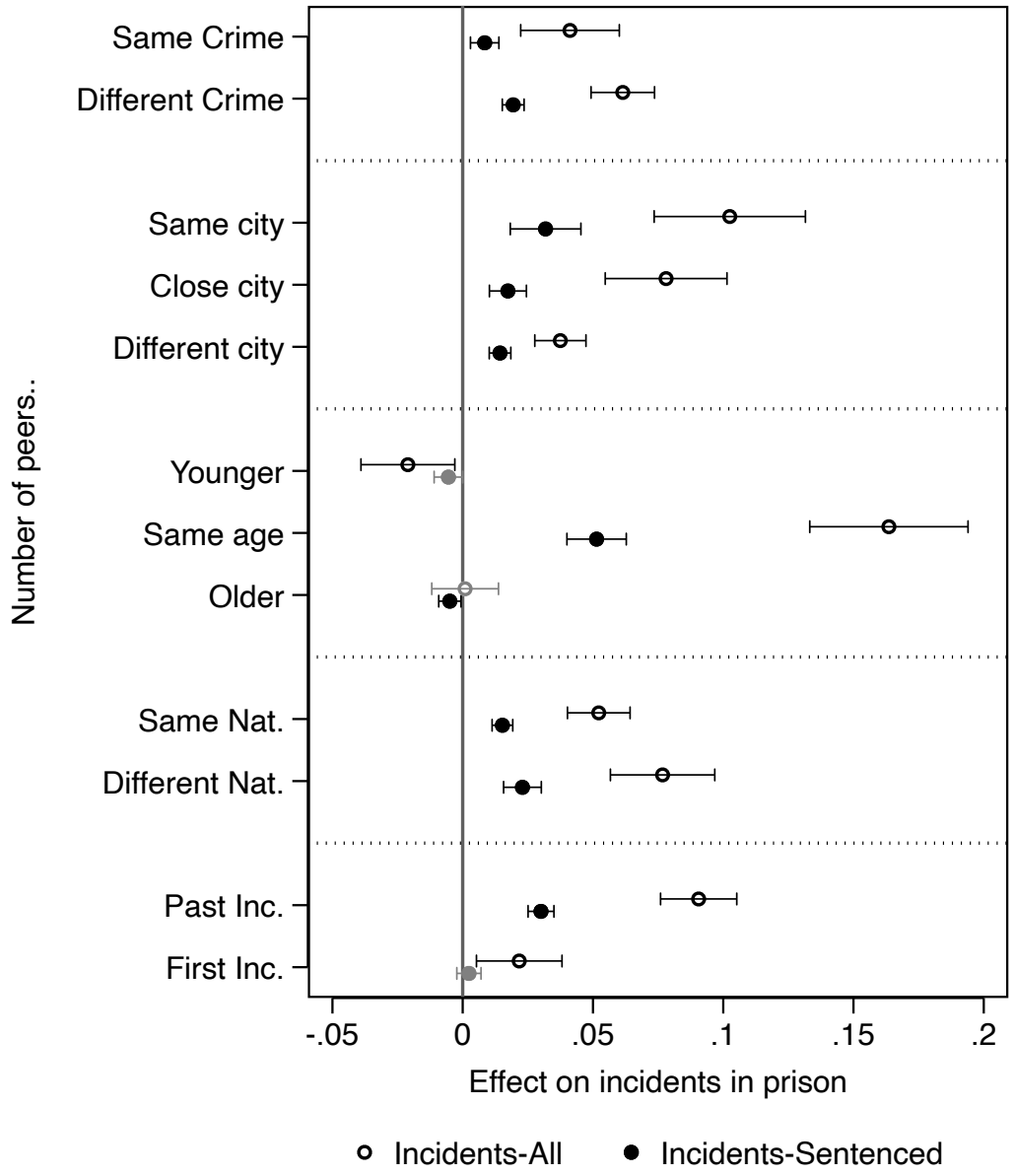
Notes: This Figure presents estimates of the effects of the number of cellmates coming from one's home county vs another county on reincarceration in one's home county vs in another county. We define one's county as the place in which one lives and (if different) the place in which one was incarcerated. Estimates come from Equation 1. We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars plot the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure 3: Peer Composition and Recidivism: Heterogeneity by Peer Characteristics



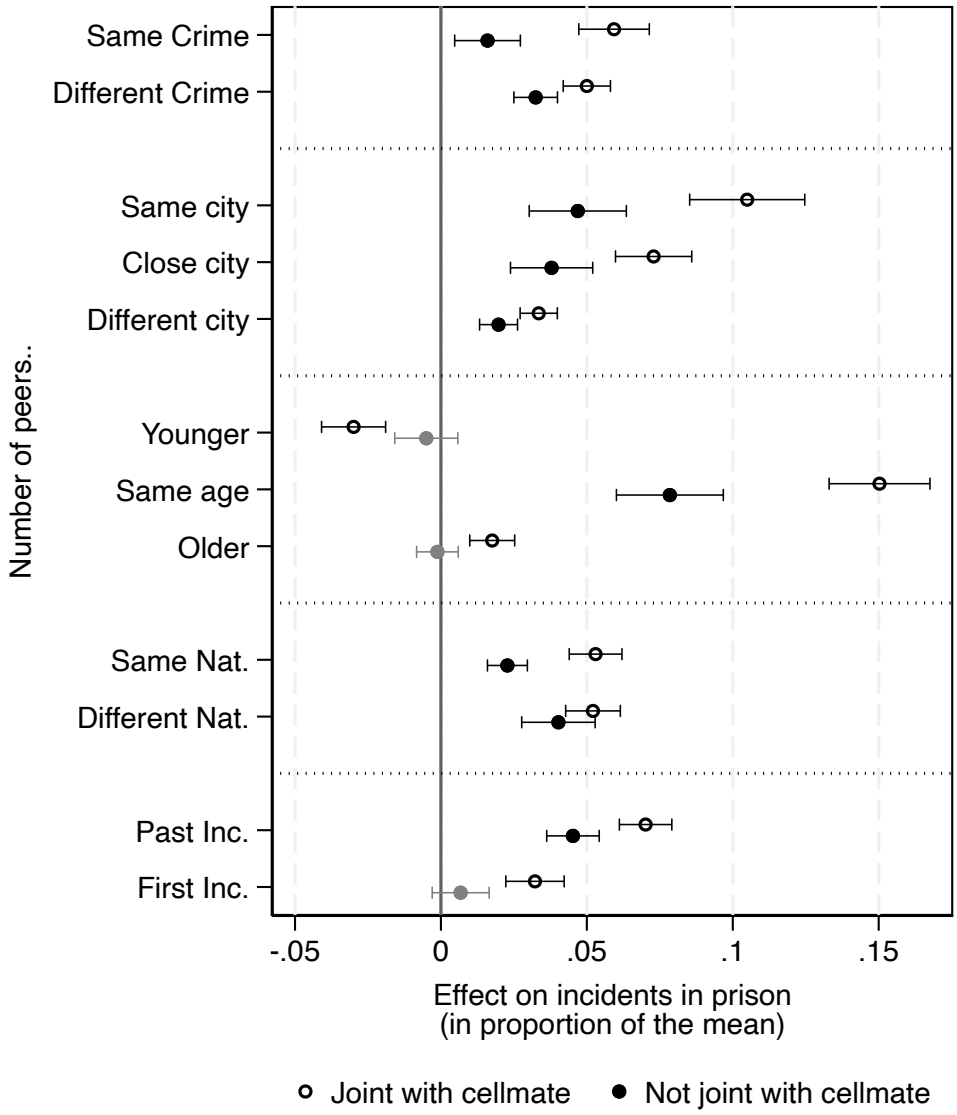
Notes: This Figure presents heterogeneity in the estimated effects of peer composition on recidivism. The outcome is reincarceration for any crime type. All characteristics are binary: whether peers are French citizens, have past incarcerations, share the same crime type, come from the same city, county, or another county, or are younger, of the same age, or older. Bars represent 95% confidence intervals. Standard errors are clustered at the prison level.

Figure 4: Peer composition and facility-wide misconduct: all incidents vs. sentenced incidents



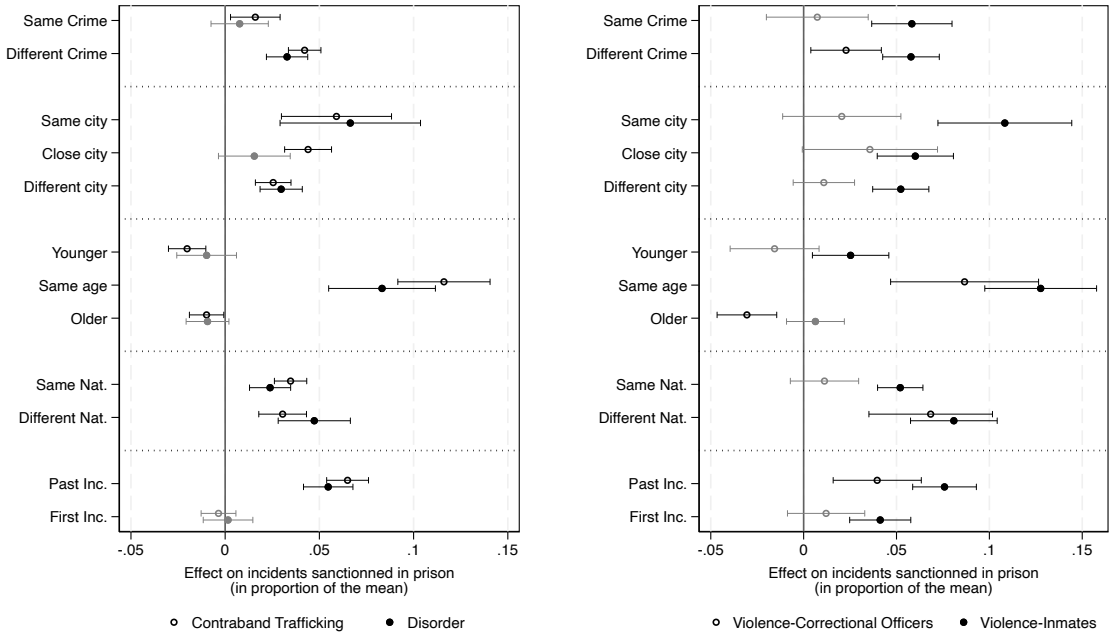
Notes: This figure plots the estimated effects of peer characteristics on facility-wide misconduct during incarceration. Each coefficient measures how the number of peers sharing a given characteristic – crime type, city of origin, age, nationality, or prior incarceration – affects the number of disciplinary reports (hollow circles) and of incidents resulting in formal sanctions (full circles). All regressions include controls for sentence length, criminal history, socio-demographic characteristics, and prison, incarceration-length, and offense-type fixed effects. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure 5: Peer composition and misconduct in prison: incidents with and without cellmates



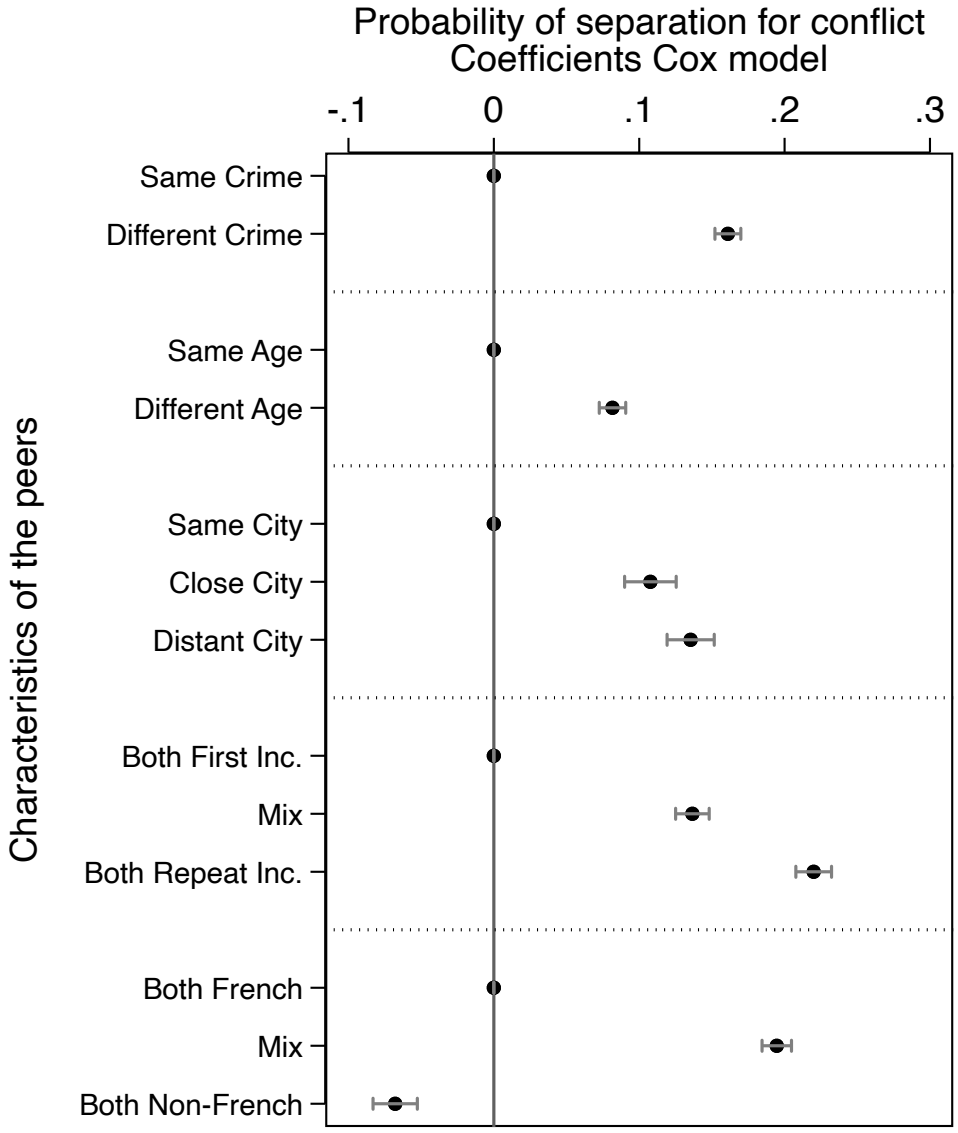
Notes: This Figure reports estimates of how the number of cellmates convicted of different crime types affects facility-wide misconduct committed with a cellmate (white circles) or without a cellmate (black circles). Estimates come from Equation 2. We classify an incident as "joint" if two cellmates received a report on the same day in the same facility. Peer crime types appear on the x-axis, and the type of misconduct is indicated in the panel headers. All regressions include controls for sentence length, criminal history, socio-demographic characteristics, and prison, incarceration-length, and offense-type fixed effects. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure 6: Peer composition and sanctioned disciplinary incident types.



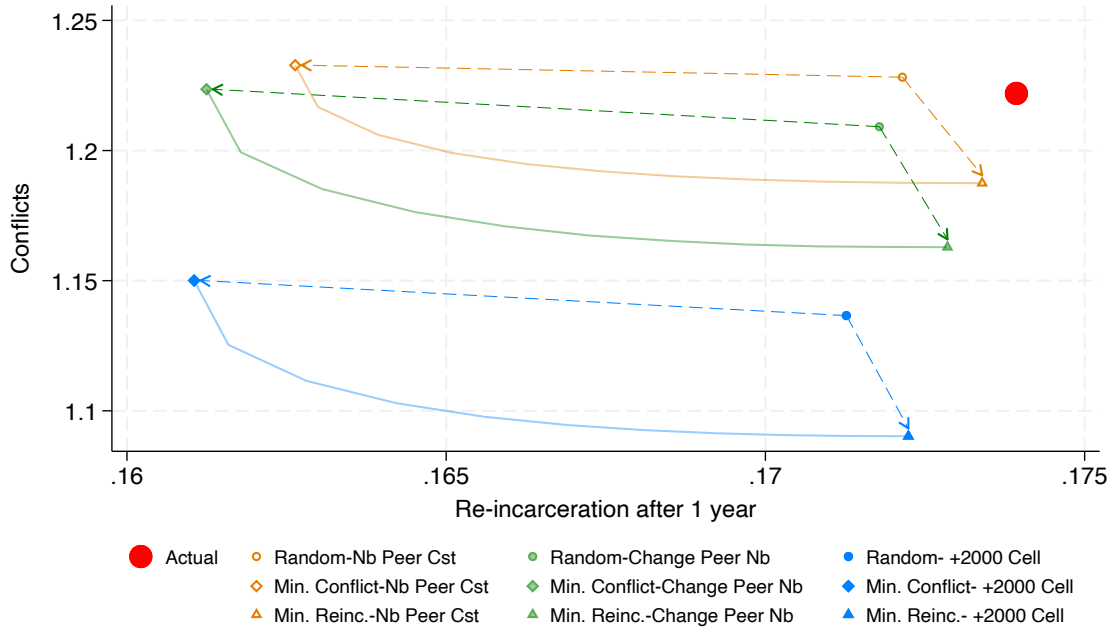
Notes: This figure looks at the effect of peer composition on sanctioned facility-wide misconduct, by type of sanctioned misconduct. Panel (a) reports results for contraband trafficking (hollow circles) and disorderly behavior (filled circles); Panel (b) reports results for violence against correctional officers (hollow circles) and against other inmates (filled circles). Each point represents the effect of the number of peers with the listed characteristic on the number of sanctioned incidents of that type (expressed as a proportion of the mean). We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure 7: Peer composition and risk of conflicts in cells



Notes: This Figure presents estimates of the effects of peer characteristics on conflicts in cells, using a Cox proportional hazard model (Equation 3). We define peers as being close in age if the age difference is less than 5 years; different in age if they are at least 5 years apart. "Same city" means that peers lived in the same city before incarceration; "close city" refers to peers from a different city located within 30 km; and "distant city" refers to peers from a city more than 30 km away. Coefficients come from a single regression. We control for prison fixed effects and age at entry of the two individuals. Bars represent the 95% confidence intervals.

Figure 8: Changing cell composition: policy simulations.



Notes: This Figure presents the estimated reincarceration rates (x-axis) and estimated number of conflicts in prison (y-axis) observed in our data and under different policy simulations. The red dot shows the current reincarceration rate and number of incidents in prison. The full dots correspond to a random reshuffling of people, while the hollow dots show optimized allocations that either minimize recidivism (diamonds) or minimize conflicts (triangles). The orange dots keep the number of peers constant. The green dots change the number of peers that a person interacts with. The blue dots represent a counterfactual with 2,000 additional available cells,.

Table 1: Descriptive statistics for the main study sample

	Mean	Sd		Mean	Sd
1. Individual characteristics:			**3. Outcomes:**		
Time in prison	213.96	164.21	*Reincarceration (1y)*		
Property	0.3	0.46	All	0.17	0.38
Drug	0.21	0.41	Property	0.06	0.24
Violence	0.25	0.43	Drug	0.03	0.17
Some pretrial	0.44	0.5	Violence	0.05	0.21
Age	32.43	10.76			
Female	0.04	0.21	*Misconduct*		
French	0.75	0.43	All - at least one	0.51	0.5
Illiterate	0.29	0.45	Number	1.79	3.58
Substance abuse	0.58	0.49	Sanctioned - At least one	0.23	0.42
Mental health issues	0.19	0.39	Any	0.5	1.41
			Violence, correctional officers	0.05	0.34
2. Peer characteristics:			Violence, other inmates	0.06	0.31
Time with cellmates	160.7	132.16	Contraband trafficking	0.22	0.68
Nb of cellmates - All	8.26	6.1	Disorder	0.18	0.8
Property	2.48	2.37			
Drug	1.71	2	*Conflicts*		
Violence	2.22	2.3	At least one	0.4	0.49
Same city	0.8	1.76	Number	1.28	2.32
Close city	2.78	3.45			
Distant city	4.81	4.71			
Younger	2.42	2.91			
Same age	3.41	3.2			
Older	2.43	3.45			
Same crime	2.56	2.5			
Different crime	5.7	4.6			
Observations	189,842				

Notes: This table presents descriptive statistics for our main analysis sample. Panel 1 presents individual characteristics; Panel 2 presents peer characteristics; and Panel 3 presents outcomes. Means and standard deviations are shown for all variables. Our primary data source is incarceration records for people incarcerated in France between June 2016 and December 2019 with prison spells of two years or less.

Table 2: Evidence of quasi-random assignment: correlation between peer characteristics and predicted recidivism

	Predicted Recidivism after 1 year		
	(1)	(2)	(3)
Nb Peers, property	0.0011**	-0.00071**	0.00012
	[0.0005]	[0.00029]	[0.00016]
Nb Peers, drug	0.0021***	0.00036	6.70E-06
	[0.00076]	[0.00028]	[0.00021]
Nb Peers, violent	0.00062**	0.00078***	0.000044
	[0.00031]	[0.00018]	[0.00012]
Nb Peers, other	-0.00063	0.000034	-0.0002
	[0.00041]	[0.00023]	[0.00015]
Controls			
Crime, sentence length	X	X	X
Prison, sex, age, pretrial		X	X
Smoker, French			X
F-test	5.11	6.65	0.7
Mean outcome		0.17	
Observations		185,996	

Notes: This table presents estimates of the correlation between an individualâs predicted probability of recidivism and the characteristics of their peers, for each crime type. Predicted recidivism is constructed from regressions of recidivism on individual-level characteristics (offense type, sentence length, criminal history, and socio-demographics). Each column reports coefficients from separate regressions where peer variables (number of peers convicted of each crime type) are included alongside an increasing set of controls. Estimates are presented in percentage points. Standard errors are in brackets and clustered at the prison level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Testing for peer effects in recidivism: crime type and location

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: reincarceration after 1 year for/at...					
	Property	Drug	Violence	Other	Home	Non-home
Nb Peers, property	0.0021***	0.0004*	0.0005**	0.0001		
	[0.0003]	[0.0002]	[0.0003]	[0.0002]		
Nb Peers, drug	-0.0005	0.0019***	-0.0002	0.0000		
	[0.0004]	[0.0004]	[0.0003]	[0.0002]		
Nb Peers, violent	0.0006*	-0.0003	0.0009***	-0.0002		
	[0.0003]	[0.0002]	[0.0003]	[0.0003]		
Nb Peers, other	-0.0005	-0.0002	0.0006**	0.0003		
	[0.0003]	[0.0003]	[0.0003]	[0.0003]		
Nb Peers, home					0.0019***	-0.0001
					[0.0003]	[0.0001]
Nb Peers, non home					-0.0007	0.0024***
					[0.0005]	[0.0004]
Observations	189,016	189,016	189,016	189,016	148,618	148,618
Mean outcome	0.059	0.030	0.047	0.030	0.14	0.038

Notes: Each column reports OLS estimates of Equation (1), where the dependent variable is an indicator for reincarceration within one year of release, for the crime type or location shown in the column header. Coefficients measure the effect of one additional cellmate convicted of a given offense type (or from a given location) on the probability of reincarceration. All regressions include controls for sentence length, criminal history, and socio-demographic characteristics, as well as prison, incarceration-length, and offense-type fixed effects. Standard errors are clustered at the prison level.

Table 4: Cell composition across observed, randomized, and optimized scenarios.

Group	Optimisation	City of residence			Age		Crime	
		Same	Close	Distant	Close	Different	Same	Different
Real	-	7.5	25.9	66.5	44.1	55.9	33.1	66.9
Nb peer cst	-	6.9	25.5	67.5	38.3	61.5	31	68.9
Nb peer cst	Conflict	8.8	24.8	65.8	45.5	53.8	46.2	53.1
Nb peer cst	Reincarceration	6.9	26.5	66.7	30.7	69.4	32.3	67.8
Change peer nb	-	6.8	25.3	67.8	37.6	62.2	30.8	69.1
Change peer nb	Conflict	8.4	24.5	65.6	43.3	55.3	43.9	54.6
Change peer nb	Reincarceration	6.9	26.9	66.7	29	71.5	32.1	68.3
+2000 cells	-	6.5	24	64.4	35.7	59.2	29.2	65.6
+2000 cells	Conflict	8	23.3	62.2	40.9	52.6	41.6	51.9
+2000 cells	Reincarceration	6.5	25.7	63.3	27.4	68.1	30.5	65

Notes: This table reports the percentage of cellmate pairs that are similar ("same") or dissimilar ("close" or "distant") along three dimensions – city of residence, age, and crime type – under alternative cell allocation scenarios. "Observed" corresponds to the pairing patters in the data. "Nb peer cst" randomizes pairings while keeping the number of peers per inmate constant; "Change peer nb" allows the number of peers to vary; "+2000 cells" adds 2,000 simulated beds, reducing the likelihood of encounters. For each scenario, "Conflict" and "Reincarceration" columns present optimized allocations that respectively minimize within-cell conflict or post-release reincarceration.

ONLINE APPENDIX

A Defining the main variables

In this Appendix, we describe how we construct our main penal and socio-demographic variables.

Penal variables.

- *Incarceration length.* We consider the number of days that a person was incarcerated in prison. We have 720 indicators for incarceration length, ranging from 1 to 720
- *Sentence length.* We consider the number of days that a person was sentenced to prison.
- *Month of incarceration.* We consider indicators for the month of incarceration from 1 (July 2016) to 42 (December 2019).
- *Prison.* Indicators for prisons in which a person is incarcerated. There are 149 prisons in our sample.
- *Crime type.* This is the crime type that is reported on a person's prison file. It typically includes the lead charge for which a person was convicted. We include indicators for the 1,100 crime types established by the French Ministry of Justice.
- *Pretrial.* Indicator if a person is in pretrial detention, versus if they have already been convicted of a crime.
- *Reincarceration.* Our yearly recidivism variable is defined as being reincarcerated in France within 12 months.
- *Prior incarceration as an adult.* Indicator of prior incarceration spells at age 18 or more.
- *Prior incarceration as a juvenile.* Indicator of prior incarceration spells before age 18.

Behavior in prison.

- *Incident.* Number of behavioral incident reported in prison.
- *Incident-Sentenced.* Number of behavioral incident that led to a disciplinary sanction.
- *Contraband trafficking, disorder, violence.* Number of disciplinary sanction for contraband trafficking, disorder, violence against a correctional officer, or violence against another inmate.

- *Conflict.* Indicator for whether a pair of cellmates was separated because of a reported conflict within that cell. This outcome is defined at the pair level, except in descriptive statistics Table 1 where it is aggregated at the individual level.

Socio-demographic characteristics.

- *Region of citizenship.* Categorical indicators for whether an individual holds citizenship from a country located in one of the following regions: Europe, Maghreb, Sub-Saharan Africa, Asia, the Americas, or Oceania.
- *French.* Indicator for if a person is French.
- *Children.* Indicator if a person reports having children before incarceration.
- *Illiterate.* Indicators if a person does not know how to read, has difficulties, reads well, or hasn't been assessed.
- *Educational attainment.* Level of qualification: low, medium, high, unknown.
- *Female.* Sex is captured in the prison files.
- *Age.* We consider indicators for age (in full years) upon entry in prison.

Behavioral health and addiction.

- *Physical and mental status.* Set of 13 categorical variables measured as entry. Seven capture "objective" characteristics: health problem, disability, addictions, past hospitalisation in mental health unit, past self-mutilation, past suicidal attempts, past suicidal attempts in the family. Six other variables reflect the prison clerk's evaluation at entry: state of shock at entry, delirious, aggressive, suicidal, depressed, and agitated.
- *Smoker.* Indicator if a person reports smoking.

B Stricter test of peer effects in crime

B.1 Principle of the test

Below, we reproduce Equation (1) from Section 3.1:

$$Y_i^{CR} = \sum_{CP=1}^{g} \alpha_{CP}^{CR} NbPeer_i^{CP} + \beta^{CR} X_i + \psi_C + \gamma_p + \delta_t + \varepsilon_i$$

Following the existing literature, in our main analysis we define a peer effect of type CP on recidivism for crime CR whenever $\alpha_{CP}^{CR} > 0$. In the stricter version, we rely on the same equation but impose additional conditions. Specifically, we say that peers convicted of crime CP increase recidivism for crime CR if the following hold:

1. $\alpha_{CP}^{CR} > 0$
2. $\alpha_{CP}^{CR} > \alpha_{\backslash CP}^{CR}$
3. $\alpha_{CP}^{CR} > \alpha_{CP}^{\backslash CR}$

To illustrate, consider the case where CR is recidivism for violent crime and CP represents peer drug offenses. We say that peers convicted of drug crimes influence recidivism for violent crime if the coefficient on the number of peers convicted of a drug crime, $\alpha_{drug}^{violent}$ satisfies the following three criteria: (i) it is significant; (ii) it is greater than the coefficient on the number of peers not convicted of drug crimes in the same regression; (iii) it is greater than the coefficient on the number of peers convicted of drug crimes in regressions where the outcome is recidivism for non-violent crimes.

By adding in conditions (ii) and (iii), we can rule out many patterns of sorting. Suppose individuals with characteristics Z are more likely to be paired with peers who have characteristic W (strategic matching).[23] Under the stricter definition of peer effects, such sorting is problematic only if Z is correlated with Y^{CR} (recidivism for crime CR), and W is correlated with $NbPeer^{CP}$ (the number of peers convicted of CP). The additional conditions help to rule out several other forms of sorting.

Returning to the drug-violent crime example:

[23] A special case arises when $W = Z$, in which case there is sorting on characteristic Z.

- Condition (ii) is violated if W is correlated with recidivism for violent crimes across all types of peers, rather than specifically with peers convicted of drug crimes. For instance, if individuals with mental health challenges are more likely to both reoffend for violent crimes and interact with a wide range of cellmates (convicted of different crimes), then condition (ii) would fail. For (ii) to hold, the correlation must be specific to drug peers.
- Condition (iii) is violated if Z is correlated with both exposure to drug peers and recidivism for all crime types (not just violent crime). For example, if younger individuals are more likely to meet drug peers, condition (iii) would fail, since age is correlated with recidivism across various crime types, not just violent crime.

This definition of peer effects is broadly applicable beyond the prison setting, especially where different peer traits may affect different outcomes and peer assignment is only plausibly exogenous. In education, for instance, one could study whether peer ability in a subject affects student test performance in that subject and in other subjects. Peer ability in math would be said to influence math performance if: (i) peer math scores influences individual math scores; (ii) they do so more strongly than peer ability in other subjects; and (iii) they influence math scores more than they influence performance in non-math subjects. This approach distinguishes subject-specific peer learning from general academic spillovers, offering a sharper test of targeted influence versus broader associations.

B.2 Results

In Table B.1, we report p-values for the peer effect estimates outlined in Section 3.1. Column 1 shows the estimate of α_{CP}^{CR} for each pairing of peer crime CP and recidivism crime CR; column 2 reports the p-value for the null hypothesis $\alpha_{CP}^{CR} = 0$; columns 3–6 report p-values for the null $\alpha_{CP}^{CR} = \alpha_{\backslash CP}^{CR}$, testing whether exposure to peers convicted of offense CP affects recidivism in offense CR differently than for all other offenses (condition ii); Columns 7–10 present p-values for the null $\alpha_{CP}^{CR} = \alpha_{CP}^{\backslash CR}$, testing whether exposure to peers convicted of offense CP affects recidivism in CR differently than exposure to peers convicted of other crime types (condition iii). We reject all three nulls only for property and drug offenses (rows 1 and 6), suggesting that these are the two crime types where peer exposure matters most. Table B.2 presents similar analyses for crime location.

Table B.1: Testing for peer effects in crime type: stricter test

Nb peers, CP	Recidivism, CR	α_{CP}^{CR}	P-value for... $\alpha_{CP}^{CR}=0$	$\alpha_{CP}^{CR}=\alpha_{\backslash CP}^{CR}$				$\alpha_{CP}^{CR}=\alpha_{CP}^{\backslash CR}$			
				Property	Drug	Violent	Other	Property	Drug	Violent	Other
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Property	Property	0.002	0.00		0.00	0.00	0.00		0.00	0.00	0.00
Drug	Property	-0.001	0.13	0.00		0.02	0.89		0.00	0.43	0.20
Violent	Property	0.001	0.07	0.00	0.02		0.04		0.03	0.47	0.07
Other	Property	-0.000	0.15	0.00	0.89	0.04		0.68	0.02	0.07	
Property	Drug	0.000	0.07		0.00	0.05	0.05	0.00		0.69	0.28
Drug	Drug	0.002	0.00	0.00		0.00	0.00	0.00		0.00	0.00
Violent	Drug	-0.000	0.19	0.05	0.00		0.98	0.03		0.00	0.78
Other	Drug	-0.000	0.26	0.05	0.00	0.98		0.68		0.02	0.11
Property	Violent	0.001	0.05		0.06	0.40	0.81	0.00	0.69		0.18
Drug	Violent	-0.000	0.50	0.06		0.03	0.06	0.43	0.00		0.58
Violent	Violent	0.001	0.01	0.40	0.03		0.57	0.47	0.00		0.01
Other	Violent	0.001	0.04	0.81	0.06	0.57		0.02	0.02		0.42
Property	Other	0.000	0.76		0.89	0.44	0.54	0.00	0.28	0.18	
Drug	Other	0.000	0.95	0.89		0.63	0.41	0.20	0.00	0.58	
Violent	Other	-0.000	0.47	0.44	0.63		0.25	0.07	0.78	0.01	
Other	Other	0.000	0.26	0.54	0.41	0.25		0.07	0.11	0.42	

Notes: This table presents results for our stricter tests for peer effects. For each peer crime CP and recidivism type CR, Column 1 reports the estimated coefficient α_{CP}^{CR} (defined in Equation 1), which captures the effect of the number of peers convicted of crime CP on the probability of recidivism in crime type CR. Column 2 reports the p-value testing the null hypothesis $\alpha_{CP}^{CR}=0$. Columns 3–6 report p-values for tests of the null $\alpha_{CP}^{CR}=\alpha_{\backslash CP}^{CR}$, which compares peer effects across peer crime types, holding the recidivism type constant. Columns 7–10 report p-values for tests of the null $\alpha_{CP}^{CR}=\alpha_{CP}^{\backslash CR}$, which compares peer effects across recidivism types, holding the peer crime type fixed. All models include fixed effects for prison, time in prison, sentence, aggregated crime, age at entry, calendar month of incarceration and aggregated nationality and controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Standard errors are clustered at the prison level.

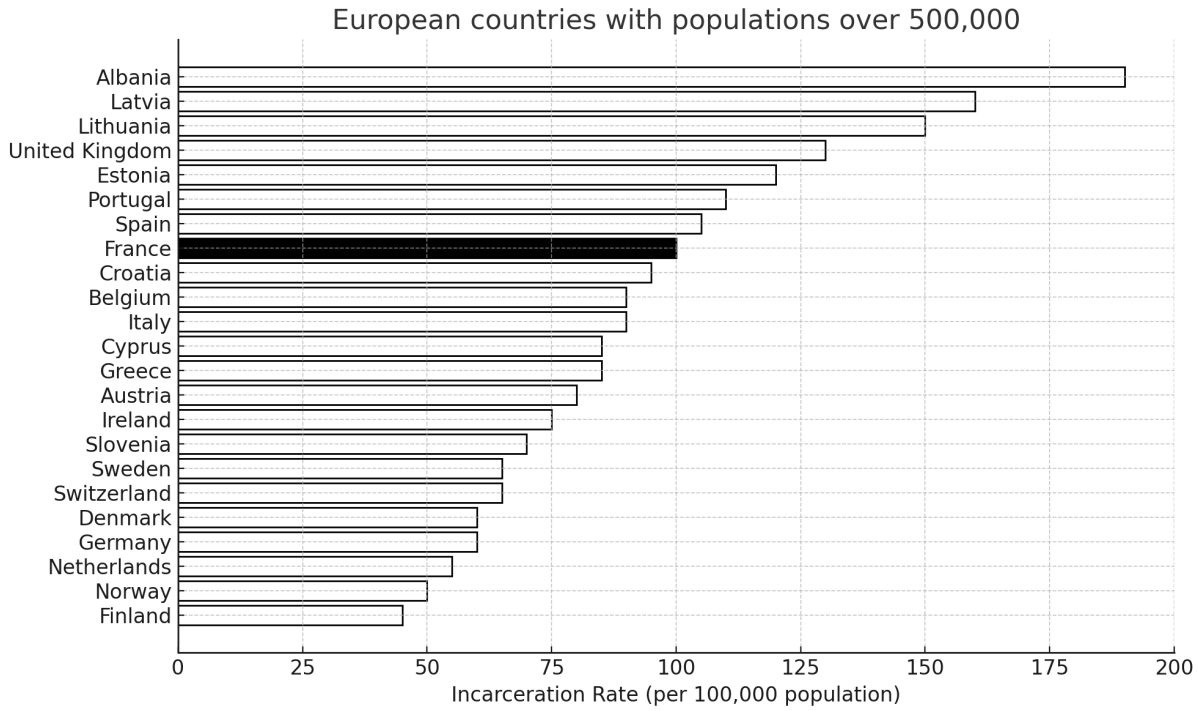
Table B.2: Peer composition and recidivism, by place of residence.

Peer county...	New offense county...	Mean DV	α_{LP}^{LR}	SE	P-value for H_0: $\alpha_{LP}^{LR} = 0$	P-value for H_0: $\alpha_{LP}^{LR} = \alpha_{\setminus LP}^{LR}$	P-value for H_0: $\alpha_{LP}^{LR} = \alpha_{LP}^{\setminus LR}$
		(1)	(2)	(3)	(4)	(5)	(6)
same	same	0.138	0.0019	0.0003	0.00	0.00	0.00
different	same	0.138	-0.0007	0.0005	0.17	0.00	0.00
same	different	0.040	-0.0001	0.0001	0.64	0.00	0.00
different	different	0.040	0.0024	0.0003	0.00	0.00	0.00

Notes: This table reports estimates how cellmate county of origin affects the location of recidivism. Each row represents a different combination of peer and individual outcomes. Peer counties can be same or different as the focal inmate; and inmate recidivism is considered separately for new crimes in the same county or in a different county from where they were residing before prison. For example, "same/same" refers to the effect of peers from the same county on reincarceration in that same county. For each peer location LP and location of recidivism LR, column 1 reports the mean of the dependent variable, column 2 presents estimated coefficient α_{LP}^{LR} (defined in Equation 1, except that we consider location, L, instead of crime type, C), which captures the effect of the number of peers living in location LP on the probability of recidivism in location type LR, and column 3 reports the standard error of the estimated α_{LP}^{LR}. Column 4 reports the p-value testing the null hypothesis $\alpha_{LP}^{LR} = 0$. Column 5 reports p-values for tests of the null $\alpha_{LP}^{LR} = \alpha_{\setminus LP}^{LR}$, which holds the recidivism place fixed. Columns 6 report p-values for tests of the null $\alpha_{LP}^{LR} = \alpha_{LP}^{\setminus LR}$, which holds peer location fixed. All models include fixed effects for prison, time in prison, sentence, aggregated crime, age at entry, calendar month of incarceration and aggregated nationality and controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Standard errors are clustered at the prison level.

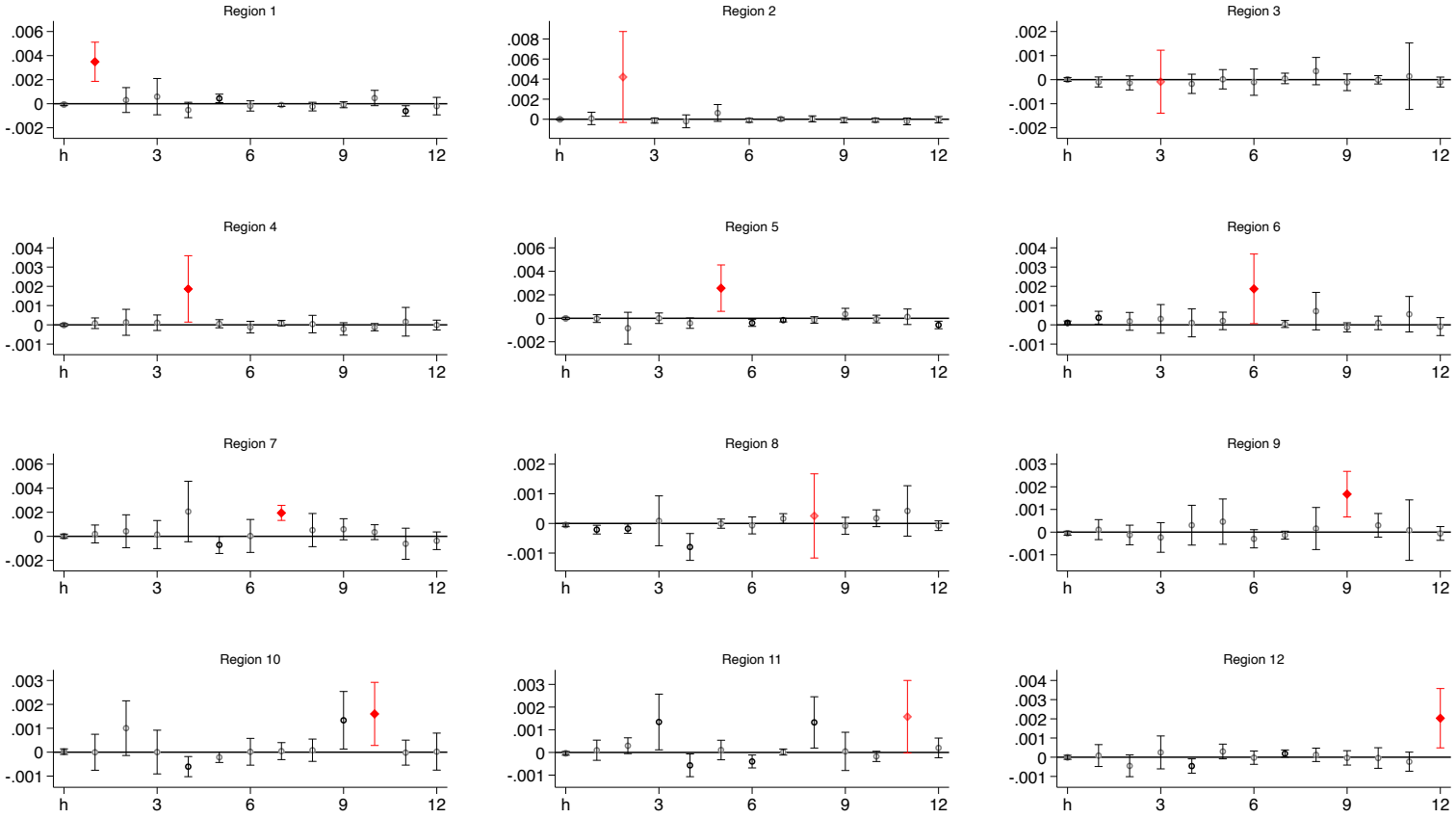
C Additional figures and tables: recidivism

Figure C.1: Incarceration rates in Europe



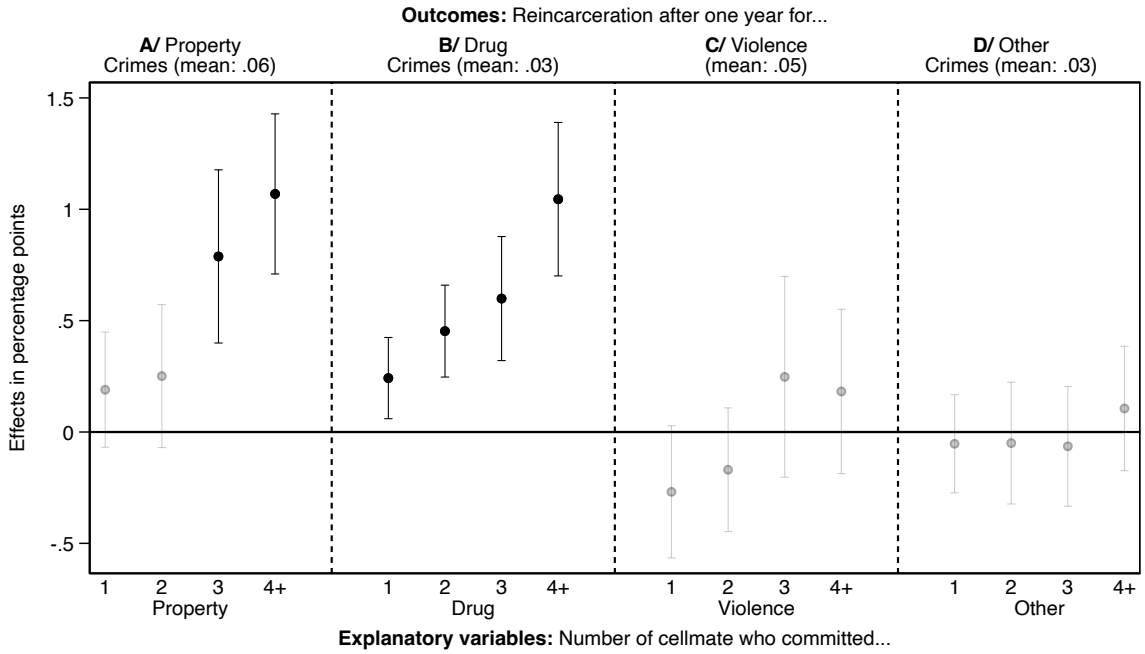
Notes: This figure reports incarceration rates in European countries with populations over 500,000. Source: Fair and Walmsley (2024)

Figure C.2: Effect of the number of cellmates from different regions on reincarceration by region



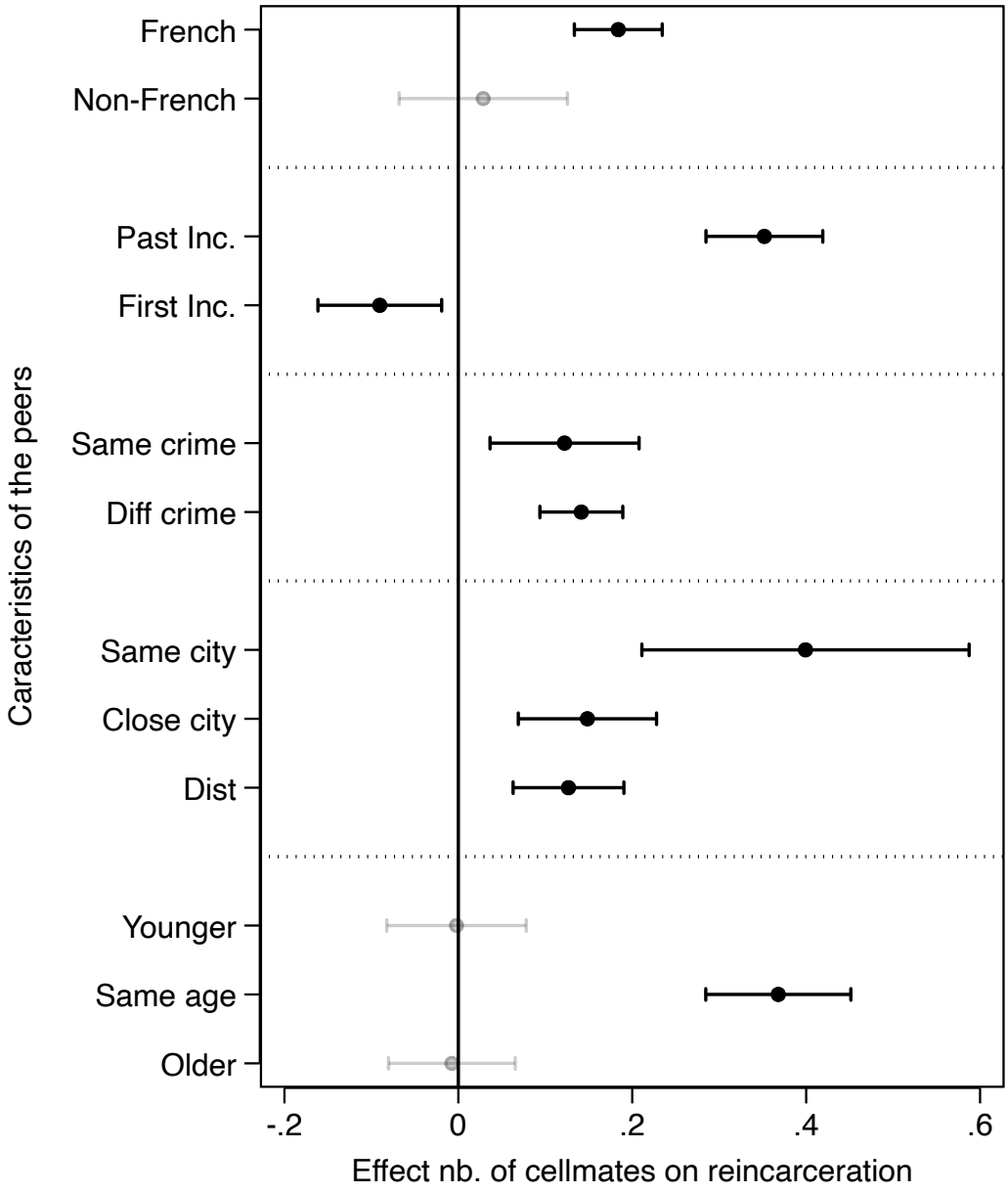
Notes: This Figure presents the correlations between the number of cellmates who used to live in the *home* region (h on the x-axis) or in administrative region 1-12 before incarceration and reincarceration after 1 year in the region indicated in the header. Each sub-graph presents the results of one regression that includes baseline controls for characteristics observed at prison entry. Effects are presented in proportion to the means. Bars represent the 95% confidence intervals (cap at 2.4). Standard errors are clustered at the prison level.

Figure C.3: Effect of peer composition on recidivism, by crime type (intensive margin)



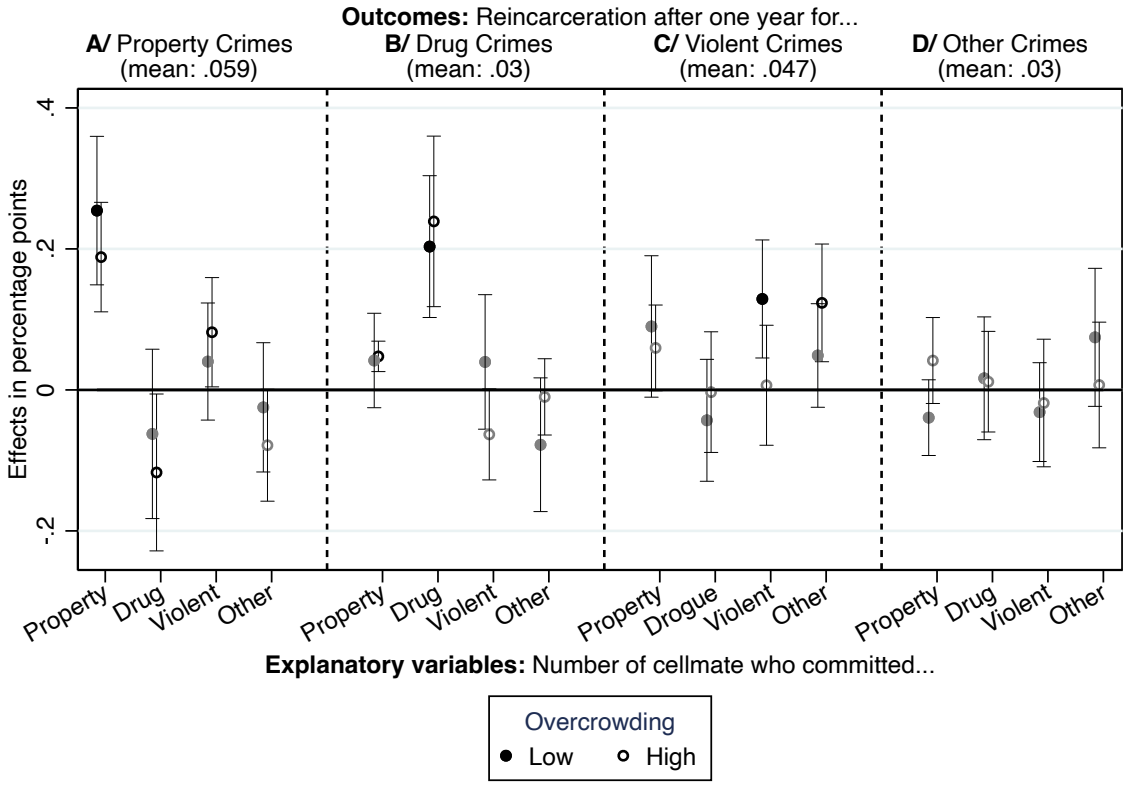
Notes: This figure estimates the effect of the number of cellmates convicted for a given crime type on reincarceration after one year for that same crime type. Peer crime categories appear on the x-axis, and each sub-panel corresponds to a separate regression. All regressions estimate the effect of the other types of peers (not shown on the graph) and control for prison, time in prison, sentence length, crime type, age at entry, calendar month of incarceration, and nationality (French vs. non-French), as well as individual characteristics measured at entry, including gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars present 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.4: Peer Composition and Recidivism for income generating crimes: Heterogeneity by Peer Characteristics



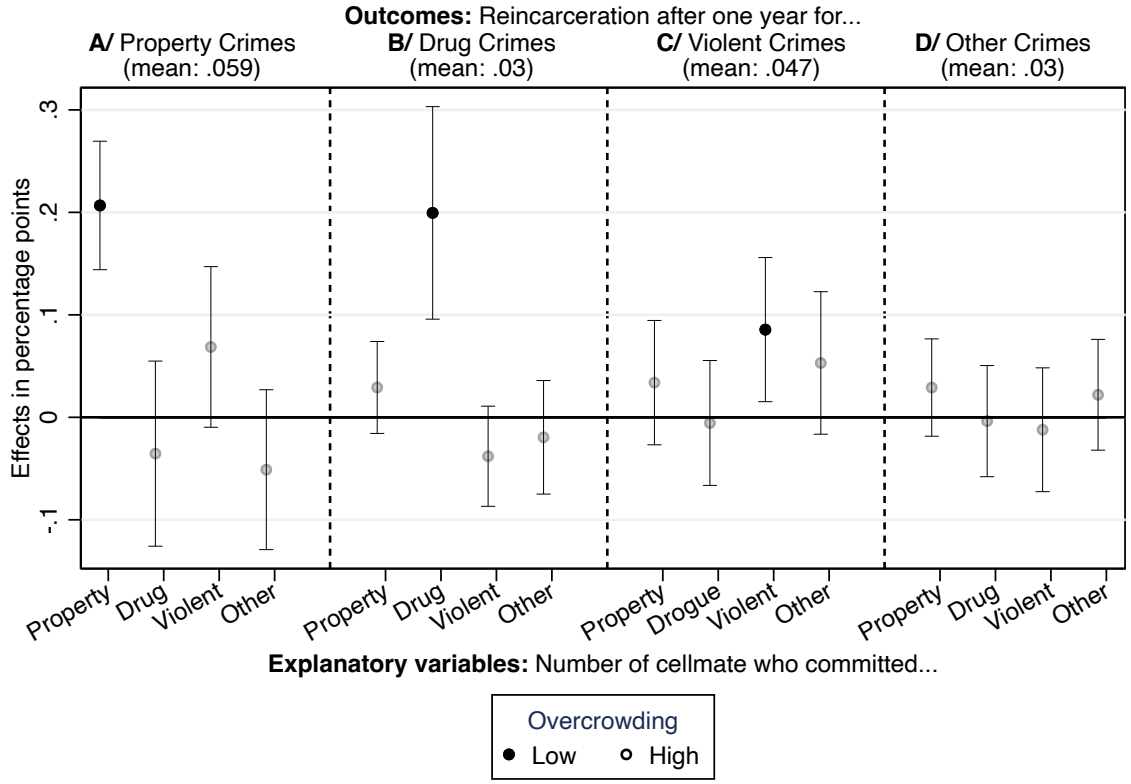
Notes: This Figure presents heterogeneity in the estimated effects of peer composition on recidivism. The outcome is reincarceration for an income-generating crime (property or drug distribution crimes). All characteristics are binary: whether peers are French citizens, have past incarcerations, share the same crime type, come from the same city, county, or another county, or are younger, of the same age, or older. Bars represent 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.5: Effect of peer composition on recidivism, by crime type and jail overcrowding



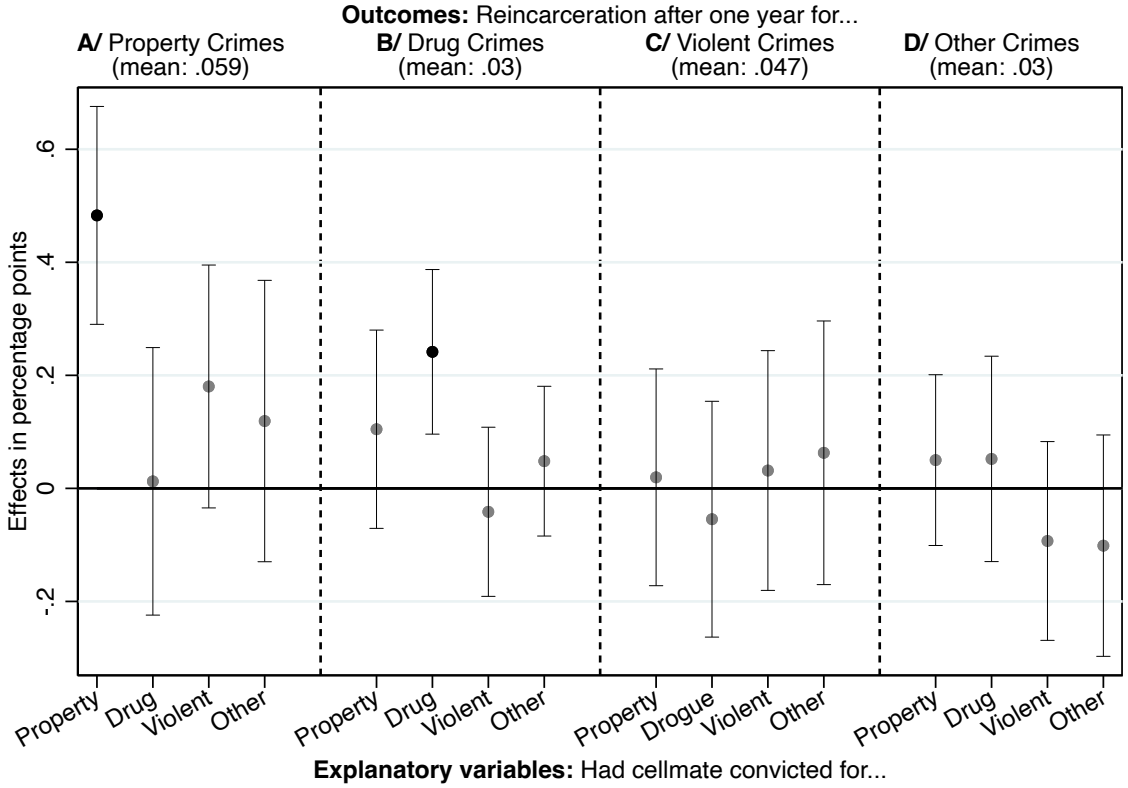
Notes: This Figure presents the correlation between the number of cellmates convicted for the type of crime indicated in the x-label and reincarceration after 1 year for the type of crime indicated in the header. The numbers of cellmates of different types are interacted with dummies for low (i.e. below the median) and high (above) overcrowding rates. Each panel present the result of a unique regression including baseline controls and controls for characteristics at entry. Bars present 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.6: Effect of peer composition on recidivism: people only incarcerated in jail



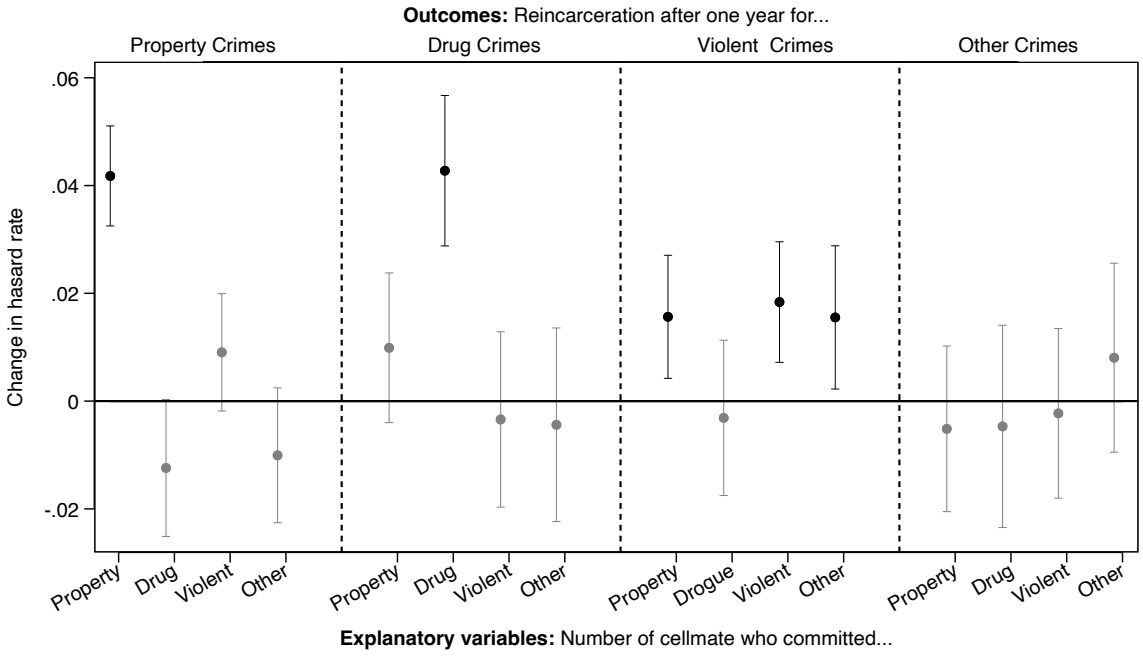
Notes: This Figure presents estimates of the effects on recidivism by crime type of the number of cellmates convicted of each crime type, for people who were only incarcerated in jail. Estimates come from Equation 1. Peer crime types appear on the x-axis, and the crime type of reincarceration after one year is indicated in the panel headers. Black circles plot the estimated effects of peer crime type on reincarceration, controlling for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Red triangles replace actual recidivism with predicted recidivism, allowing us to assess whether peer characteristics are correlated with unobserved determinants of recidivism. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.7: Effect of peer composition on recidivism: cellmates encountered in the first 4 weeks of incarceration



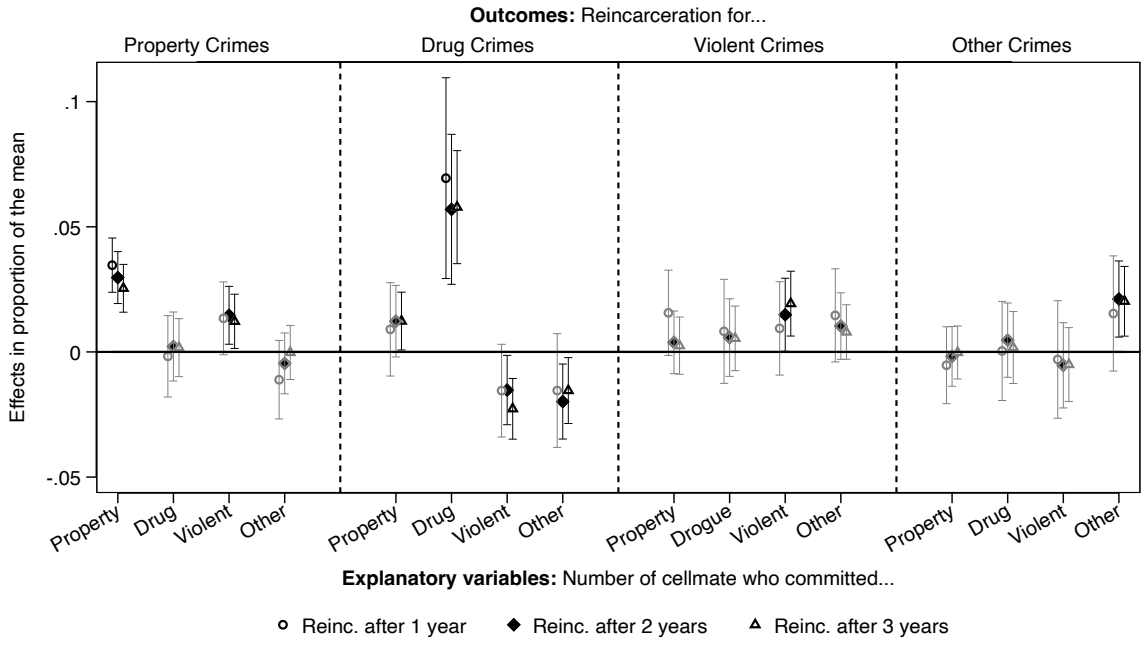
Notes: This Figure presents estimates of the effects on recidivism by crime type of the number of cellmates convicted of each crime type, encountered during the first four weeks of incarceration. Estimates come from Equation 1. Peer crime types appear on the x-axis, and the crime type of reincarceration after one year is indicated in the panel headers. Black circles plot the estimated effects of peer crime type on reincarceration, controlling for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Red triangles replace actual recidivism with predicted recidivism, allowing us to assess whether peer characteristics are correlated with unobserved determinants of recidivism. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.8: Effect of peer composition on recidivism: Cox duration models



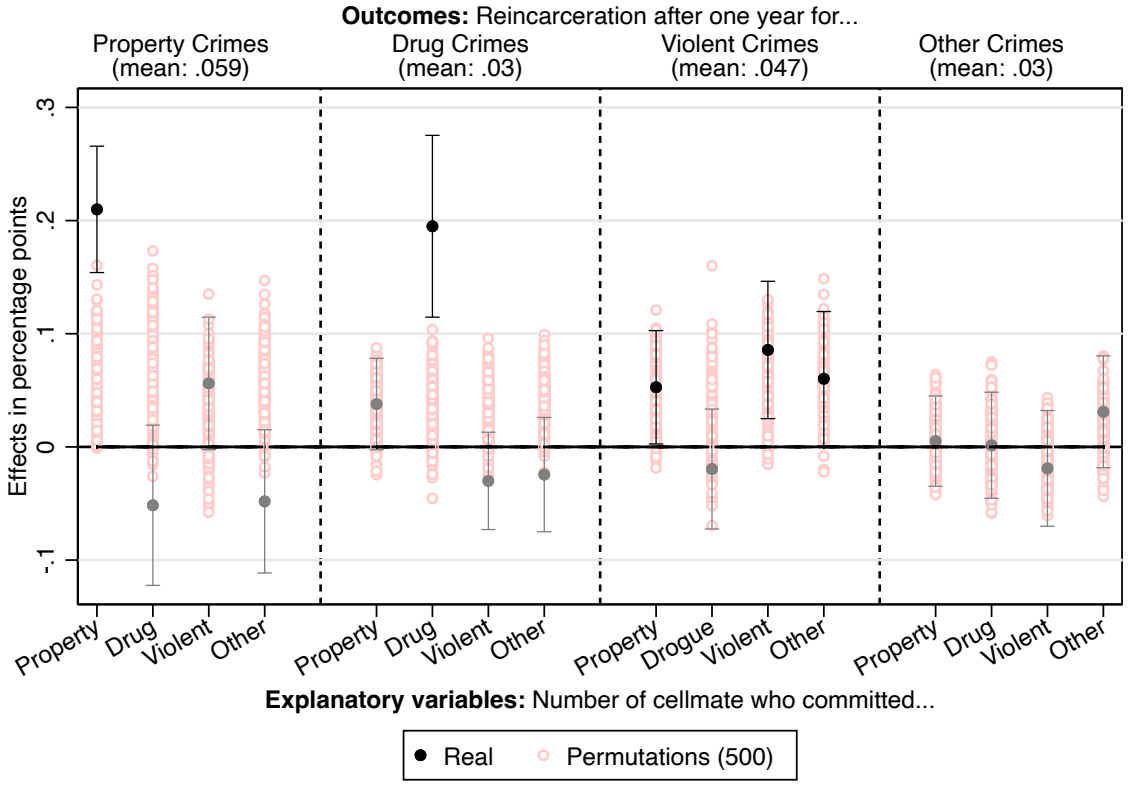
Notes: This Figure presents the correlation between the number of cellmates convicted for the type of crime indicated in the x-label and reincarceration after 1 year for the type of crime indicated in the header. Effects are measured using Cox competitive-duration models, and being reincarcerated for a type of crime is considered as a right truncation when measuring the probability of being reincarcerated for other types of crime. All models include prison, time in prison, sentence length, crime type, age at entry, calendar month of incarceration, and nationality fixed effects, as well as individual characteristics measured at entry. Bars present 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.9: Effect of peer composition on recidivism: different recidivism observation windows



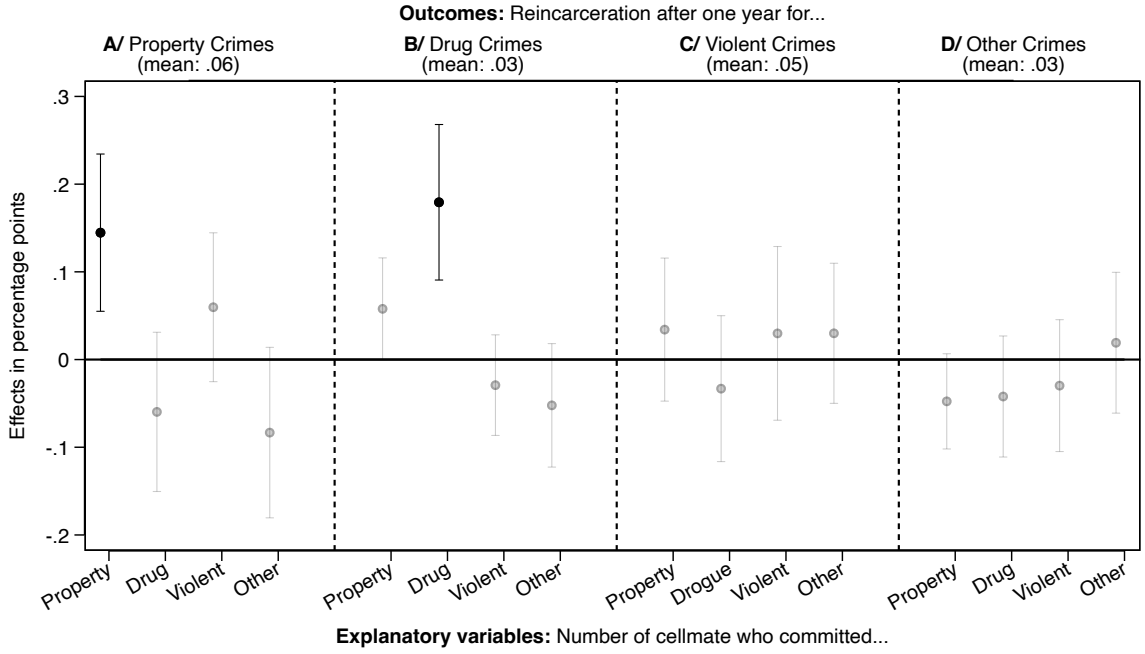
Notes: This Figure presents estimates of the effects on recidivism by crime type of the number of cellmates convicted of each crime type. In addition to reincarceration within 1 year (main estimates, in circles), we report results for reincarceration within 2 and 3 years (in diamonds and triangles, respectively). Models include controls for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars present 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.10: Effect of peer composition on recidivism by crime types, permutation exercise



Notes: This figure presents estimates of the effects of the number of cellmates convicted of each crime type on reincarceration after one year for the crime type indicated in the panel headers. The permutation estimates are based on 500 permutations in which individuals are randomly assigned placebo cellmates from others who began a new cohabitation in the same week in the same facility. All regressions include prison, time in prison, sentence length, crime type, age at entry, calendar month of incarceration, and nationality fixed effects, as well as individual characteristics measured at entry. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure C.11: Effect of peer composition on recidivism, dropping people who changed cells because of conflict



Notes: This Figure presents estimates of the effects on recidivism by crime type of the number of cellmates convicted of each crime type, after dropping anyone who changed cells because of a conflict. Estimates come from Equation 1. Peer crime types appear on the x-axis, and the crime type of reincarceration after one year is indicated in the panel headers. Black circles plot the estimated effects of peer crime type on reincarceration, controlling for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Red triangles replace actual recidivism with predicted recidivism, allowing us to assess whether peer characteristics are correlated with unobserved determinants of recidivism. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

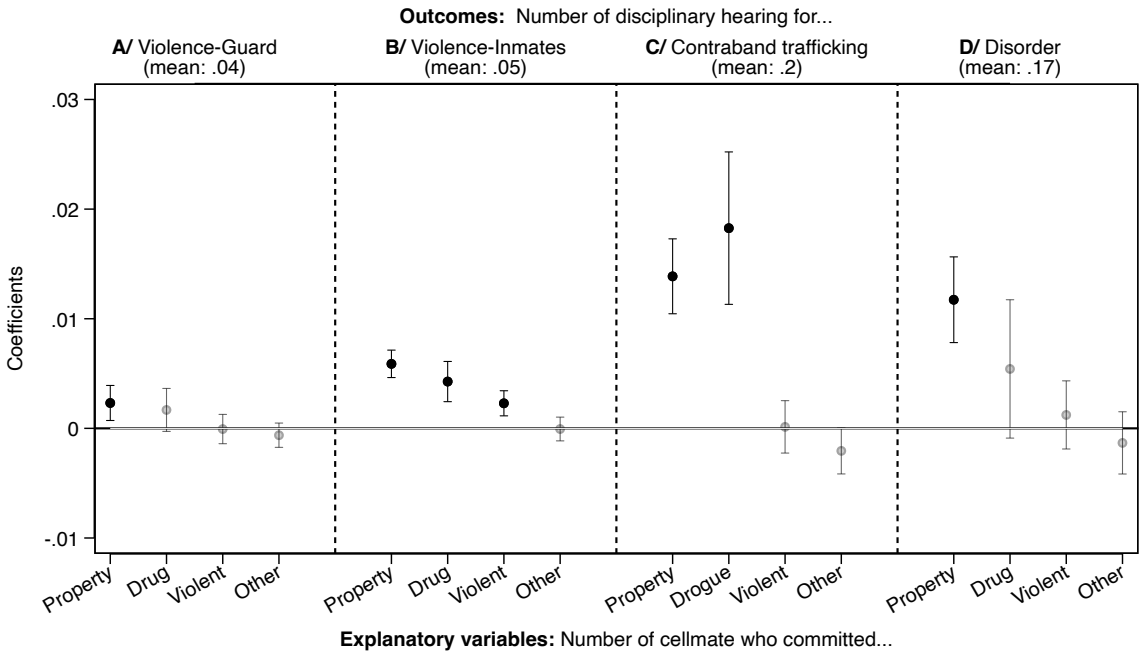
Table C.1: Effect of peer composition on recidivism: number of peers versus length of exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Outcome: reincarceration after 1 year for...											
	Property			Drug			Violence			Other		
Nb Peers:												
Property	0.0050***		0.0073***	0.00090*		0.00096	0.0012**		0.0027***	0.00012		0.0017***
	(0.00067)		(0.00091)	(0.00049)		(0.00064)	(0.00060)		(0.00079)	(0.00048)		(0.00056)
Drug	-0.0010		0.0014	0.0039***		0.0038***	-0.00039		0.0012*	0.000029		0.0010**
	(0.00072)		(0.00086)	(0.00082)		(0.00096)	(0.00054)		(0.00065)	(0.00048)		(0.00048)
Violent	0.0013*		0.0040***	-0.00069		-0.00052	0.0020***		0.0042***	-0.00044		0.00026
	(0.00069)		(0.00089)	(0.00050)		(0.00057)	(0.00071)		(0.00089)	(0.00060)		(0.00074)
Other	-0.00094		0.00022	-0.00048		-0.00034	0.0012**		0.0020**	0.00061		0.00072
	(0.00063)		(0.00088)	(0.00050)		(0.00061)	(0.00059)		(0.00078)	(0.00049)		(0.00064)
Exposure:												
Property		0.0025***	-0.00030		0.0017	0.0014		-0.00027	-0.00076		-0.0011	-0.0017**
		(0.00090)	(0.0010)		(0.0012)	(0.0013)		(0.0012)	(0.0013)		(0.00076)	(0.00082)
Drug		0.000014	-0.0011		0.00038	0.00089		-0.00073	-0.0019		-0.00048	-0.00029
		(0.0012)	(0.0013)		(0.0013)	(0.0013)		(0.0010)	(0.0012)		(0.00086)	(0.00096)
Violent		-0.00077	-0.00064		0.0032***	0.0014		-0.0010	-0.00076		-0.00032	-0.00055
		(0.00091)	(0.0010)		(0.0012)	(0.0012)		(0.0010)	(0.0010)		(0.00084)	(0.00083)
Other		0.00029	0.00062		0.00069	0.00096		0.00053	0.00017		0.00052	0.00040
		(0.00074)	(0.00081)		(0.00090)	(0.00090)		(0.00075)	(0.00075)		(0.00061)	(0.00063)
Obs	189,016	188,777	188,777	189,016	188,777	188,777	189,016	188,777	188,777	189,016	188,777	188,777

Notes: This table examines the effect of peer group size and duration of exposure to peers on recidivism. The outcomes are recidivism for property crimes (columns 1â3), drug distribution crimes (columns 4â6), violent crimes (columns 7â9), and other crimes (columns 10â12). For each offense type, the first column reports the effect of the number of peers, the second column reports the effect of the length of exposure to peers (in days), and the third column includes both peer measures jointly. All models include fixed effects for prison, time served, sentence length, aggregated crime type, age at entry, calendar month of incarceration, and aggregated nationality, as well as controls for gender, educational qualification, literacy, prior incarceration, mental health status, number of children, pretrial detention, and smoking behavior. Standard errors are clustered at the prison level.

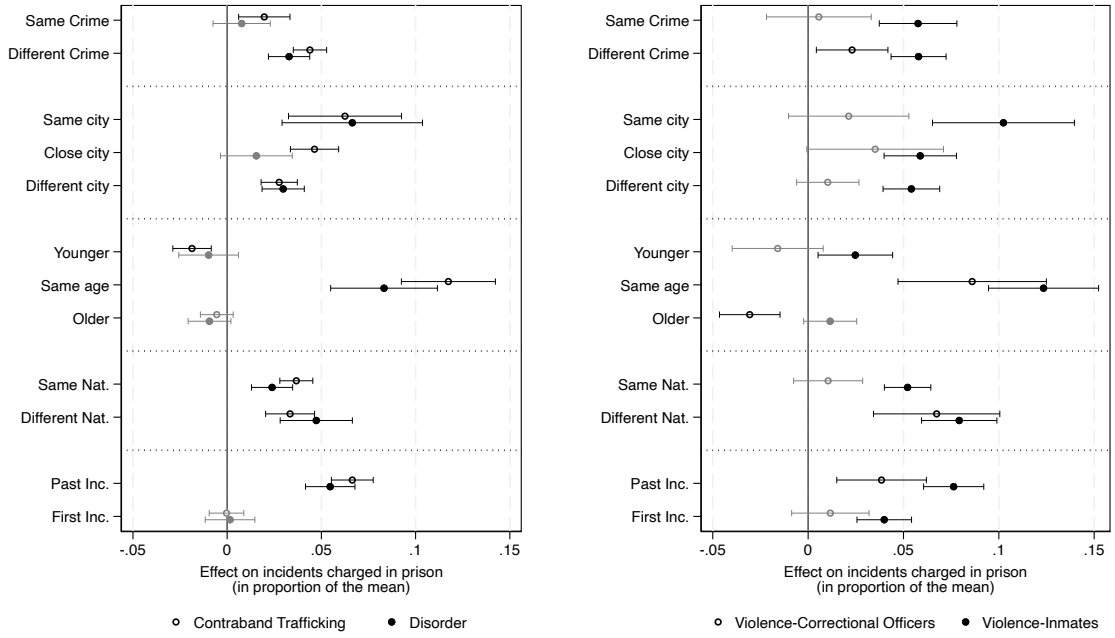
D Additional figures and tables: facility-wide misconduct

Figure D.1: Peer composition and facility-wide misconduct, by cellmates crime



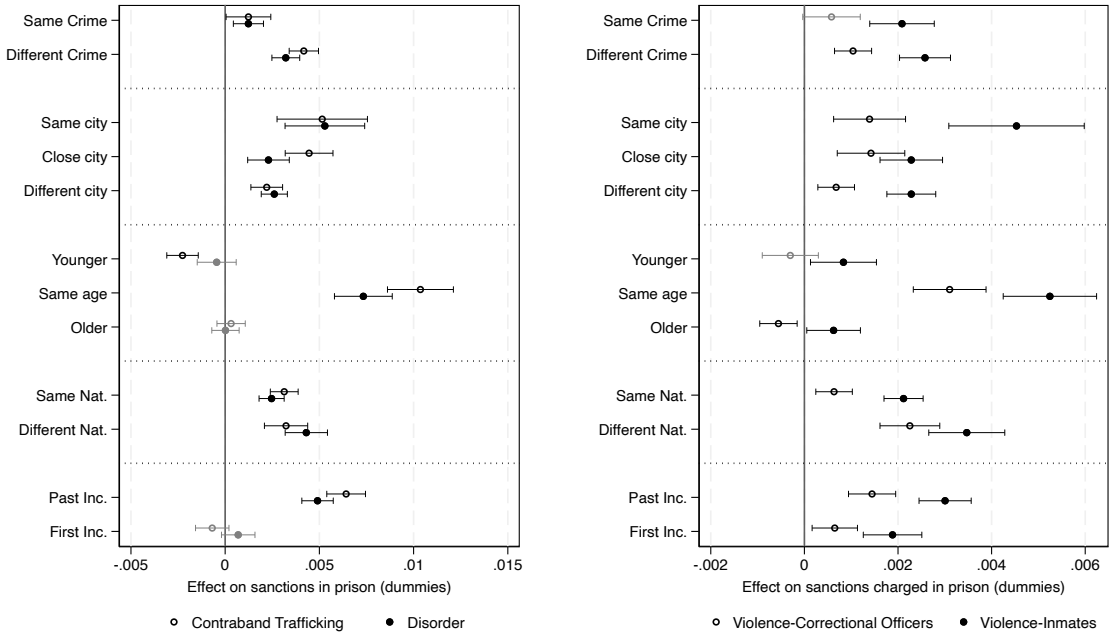
Notes: This Figure presents estimates of the effects of the number of cellmates convicted of different crime types on facility-wide misconduct. Estimates come from Equation 2. Peer crime types appear on the x-axis, and the type of misconduct is indicated in the panel headers. Regressions include controls for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure D.2: Peer composition and charged disciplinary incidents.



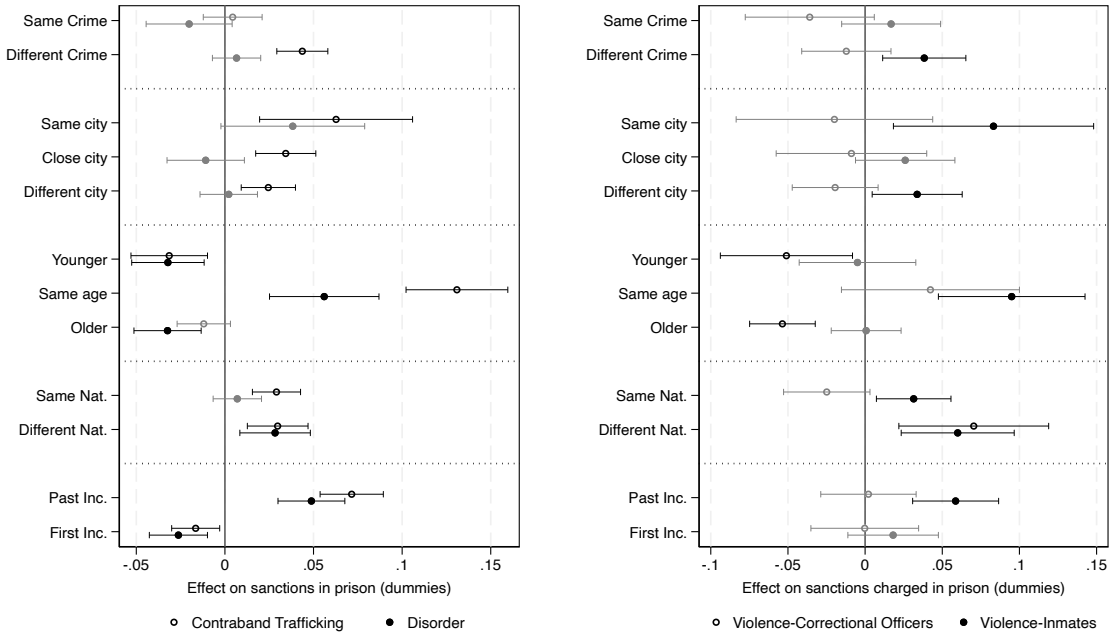
Notes: This figure looks at the effect of peer composition on charged facility-wide misconduct, by type of charged misconduct, regardless of whether the charges led to any sanction or not. Panel (a) reports results for contraband trafficking (hollow circles) and disorderly behavior (filled circles); Panel (b) reports results for violence against correctional officers (hollow circles) and against other inmates (filled circles). Each point represents the effect of the number of peers with the listed characteristic on the number of charged incidents of that type (expressed as a proportion of the mean). We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure D.3: Peer composition and disciplinary incidents, binary outcomes.



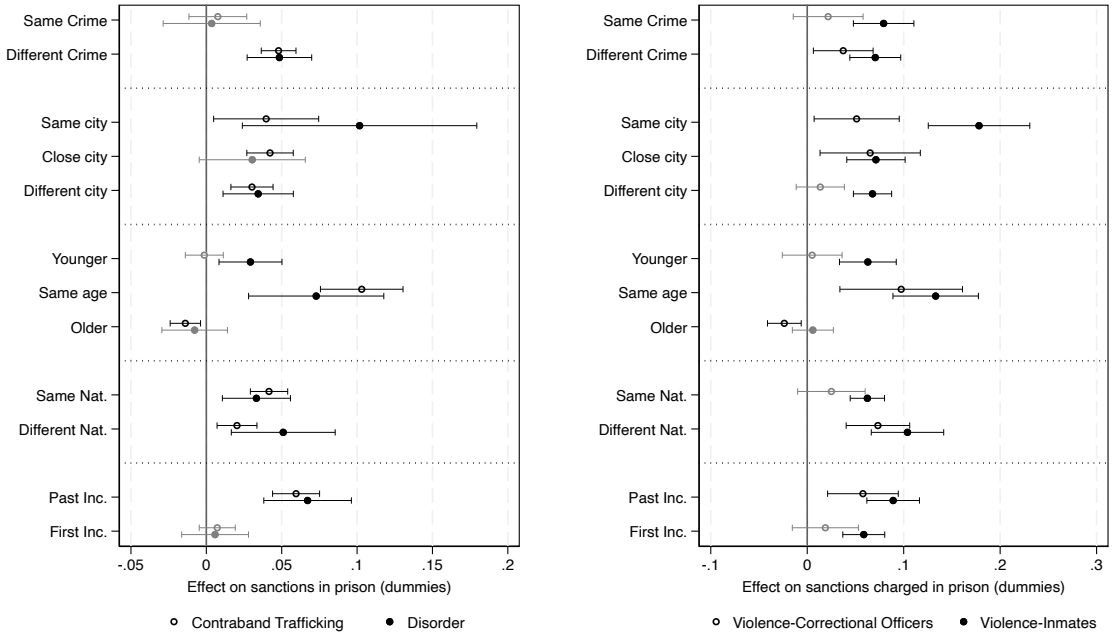
Notes: This figure presents the effect of peer composition on the probability of sanctioned facility-wide misconduct, by misconduct type. Panel (a) reports results for contraband trafficking (hollow circles) and disorderly behavior (filled circles); Panel (b) reports results for violence against correctional officers (hollow circles) and against other inmates (filled circles). Each point represents the effect of the number of peers with the listed characteristic on the existence of sanctioned incidents of that type (expressed as a proportion of the mean). We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure D.4: Peer composition and disciplinary incidents, dropping people who changed cells because of conflict.



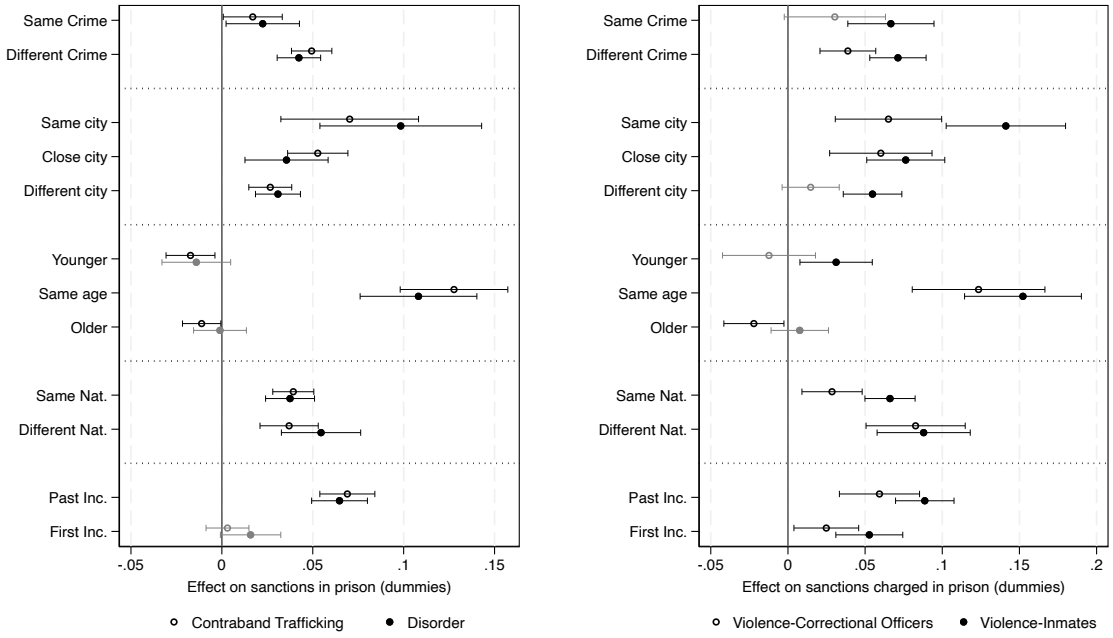
Notes: This figure presents the effect of peer composition on the number of incidents of sanctioned facility-wide misconduct, by misconduct type, dropping people who changed cells because of a conflict. Panel (a) reports results for contraband trafficking (hollow circles) and disorderly behavior (filled circles); Panel (b) reports results for violence against correctional officers (hollow circles) and against other inmates (filled circles). Each point represents the effect of the number of peers with the listed characteristic on the number of sanctioned incidents of that type (expressed as a proportion of the mean). We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

Figure D.5: Peer composition and disciplinary incidents, overcrowded facilities.



Notes: This figure presents the effect of peer composition on the number of incidents of sanctioned facility-wide misconduct, by misconduct type, for people who were incarcerated in facilities which had overcrowding above the median. Panel (a) reports results for contraband trafficking (hollow circles) and disorderly behavior (filled circles); Panel (b) reports results for violence against correctional officers (hollow circles) and against other inmates (filled circles). Each point represents the effect of the number of peers with the listed characteristic on the number of sanctioned incidents of that type (expressed as a proportion of the mean). We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

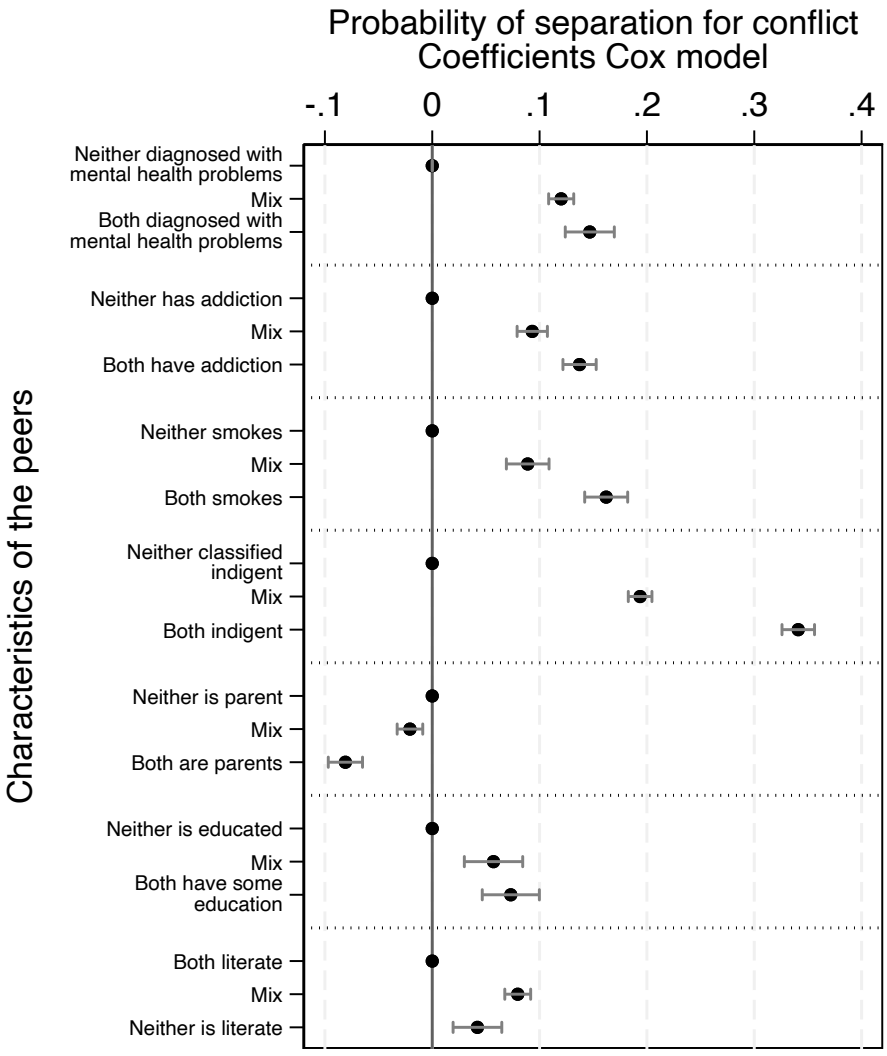
Figure D.6: Peer composition and disciplinary incidents, jail only.



Notes: This figure presents the effect of peer composition on the probability of sanctioned facility-wide misconduct, by misconduct type, for people who served their whole sentence in jail. Panel (a) reports results for contraband trafficking (hollow circles) and disorderly behavior (filled circles); Panel (b) reports results for violence against correctional officers (hollow circles) and against other inmates (filled circles). Each point represents the effect of the number of peers with the listed characteristic on the number of sanctioned incidents of that type (expressed as a proportion of the mean). We control for prison, time-in-prison, sentence, crime type, age at entry, calendar month of incarceration and nationality (French vs. non-French); as well as individual controls for gender, qualification, literacy, past incarceration, mental health, children, pretrial incarceration, and smoking. Bars represent the 95% confidence intervals. Standard errors are clustered at the prison level.

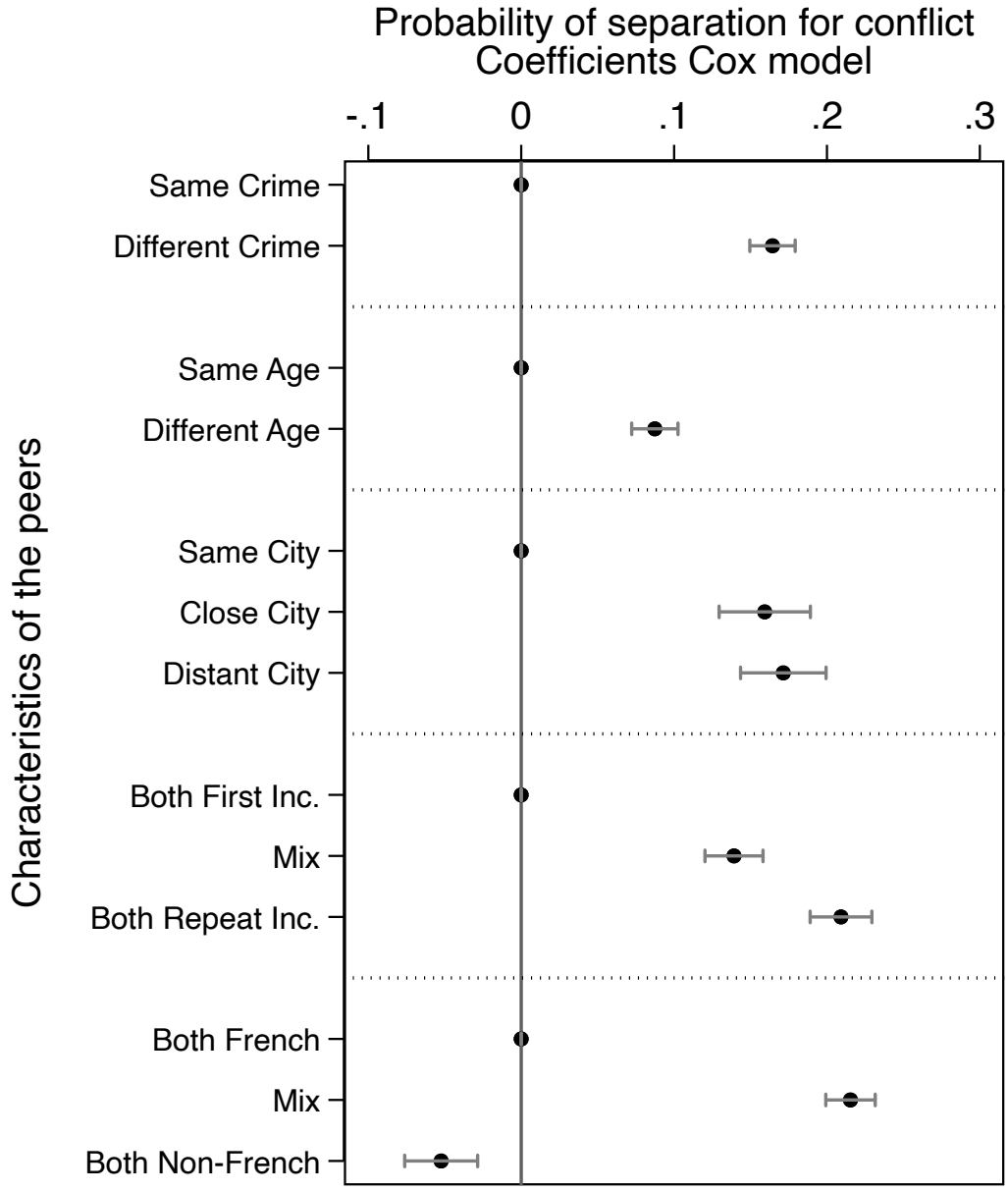
E Additional figures and tables: conflicts in cells

Figure E.1: Peer composition and conflicts in cells: health and socio-economic characteristics



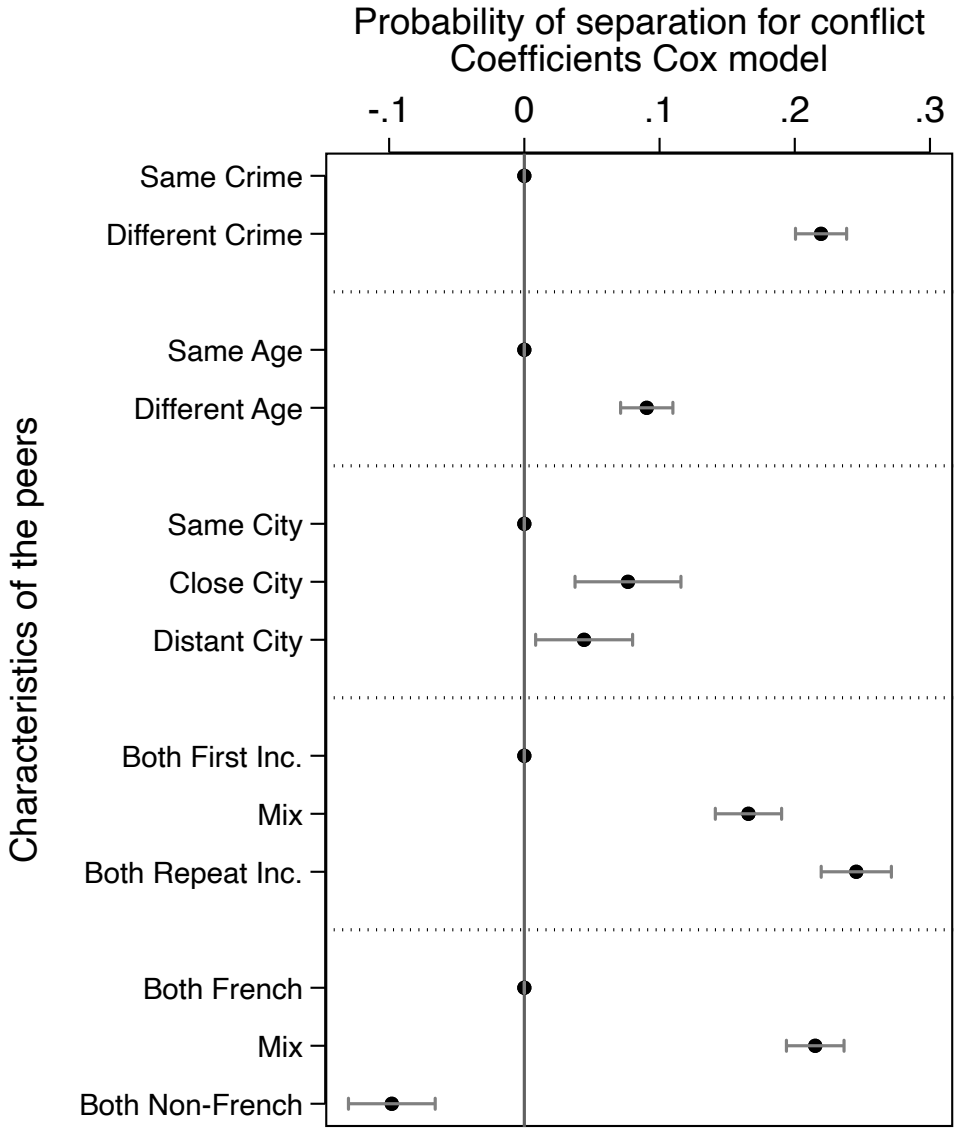
Notes: This figure presents estimates from a Cox proportional-hazard model of the effect of peer composition on the probability of being separated from a cellmate because of a conflict. Each row compares dyads in which both, neither, or only one cellmate exhibits a given characteristic, including mental-health problems, substance addiction, smoking, indigence, parenthood, educational attainment, and literacy. The dimensions presented in Figure 7 — differences in crime type, age, city, past incarceration, nationality — are also included in the model but not presented on the Figure. Each point represents the estimated hazard of conflict relative to the omitted category. All models include prison fixed effects, and control for age at entry of the peers.

Figure E.2: Peer composition and conflicts in cells: overcrowded jails



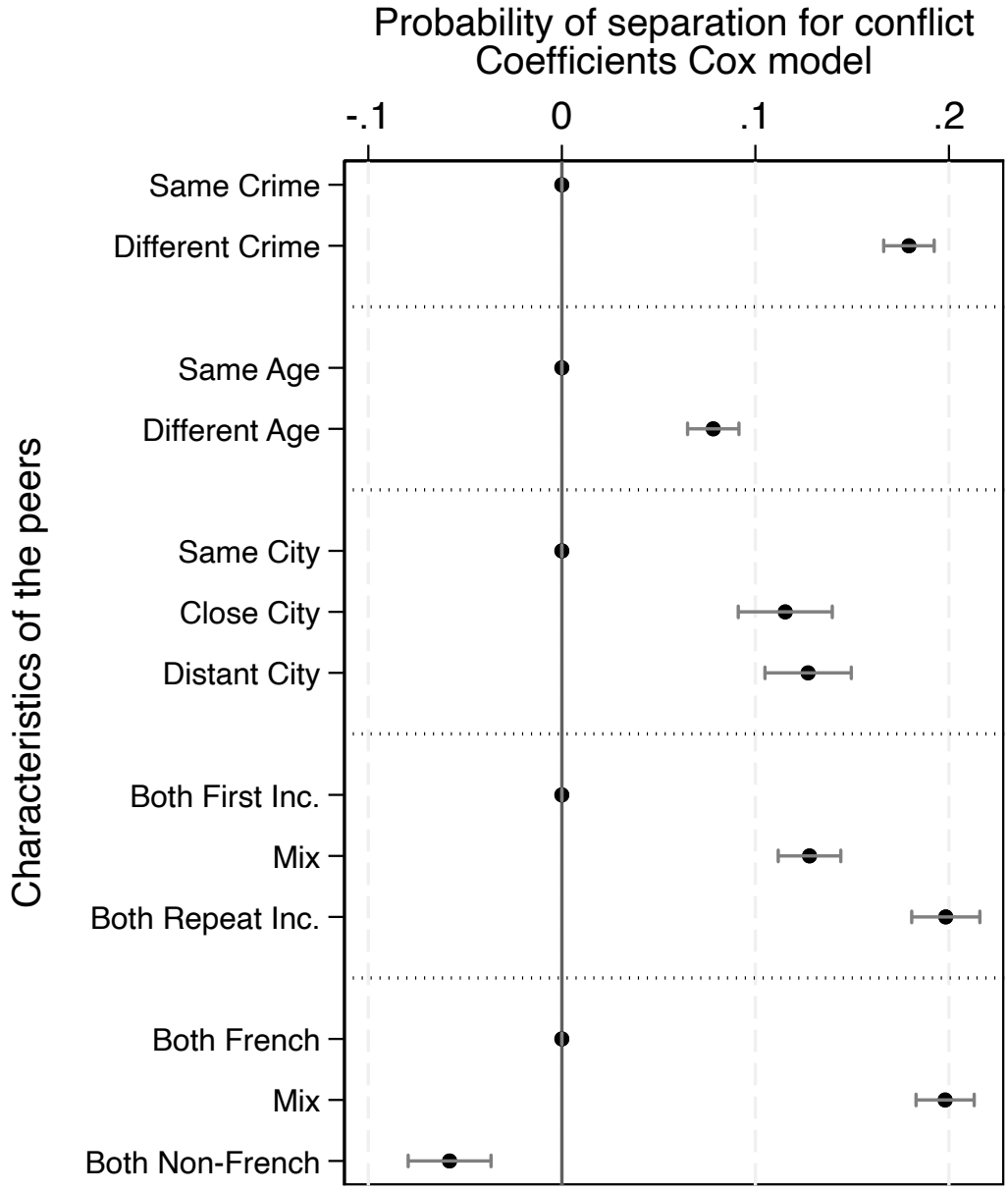
Notes: This Figure presents estimates of the effects of peer characteristics on conflicts in cells for people who are housed in overcrowded jails, using a Cox proportional hazard model (Equation 3). We define peers as being close in age if the age difference is less than 5 years; different in age if they are at least 5 years apart. "Same city" means that peers lived in the same city before incarceration; "close city" refers to peers from a different city located within 30 km; and "distant city" refers to peers from a city more than 30 km away. We control for prison, and age at entry of the peers Bars represent the 95% confidence intervals.

Figure E.3: Peer composition and conflicts in cells: first cohabitation for at least one of the cellmates



Notes: This Figure presents estimates of the effects on conflicts in jail of peer characteristics on conflicts in cells, for pairs in which at least one cellmate is in the first four weeks of his incarceration, using a Cox proportional hazard model (Equation 3). We define peers as being close in age if the age difference is less than 5 years; different in age if they are at least 5 years apart. "Same city" means that peers lived in the same city before incarceration; "close city" refers to peers from a different city located within 30 km; and "distant city" refers to peers from a city more than 30 km away. We control for prison and age at entry of the peers. Bars represent the 95% confidence intervals.

Figure E.4: Peer composition and conflicts in cells, jail only.



Notes: This Figure presents estimates of the effects on conflicts in jail of peer characteristics on conflicts in cells for people whose full incarceration spell was in a jail, using a Cox proportional hazard model (Equation 3). We define peers as being close in age if the age difference is less than 5 years; different in age if they are at least 5 years apart. "Same city" means that peers lived in the same city before incarceration; "close city" refers to peers from a different city located within 30 km; and "distant city" refers to peers from a city more than 30 km away. We control for prison and age at entry of the peers. Bars represent the 95% confidence intervals.

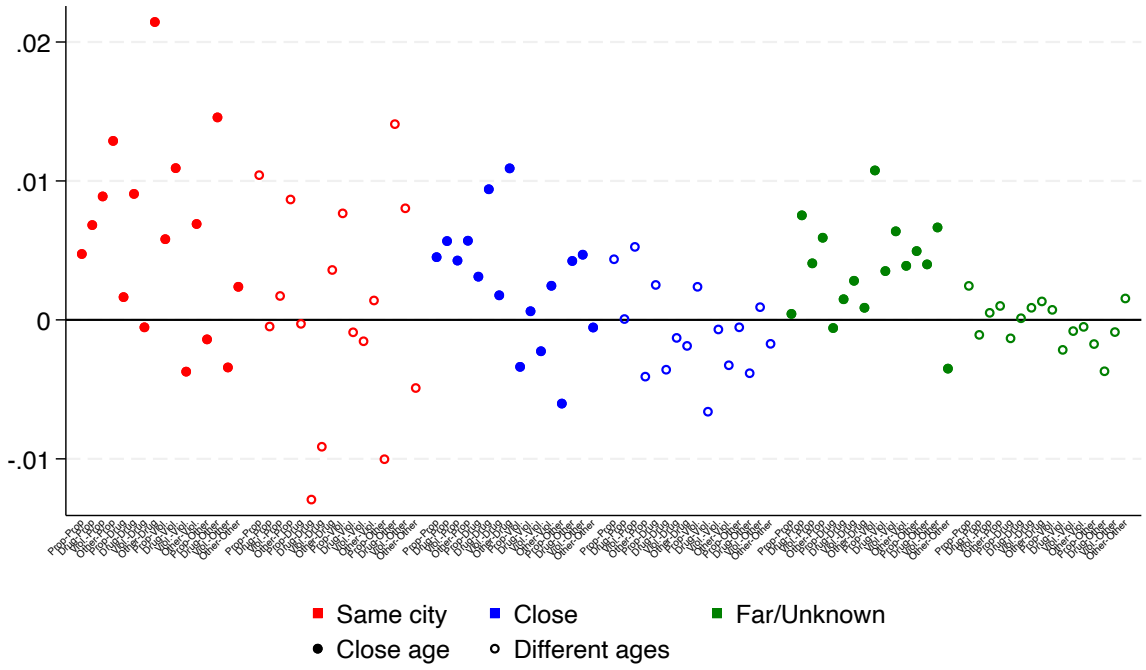
F Additional figures and tables: policy simulations

Table F.1: Peer effects in prison: mechanisms and empirical predictions

Mechanisms	Empirical prediction for recidivism		Conflicting policy recommendations?
	Crime type and place	Who is more influential?	
Social contagion	Non income-generating No displacement	None in particular	Ambiguous
Skill transfer	Income-generating No displacement	Older / experienced peers	No
Network	Income-generating Crime in peer location	Similar peers	Yes

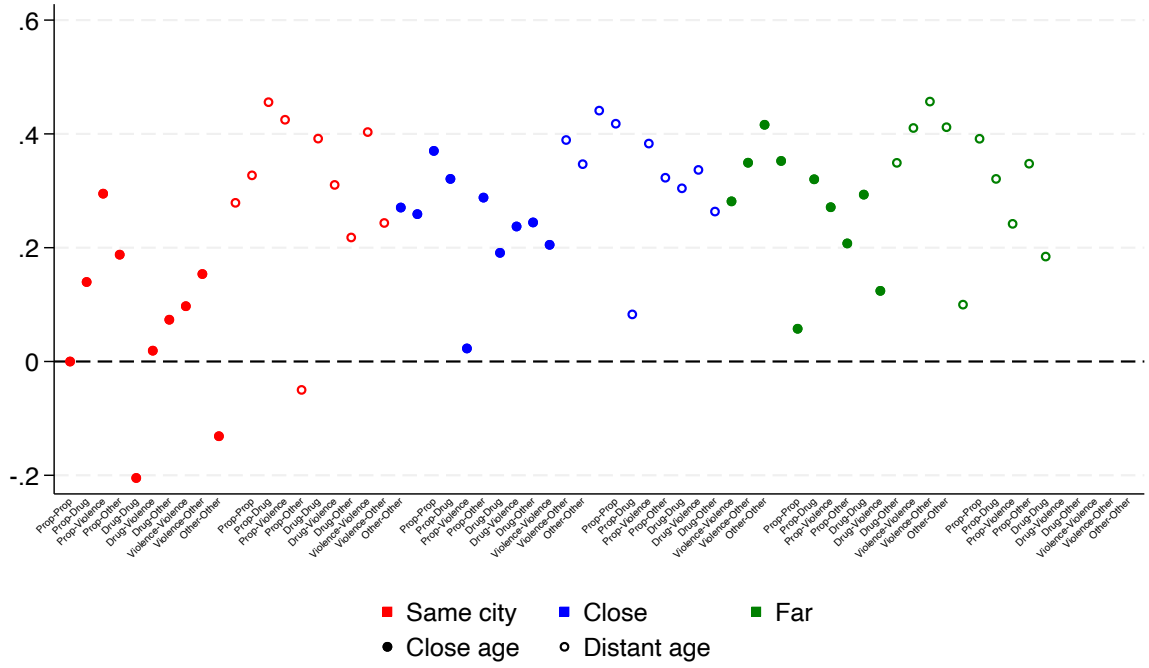
Notes: This table summarizes the main theoretical channels through which peers may affect post-release recidivism, as well as the empirical predictions each mechanism generates for crime type, crime location, and the relative influence of different peers. The final column indicates whether the mechanism would lead to conflicting policy recommendations – particularly regarding whether mixing inmates with similar backgrounds is beneficial or harmful. This conceptual tables aims to clarify how different peer mechanisms map into potentially observable patterns.

Figure F.1: Effect of the number of cellmates of different types on reincarceration



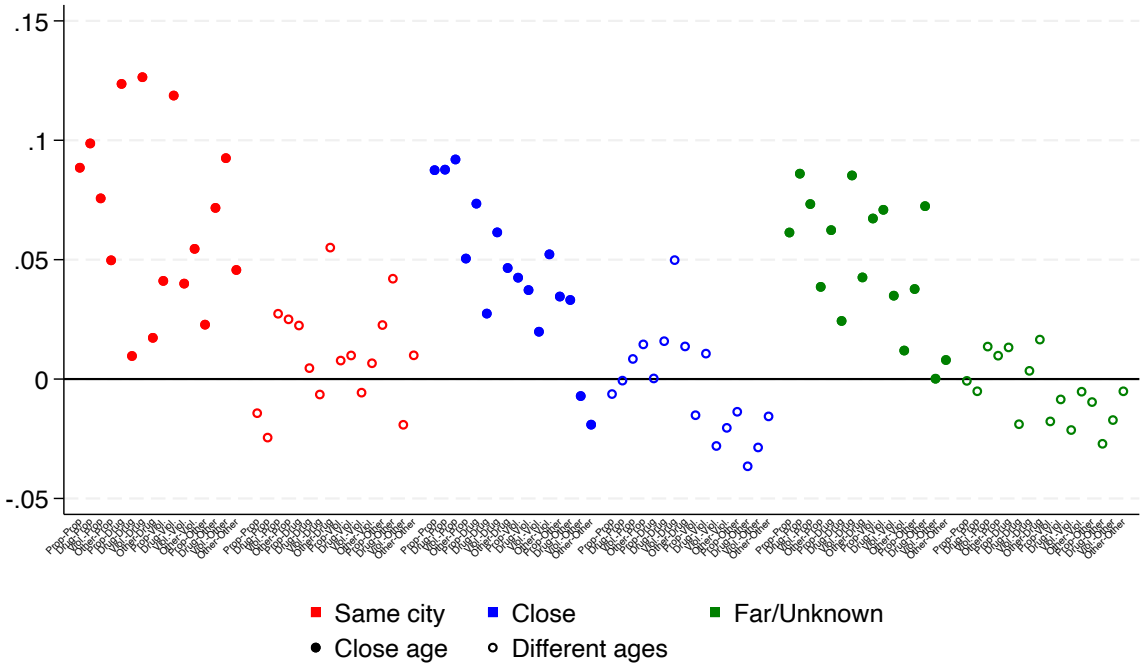
Notes: The figure presents the effect of inmates' characteristics on reincarceration for any crime. Three dimensions are combined: crime types, indicated in the x-labels — for example, property-drug gives the effect of having an additional cellmates convicted for drug criminals on offenders convicted of a property crime —, geographical distance, indicated with colours — the effect of cellmates coming from same, close, or distant cities are indicated in red, blue and green, respectively —, and age difference — the effects of cellmates of the same age are indicated with full dots, while the effects of cellmates of different age are indicated with empty dots.

Figure F.2: Peer composition and conflicts in cells.



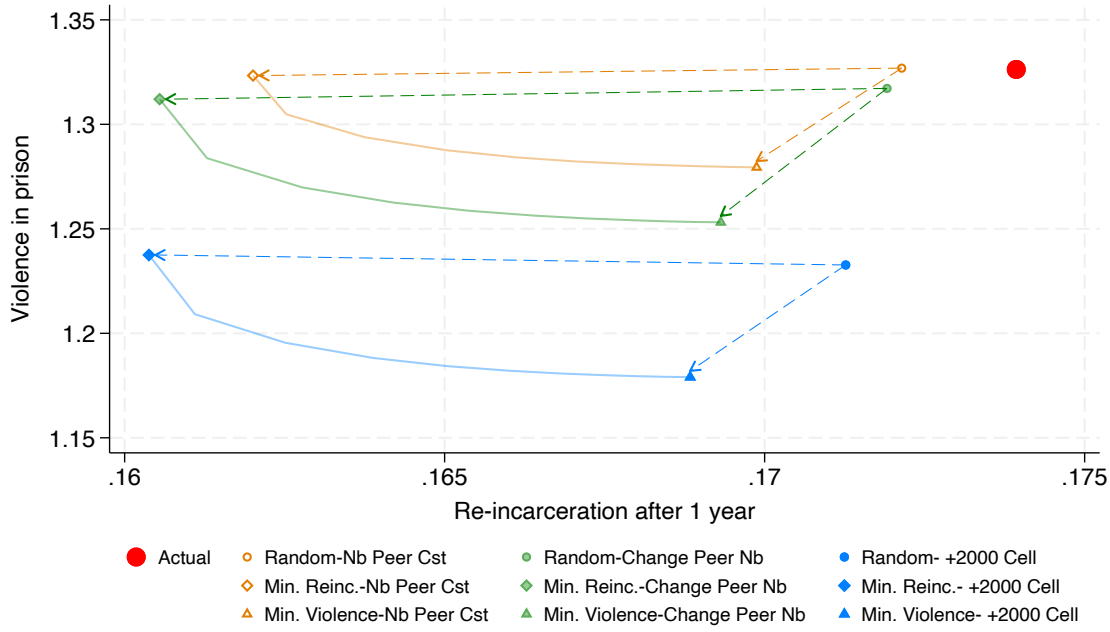
Notes: The figure presents the coefficients extracted from a Cox duration model. The dimension of interest is the time before a conflict occurs. Separations of the cellmates for other reasons are treated as right-censorship. Coefficients capture the effect of the characteristics of the inmates. Labels on the x-axis indicate the crime types, for example, property-property when both inmates are incarcerated for a property crime (Note that, in this exercise, effects are symmetrical and there is no difference between Property-Drug and Drug-Property, which explains why only one exists in the labels). The effect of groups coming from the same city, close cities, or distant cities, are indicated in red, blue, and green respectively. The coefficients of the effect of groups being of similar age or distant age are presented with plain dots or empty dots. Cellmates who are both property criminals, who are coming from the same city, and who are of similar age are taken as reference. Coefficients indicate the difference with them.

Figure F.3: Peer composition and facility-wide misconduct.



Notes: The figure presents the effect of inmates' characteristics on the number of sanctioned facility-wide misconduct. Three dimensions are combined: crime types, indicated in the x-labels — for example, property-drug gives the effect of having an additional cellmates convicted for drug criminals on offenders convicted of a property crime —, geographical distance, indicated with colors — the effect of cellmates coming from same, close, or distant cities are indicated in red, blue and green, respectively —, and age difference — the effects of cellmates of the same age are indicated with full dots, while the effects of cellmates of different age are indicated with empty dots.

Figure F.4: Changing cell composition: policy simulations accounting for both in-cell conflicts and violence against other inmates or correctional officers.



Notes: This Figure presents the estimated reincarceration rates (x-axis) and estimated number of violent incidents in jail (y-axis) observed in our data and under different policy simulations. "Violent incidents in jail" are defined as either separations due to conflicts, or disciplinary incidents for violence against a correctional officer or another inmate. The red dot shows the current reincarceration rate and number of incidents in prison. The full dots correspond to a random reshuffling of people, while the hollow dots show optimized allocations that either minimize recidivism (diamonds) or minimize conflicts and violence (triangles). The orange dots keep the number of peers constant. The green dots change the number of peers that a person interacts with. The blue dots represent a counterfactual with 2,000 additional available cells,.