Who You Serve Time With: Peer Effects and Recidivism*

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Abstract

I provide empirical evidence on how inmate allocation within prisons influences post-release criminal behavior in Chile. Employing a sharp regression discontinuity design, I show that first-time offenders placed with peers who are more actively involved in criminal activities are almost twice as likely to be re-incarcerated after release. The specific Chilean context allows me to rule out job market stigma and prison infrastructure as significant factors explaining the allocation effect. I provide evidence suggesting that the primary findings are most likely driven by peer effects. In addition, I present novel evidence showing that peers also influence the decision to participate in rehabilitation programs. Furthermore, peer effects appear to be more substantial among individuals with higher criminal profiles. This finding implies that mixing inmates with diverse criminal profiles may be a potential strategy to reduce overall recidivism. These results carry significant implications for policymakers and stakeholders striving to lower recidivism rates via improved strategies in prison allocation.

Keywords: prison allocation, recidivism, peer effects, rehabilitation, regression discontinuity design

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1 Introduction

International incarceration rates are concerning. According to 2020 figures, there were approximately 11 million inmates around the world (Tobón 2020). In the United States alone, the decade spanning 2010 to 2020 witnessed an incarceration rate of 865 per 100,000 individuals, and a concerning 68% recidivism rate within three years post-release (Alper 2018). Similarly, in Chile, the prison population has increased by 73% from 2000 to 2020, with a high recidivism rate of 50% within two years of release from prison.[1][2] These figures underscore the urgency for policymakers to better understand incarceration's effects and develop strategies to mitigate adverse post-release outcomes.

The literature on incarceration's effects on recidivism offers mixed findings. Some studies suggest that harsher sentences can reduce recidivism (Hjalmarsson 2009; Loeffler et al. 2015; Estelle and Phillips 2018; Franco et al. 2018; Rose and Shem-Tov 2021), while others argue that incarceration has little to no effect or even increases the likelihood of reoffending (Rose and Shem-Tov 2021; Green and Winik 2010; Mueller-Smith 2015; Nagin and Snodgrass 2013; Cortés, Grau Veloso, and Rivera Cayupi 2019). Additionally, alternative sentencing options have been found to be more effective in lowering recidivism rates (Mastrobuoni and Terlizzese 2022).

Correctional facilities may influence recidivism through multiple channels. Incarceration could discourage reoffending by deterring criminal behavior, but it can also limit job prospects (Bhuller et al. 2020), disrupt social and human capital formation (Aizer and Doyle 2013), and foster criminal networks (Mastrobuoni and Rialland 2020; Jaramillo Calderon 2024; Sviatschi 2022). These mixed results highlight the need to investigate specific mechanisms, such as inmate allocation and peer interactions.

This study investigates the effects of inmate allocation based on their estimated criminality levels in Chilean facilities. Upon arrival, inmates undergo an assessment that generates a score measuring their proximity to the criminal subculture. This score is then used to assign inmates to specific sections within the same facility, based on the inmates' estimated levels of criminality. The primary objective of this approach is to minimize interactions between prisoners with different criminal backgrounds, aiming to reduce the reproduction of criminal behavior, prevent social maladjustment and conflicts, and enhance internal security.[3] The unique environment of this policy implementation offers a quasi-experimental opportunity

[1] Gendarmería de Chile. (2018). Informe de análisis estadísticos de la tasa de reincidencia delictual móvil de los egresados del subsistema cerrado en los años 2014 y 2015. https://html.gendarmeria.gob.cl/doc/reinsercion/INFORME_TASA_REINCIDENCIA_MOVIL_SC2014-2015(NOV2018).pdf

[2] It is consistent with previous analyses estimating rates between 50%-70% depending on the post-release time frame examined.

[3] Technical Document on Penitentiary Classification and Segmentation.

to explore the impacts of such inmate allocation on post-incarceration outcomes. I use a regression discontinuity design to examine the impact on recidivism when first-timer inmates are placed in sections with peers who exhibit a higher criminal profile.

My findings indicate that placing an first-time offender in a section with more criminally active individuals significantly increases their chances of reoffending. Specifically, this allocation raises the likelihood of recidivism by about 14 percentage points, doubling the average reoffending rate observed in the low-criminality group. The Chilean context allows me to rule out job market stigma and facility characteristics as primary drivers of this allocation effect, suggesting peer effects as the most plausible explanation.

To estimate peer effects, I utilize a detailed dataset from private prisons. My findings indicate that a one-standard-deviation increase in the peer score used for inmate classification increases recidivism probability by approximately 4.4 percentage points. These results suggest that direct peer effects contribute significantly to the overall allocation effect. I also find evidence of nonlinear peer effects, with stronger impacts observed among individuals with higher criminal profiles. Furthermore, peers influence both the likelihood of exhibiting good behavior and the decision to participate in rehabilitation programs. These findings are significant, as evidence suggests that rehabilitation programs can reduce recidivism (Alsan et al. 2024).

In analyzing the heterogeneous effects of allocation, I examine key variables such as incarceration duration and experience in skill-intensive crimes like robbery and theft. My results show that individuals with longer incarceration durations and a history of skill-intensive crimes exhibit a stronger allocation effect.

This paper makes several contributions to the literature. First, it adds to the literature on prison characteristics and recidivism (Berk and Leeuw 1999; Chen and Shapiro 2007; Tobón 2020). For instance, Chen and Shapiro 2007 find that placement in prisons with harsher conditions increases recidivism but are unable to disentangle the effects of prison characteristics from those of peer composition. This paper addresses that gap by isolating the impact of peer composition, offering clear evidence of its influence within correctional facilities.

Secondly, this paper contributes to the literature on peer effects and network formation within prisons. Previous studies highlight crime-specific peer effects (Bayer, Hjalmarsson, and Pozen 2009; Damm and Gorinas 2020; Tan and Zapryanova 2021), peer effects using different identification strategies (Ouss 2011; Stevenson 2017; Philippe 2024; Johnsen and Khoury 2024), and network dynamics (Sviatschi 2022), although some report limited evidence (Harris, Nakamura, and Bucklen 2018). I show that peer composition significantly influences recidivism, with nonlinear effects disproportionately impacting higher-criminality individuals. These findings suggest that mixing inmates with varying criminal profiles could be a cost-effective strategy to reduce recidivism.

Third, this paper contributes to the literature on the effectiveness of rehabilitation programs. While previous studies have examined this topic (Northcutt Bohmert and Duwe 2012; Gomez and Grau 2017; Lee 2017; Bhuller et al. 2020; Arbour, Lacroix, and Marchand 2021; Alsan et al. 2024), none have specifically analyzed how peer influence shapes participation decisions. I provide new evidence that peer composition significantly impacts inmates' engagement in rehabilitation programs, highlighting the need to consider this factor in program design.

Finally, to the best of my knowledge, this is the first study to analyze the effects of prisoner allocation in a middle-income context, providing novel insights into peer dynamics within correctional facilities.

This paper is organized as follows. In Section 2 the Chilean background, Section 3 describes data, Section 4 the empirical approach, Section 5 the main results, Section 6 potential channels and Section 7 conclusion.

2 Background

2.1 Chilean system

Chile, a middle-income country, utilizes a mixed prison system that comprises both public and private prisons, as well as two types of convictions: the free-system and closed-system. Free-system involves non-custodial sentences, whereas closed-system involves imprisonment. The regulatory oversight of both private and public prisons in Chile is carried out by Gendarmería de Chile (GENCHI), a public institution responsible for formulating and enforcing prison-related procedures and protocols.

This study is based on the Chilean offender classification system after 2007. In 2007, GENCHI developed and implemented a detailed manual for the classification and segmentation of prisoners within its facilities. This initiative aims to reduce internal conflicts and prevent criminological contagion among inmates (Sanhueza, Ortúzar, and Valenzuela 2015; BID 2013).

Upon arrival at the prison, a specialist team comprising psychologists, sociologists, and high-ranking military personnel[4] conducts an interview with the convict within 72 hours. The interview assesses the convict's criminal history, reference groups, level of preparation,

[4]The National Classification Office (Oficina Nacional de Clasificación de Gendarmería) provides training to specialists, who are psychologists, sociologists, and high-ranking military personnel, to conduct interviews.

and appearance, resulting in a score that measures the degree of internalization of patterns typical of the "prison subculture."

The final score in the prisoner classification system by the GENCHI does not account for the type of crime or the length of the sentence. For example, even if two individuals committed similar crimes and received similar sentences, the level of criminal involvement of one may be higher due to factors such as a history of criminal activity, association with criminal groups, or if it has any physical marks related to criminal activity. This results in a higher score assigned to the more criminally involved individual during the classification process and a different allocation inside the facility.

Upon receiving a sentence, the GENCHI assigns the convicted person to a facility, with the decision typically based on availability and proximity. However, the classification and segmentation manual determines the allocation of prisoners within the facility.

GENCHI employs various forms of segmentation beyond criminal involvement, as noted in this study. Older prisoners are typically assigned to blocks with lower levels of criminal involvement to minimize the risk of physical harm, while rapists may be placed in separate blocks. Additionally, those with different sexual orientations or who are HIV-positive may be assigned to different facilities based on availability. While my data does not permit the identification of individuals with HIV or a different sexual orientation, it is worth noting that the HIV-positive population constituted less than 2% of the total prison population in Chile in 2008.[5]

2.2 Score

Table 1 presents the 13 variables used to construct the score for male and female prisoners, each assigned a score between 1 and 5.[6] GENCHI assigns weights to each variable in its classification system to derive a final score that ranges from 34.2 to 171. This score is then utilized to classify prisoners into one of three distinct categories. Table 2 shows the cutoffs and categories, with scores below 80 indicating "low criminal involvement," scores between 80 and 125.5 indicating "medium criminal involvement," and scores above 125.5 indicating "high criminal involvement." It is worth noting that these cutoffs were chosen based on the even division of the total score and not any specific belief that a change occurs at those specific values. The classification into these categories determines the distribution of prisoners within the facility, with inmates assigned to different blocks according to their

[5] El Mostrador. (2008, December 10). El Sida y la cárcel en el día de los DD.HH. Pamela Donoso. https://www.elmostrador.cl/noticias/opinion/2008/12/10/el-sida-y-la-carcel-en-el-dia-de-los-dd-hh/

[6] See Appendix 9.11 for details on each variable.

category.

Table 1: Score components.

Type	Definition	Male	Female
Drugs	Frequency of drug consumption.	x	x
Crimes as a child	Crime, drug use, petty crime, etc.	x	x
Age of first crime	Some ranges.	x	x
Previous sentences	Type of sentences.	x	x
Belong to organized criminal group.	Type of relationship.	x	x
Guns	Type of gun used during the crime.	x	
Family criminal records	If family have a criminal record.	x	
Criminal continuity	Number of crimes in the last two years.	x	x
Language	Frequency and understanding of criminal language.	x	x
Physical marks	Scars, bullet scars, band tattoos, etc.	x	x
Goals and planning for life	Education, concrete work goals, etc.	x	x
Family relationships	Economic contribution, childcare.		x
Couple and groups of friends	Couple and groups of friends with criminal records.	x	x
Leisure time	If they spend their free time in places with a criminal environment.	x	x

Notes: This table displays the variables included in the final score calculation, with availability indicated by an "x" for each gender. For male inmates, the score consists of 13 variables, while for female inmates, it includes 12.

Table 2: Classification and assignment of inmates.

Type	Range
Low criminal involvement	34.2-79.9
Medium criminal involvement	80-125.5
High criminal involvement	125.6-171

Note: The scoring system is structured so that higher values indicate greater criminal involvement. The cutoff points, set at 80 and 125.6, were chosen to ensure balanced distribution across categories.

2.3 Chilean criminal records

The Chilean criminal history certificate, utilized for accessing an individual's criminal record, omits details about the specific prison or block of assignment. As depicted in Picture 6 in Appendix 9.1, the certificate merely distinguishes between a prison sentence and an alternative non-prison sentence.

This omission is critical for interpreting the findings of this study. In many contexts, criminal history records can contribute to job market stigma (Sherrard 2020; Agan and Starr 2018; Doleac and Hansen 2020), particularly if they reveal specific details that imply higher levels of criminality or recidivism risk. Such stigma can increase the likelihood of reoffending, as unemployed ex-convicts may face significant barriers to reintegration. However, the lack of information about block assignments on the Chilean criminal history certificate makes it unlikely that any stigma associated with such assignments affects post-release outcomes. This ensures that the observed effects in this study are not confounded by external perceptions tied to block placement, allowing a clearer focus on the role of peer composition within the prison environment.

2.4 Facilities and amenities

The facilities and amenities could play a crucial role in future criminal behavior (Tobón 2020; Chen and Shapiro 2007). However, this hypothesis is unlikely to be a significant factor, given the unique setup in the Chilean case. In this context, the infrastructure of the blocks is similar within facilities, and prisoners have right to the same benefits, regardless their category. Such benefits encompass the type of food, number of visits, and time spent outside the cells, which provide opportunities for prisoners to interact with more people, are also similar across different blocks, except in cases where dangerous individuals are isolated from the general population.[7]

This setup contrasts with the findings of Chen and Shapiro (2007), where differences in allocation between prisons made it difficult to disentangle the impact of peer effects from facility-level differences. In their context, factors such as varying numbers of visitors and unequal opportunities for inmates to be outside their cells could have contributed to differences in outcomes. By contrast, the Chilean system's uniform infrastructure and benefits provide a more controlled environment, strengthening the validity of the peer effects identified in this study.

3 Data

This study utilizes two databases provided by GENCHI. The primary focus is to analyze the recidivism rates of first-time adult male prisoners who released between 2007 and 2010. The research aims to determine if these individuals re-entered prison within a three-year period following their initial release. I restrict the data to this period due to changes in score classification in 2007.[8] To isolate the effect of prior convictions within the facility, the study focuses on individuals entering an adult facility for the first time. I restrict the analysis to the specific types of crimes (see Appendix 9.14) since some types of crime do not follow this allocation process. The crimes under consideration account for approximately 57% of the

[7]This type of convicts are not considered in this work.

[8]This study is based on first-time prisoners affected by the Chilean offender classification system after 2007. Previously, the classification system only classified offenders based on their level of criminal involvement, while the 2007 classification included additional factors such as gender, leading to a more nuanced categorization. The previous classification used fewer variables, but the score still ranges from 34.2 to 171. This study does not analyze the impact of these changes on the scoring system, an area that merits further investigation.

total spectrum of criminal offenses. Individuals convicted of fines, non-payment of alimony, and drunk driving, among others, are not included in the analysis. Due to the limited number of first-timer individuals classified as high criminal involvement, and evidence of manipulation near the cutoff, this study focuses only on individuals with low and medium criminal involvement (see Appendix 9.8). Finally, I consider a minimum stay of three weeks in prison to account for the possibility of social interaction effects. Still, similar results are obtained using two weeks as minimum stays (see Appendix 9.5).

The initial sample consists of 2,599 individuals and is gradually reduced by applying the restrictions outlined above: limiting age to 18–60 years reduces the sample to 2,558; applying the first cutoff further reduces it to 2,173; and requiring a minimum stay of three weeks results in a final sample of 1,887 individuals. A summary of the main variables is presented in Table 3. This sample predominantly comprises short-term sentences, aligning with the general trend in Chilean incarcerations. According to Morales et al. (2012), in 2007, 59% of released inmates served less than a year, 74.3% less than three years, and 88% less than five years.

Table 3 summarizes the main characteristics of the individuals in the target population. The first and second columns show the means for the low and medium criminal involvement groups, respectively, while the last column reports the means for the entire target population. Most inmates in the sample are Chilean, with foreigners representing only 9.2% of the total. The average age of the individuals in the different groups ranges from 25 to 32 years old. The years of education of the prisoners are generally low. Theft and robbery are the most frequent crimes committed in the sample, with the latter being more prevalent. The average month in the facility for the different groups is 12 and 16 months, which is consistent with official statistics indicating short periods of incarceration in Chile. The data set also includes facility name and region, individual's pre-imprisonment residence, score components used for classification, and sentence information.

The primary dataset used to estimate the main result unfortunately lacks detailed information on specific block assignments within the correctional facilities. Therefore, I use the allocation rule to determine the potential assignment based on the score. That is why, in Section 6, I use a secondary data source to test potential channels such as peer effects. My second data set includes all prisoners who left private prisons between 2009 and 2012, regardless of the year of entry.

The second database, while containing the same variables as the main one, additionally provides details on inmates' participation in educational, work, and training programs. It also includes information on benefits like Sunday outings, weekend outings, and controlled outings to the outside environment. On average, 36.15% of inmates participated in educa-

Table 3: Summary statistics

	Low	Medium	Total
Chilean	0.865	0.982	0.908
	(0.342)	(0.135)	(0.289)
Years of Education	9.412	8.830	9.195
	(3.358)	(2.859)	(3.193)
Score	60.763	96.953	74.246
	(11.092)	(12.690)	(21.058)
Recidivism rate	0.104	0.407	0.217
	(0.305)	(0.492)	(0.412)
Single	0.593	0.791	0.667
	(0.492)	(0.407)	(0.472)
Months in facility	12.429	16.862	14.081
	(14.072)	(19.270)	(16.341)
Age	32.881	25.855	30.263
	(10.441)	(7.250)	(9.975)
Private prison	0.247	0.280	0.260
	(0.432)	(0.449)	(0.439)
Robbery	0.264	0.528	0.362
	(0.441)	(0.500)	(0.481)
Theft	0.158	0.219	0.181
	(0.365)	(0.414)	(0.385)
Injury	0.133	0.044	0.100
	(0.339)	(0.205)	(0.300)
Receiving	0.061	0.105	0.077
	(0.239)	(0.307)	(0.267)
Homicide	0.103	0.050	0.083
	(0.304)	(0.218)	(0.276)
Drug-trafficking	0.234	0.115	0.190
	(0.424)	(0.320)	(0.392)
Others crimes	0.123	0.077	0.106
	(0.329)	(0.266)	(0.308)
Catholic	0.592	0.452	0.540
	(0.492)	(0.498)	(0.499)
Observations	1,184	703	1,887

Note: The table provides summary statistics for the primary variables used in the analysis. The unit of observation is at the individual level. The first column reports the mean and standard deviation (in parentheses) for first-time offenders potentially assigned to the low-level group based on their initial scores. The second column presents the same statistics for those assigned to medium-level blocks, while the third column aggregates these statistics for the full sample under study.

tional programs, 35.51% worked, and 6.40% received some type of benefit. Additionally, it contains the specific block allocation (dependencia in Spanish). This dataset encompasses 10,393 individuals, 2,246 of whom are first-time adult prison entrants. Although I observe positive assortative matching between individual scores and peer scores in the private prison (see 39), these facilities did not strictly follow the cutoff rule during this period. Therefore, I restrict the use of the second dataset to estimating peer effects rather than the allocation effect. Previous research by BID (2013) found no significant difference in the effect of public or private prisons on future recidivism rates in Chile. Although private prisons in Chile follow the same national rules established by GENCHI and are supervised by the institution, the study found a higher proportion of inmates with slightly higher levels of criminal involvement during the analyzed years. In addition, private prisons use the same rehabilitation programs as public prisons, based on the *pro-social* competence model. This model provides opportunities for low, medium, and high criminal-risk prisoners to participate in programs to reduce future recidivism rates (BID 2013).

My second dataset also indicates that the time individuals spend in the facility is relatively short. It reveals that 90% of these individuals served sentences of up to three years, and 75% were incarcerated for 15 months or less. These statistics are consistent with the findings from the primary dataset.

4 Empirical framework

4.1 Empirical strategy

This study employs a sharp regression discontinuity design to estimate the effects of block allocation on recidivism. I use the sharp cutoff score used in determining the allocation of inmates to different blocks. Those who receive a score lower than 80 are allocated to the low-criminal involvement block, while offenders with a score higher than 80 are allocated to medium involvement blocks. I use a standard regression model for regression discontinuity design, which is specified as follows:

$$Recidivism_{ibf} = \alpha + \beta_1 Medium_{ibf} + g(score_{if}) + g(score_{if}) * Medium_{ibf} + \delta_f + \omega_{ibf}. \quad (1)$$

Equation (1) specifies the relationship between recidivism and allocation. The dependent variable, $Recidivism_{ibf}$ indicates whether an individual i has returned to prison within three years of release, and equal to zero if he does not re-enter prison.[9] The variable $Medium_{ib}$ is

[9]Note that this is a measure that is a lower bound for recidivism, since the person could re-offend and not be caught by the police.

an indicator of the individual i that should be allocated in the medium-criminal involvement block according to the score, or zero otherwise ($Medium_{ibf} = 1\{score_i >= 80\}$). It means, $Medium_{ibf}$ is an indicator that the individual i is in a block b, in the facility f, with offenders with higher average scores, $sc\bar{o}re_{-ibf}$. The expression $g(score_{if})$, is a flexible function of the offender's score. The relationship between recidivism and score may be flexible and can vary across different types of blocks. Finally, δ_f represents a fixed effect associated with each facility. In the model, α is the intercept, and β_1 is the treatment effect of being allocated to the medium-criminal involvement block. The interaction term $g(score_{if}) * Medium_{ibf}$ allows the effect of the score on recidivism to differ between the two types of blocks. While the model does not include any baseline covariates, robustness checks incorporate these variables to ensure that the results are not driven by omitted variables in the main regression. Furthermore, for a comprehensive understanding, Appendix 9.4 presents the findings from the model when facility fixed effects are excluded.

A limitation of the primary dataset is its lack of specific block allocation information for each individual. To address this, I assign the potential allocation for each individual based on their calculated score, given that the exact allocation details are not directly observable. Consequently, the findings of this study should be interpreted as an intent-to-treat (ITT) effect. I estimate the ITT effect, providing an unbiased estimate of the treatment effect for those assigned to blocks near criminal activity. Note that the ITT effect may be different from the average treatment effect, particularly if the compliance with the treatment assignment is not perfect.

I estimate a local linear and quadratic regression discontinuity design with a triangular kernel as the chosen specification for the results. In Appendix 9.10, I present various results using other polynomials for the entire target sample. The optimal bandwidths in this study were selected using the mean squared error (MSE) optimal bandwidth selector, as recommended by Cattaneo, Idrobo, and Titiunik (2019). These bandwidths were then adjusted based on the polynomial used and the inclusion of covariates. The choice of a local linear and quadratic design aligns with recent literature on regression discontinuity, as discussed by Gelman and Imbens 2019 and Cattaneo, Idrobo, and Titiunik 2019.

4.2 Testing for manipulation

As an initial step in the estimation process, I conduct an analysis to determine if there is any evidence of sorting around the cutoff based on observable characteristics. This approach follows the methodology employed by Tuttle (2019). Using all the individuals outside the optimal bandwidth, I estimate the risk of recidivism for each inmate by running a logistic regression on all the observable characteristics. Then, predict a *risk score* for each individual, including the people inside the optimal bandwidth. If the identification assumption is violated, we should expect a discontinuity in the predicted risk score at the cutoff. This would imply that any observed discontinuity in the cutoff is a result of a change in the characteristics of the individuals at the cutoff. The results are presented in Figure 1 (and Table 12 in Appendix). Based on the analysis, there is no evidence of sorting around the cutoff on observable characteristics.[10]

When evaluating the validity of the score as a block allocator, it is important to take into account the potential for manipulation by specialists or offenders. Although specialists are trained to conduct the interviews, intentional manipulation of the score to assign offenders to a specific block is still possible. To address this concern, I conducted a McCrary density test (McCrary 2008) to analyze the number of offenders on both sides of the discontinuity. This test examines the null hypothesis that there is no difference in the density of treated and control observations at the cutoff. The results of the test, shown in Figure 2, indicate that there is no evidence of manipulation near the cutoff, as I cannot reject the null hypothesis with a p-value of 0.52. Thus, the evidence suggests that specialists and offenders are not manipulating the score to assign offenders to a specific block.

To ensure empirical rigor, Section 5.3 presents robustness check by incorporating covariates and fixed effects associated with the time of release in the primary regression analysis. Additionally, I test for potential discontinuities in observable characteristics at the designated cutoff point. This examination covered a broad spectrum of variables, embracing a wide range of demographic characteristics, various types of crimes, and the detailed individual elements that form the scoring metric. Such comprehensive analysis is essential for validating the empirical strategy.

[10] To estimate the jump at the cutoff, I use the predicted values and the score. The result is an estimated jump of 0.0079 with a p-value of 0.51, indicating that there is no evidence of sorting related to the observed characteristics.

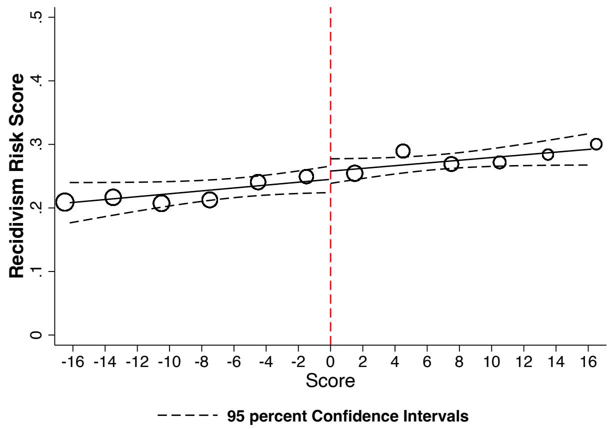

Figure 1: Risk score

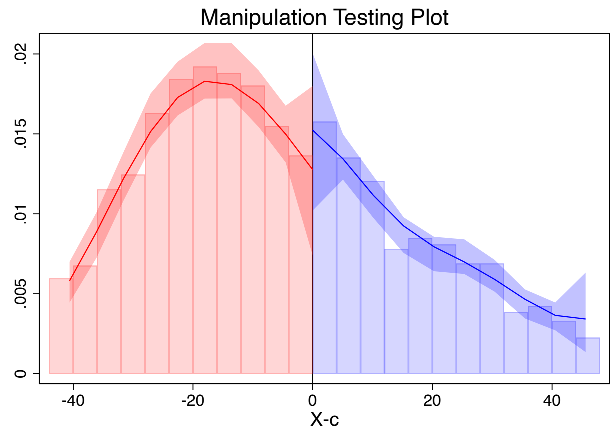

Figure 2: McCrary density test

Note: Figure 1 illustrates the predicted risk score, which represents the component of recidivism explained by pre-treatment characteristics. The figure indicates no discontinuity at the cutoff. Similarly, Figure 2 presents the results of the McCrary density test, which evaluates potential manipulation around the cutoff. The results show no evidence of a discontinuity in the density at the cutoff.

5 Results

5.1 Main results

I estimate the likelihood of re-entering any facility within three years post-release as outlined in Equation (1), presenting the primary results in Table 4. The optimal bandwidth for these regressions, selected based on the mean squared error, is 11.52 for first-degree polynomial and 20.41 for second-degree polynomial.[11] Standard errors are clustered at the facility level to address within-prison error correlation.

The analysis indicates that assignment to a block with peers more involved in criminal activities elevates the recidivism probability by around 13.7 percentage points. Considering the baseline recidivism rate of first-timers is 14% on the lower side of the bandwidth, this represents a substantial relative increase of approximately 100%. However, the wide confidence intervals, such as the 95% interval for the first-degree polynomial ranging from 2 to 25.7 percentage points, suggest caution in interpreting the magnitude of these results, likely due to the small sample size near the cutoff.

Additionally, I conduct a parallel regression analysis, substituting the dependent variable with the probability of re-entry within a two-year time-frame post-release and I find similar results. These findings are detailed in Appendix 9.3.

The empirical outcomes are graphically depicted in Figures 3 and 4. The graphs provide

[11] Note that the optimal bandwidth selector is the mean squared error.

Table 4: Sharp RDD

Polynomial					
		Std. Err.	[95% conf.	interval]	Obs.
First-degree polynomial	0.1374**	0.0598	0.0178	0.2571	617
Second-degree polynomial	0.1583**	0.0678	0.0232	0.2934	1,080
Control Group (LHS): 14%					

Notes: Table 4 shows a Sharp RDD. The unit of observation is at the individual level. The dependent variable is recidivism within three years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first row estimates the intent-to-treat effect using a polynomial of degree one and the second row estimates the intent-to-treat using a polynomial of degree two. The estimation includes 61 facility fixed effects. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

evidence of a noticeable increase in the probability of recidivism when individuals are placed in blocks with peers exhibiting higher levels of criminal involvement. The coefficients exhibit consistent stability across different specifications. The bins used in the figures were selected following the IMSE-optimal evenly spaced method by Cattaneo, Idrobo, and Titiunik (2019).

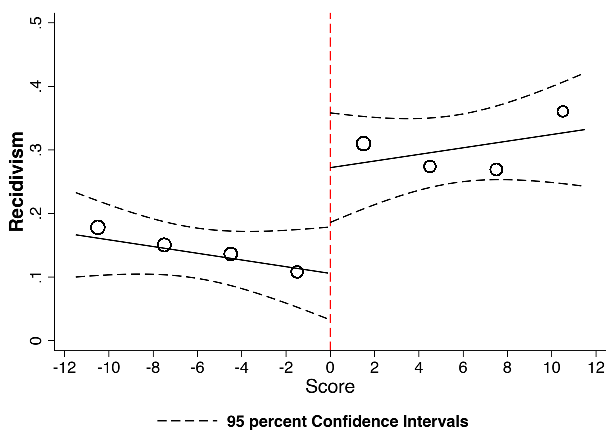

Figure 3: First-degree polynomial

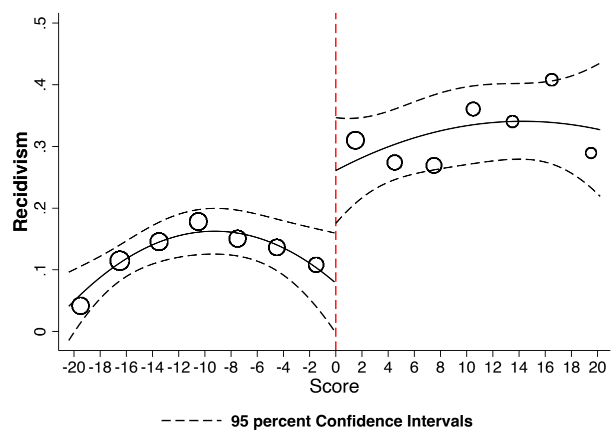

Figure 4: Second-degree polynomial

Notes: Figure 3 displays a first-degree polynomial in the optimal bandwidth, while Figure 4 uses a second-degree polynomial. The optimal bandwidth was selected using the mean squared error (MSE)-optimal bandwidth selector. The bins were selected following the IMSE-optimal evenly spaced method. Both figures show a significant and stable discontinuity at the cutoff.

5.2 Heterogeneity

The impact of being assigned to a block with individuals with higher criminal activity may be intensified by various factors, such as individual and peer heterogeneity. I focus on individual heterogeneity, positing that the effects of facility placement significantly vary in accordance with individual characteristics. For instance, prisoners serving longer sentences may be more strongly influenced by their environment due to prolonged exposure and deeper connections with criminal peers. Furthermore, inmates with a history of crimes like robbery and theft, skill-intensive types of crimes, may learn from their peers while incarcerated (Ouss 2011). New criminal connections could potentially increase the likelihood of reoffending after their release.

Owing to the limited sample size, the data for robbery and theft have been merged into a unified “skill-intensive” category. Furthermore, I created a variable, “Months Above,” to indicate whether an inmate’s duration of incarceration exceeds the median length of stay (in months) at the facility.

To test for heterogeneity, I estimate the baseline regression from Equation 1 for each sub-sample. Table 5 shows the results of these regressions.

The results presented in Table 5 confirms the expected signs, consistent with the anticipated outcomes discussed earlier. For individuals who spend more time in the facility (“Months above the median”), the probability of recidivism increases by 21 percentage points, and this effect is statistically significant. In contrast, for those spending less time than the median, the effect is only 1 percentage point and not statistically significant. The difference between the coefficients for durations above and below the median is statistically significant.

Similarly, the analysis shows that recidivism is more likely for individuals with a history of committing skill-intensive crimes. For this group, the probability of recidivism increases by 20 percentage points and is statistically significant, compared to only a 2 percentage-point increase for those with experience in other types of crimes. However, the difference between the coefficients for individuals with and without a history of skill-intensive crimes is not statistically significant.

These findings suggest that the effect of allocation is stronger when individuals spend more time together, likely due to the formation of larger and stronger criminal networks within the facility. Additionally, the pronounced effect for individuals with experience in skill-intensive crimes, such as robbery and theft, may reflect the accumulation of criminal capital and the development of a criminal network. Figures 8 - 11 in Appendix 9.6 illustrate these results.

Table 5: Heterogeneity

Variables	**Months above the median (MA)**		**Skill-intensive (robbery + theft)**	
	(MA=0)	(MA=1)	(Skill-i=0)	(Skill-i=1)
	Recidivism	Recidivism	Recidivism	Recidivism
Medium	0.0123	0.2198**	0.0231	0.2090**
	(0.1086)	(0.0836)	(0.0776)	(0.1074)
Facility FE	YES	YES	YES	YES
F	2.34	3.25	0.71	5.81
R^2	0.2088	0.2511	0.2103	0.2136
Obs.	252	339	249	338
Mean	0.27	0.17	0.19	0.23
Difference	p-value 0.0874		p-value 0.1243	

Notes: Table 5 presents four regressions for different groups: individuals who spend more or less time in prison than the median and individuals with or without prior experience in skill-intensive crimes. The unit of observation is at the individual level. The variable Medium equals one if the individual is potentially allocated to a medium-block. The dependent variable is recidivism within three years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). All regressions are estimated using a first-degree polynomial. The second and third columns present separate regressions for individuals who spent fewer (second column) or more (third column) months in the facility compared to the median. The fourth and fifth columns display separate regressions for individuals who did not commit (fourth column) or did commit (fifth column) robbery or theft. The p-value indicates whether the difference in the coefficients is statistically significant. Standard errors in parentheses are clustered at the facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

5.3 Robustness checks

5.3.1 Covariates and FE

In order to test the robustness of the findings from the main regression, several additional covariates are incorporated into the model. Additionally, fixed effects for the year of release, represented by γ_t, are incorporated to account for macroeconomic fluctuations potentially influencing outcomes in the year of an individual's release. In Equation (2), $Recidivism_{ibt}$ represents recidivism for person i in prison-block b who was released in year t. Z_i includes individual-level covariates such as nationality, age at entry into prison, years of education, marital status, religion, months spent in the facility, and the types of crime committed (including robbery, theft, injury, homicide, traffic, and other offenses). The inclusion of these year-of-release fixed effects is critical for controlling for temporal variations in external factors that might influence recidivism rates, such as shifts in economic conditions or social policies:

$$Recidivism_{ibft} = \alpha + \beta_1 Medium_{ibf} + g(score_{if}) + g(score_{if}) * Medium_{ibf} + \beta_2 Z_i + \delta_f + \gamma_t + \omega_{ibft}. \quad (2)$$

The outcomes from estimating Equation (2) are shown in Table 6. The coefficient for the treatment variable are between 12 and 15 percentage point increase, with all of the regressions yielding statistically significant results upon the inclusion of additional covariates. This suggests that the treatment effect, denoted by $Medium_{ibf}$, is largely unaffected by individual-level covariates Z_i in the sample. The coefficients for $Medium_{ibf}$ display stability even when controlling for these covariates, indicating a robust treatment effect. This is further supported by analysis using the full sample across various polynomial models, where I consistently find a significant and positive effect, as detailed in Appendix 9.10.

Table 6: Covariates and fixed effects

	(First-degree polynomial)			(Second-degree polynomial)		
	Recidivism	Recidivism	Recidivism	Recidivism	Recidivism	Recidivism
Medium	0.1288**	0.1270**	0.1275**	0.1491**	0.1566**	0.1576**
	(0.0576)	(0.0552)	(0.0552)	(0.0656)	(0.0644)	(0.0645)
Prison FE	YES	YES	YES	YES	YES	YES
Demographic Cov	YES	YES	YES	YES	YES	YES
Type of crime	NO	YES	YES	NO	YES	YES
Year exit FE	NO	NO	YES	NO	NO	YES
F	10.9487	12.5417	13.5186	10.5050	15.3613	17.9002
R^2	0.2213	0.2421	0.2441	0.2001	0.2198	0.2211
Obs.	617	617	617	1074	1074	1074
Mean (LHS)	14%	14%	14%	13%	13%	13%

Notes: Table 6 presents various Sharp RDD estimations, including covariates and time fixed effects. The unit of observation is at the individual level. The variable Medium equals one if the individual is potentially allocated to a medium-block. Demographic covariates include age, nationality, years of education, religion, and months spent in prison. Crime type categories encompass robbery, receiving, theft, homicide, injury and drug-trafficking. The dependent variable is recidivism within three years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first three columns present the intent-to-treat effect using a polynomial of degree one and the next columns show the intent-to-treat using a polynomial of degree two. Standard errors in parentheses are clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

5.3.2 Continuity of covariates

The continuity assumption, essential for identifying causal effects in Regression Discontinuity Designs, posits that both observable and unobservable individual characteristics do not exhibit a discontinuity at the cutoff. The validity of this assumption can be evaluated by testing for discontinuities in observable covariates at the cutoff.

To test the continuity assumption, I estimate a regression model as described in Equation (3). This equation includes a set of observable characteristics of the offender, such as education, age, types of crime, months in prison, and score components, as dependent variables. These regressions aim to investigate whether there is a discontinuity in these covariates at the cutoff. If the continuity assumption holds, the estimated coefficient for $Medium$ should be statistically insignificant, then the covariates do not exhibit a discontinuity at the cutoff. Here, Z_i represents a set of observable characteristics of the offender i, such as education, age, types of crime, months in prison, and score components.

$$Z_{ibf} = \alpha + \beta_1 Medium_{ibf} + g(score_{if}) + g(score_{if}) * Medium_{ibf} + \delta_f + \xi_{ibf}. \quad (3)$$

The results of the regression analysis using demographic characteristics as the dependent variable are presented in Table 7. The table indicates that there is no statistically significant jump in any of the observable variables that impact recidivism at the score cutoff. These findings suggest that the continuity assumption holds, and RDD is an appropriate approach for measuring the effect of this allocation on recidivism. Appendix 9.9.1 provides a graphical representation of the density of individuals and their observable characteristics around the score cutoff, which indicates the absence of a discontinuity in the covariates at the cutoff point using a polynomial of degree one.

Table 7: Covariates: Demographic characteristics

	Months in prison	Years of education	Age	Single	Catholic
Medium	0.9157	0.6705	1.5250	-0.0053	0.0272
	(2.1367)	(0.4266)	(0.9468)	(0.0696)	(0.0737)
F	0.0652	0.9029	8.5422	1.1096	1.1734
R^2	0.2937	0.1647	0.1554	0.1111	0.1408
Obs.	617	617	617	617	617
Mean (LHS)	15	9	35	0.70	0.55

Notes: Table 7 shows Sharp RDD regressions. The unit of observation is at the individual level. The variable Medium equals one if the individual is potentially allocated to a medium-block. The dependent variables are months in prison, years of education, age, single and catholic. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). All the regressions are estimated using a polynomial of degree one. Standard errors in parentheses are clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 8 presents a similar analysis, this time using the types of crimes identified in the dataset as the dependent variable. The results show that there is no significant jump in all of the identified crimes. It is important to note that the score does not consider the type of crime itself. However, the person assigning the score may be more severe with individuals who have committed certain kinds of crimes. The graphical representation of these variables is presented in Appendix 9.9.2.

Finally, to investigate if there is a jump in the cut-off of the score components, I analyzed each of the components presented in Table 1 as a dependent variable through a regression

Table 8: Covariates: types of crime

	Robbery	Receiving	Theft	Homicide	Injury	Drug-trafficking
Medium	0.1105	0.0322	-0.0170	-0.0355	0.0245	-0.0840
	(0.1109)	(0.0455)	(0.0617)	(0.0420)	(0.0349)	(0.0648)
F	1.7507	1.5669	0.7078	1.8440	0.3774	4.9586
R^2	0.2170	0.1100	0.1161	0.2583	0.1422	0.2027
Obs.	617	617	617	617	617	617
Mean (LHS)	0.38	0.05	0.14	0.10	0.07	0.24

Notes: Table 8 shows Sharp RDD regressions. The unit of observation is at the individual level. The variable Medium equals one if the individual is potentially allocated to a medium-block. The dependent variables are robbery, receiving, theft, homicide, injury and drug-trafficking. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). All the regressions are estimated using a polynomial of degree one. Standard errors in parentheses are clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

analysis using a similar methodology. The variable *prior conviction* was excluded as it is used to filter individuals without prior sentences, meaning that all individuals in the sample have the same value of this variable. The resulting regressions, presented in Table 9, feature 12 columns: (1) Language; (2) Physical marks; (3) Goals and life planning; (4) Partner and groups of friends; (5) Leisure time; (6) Drugs; (7) Crimes as a child; (8) Age of first crime; (9) Belonging to organized criminal groups; (10) Guns; (11) Family criminal records; and (12) Criminal continuity, with the graphics presented in Appendix 9.9.2. The analysis shows that while 11 of the variables do not display a considerable and statistically significant jump, the variable of criminal continuity shows a statistically significant but small jump.

Two key observations substantiate the empirical strategy employed in this study. Firstly, the ‘’criminal continuity” variable exhibits a modest discontinuity at the threshold (0.4), with estimated shifts ranging between 1 to 2 on a 1-to-5 scale, as detailed in Appendix 9.9.3. This suggests the presence of comparably similar individuals within the selected optimal bandwidth. Secondly, a robustness check was implemented by narrowing the sample to only those individuals where no variable demonstrates a jump at the cutoff, specifically constraining the ‘’criminal continuity” variable to values of two or less. A re-analysis of the main regression, documented in Table 15, yielded results congruent with the primary findings. There is a positive and significant jump in the cutoff. Consequently, the ‘’criminal continuity” variable does not appear to significantly influence the main outcomes of this study.

Table 9: Covariates: score components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Medium	-0.0387	0.0142	0.0379	0.0468	-0.0223	-0.1927	0.0466	-0.1229	0.0050	-0.0326	0.0141	0.4038**
	(0.0863)	(0.1444)	(0.0909)	(0.1108)	(0.1077)	(0.1431)	(0.1033)	(0.1067)	(0.1685)	(0.1543)	(0.1888)	(0.1768)
F	8.6330	8.2912	2.9583	6.2792	6.1973	16.4966	4.2421	8.8083	3.4643	1.5209	2.3380	9.2012
R^2	0.2576	0.2054	0.2131	0.2569	0.2583	0.2383	0.1982	0.1750	0.1907	0.2158	0.1324	0.3643
Obs	615	615	615	615	615	615	615	615	456	456	456	456
Mean (LHS)	2.23	1.99	2.68	2.87	2.81	2.69	1.21	3.14	1.87	1.51	1.66	1.51

Notes: Table 8 shows Sharp RDD regressions. The unit of observation is at the individual level. The variable Medium equals one if the individual is potentially allocated to a medium-block. The dependent variables are: (1) Language; (2) Physical marks; (3) Goals and life planning; (4) Partner and groups of friends; (5) Leisure time; (6) Drugs; (7) Crimes as a child; (8) Age of first crime; (9) Belonging to organized criminal groups; (10) Guns; (11) Family criminal records; and (12) Criminal continuity. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). All the regressions are estimated using a polynomial of degree one. Standard errors in parentheses are clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

6 Peer effects

The main result suggests a notable increase in recidivism among individuals assigned to the medium-involvement blocks. However, the robustness of these findings warrants further examination. As detailed in Section 2, neither job market stigma nor the facilities and amenities seem to significantly influence the allocation results. Consequently, this section concentrates on examining the role of peers in shaping the allocation effect.

6.1 Peers effects on recidivism

Empirical and theoretical evidence suggests that peers can influence individual decision-making (see, for example Patacchini and Zenou 2012, Liu, Patacchini, and Zenou 2014, Ushchev and Zenou 2020). Therefore, another potential explanation for the observed differences in recidivism rates across blocks is the presence of peer effects. As previously mentioned, the Chilean case presents a unique setup with some sorting according to the score across facilities with similar characteristics. Inmates in the block with medium criminal involvement have higher criminal capital, and inmates close to the cutoff on the right side could have the opportunity to learn from them and create networks with peers who are closer to the criminal culture, potentially leading to higher rates of recidivism (Philippe 2024). This idea is consistent with the notion of social learning, which suggests that individuals can acquire attitudes and behaviors through observation, and interaction with others in their social environment. Thus, the difference in peers could contribute to the differences in recidivism rates across blocks.

In the ensuing subsection and the one that follows, I employ my secondary dataset[12], which includes detailed data on the placement of individuals within the private correctional

[12]It is important to note that this dataset diverges from the primary dataset in its composition and temporal focus. Specifically, it encompasses only data pertinent to private prisons and details on individuals who were released from these institutions between 2009 and 2012. Consequently, both the structural attributes of the data and the years under analysis differ.

facility. Additionally, this dataset includes records of inmates' participation in any rehabilitation programs, as well as their receipt of any form of benefits during their incarceration period.

To address this question, and following Stevenson (2017), I create a peer measure. The peer variable is presented in Equation (4). Here, d_{ij} represents the observed number of days that individual i and individual j overlap in the same block. Lastly, $Score_j$ represents the score of the individual j. Consequently, the final variable represents the mean of the scores associated with peers, adjusted by the duration (in days) of their overlap in the same block.

$$\text{Peer Score}_{\text{ib}} = \frac{\sum_{j \neq i} (d_{ijb}) \cdot \text{Score}_{jb}}{\sum_{j \neq i} (d_{ijb})}. \tag{4}$$

Investigating the impact of peer influence on recidivism, I employ Equation (5). The dependent variable, R_{ibt}, represents the recidivism of individual i in block b, who was incarcerated in period t and subsequently re-incarcerated within three years. The key explanatory variable, $Peer\,Score_{ibt}$, is the weighted average of the peer scores within the block. $Score_i$ denotes the individual's own score, while $\mathbf{X}$ contains a range of demographic characteristics including age, education, marital status, duration of incarceration, and types of crimes committed. The model also includes fixed effects for prison-block (δ_b), and entry quarter (η_t). This framework allows for the estimation of peer effects on recidivism, controlling for individual scores and block-specific characteristics:

$$R_{ibt} = \beta_0 + \beta_1 Peer\ Score_{ibt} + \beta_2 Score_i + \mathbf{X}_i\gamma + \delta_b + \eta_t + \epsilon_{ibt}. \tag{5}$$

I use the variable $Peer\_score_{ibt}$ as a key measure of peer influence. $Peer\_score_{ibt}$ is the standardized weighted average score of peers, and serves as a pre-treatment measure of the extent to which peers are involved in criminal activities and potentially influence the behavior of an individual. To address non-randomization concerns, I employ a prison-block fixed effects strategy that assumes the average score of an individual's peers is uncorrelated with their individual characteristics within the block, and I control for the individual score. By incorporating prison-block fixed effects, I adopt the same identification strategy as Bayer, Hjalmarsson, and Pozen 2009, Damm and Gorinas 2020, and Tan and Zapryanova 2021, but applied at the block level rather than the facility level. This fixed effects strategy allows for variation in the peer variable within each block; therefore, the variation of this variable is only given for the flow of individuals who enter and leave the prison. This allows for the identification of the causal impact of the average peer score on recidivism through the utilization of within-block variation.

To maintain consistency with the initial sections of the investigation, this section also focuses on first-time offenders and individuals who have spent at least three weeks in prison. However, the results and conclusions remain unchanged if I do not restrict the data based on time spent in prison. Table 10 shows that the estimated effect of peer score on recidivism is approximately 0.04, indicating that a one-standard-deviation increase in the peer score raises the likelihood of recidivism by 4.4 percentage points, an increase of approximately 13% from the mean. Given that the standard deviation of the peer score variable is 16.19, and the mean score difference between the low and medium blocks in Table 3 is approximately 36 points, this difference equates to about 2.2 standard deviations. Therefore, if an individual is transferred from a low to a medium block, they would experience an increase of 2.2 standard deviations in the mean peer score, which would raise the probability of recidivism by approximately 10 percentage points. Since the total allocation effect is 14 percentage points in Section 5, these findings suggest that direct peer effects account for a significant portion of the allocation effect. However, other factors may also contribute to the main outcome, such as guard behavior and its influence on recidivism. In this paper, I refer to this as an indirect peer effect, as guard behavior can be influenced by the composition of the peer group.

Table 10: Peer effects

	Recidivism	Recidivism	Recidivism
Peer Score	0.0545**	0.0492**	0.0420**
	(0.0217)	(0.0203)	(0.0199)
$Score_i$	0.0080***	0.0077***	0.0073***
	(0.0006)	(0.0007)	(0.0007)
Block FE	YES	YES	YES
Quarter entry FE	YES	YES	YES
Indiv. Covariates		YES	YES
Crime history			YES
Mean outcome variable	0.32	0.32	0.32
F	162.4648	65.3929	51.2739
R^2	0.3915	0.4003	0.4197
Obs.	1,162	1,159	1,159

Notes: Table 10 presents peer effects regressions both with and without controls. The unit of observation is at the individual level. The variable $PeerScore$ is a weighted average of the scores of the peers of individual i, $Score_i$ represents the score of individual i. Individual covariates include age, marital status (single), years of education, and months spent in prison. Criminal history variables encompass robbery, receiving, theft, homicide, injury, and drug trafficking. The dependent variable is recidivism within three years after release. The first column only control for the individual score. The second column adds individuals characteristics Standard errors in parentheses are clustered at the prison-block level. * $p < .1$, ** $p < .05$, *** $p < .01$.

The score components offer valuable insights into individuals' proximity to criminal culture. As depicted in Figure 40, empirical evidence suggests that most score components exhibit a positive correlation between peer score components and the likelihood of recidivism.[13] I therefore calculated a standardized weighted average for each component of the peer score. Subsequently, I conducted thirteen regressions—one for each component of the peer score—in accordance with Equation (5). In this analysis, the variable $Peer\ Score_{ibt}$ was substituted with the distinct components of the peer score. Table 20 and Figure 41 display the outcomes of the aforementioned regression analyses. Most components show a positive influence on recidivism; however, certain components have a more substantial and statistically significant effect. The peer score components with a slightly statistically significant impact include age at first offense, language, and prior sentences.[14] This evidence suggests that peers with a higher criminal profile exert a stronger influence on their peers.

6.1.1 Testing for nonlinear peer effects

To test a more flexible alternative to Equation (5), I divide individuals into three groups based on the quartiles of their score distribution, and interact these quartiles with the peer score variable in Equation (5). The result in Figure 5 shows that the peer effect is stronger for individuals with higher scores. Specifically, this suggests that placing first-time offenders with high scores in groups where the weighted average peer score is also high substantially increases their likelihood of recidivism.

From a policy perspective, these results provide valuable insights for improving offender management and reducing recidivism. The finding that high-score individuals are more susceptible to peer effects suggests that grouping strategies that cluster such individuals together may inadvertently reinforce criminal behaviors. Consequently, the strategy of concentrating high-score individuals within the same peer groups appears suboptimal.

An alternative approach might involve adopting grouping strategies that mix individuals with varying criminal profiles to dilute the negative peer effects experienced by high-score offenders. However, this strategy carries its own challenges, as low-score individuals might face heightened risks of intimidation or harm in groups with higher-risk peers. While the results suggest that mixing risk profiles could mitigate criminogenic peer effects for high-score individuals, it is essential to carefully assess the potential dangers and ensure that such strategies do not compromise the safety of low-risk inmates.

[13] I included only twelve graphs because I used the variable "previous convictions" to restrict the data to first-time offenders.

[14] These variables do not remain significant under multiple hypothesis testing (see Table 20).

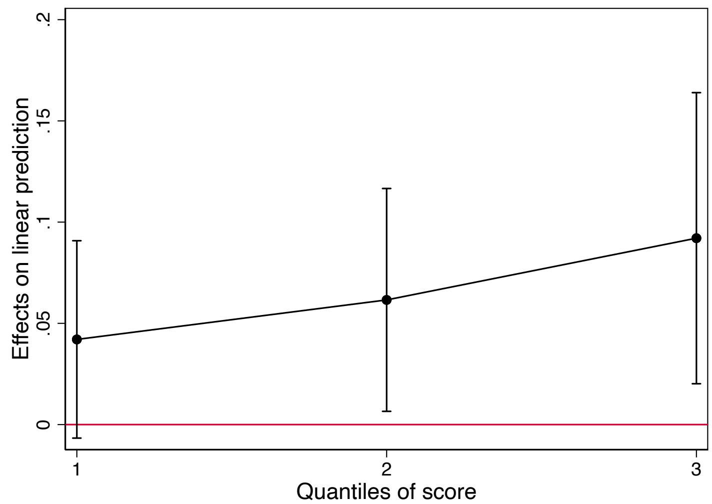

Figure 5: Effect of peer score (std) at different levels of score

Notes: This figure illustrates the standardized effect of peer scores at different levels of the score distribution. The horizontal axis represents the score quartiles, while the vertical axis shows the estimated effects. Confidence intervals are included. Results suggest peer effects are stronger in the upper quartiles.

6.2 Peer effects on participation in rehabilitation programs and good behavior

This research fills a critical gap in the existing literature and, to the best of my knowledge, represents the first study to examine how prisoner allocation affects their decisions to engage in rehabilitative activities, such as educational and work programs, with a specific emphasis on the influence of peers. This study provides new insights into how the prison environment and inmate interactions influence participation in rehabilitation programs.

This is particularly pertinent in contexts where participation in such programs is contingent upon good behavior. In the Chilean correctional system, inmates are required to demonstrate twelve months of good behavior as a prerequisite for eligibility to participate in rehabilitation programs or to qualify for any associated benefits. The intricate social dynamics within prison settings raise the possibility that peer groups may significantly impact these choices. For instance, inmates striving to improve their conduct could face peer-induced stigma or may become embroiled in conflicts influenced by their peer.

Building on the methodological framework outlined in the previous section, this study employs a similar regression model to investigate the potential impact of peer interactions on inmates' decision-making, particularly in relation to their participation in rehabilitation programs and their behavior during incarceration. Employing Equation (6), this analysis focuses on first-time inmates serving sentences of twelve months or longer. The equation facilitates a preliminary exploration of the dynamics between peer influence and the propensity of prisoners to partake in rehabilitation programs, alongside examining their behavior within the correctional facility.

Equation (6) delineates the probability, denoted as P_{ibt}, that an individual i, situated in block b, and entered at time t, participates in a rehabilitation program or exhibits commendable behavior. Good behavior is operationalized as a proxy binary variable, assigned a value of one if the inmate is released from prison before his sentence, indicating positive conduct.

The decision model encapsulated by Equation (6) posits the likelihood of an inmate's participation in rehabilitation programs or demonstrating positive behavior as a function of the peer group's influence, quantified through the average score, $Peer\ score_{ibt}$. This score represents the standardized weighted average of peer scores for the individual i, within block b, who entered at the specified time t. Additionally, δb encapsulates prison-block fixed effects, accounting for unobserved heterogeneity within the block. The remaining variables, are defined in the same manner as in the previous section.

In addition, I investigate whether the allocation of inmates within prisons has a peer spillover effect on their likelihood of obtaining benefits such as Sunday outings, weekend outings, and controlled outings. These benefits are conditional upon positive conduct, thereby encouraging inmates to exhibit good behavior. Drawing from the same empirical approach as in the previous analysis, I seek to estimate whether there are any peer effects on the probability of obtaining these benefits.

Intuitively, one might expect that inmates who are surrounded by peers with a higher propensity for criminal activity are more likely to engage in fights or other forms of misconduct, which in turn may lower their likelihood of obtaining benefits. The proposed regression model, specified in Equation (6), allows us to examine the relationship between the average peer score and the probability of obtaining benefits, as captured by the coefficient β_1:

$$P_{ibt} = \beta_0 + \beta_1 Peer\ Score_{ibt} + \beta_2 Score_i + \mathbf{X}_i\gamma + \delta_b + \eta_t + \epsilon_{ibt}. \tag{6}$$

The results are detailed in Table 11. The analysis reveals that the variable $Peer\ Score_{ibt}$ is statistically significant exclusively in the context of work-related decisions within the prison environment and good behavior, suggesting a negative influence of peers on these choices. An increment of one standard deviation of the variable peer scores implies a decrease of approximately seven percentage points in the probability of working inside prison. In addition, an increment of one standard deviation of the variable peer scores implies a decrease of eight percentage points in the probability of having good behavior. Despite exhibiting the anticipated negative sign for benefits decisions, this effect does not reach statistical significance. Furthermore, the coefficient for study is positive, yet it too lacks statistical significance.

Table 11: Participation in rehabilitation programs

	Good behavior	Study	Work	Benefit
Peer Score	-0.0860***	0.0074	-0.0649**	-0.0327
	(0.0265)	(0.0247)	(0.0317)	(0.0230)
Indiv. Covariates	YES	YES	YES	YES
Crime history	YES	YES	YES	YES
Block FE	YES	YES	YES	YES
Quarter entry FE	YES	YES	YES	YES
Mean outcome variable	0.37	0.78	0.67	0.10
F	5.6450	2.2781	2.3966	1.8265
R^2	0.5331	0.737	0.3774	0.3075
Obs.	1,159	737	739	739

Table 11 presents peer effects regressions. The unit of observation is at the individual level. The independent variables include $PeerScore$ a weighted average of the scores of the peers of individual i, and $Score_i$ which represents the score of individual i. Additional covariates include individual characteristics such as age, marital status (single), years of education, and months spent in prison. Criminal history variables encompass robbery, receiving, theft, homicide, injury, and drug trafficking. The dependent variables are good behavior, study, work, and benefit. The first column only control for the individual score. The second column adds individuals characteristics Standard errors in parentheses are clustered at the prison-block level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Similar to the previous peer effect subsection, I estimate separate regressions using the components of the score to identify which elements most significantly impact good behavior and participation in work activities. The results are presented in Figure 42. Most peer score components negatively affect the probability of exhibiting good behavior, particularly if peers have higher scores in drug and alcohol consumption. Additionally, Figure 43 shows that most components negatively affect participation in work activities. In general, these score components are not statistically significant, except for prior sentences and criminal continuity, which capture the frequency of peers' involvement in criminal activities.

7 Conclusion

In this research, I explore the impact of prisoner placement on recidivism rates among first-time offenders in Chile, specifically focusing on allocations based on the proximity to criminal activity. My results indicate that individuals with scores close to the cutoff, assigned to blocks with inmates with greater involvement in criminal activities, have a higher likelihood of recidivism compared to those assigned to blocks with less criminally involved individuals. The estimated effect size is approximately 14% percentage points and is found to be robust to various model specifications.

Additionally, I shed light on the mechanisms underlying the primary results. I provide evidence of peer effects: interactions with peers who have higher criminal scores increase the likelihood of recidivism and may influence participation in prison work programs as well as the probability of exhibiting good behavior while incarcerated. Peer effects might particularly explain a large part of the allocation effect.

This study underscores the importance of addressing recidivism in middle-income countries, where resources for rehabilitation programs are often limited. Identifying cost-effective strategies to reduce crime is essential, and this research highlights the strategic allocation of inmates within prisons as a key factor, particularly for first-time offenders. By considering the impact of in-prison placement on post-release behavior, policymakers can make more informed decisions to help lower recidivism rates.

The findings indicate that peer effects are especially strong among first-time inmates with higher criminal scores. This has policy implications, as placing individuals with similar, higher-risk profiles together may be contributing to elevated recidivism rates. As an alternative, policymakers might consider mixing individuals with diverse criminal profiles. However, such strategies should prioritize the safety of all inmates and be paired with enhanced security and surveillance measures.

In addition, adapting allocation practices for individuals with specific risk profiles—such as those who have committed skill-intensive crimes or those who spend long periods incarcerated—can be beneficial, as they may be more affected by their prison environment. However, it is important to note that this study does not offer definitive solutions for the most efficient methods of prisoner assignment in correctional facilities. Its primary aim is to show how allocation influences outcomes after release, offering a foundation for future policy development and research.

Finally, recognizing the effects of inmate allocation can guide the redistribution of resources to blocks with greater criminal involvement. This could entail augmenting guard presence, expanding educational and job opportunities, and other similar measures. Such strategic resource allocation can enhance the effectiveness of interventions aimed at curbing future criminal behavior, potentially yielding long-term cost benefits.

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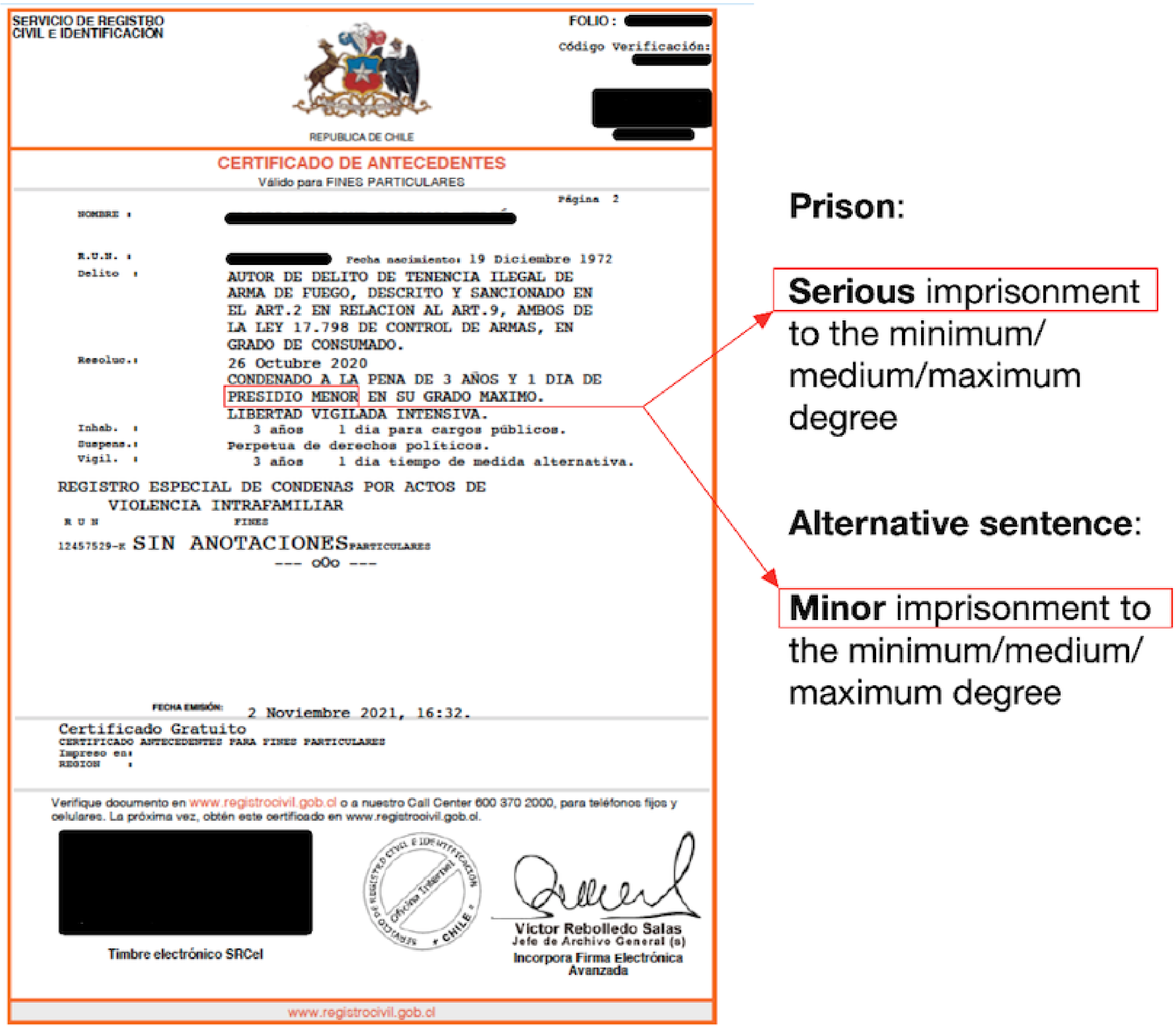
9 Appendix

9.1 Chilean criminal records


SERVICIO DE REGISTRO CIVIL E IDENTIFICACIÓN

FOLIO : [redacted]

Código Verificación: [redacted]

REPUBLICA DE CHILE

[redacted]

CERTIFICADO DE ANTECEDENTES

Válido para FINES PARTICULARES

Página 2

NOMBRE : [redacted]

R.U.N. : [redacted] Fecha nacimiento: 19 Diciembre 1972

Delito : AUTOR DE DELITO DE TENENCIA ILEGAL DE ARMA DE FUEGO, DESCRITO Y SANCIONADO EN EL ART.2 EN RELACION AL ART.9, AMBOS DE LA LEY 17.798 DE CONTROL DE ARMAS, EN GRADO DE CONSUMADO.

Resoluc.: 26 Octubre 2020

CONDENADO A LA PENA DE 3 AÑOS Y 1 DIA DE PRESIDIO MENOR EN SU GRADO MAXIMO.

LIBERTAD VIGILADA INTENSIVA.

Inhab. : 3 años 1 dia para cargos públicos.

Suspens.: Perpetua de derechos políticos.

Vigil. : 3 años 1 dia tiempo de medida alternativa.

REGISTRO ESPECIAL DE CONDENAS POR ACTOS DE VIOLENCIA INTRAFAMILIAR

R U N FINES

12457529-K SIN ANOTACIONES PARTICULARES

--- oOo ---

FECHA EMISIÓN: 2 Noviembre 2021, 16:32.

Certificado Gratuito

CERTIFICADO ANTECEDENTES PARA FINES PARTICULARES

Impreso en:

REGION :

Verifique documento en www.registrocivil.gob.cl o a nuestro Call Center 600 370 2000, para teléfonos fijos y celulares. La próxima vez, obtén este certificado en www.registrocivil.gob.cl.

[redacted]

Timbre electrónico SRCeI

Victor Rebolledo Salas

Jefe de Archivo General (s)

Incorpora Firma Electrónica Avanzada

www.registrocivil.gob.cl

Figure 6: Criminal records

Note: Figure 6 displays the Chilean criminal records. This figure shows that the Chilean criminal records do not contain information about prison or block allocation.

9.2 logit model: Risk of recidivism

Table 12: Risk of Recidivism

	Recidivism
Chilean	1.504***
	(3.11)
Age	-0.0530***
	(-5.71)
Years of Education	-0.0251
	(-1.12)
Single	-0.223
	(-1.32)
Catholic	-0.302**
	(-2.17)
Months in facility	-0.00369
	(-0.72)
Drug-trafficking	-0.0898
	(-0.28)
Robbery	0.453*
	(1.90)
Theft	0.753***
	(3.19)
Injury	0.0829
	(0.28)
Receiving	0.386
	(1.49)
Homicide	-0.0649
	(-0.19)
Others crimes	0.377
	(1.42)
Constant	-0.940
	(-1.42)
Observations	1393

Table 12 presents a logit model analyzing the factors associated with recidivism. The unit of observation is the individual. Independent variables include demographic characteristics and criminal history, while the dependent variable is recidivism within three years post-release. t statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

9.3 Re-entering two years post release

Table 13: Sharp RDD

Polynomial		Std. Err.	[95% conf.	interval]	Obs.
First-degree polynomial	0.1446**	0.0554	0.0335	0.2556	577
Second-degree polynomial	0.1511*	0.0848	-0.0183	0.3206	730
Mean LHS: 11%					

Notes: Table 13 shows a Sharp RDD. The unit of observation is at the individual level. The dependent variable is recidivism within two years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first row estimates the intent-to-treat effect using a polynomial of degree one and the second row estimates the intent-to-treat using a polynomial of degree two. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$

9.4 RDD without FE

Table 14: Sharp RDD

Polynomial					
		Std. Err.	[95% conf.	interval]	Obs.
First-degree polynomial	0.1664**	0.0511	0.0647	0.2681	641
Second-degree polynomial	0.1824**	0.0569	0.0694	0.2954	1,095
Mean LHS: 15%					

Notes: Table 14 shows a Sharp RDD. The unit of observation is at the individual level. The dependent variable is recidivism within two years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first row estimates the intent-to-treat effect using a polynomial of degree one and the second row estimates the intent-to-treat using a polynomial of degree two. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

9.5 RDD for different samples

These coefficients correspond to the variable $Medium$ from the main Equation (1), estimated using various samples and polynomial specifications. The first set of results is obtained without restricting the sample. The subsequent regressions are conducted on individuals who spent at least one week in the facilities, followed by those who spent at least two weeks in prison[15]. Figure 7 demonstrates that the coefficients remain stable across different samples and polynomial specifications. However, the second-degree polynomials are not statistically significant for the first two samples.

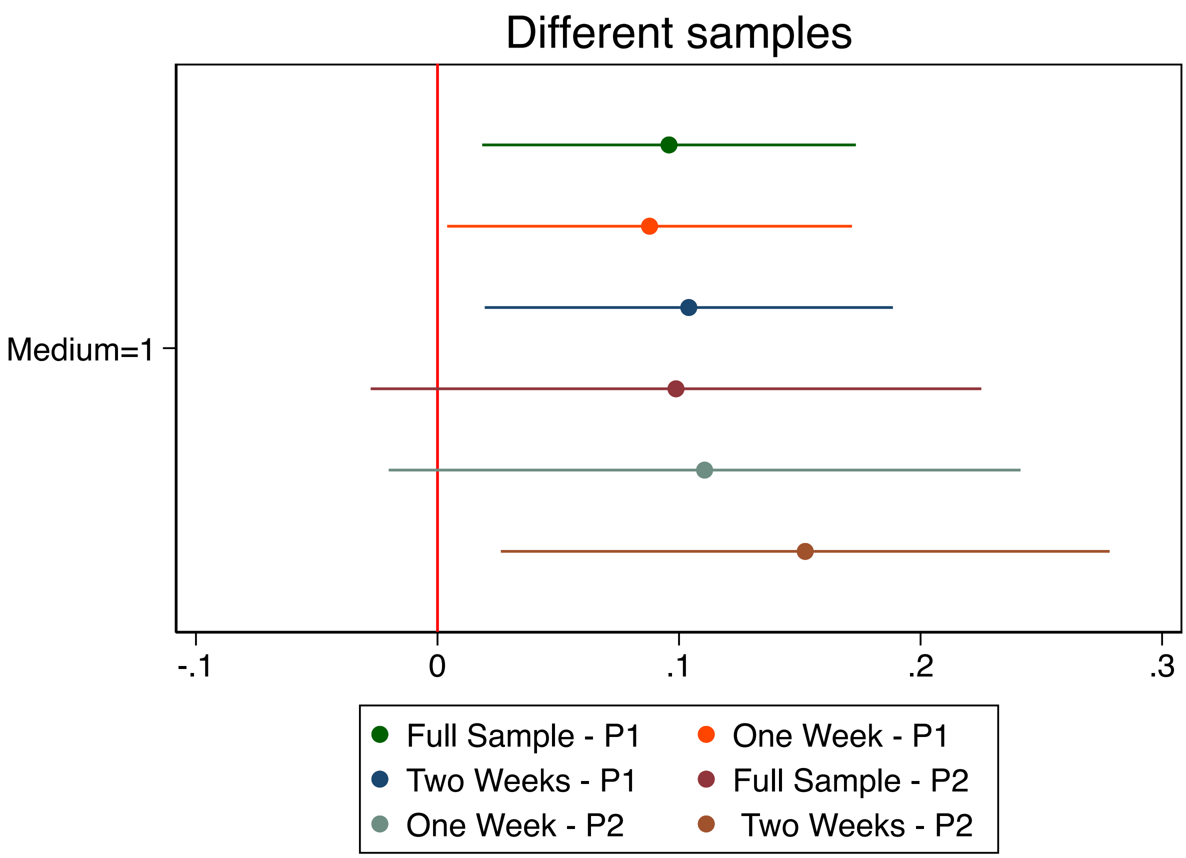


Figure 7: Samples

Notes: Figure 7 illustrates the various samples used in the analysis. The horizontal axis represents coefficient size, while the vertical axis indicates the effect for the treated group (Medium = 1). While the results are generally consistent in magnitude, some effects exhibit greater variability (noise) than others.

[15] All graphs include 90% confidence intervals

9.6 Heterogeneity

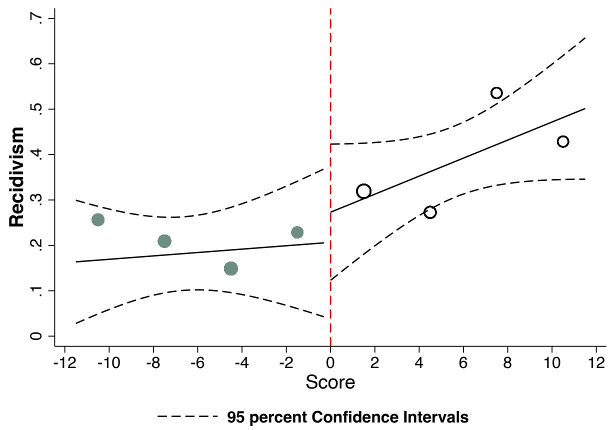


Figure 8: Individuals who spend less time in the facility compared to the median

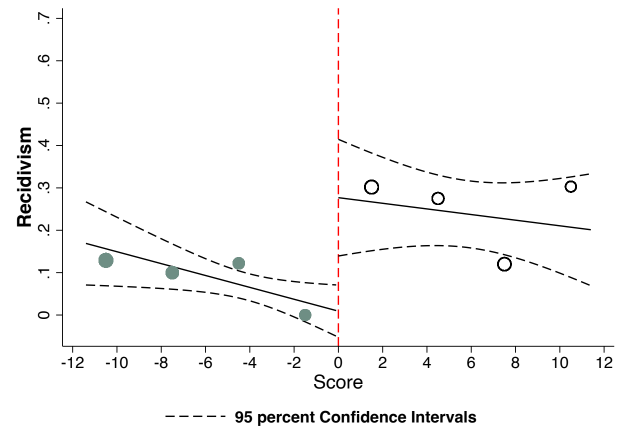


Figure 9: Individuals who spend more time in the facility compared to the median

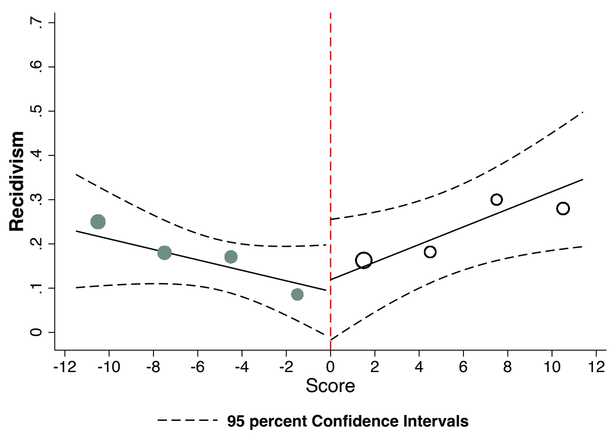


Figure 10: Individuals who have not committed skill intensity type of crimes

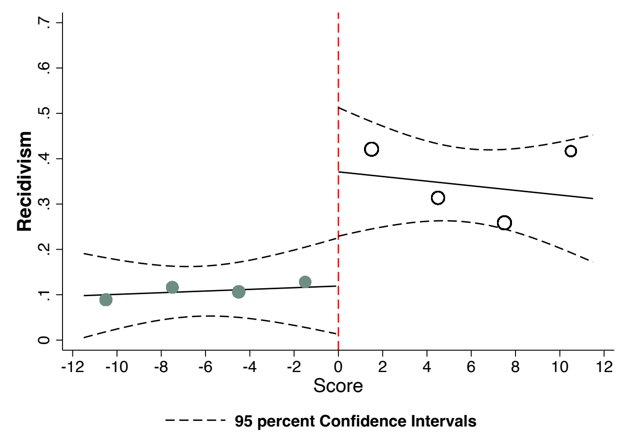


Figure 11: Individuals who have committed skill intensity type of crimes

9.7 Censoring the criminal continuity variable

Table 15: Main result censoring the criminal continuity variable

Polynomial		Robust inference				
		Std. Err.	P-value	Conf. Int		Obs.
First-degree polynomial	0.1631**	0.0643	0.014	0.0340	0.2923	501
Second-degree polynomial	0.2462**	0.0762	0.002	0.0939	0.3984	776
Third-degree polynomial	0.2738**	0.0850	0.002	0.1045	0.4431	1,021
Control Group	14%					

Notes: Table 15 shows a Sharp RDD. The unit of observation is at the individual level. The dependent variable is recidivism within two years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first row estimates the intent-to-treat effect using a polynomial of degree one, the second row estimates the intent-to-treat using a polynomial of degree two and the third row implement a polynomial of degree three. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

9.8 RDD second cutoff

The second cutoff (125.6) presents challenges as it fails to pass McCrary's density test and involves a small number of first-time offenders classified as "high criminal involvement." However, running a regression similar to the main analysis reveals a positive, though not statistically significant, jump at this cutoff.

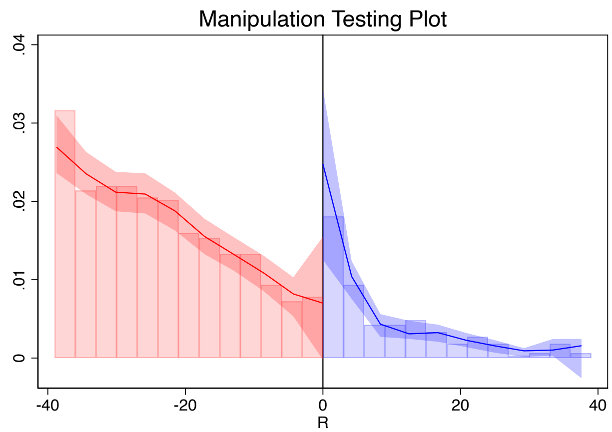


Figure 12: McCrary's density test - p-value: 0.0247

Notes: This figure presents the results of McCrary's density test at the second cutoff. The horizontal axis represents the running variable, and the vertical axis indicates the density estimate. The p-value (0.0247) suggests a statistically significant discontinuity at the threshold, indicating potential manipulation of the running variable.

Table 16: Sharp RDD

Polynomial		Robust inference			
		Std. Err.	[95% conf.	interval]	Obs.
First-degree polynomial	0.0265	0.1644	-0.3103	0.3633	164
Second-degree polynomial	0.1382	0.2106	-0.2893	0.5658	240
Mean LHS: 14%					

Notes: Table 16 shows a Sharp RDD in the second cutoff (125.6). The unit of observation is at the individual level. The dependent variable is recidivism within three years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first row estimates the intent-to-treat effect using a polynomial of degree one and the second row estimates the intent-to-treat using a polynomial of degree two. The estimation includes 61 facility fixed effects. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

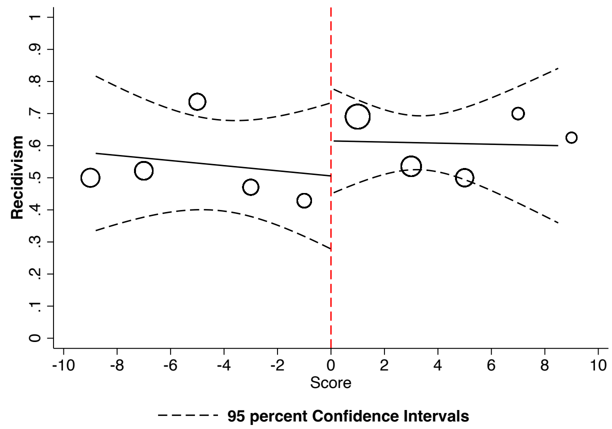


Figure 13: First-degree polynomial

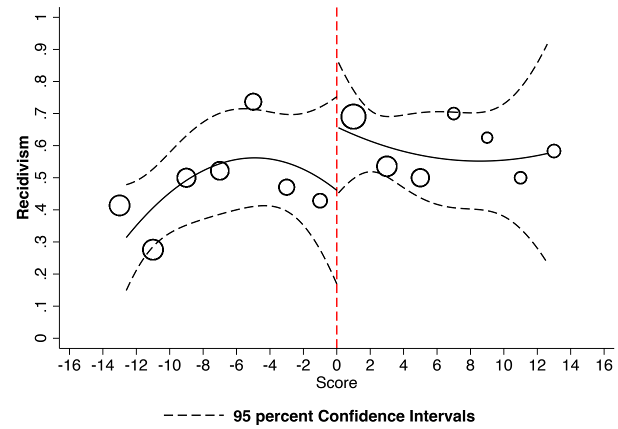


Figure 14: Second-degree polynomia

9.9 Covariates

9.9.1 Covariates: Demographic characteristics

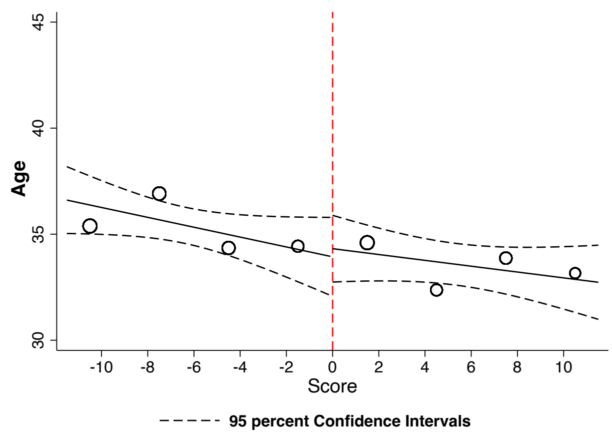


Figure 15: Age when the entered

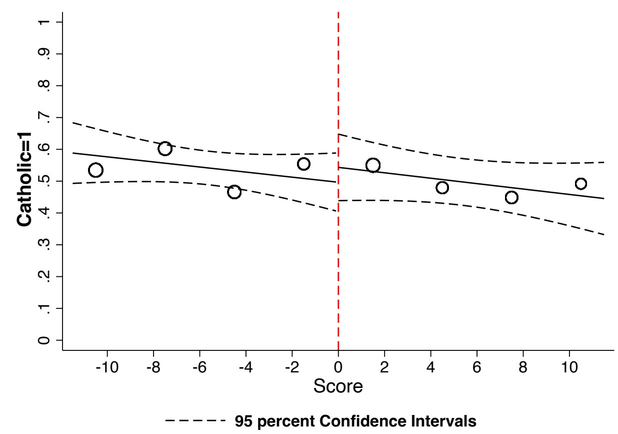


Figure 16: Catholic

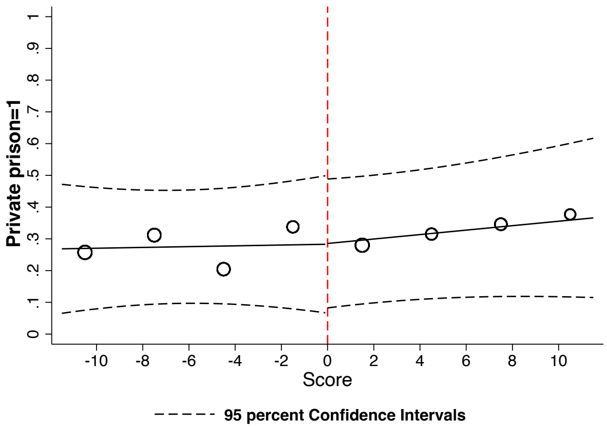


Figure 17: Private prison

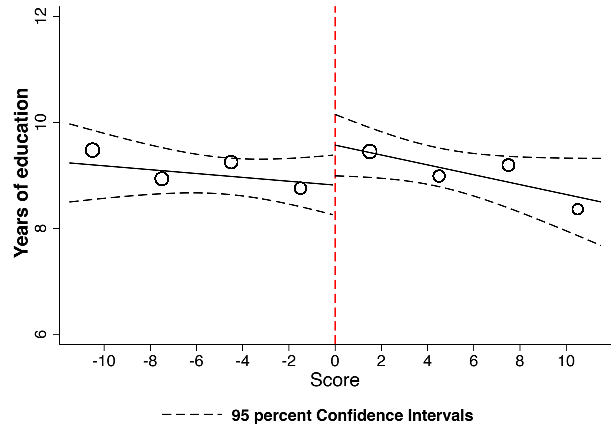


Figure 18: Years of education

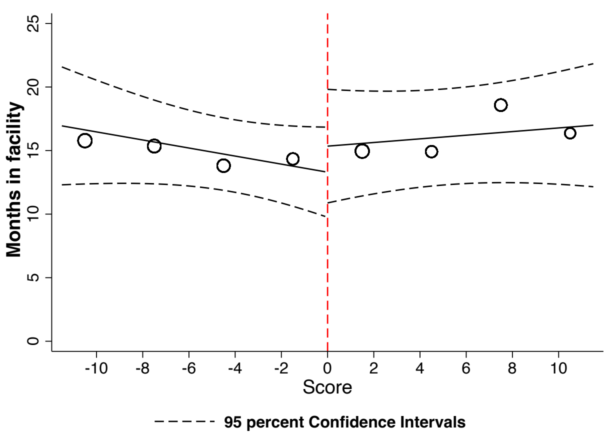


Figure 19: Months in prison

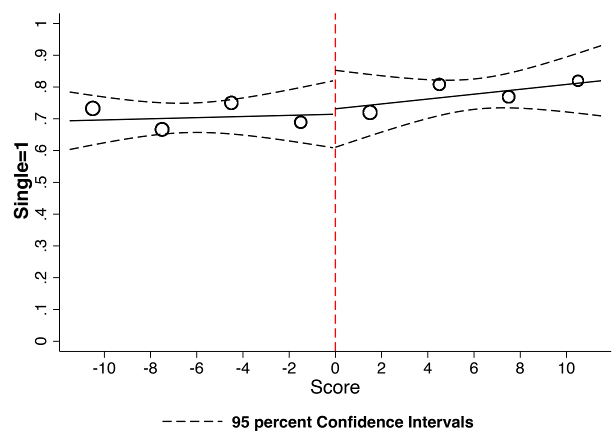


Figure 20: Single

9.9.2 Covariates: Types of crime

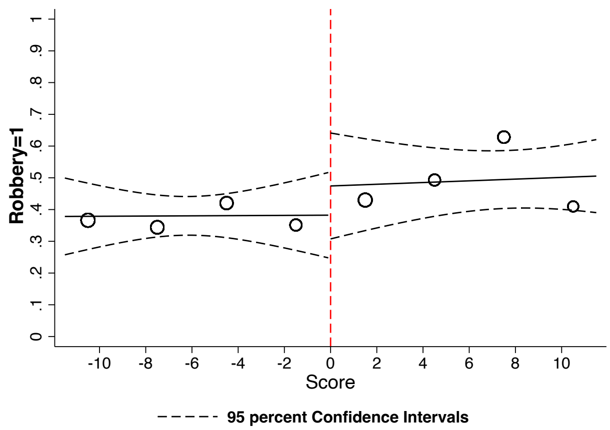


Figure 21: Crime: Robbery

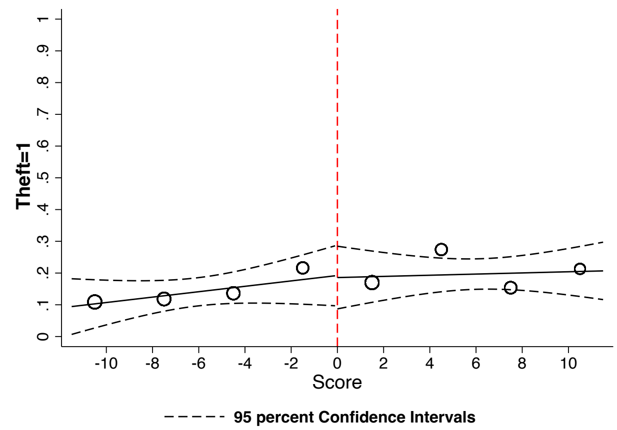


Figure 22: Crime: Theft

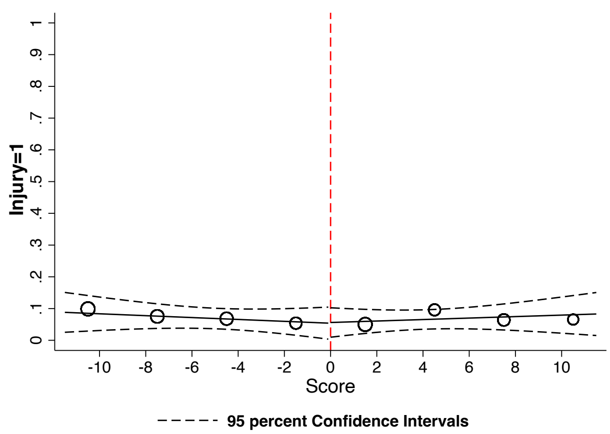


Figure 23: Crime: Injury

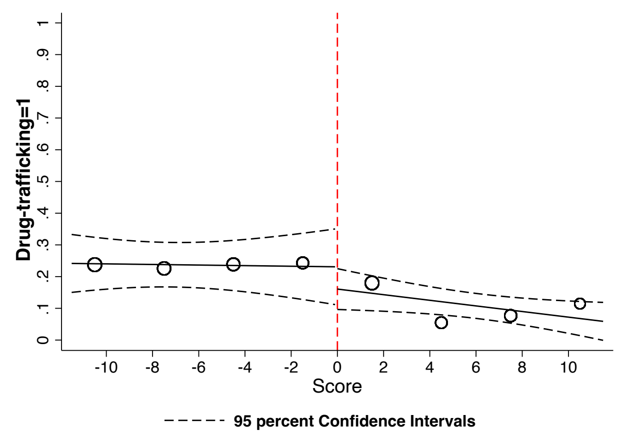


Figure 24: Crime: Traffic

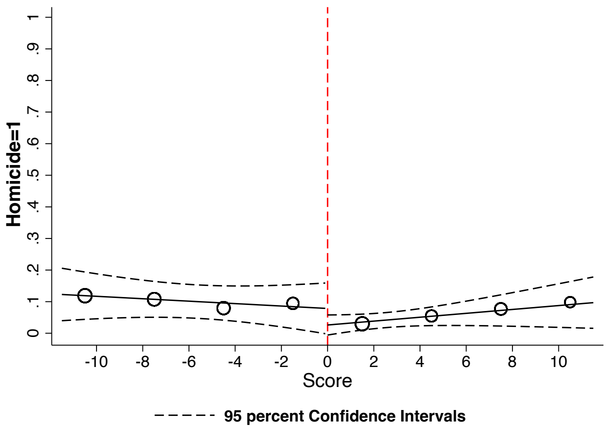


Figure 25: Crime: Homicide

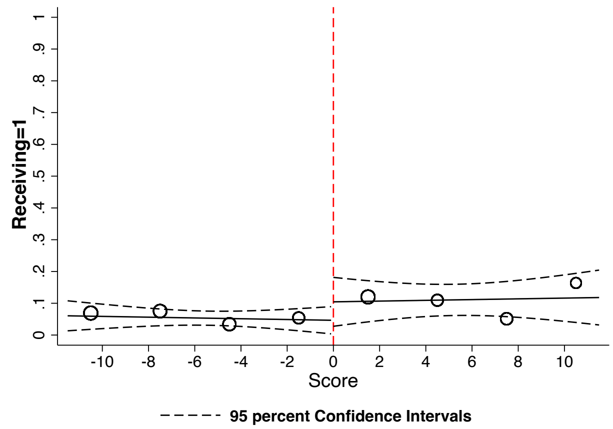


Figure 26: Crime: receiving

9.9.3 Covariates: Score components

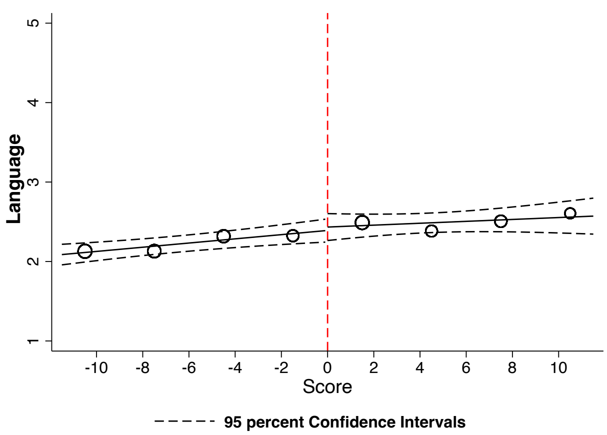


Figure 27: Language

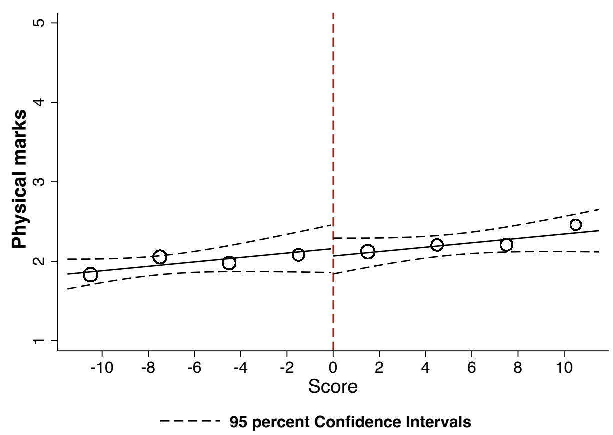


Figure 28: Physical Marks

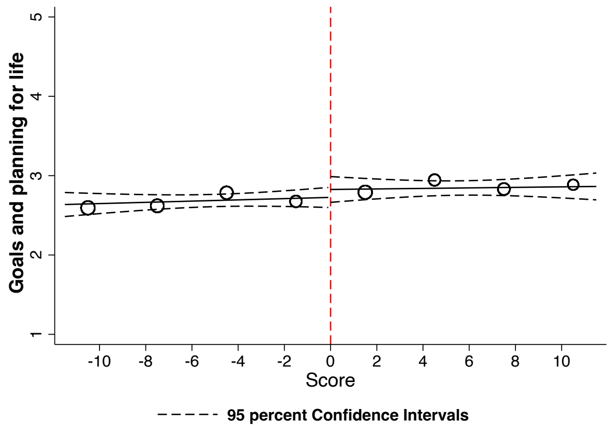


Figure 29: Goals and planning for life

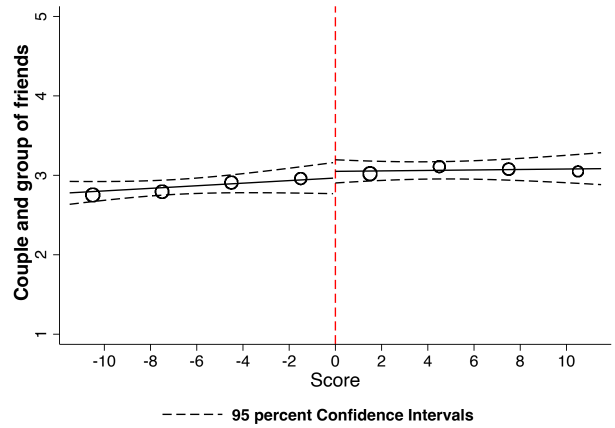


Figure 30: Couple and group of friends

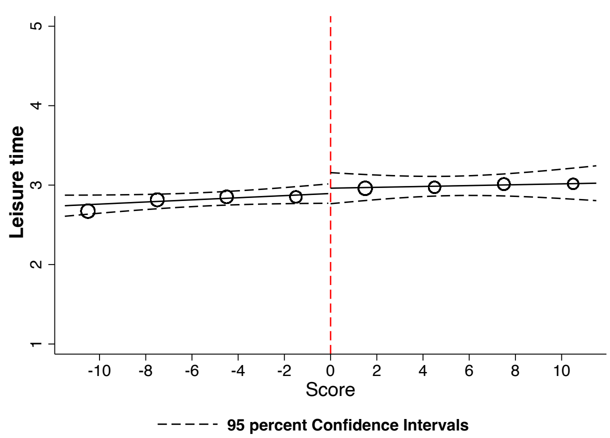


Figure 31: Leisure time

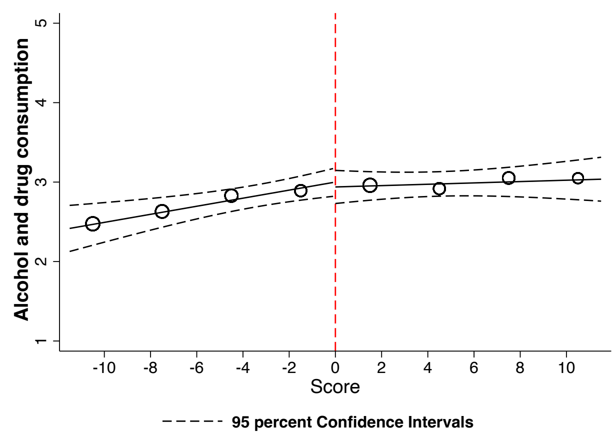


Figure 32: Alcohol and drug consumption

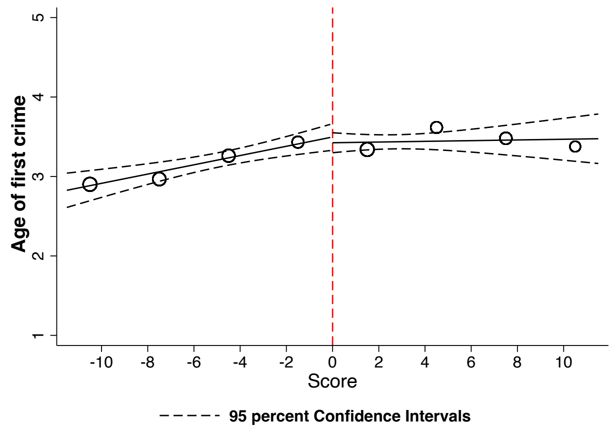


Figure 33: Age of first crime

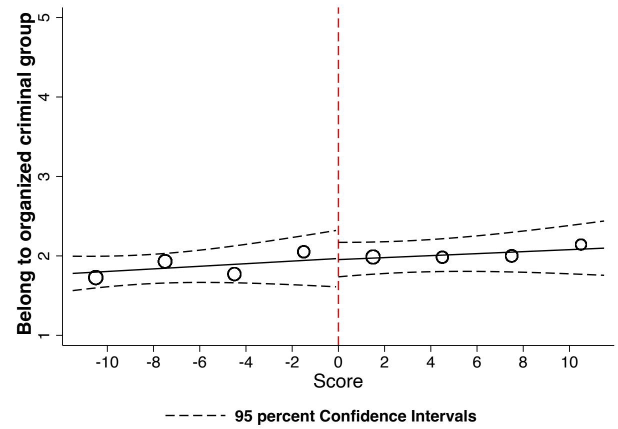


Figure 34: Belong to organized criminal group

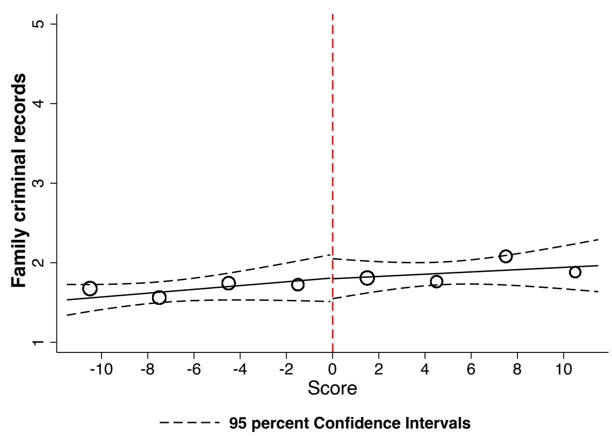


Figure 35: Family criminal records

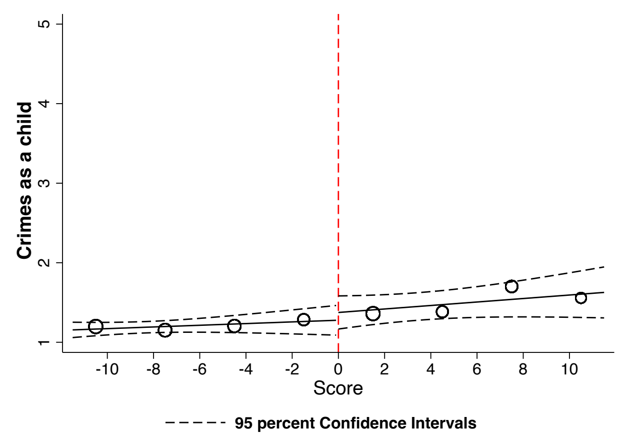


Figure 36: Crimes as a child

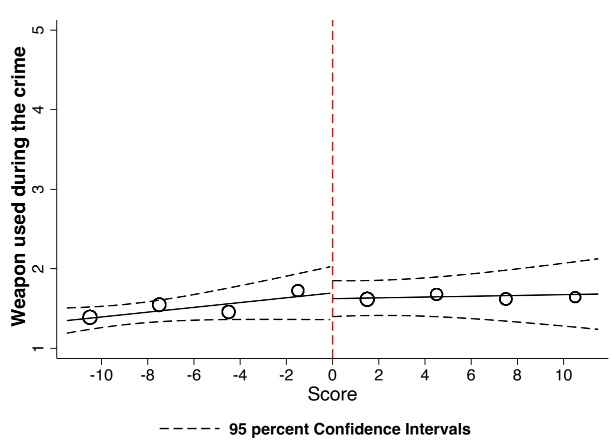


Figure 37: Guns

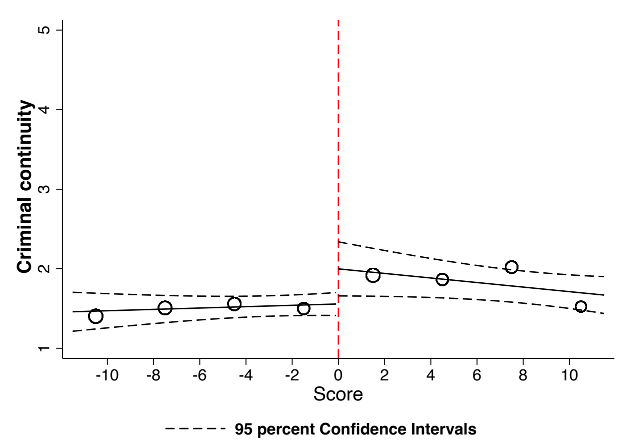


Figure 38: Criminal continuity

9.10 Different polynomials

Table 17: Regression using the entire sample

Variable	Recidivism Poly 2	Recidivism Poly 3	Recidivism Poly 4	Recidivism Poly 5
Medium	0.1057**	0.1471**	0.2036**	0.2067**
	(0.0398)	(0.0482)	(0.0668)	(0.0865)
Prison FE	YES	YES	YES	YES
Demographic Cov	YES	YES	YES	YES
Type of crime	YES	YES	YES	YES
Year exit FE	YES	YES	YES	YES
F	43.4155	40.7001	38.7183	42.7249
R^2	0.2636	0.2642	0.2653	0.2653
Obs.	1863	1863	1863	1863

Notes: Table 17 reports results from Sharp RDD regressions using the full sample, with the unit of observation at the individual level. The variable Medium equals one if the individual is potentially assigned to a medium-block. The dependent variable is recidivism within three years of release. Each column corresponds to a different polynomial specification, ranging from degree two in the first column to degree five in the last column. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$

9.11 Score components

1. Use of Criminal Jargon

    - DEFINITION: Knowledge, comprehension, and use of the prison lingo known as "Coa".
    - Criteria
        - Regularity of Coa use.
        - Comprehension of Coa

Score	Characteristics
1	No Understanding nor use of Coa
2	Comprehesion but no use of Coa
3	Occasional us of Coa
4	Regular use of Coa
5	Permanently uses Coa

2. Physical Marks

    - DEFINITION: Set of body marks related to symbols of the criminal and/or prison subculture or marks resulting from criminal activity and its repression.
    - Criteria
        - Presence/absence, together or not, of tattoos, scars from wounds caused by sharp weapons or firearms.

Score	Features
1	No tattoos, no scars from stab wounds or bullet wound scars
2	Has only tattoos or only scars from puncture wounds
3	Has prison tattoos and stab wound scars, or has only bullet wound scars
4	Has bullet scars as well as tattoos or scars from stab wounds
5	Has the three types of marks: tattoos, scars from stab wounds, or scars from bullets.

3. Goals and Planning for Life

    - DEFINITION: Ability to organize and apply skills and potential for the achievement of goals in areas to be resolved for social adaptation (labor and/or educational integration, family functioning, adaptation to the law, etc.).
    - Criteria
        - Concreteness, aspects of the goal that can be effectively realised.

    - Adequacy, efficient use of capacities and possibilities, which allow goal achievement, and which do not contravene legal norms.
    - Timeframe: Optimal planning period for goal achievement as defined in the plan. See the ease and difficulty of realization of plans. Measuring period: two years before completing the sentence.

Score	Features
1	Concrete and/or adequate and/or achievable plans and targets in an optimal timeframe
2	Concrete and/or adequate and/or achievable plans and targets in a near-optimal timeframe
3	Plans and goals that are vague and/or relatively adequate and/or difficult to achieve
4	Plans and goals too vague and/or inadequate and/or too difficult to achieve
5	No and/or inadequate and/or unrealisable plans

4. Family Relationships **Women only**

    - DEFINITION: It is the responsibility assumed towards their family. That is all those concrete behaviors with regard to the economic support of their family and the care of their children.

Score	Features
1	High responsibility and concern for their family.
2	Is responsible for the family group
3	Low responsibility
4	Absolutely irresponsible
5	Economically exploits their family

5. Couples and Groups of Friends

    - DEFINITION: Couple relationship: marital or cohabiting relationship. Peer group: Group of belonging and/or reference in which they interact, assimilating its norms and models of conduct.-
    - Criteria
        - Criminogenic quality of the partner and peer group.
        - Refers to the partner relationship in the last year of detention and/or current at the time of detention.

6. Use of Free time

    - DEFINITION: Environments frequented and activities (recreational or not) that occupy most of their free time (including criminal activity and other deviant behavior).

Score	Features
1	Friends and partner with no criminal record or criminal behaviour
2	Friends and/or partner exhibit non-criminal deviant behaviour (prostitution, drug addiction, alcoholism, etc.).
3	Friends and/or partner have occasional criminal activity, arrests, charges or prosecutions
4	Friends and/or partners are regularly involved in criminal activity, with prosecutions, charges and/or convictions.
5	Friends and/or partner with 2 or more convictions, multiple offenders.

- Criteria
  - Criminogenic quality of the environments and activities in which individuals engage in their leisure time.

Score	Characteristics
1	Only attends non-deviant and non-criminal environments
2	Occurs mainly in non-deviant environments, but occasionally in deviant environments.
3	Occurs with moderate frequency in environments where deviant and/or criminal behaviour takes place
4	Frequently attends deviant and/or criminal environments.
5	Exclusively only attends deviant and/or criminal environments.

7. Drug Consumption

- DEFINITION: Illicit drug use Drug use often precedes deviant and criminal acts, with negative consequences for the family, job opportunities and social relations.
- CRITERIA
  - Habituality of use.
  - Degree of dysfunctionality in their life as a whole, in their responsibilities.

Score	Characteristics
1	Doesn't consume drugs
2	Initial use. Corresponds to situations of initial contact with one or more substances
3	Occasional use. This corresponds to intermittent use of the substance(s), without any fixed periodicity and with long intervals of abstinence.
4	Habitual use. This involves frequent use of the drug. This can lead to other forms of consumption, depending on the substance in question, the frequency with which it is used, the characteristics of the person, the environment, etc. Involves degrees of partial dysfunctionality.
5	Compulsive or drug-dependent use. The individual needs the substance and their life revolves around it, despite the complications and dysfunctionality it may cause.

8. Crimes as a Child

- Definition: Socially deviant behavior, criminal or otherwise, prior to the legal age of termination of minority.
- CRITERIA

Score	Characteristics
1	No History/record
2	Deviant behaviour such as homelessness, drug addiction, vagrancy, sexual exploitation, etc.
3	Has crimes without arrests and/or prosecutions
4	Arrests and/or prosecutions and/or indictments (without conviction)
5	Convictions for a criminal offence, while a juvenile is a minor who can be charged

  - Deviant behavior. - Age of termination of minority (18).

9. Age of First Crime

   - REMARKS: Criminal initiation refers to the first offense committed and recognized, even if not arrested or convicted. Special care should be taken to try to identify this

Score	Characteristics
1	40 years or older
2	31 to 39 years old
3	21 to 30 years old
4	18 to 20 years old
5	Under 18 years old

10. Previous Sentences

   - DEFINITION: Types of previous records, arrests, prosecutions, charges, and convictions.

Score	Characteristics
1	No arrests, prosecutions, indictments or convictions.
2	1 prior arrest for misdemeanour, with a sentence of less than 60 days, quasi-delinquency Previous charges or proceedings without conviction (acquitted or dismissed)
3	1 previous conviction with an alternative measure (Probation, Conditional Remission or Overnight Confinement) or 1 conviction of less than 1 year imprisonment. Several convictions for misdemeanours (petty theft)
4	1 prior conviction between 1 – 3 years imprisonment
5	2 previous convictions of between 1 and 3 years or 1 conviction of 3 years or more

11. Belong to Organized Criminal Group

   - CRITERIA
     - Temporary or permanent participation in an organized or semi-organized criminal group.

12. Carrying Weapons in Crime

Score	Characteristics
1	Does not belong to a criminal organisation, gang or gangster.
2	Frequents gangs and/or criminal gangs, (but does not belong to them).
3	Occasionally belongs to a criminal gang, less over time
4	Belongs to a permanent or larger criminal gang.
5	Belongs to a criminal organisation. Organiser, financier or leader of a gang.

- DEFINITION: Carrying and use of any type of weapons in the commission of the offense
- CRITERIA
  - Carrying and/or use of any type of weapon in the commission of the offense Carrying and/or use for purposes of intimidation, threat, or express violence

Score	Characteristics
1	Does not carry weapons
2	Carrying and/or use of sharp weapons
3	Carrying and/or use of homemade firearms (homemade)
4	Carrying and/or use of small firearms (handguns, such as pistols and revolvers)
5	Carrying and/or use of long firearms (shotguns, rifles, rifles, rifles, sub-machine guns, etc.)

13. Family Criminal Record

- DEFINITION: relatives with a criminal record and/or imprisonment.
- CRITERIA
  - Identify family ties with criminal activity.

Score	Characteristics
1	No Family members with criminal records
2	Has a close relative with a record, only of arrests
3	Has a close relative who has been charged and/or prosecuted without conviction.
4	Has a close relative with conviction(s)
5	Has 2 or more close relatives with conviction(s). NOTE: A close relative is defined as a family member with whom you have frequent contact, with whom you share a dwelling or household.

14. Criminal Continuity

- Criteria: Quantity of crimes in the last 2 years.

Score	Characteristics
1	Never
2	Only one infraction or quasi-felonies
3	One felony, or two infraction or quasi-felonies
4	Two or more offences
5	They only engage in criminal activity, in the business of crime

9.12 Nonparametric estimations

I use the command in Stata *rdrobust* provided by Cattaneo, Idrobo, and Titiunik (2019) to perform the nonparametric regressions. The first two rows in table 18 are polynomials of degree 1 and degree 2, using mean squared error (MSE)-optimal bandwidth selector and triangular kernel. I use cluster standard errors at the facility level.

Table 18: Nonparametric Estimation

Polynomial		Robust inference		Observations		
		p-value	Conf. Int	left	right	h
First-degree polynomial	0.1718**	0.010	0.0456 0.2979	356	312	12.036
Second-degree polynomial	0.1932**	0.008	0.0521 0.3539	670	446	20.942

Notes: Table 18 shows a nonparametric Sharp RDD. The unit of observation is at the individual level. The dependent variable is recidivism within three years after release. Optimal bandwidths were chosen by mean squared error (MSE)-optimal bandwidth selector Cattaneo, Idrobo, and Titiunik (2019). The first row estimates the intent-to-treat effect using a polynomial of degree one and the second row estimates the intent-to-treat using a polynomial of degree two. Standard errors clustered at facility level. * $p < .1$, ** $p < .05$, *** $p < .01$.

9.13 Individual score vs peer score

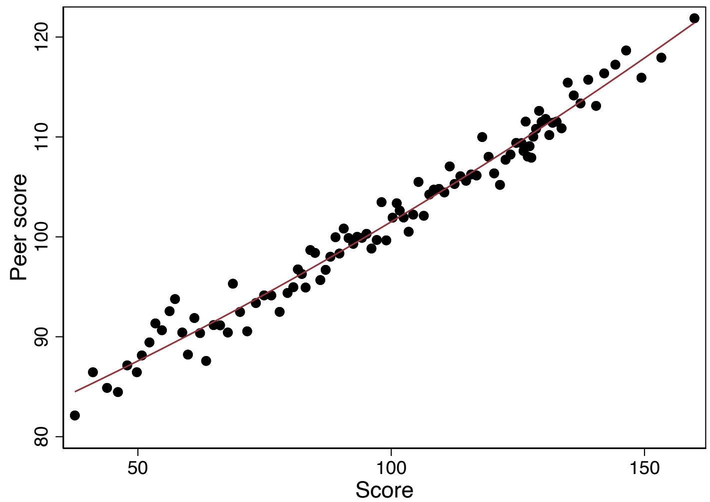


Figure 39: Relationship between individual score and peer score

Notes: This figure depicts the relationship between individual scores and peer scores. The horizontal axis represents individual scores, while the vertical axis represents peer scores. The positive slope suggests a correlation between the two, indicating that higher individual scores tend to be associated with higher peer scores.

9.14 Types of crime

Table 19: Type of crime/offend.

Type of crime/offend.	Consider
Theft	x
Robbery	x
Receiving	x
Homicide	x
Injury (Physical damage)	x
Smuggling	x
Rape	
Traffic	x
Drunk Driving	
Alimony	
Break parole	
Fine	
Abortion	
Others	x

Notes: This table classifies crimes and whether they are considered (indicated by ”x”). Blank cells represent cases where the crime is not considered. The variable definitions align with those used in the analysis dataset.

9.15 Score Components

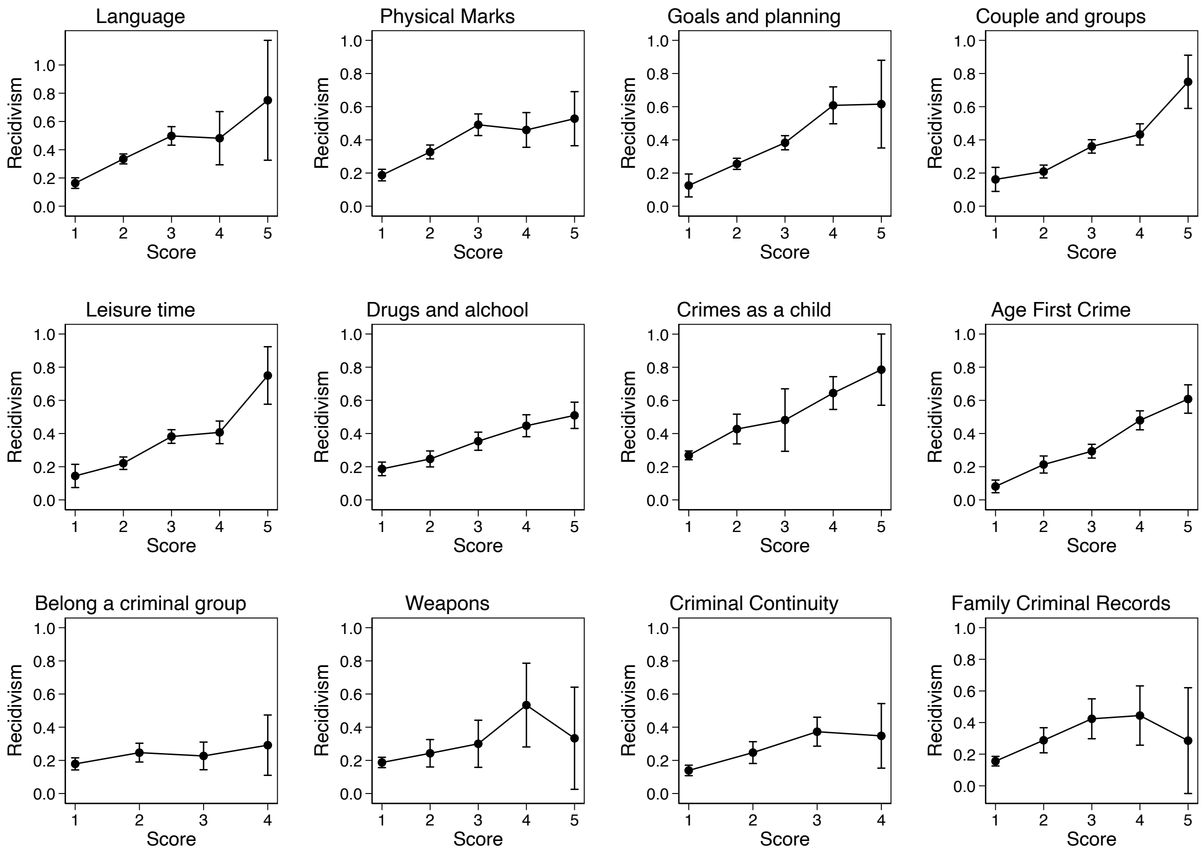


Figure 40: Relation between score components and recidivism

Notes: This figure examines the relationship between individual score components and recidivism. The horizontal axis represents the score components, while the vertical axis indicates the recidivism rate within three years post-release. Components are evaluated individually, highlighting their varying predictive power for recidivism.

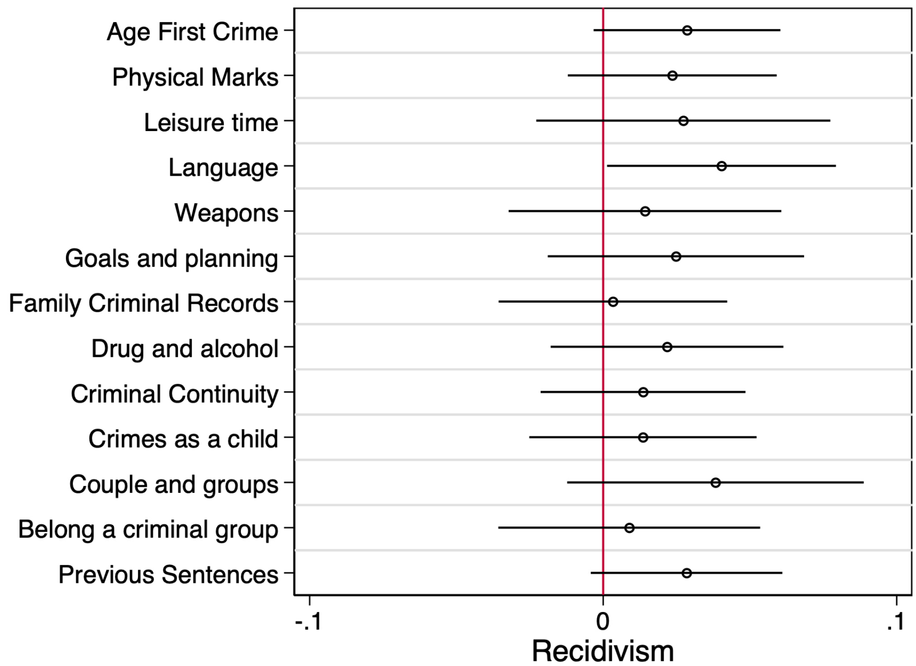


Figure 41: Effects of score components of the peers on recidivism

Notes: This figure illustrates the effects of peer score components on recidivism within three years post-release. The horizontal axis represents the estimated effect sizes, while the vertical axis lists the score components. Confidence intervals are included. The results suggest that some components, such as Couple and Groups and Language, exhibit relatively larger effects on recidivism. However, none of the components are statistically significant.

Table 20: Effect of peers score components

Variable	**Dependent variable: recidivism**	**Obs.**
Score components		
Age first crime	0.0285*	1,159
	(0.0160)	
	[0.5072]	
Crimes as a child	0.0135	1,159
	(0.0195)	
	[0.6369]	
Goals and planning	0.02477	1,159
	(0.0220)	
	[0.5706]	
Couple and groups	0.0382	1,159
	(0.0255)	
	[0.4435]	
Alcohol/Drug	0.0217	1,159
	(0.0200)	
	[0.5191]	
Leisure time	0.0272	1,159
	(0.0252)	
	[0.4597]	
Physical marks	0.0235	1,159
	(0.0179)	
	[0.5012]	
Language	0.0402**	1,159
	(0.0196)	
	[0.5575]	
Previous sentences	0.0284*	1,159
	(0.0164)	
	[0.3786]	
Weapon	0.0142	1,157
	(0.0234)	
	[0.6440]	
Criminal continuity	0.0135	1,157
	(0.0176)	
	[0.6388]	
Family records	0.0033	1,157
	(0.0196)	
	[0.8665]	
Belong to a criminal group	0.0088	1,157
	(0.0225)	
	[0.7522]	

Notes: Table 20 presents results from 13 regressions, each based on Equation (5). In each regression, the *Peer Score* variable is replaced with the average of a specific score component. The unit of observation is the individual. All regressions control for demographic characteristics—age, marital status (single), years of education, and months spent in prison—as well as criminal history variables, including robbery, receiving, theft, homicide, injury, and drug trafficking. The dependent variable is recidivism within three years post-release. Adjusted Benjamini-Hochberg p-values are shown in brackets. Standard errors in parentheses are clustered at the prison-block level. * $p < .1$, ** $p < .05$, *** $p < .01$ [unadjusted]

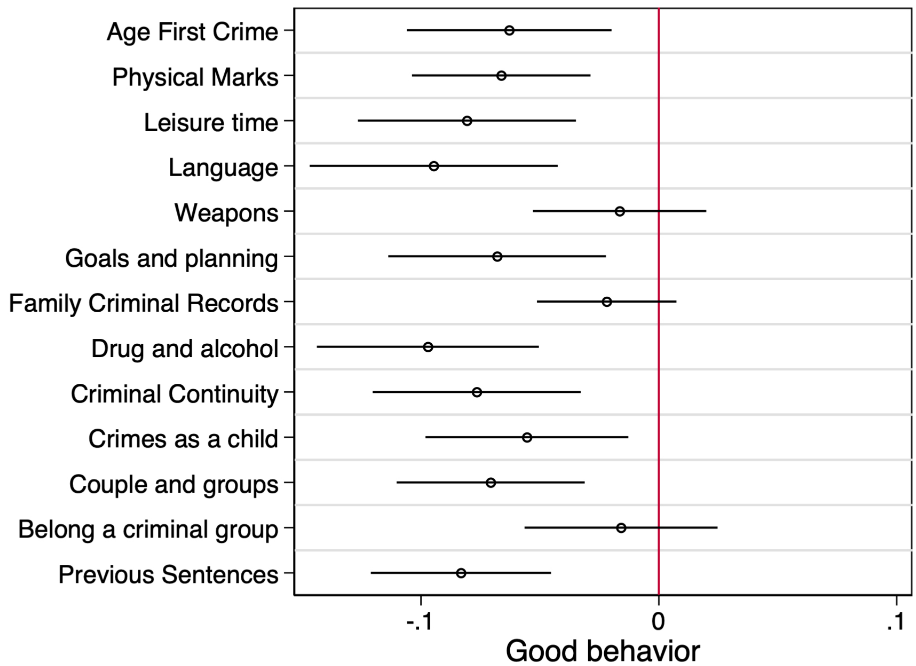


Figure 42: Effects of score components of the peers on good behavior

Notes: This figure depicts the effects of peer score components on good behavior. The horizontal axis represents the estimated effect sizes, while the vertical axis lists the score components. Confidence intervals are included. The results indicate that components such as Drug and Alcohol, Language, and Previous Sentences have relatively larger effects on the likelihood of good behavior.

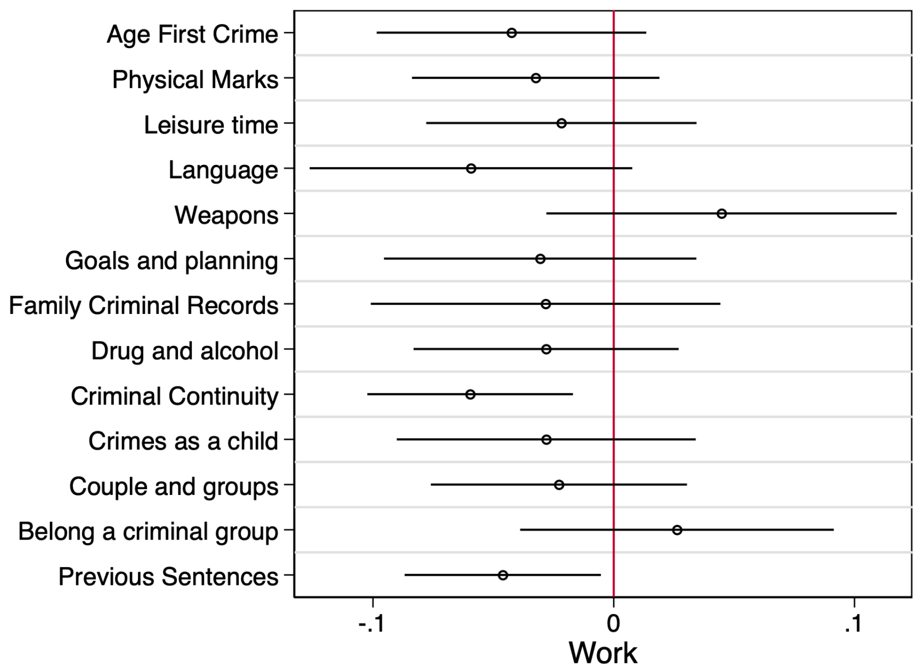


Figure 43: Effects of score components of the peers on work

Notes: This figure presents the effects of peer score components on work-related outcomes. The horizontal axis represents the estimated effect sizes, while the vertical axis lists the score components. Confidence intervals are included. Results suggest that components such as Criminal Continuity and Previous Sentences may have stronger associations with work outcomes.