Harsh or Humane? Detention Conditions and Recidivism *

Giovanni Mastrobuoni†and Daniele Terlizzese‡

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Abstract

We use quasi-random variation in the fraction of time served in the Italian "open-cell prison" of Bollate to estimate the effect of humane prison conditions on recidivism. We deal with the endogenous assignment of inmates to prison conditions by focusing on those sources of variability in the length of exposure to more humane conditions that are plausibly unrelated to recidivism. Our most stringent test restricts the analysis to inmates who are displaced to Bollate due to overcrowding in nearby prisons, controlling for measures of observed (based on a revealed preference argument) and unobserved potential selection.

Spending one more year at the experimental prison (and one less year at an ordinary one) reduces recidivism by around 10 percentage points. For the group of displaced inmates, which is shown to be negatively selected in terms of recidivism, the effects of rehabilitation efforts on recidivism are larger (even in relative terms).

While we find evidence that over time Bollate inmates become more likely to work outside the prison, more than a single mechanism underlies these effects.

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†University of Essex, gmastrob@essex.ac.uk
‡EIEF and Bank of Italy, daniele.terlizzese@eief.it

1 Introduction

Over recent decades most developed countries have witnessed high and often increasing rates of incarceration. In the United States, in 2012, almost 1 per cent of the adult population was behind bars, with a sevenfold increase in the incarceration rate since the early 70s. Incarceration rates are high in several other countries, including Italy and the United Kingdom. This process risks, however, to feed on itself, as a large fraction of those who are sent to prison are repeat offenders. In the U.S. State prisons, for example, about 40 percent of released inmates are re-incarcerated within three years.[1]

Therefore, if societies were able to reduce recidivism, victimization and incarceration rates would be reduced as well, generating large economic and social benefits (see Raphael and Stoll, 2009).Opinions differ, however, on the best way to curb recidivism, and different approaches have been followed, in different countries and at different times.

Up until the late 60's, the approach to criminal justice in the United States focussed on rehabilitation, envisaging prison conditions preparing inmates for their successful re-entry into society.[2]

Then, at the beginning of the 70's, with the intellectual backing of the work by Robert Martinson et al. (1974), the media, politicians and the public opinion converged on the idea that "nothing works" in regard to rehabilitating prisoners. Hence, the U.S. went down a different road, emphasizing the "tough-on-crime" policies, the importance of incapacitation and of deterring inmates through the experience of harsh prison conditions (usually referred to as specific deterrence). According to this view, prison life should isolate inmates not just from the outside world: movements inside the prison are regulated, and inmates often spend a large part of the day inside their cell, with little scope for rehabilitation.

At about the same time, in some European countries, and notably in the Nordic ones, "open" prisons were built with the idea that the punishment for criminal behaviour amounts to the limitation of freedom, while preserving the other fundamental human rights: within the walls, which keep prisoners secluded from the rest of society, life should be as normal as possible; inmates can work, study, have hobbies, keep their affective relationships, in an environment that allows for movement around the prison premises with little supervision. [3]. Prison conditions that "*do not infringe human dignity,*" and a life in prison that approximates "*as closely as possible the positive aspects of life in the community*" has also been an important recommendation by the Council of Europe (a

[1]Re-incarceration rates are lower than re-arrest rates, as not all arrestees are incarcerated. See http://www.bjs.gov/index.cfm?ty=daa. The Italian prison data we are going to use shows similar re-incarceration rates.

[2]The President's Commission on Law Enforcement and Administration of Justice in its report "The Challenge of Crime in a Free Society" recommended that " *the model institution would resemble as much as possible a normal residential setting. Rooms, for example, would have doors rather than bars. Inmates would eat at small tables in an informal atmosphere. There would be classrooms, recreation facilities, day rooms, and perhaps a shop and library.*"

[3]A fact sheet on criminal services in Norway reads: "The punishment is the restriction of liberty; no other rights have been removed... During the serving of a sentence, life inside will resemble life outside as much as possible... You need a reason to deny a sentenced offender his rights, not to grant them."

intergovernmental organization) to all European member states in 2006.

Recently, also in the U.S. the attention to the potential benefits of a rehabilitative approach has been on the rise. On the one hand, rehabilitation is increasingly seen as an effective way of keeping in check the long-term costs of housing inmates. Correction Corp. of America, the largest private prison firm, has recently announced a change in its business model, committing to "*play a leadership role in reducing recidivism... planning to expand the company's prison rehabilitation programs, drug counseling and its prisoner re-entry work*" [4] On the other hand, both scholarly papers (e.g., Pratt, 2008, Ward et al., 2013) and the general press (e.g., Larson, 2013, Benko, 2015) have brought the spotlight on the "Scandinavian model" of open prisons.

It is difficult, however, to directly extrapolate from the experiences of the latter.

One obstacle is size: most house less than 100 inmates, even the largest do not exceed 350 (Pratt, 2008), while in the United States the average number of inmates at maximum-security prisons is around 1,300.

Another obstacle is cost: for example, spending on the Halden open prison in Norway runs to more than 93,000 dollars per inmate per year, compared with just 31,000 dollars for prisoners in the United States (estimate by the Vera Institute of Justice, a nonprofit research and advocacy organization).

A third obstacle is, of course, the selection problem, as inmates are not randomly sent to the open prisons, and any naive comparison of recidivism rates with inmates sent to closed prisons would not have a causal interpretation. To the best of our knowledge, there is no rigorous study of the causal effect on recidivism of detention conditions which approximate as much as possible a normal life, within the boundaries posed by the restriction on freedom. In these circumstances, the treatment is a complex amalgam and inmates can choose in which initiatives to participate. But then, the causal evidence from the (few and far between) rehabilitation programs in the U.S., which usually have a coercive nature and a well defined and narrow focus, is of limited use in predicting what would happen if the "Scandinavian model" – which we succinctly characterize as offering humane prison conditions – were to be exported to the U.S..

The main contribution of this paper is to fill this gap, providing evidence on the effectiveness of humane prison conditions in reducing recidivism. We use data from an *open* prison in Italy, which is *large* (about 1000 inmates) and *costs no more* – if anything less – than traditional *closed* prison in that country. To solve the selection problem, we look at the intensive margin of the treatment – the *length* of the period spent in the open prison, conditional on the total sentence – and we exploit quasi-random variation in such margin. In particular, we focus on inmates who, due to overcrowding of the prison in which they were serving their sentence, are displaced to the open prison, controlling for the time in which the displacement occurred, the prison of origin and the total length of their sentence. This amounts to compare the recidivism of inmates who were serving the *same overall sentence* in the *same prison* and were displaced at the *same time* to the open prison, but who differ in the part of their sentence that remains to be served there,

[4] Quoted in a recent *Wall Street Journal* article (See WSJ, September 12, 2014: "*Prison Firm CCA seeks to reduce the number of repeat offenders*").

because they had started serving their sentence at different points in the past.

As a robustness check, following a revealed preference argument, we also use the information contained in the history of previous displacements of *other* inmates to proxy for the unobserved "propensity to recidivate".

The focus on displaced inmates offers two further advantages. Since in the open prison they get to be less involved than the other (selected) inmates in those aspects of the treatment more explicitly targeted to rehabilitation – for example, they are rarely given the opportunity to work outside – their experience is more telling of the effect on recidivism of prison conditions that are simply respectful of their dignity, that stress co-responsibility and trust, that allow for close-to-normal social interactions. Moreover, since the displaced inmates do not go through an explicit selection process, the external validity of our results is likely to be stronger.

More in detail, we have rich data on inmates who spent some time in the *Bollate* prison, an Italian detention center inaugurated at the end of 2000 near the city of Milan, which featured in 2003 in the New York Times article "*Italian inmates receive training in a Cisco computer program: Behind bars but learning to network*".

Bollate is the only pure open prison in Italy (as mentioned above, they are more common in Scandinavian countries and, to a lesser degree, in the United Kingdom).[5]. Bollate prison cells are kept open during the day, and prisoners are trusted to serve their sentences with minimal supervision: inmates are allowed to freely move across the prison with electronic badges, making it easier to reach the location where they either study or work. For about a third of them, even prison walls are "open," as they are given the opportunity to work outside during day releases.[6] Inmates elect their representatives and, within a given budget, have a say on several aspect of their prison life (furniture, food, etc). When children are visiting their parents they can spend their time in dedicated play rooms that are nicely furnished and full of toys. In such an environment, prison violence is contained and fewer guards are needed, which keeps costs down.

In sum, Bollate offers its inmates several opportunities to develop their human and social capital and to experience self-responsibility, within the limits posed by the restraints on freedom. [7] Additional information on the prison and a comparison with the conditions in other prisons will be provided in Section 2.

Using these data, we ask whether prison conditions as exemplified by those at Bollate are effective in reducing inmates'recidivism – measured as the occurrence of a re-incarceration of a released prisoner within three years from the end of his custodial and non-custodial (e.g. home detention, monitored liberty, etc.) sentence.[8]

To answer this question we must of course confront a serious selection problem, as

[5]Some examples are Halden Fengsel (Norway), Suomenlinna Prison (Finland), Soebysoegaard (Denmark), HM Prison Prescoed (South Wales), HM Prison Castle Huntly (Scotland), HM Prison Ford (England).

[6]Of the 9,318 inmates who have spent some time at Bollate between 2000 and 2009 four evaded prison during such day release, while one inmate managed to evade Bollate from the inside.

[7]The appendix Figures 5 to 7 provide photographic evidence on the prison conditions at Bollate.

[8]Since our sample comprises inmates released between 2000 and 2009 and we can follow them until 2013, the three year period is never truncated.

clearly prisoners sent to Bollate are not a random sample of prisoners, and we might expect the selection to negatively correlate with the unobserved "propensity to recidivate".

We deal with this issue by exploiting the variability in the *length* of the residual sentence spent at Bollate, which represents our measure of the "Bollate treatment". This means that the subjects of our analysis are *all* treated, but they differ for the *dose* of the treatment. This is not dissimilar to the standard analysis of the returns to education. The usefulness of such approach, in connection with recidivism, is noted and exploited by Di Tella and Schargrodsky (2013). One important point is that the conditions in the prisons where inmates were serving their sentence, before being sent to Bollate, are completely different, and close to the harsh model widespread in the U.S.. Conditional on the total sentence length, therefore, a longer residual sentence at Bollate corresponds to a shorter stint in a harsh prison.

Of course, we need to argue that the length of the residual sentence at Bollate itself varies in a near-random fashion. We will do this by progressively restricting the sources of variability in the length of the residual sentence.

Our stronger identification will come from the variability in the residual sentence among inmates displaced to Bollate *at the same time and from the same prison*. In this way, the variability of the residual sentence results solely from the random date in which different inmates started serving their sentence (controlling for its total length, and for many other covariates). The identification will then be achieved by comparing the recidivism of inmates who are serving the same sentence and are displaced to Bollate together, from the same prison, but since they started serving their sentence ad different times in the past, have different residual sentences when they arrive at Bollate.

We also consider the fact that each of the displacement decisions made by the sending prison contains information on the (unobserved) propensity to recidivate of the inmates *not* displaced on that occasion. Accordingly, we include as controls in the regression a vector of variables characterizing, for each inmate eventually displaced to Bollate, all the previous displacement episodes occurred during his presence at the sending prison (for short, the "missed displacements").

To briefly preview our results, comparing recidivism rates of inmates displaced to Bollate, at the same time and from the same prison, and controlling for the characteristics of the "missed displacements" (and for many other covariates), we find that, for a given total sentence, replacing one year in a traditional closed prison with one year in an open one reduces recidivism (over a three-year horizon) by about 13 percentage points (against an average three-year recidivism of about 40 percent). Considering the larger sample of all Bollate inmates, our results are broadly unchanged: the point estimate of the effect of the "Bollate treatment" on recidivism is a reduction of about 10 percentage points for every year spent at Bollate instead of the prison of origin.

The effects of the "Bollate treatment" differ across different categories of inmates: the reduction of recidivism is very strong for inmates who were convicted for economically motivated crimes (theft, robbery, extortion, fraud...), while it is not significant for inmates convicted for violent crimes; it is stronger for inmates who do not have a long history of recidivism, and who are less educated.

Taken together, these heterogeneous responses suggest that the treatment is most effective when administered early enough on those people who are driven to a criminal activity by necessity and who are less well equipped to deal with the challenges of a non criminal life.

As to the mechanisms underlying the reduction in recidivism resulting from the "Bollate treatment", we find that the latter becomes more intense as time goes by. The longer inmates stay at Bollate, the more they are likely to be given access to jobs outside of prison, and to be allowed day releases. This suggests that offering opportunities to work and facilitating the entry (or re-entry) into the labor market is an important ingredient of the treatment.

However, displaced inmates are much less likely to be given access to work opportunities while in prison. They usually remain at Bollate for a shorter period, and are less involved in the activities more explicitly aimed at rehabilitation. All the same, they experience there an environment radically different from those of other prisons, much more respectful of their dignity, stressing self-responsibility and trust. The fact that the "Bollate treatment" seems equally effective in reducing their recidivism – if anything even more effective – points to the existence of additional mechanisms. We conjecture that humane prison conditions, coupled with responsibility and productive use of time, as offered by Bollate's environment, in and of themselves positively affect the post release behavior of inmates.

The larger effect of the "Bollate treatment" on the displaced inmates, relative to the actively selected prisoners, has another interesting and almost paradoxical implication. It suggests that the selection into Bollate picks those inmates that benefit relatively less from being there (at least when the benefit is measured in terms of reduced recidivism). To rephrase in positive terms, it would seem that a less choosy selection into Bollate would generate more bang for the buck.

This would not be the case, however, if the reduced recidivism were to result from weaker deleterious peer effects: indeed, Bollate might use the selection to limit the arrival of "bad" peers. If so, the possibility to scale up the Bollate experience would be curtailed, since a less exacting selection process would undermine the effectiveness of the treatment.

We use data on the cell and the prison section to measure the effect on recidivism of being exposed to a larger group of displaced inmates during an inmate's stay. We find no evidence that such exposure increases recidivism, even when such exposure in measured at a very fine level (cells).

Differently from the broad conclusion of the Nagin et al. (2009) survey, which finds that incarceration has a null or mildly criminogenic effect, we show that the more humane prison conditions coupled with rehabilitation programs reduce recidivism.

1.1 Relationship with the literature

Our work is related to a few economic studies analysing the effect of imprisonment on recidivism. Di Tella and Schargrodsky (2013) use ideological differences of randomly assigned judges to show that Argentinean inmates who spend part of their sentence under electronic monitoring, instead of prison, have lower recidivism. They also analyze the intensity of treatment in a way that resembles our study. Focussing on the group of electronically monitored inmates, where they argue that "*the problem of selection is less relevant*", they find that increasing the fraction of time spent under electronic monitoring (as opposed to ordinary imprisonment) reduces recidivism. Their results are consistent with our own. On the one hand, the larger is the fraction of time served under conditions more respectful of human dignity (as when allowed to be outside the prison under electronic monitoring), the lower is recidivism; this is clearly reminiscent of our "Bollate treatment." On the other hand, the larger the total time served in ordinary prisons, which in the Argentinean case are often degrading, the larger is recidivism; we find the same result when lengthening the time served in an ordinary prison (holding fixed the time spent at Bollate). Aizer and Joseph J. Doyle (2013) use the same identification strategy (random assignment of judges who differ in their punitiveness) to focus on the effect of juvenile incarcerations on recidivism. The labor market prospects of incarcerated juveniles, who would otherwise be at school, might suffer more than those of adults; juveniles might also be more susceptible to criminal peer effects. While data limitations do not allow them to measure recidivism effects at the intensive margin (short vs. long incarcerations), they do indeed find compelling evidence that any juvenile incarceration increases recidivism as an adult, as well as reducing the likelihood of high school graduation. Our data does not contain any juveniles. The youngest inmates are 19 years old, and the average age is 38.[9] Opposite to the above findings, in Kuziemko (2013) an exogenous one-year increase in prison length driven by changes in Georgia's parole-board guidelines lowers three-year recidivism by a very large degree (-43 percent). Our results might provide an explanation for such opposite findings: prison time served by adult inmates in different prisons, with different rehabilitation programs, can lead to very different effects on recidivism. A longer prison time served might reduce or increase recidivism, depending on whether it takes place in a prison with rehabilitation programs, like Bollate or prisons in Georgia U.S., or in a much harsher one, like the other prisons in Lombardy or prisons in Argentina. As a background to our analysis it is also worth mentioning Raphael and Stoll (2009), who provide an insightful counterfactual analysis of the U.S. incarceration rates between 1980 and 2005. Their findings show that most of the observed growth is driven by increased admission rates into prison (as opposed to changes in release probabilities and in the average time served). While their study can not distinguish first-time prisoners from recidivists, the increase in the admission rate of inmates on parole, who represent a subset of all recidivists, explains about 20 percent of the growth in the U.S. prison population between 1980 and 2005.[10] The next Section provides additional information on Bollate and on the selection process, discusses our identification strategy and describes the data. Section 3 presents the results and a battery of robustness checks. Section 4 makes a first attempt at investigating the mechanism underlying our results. Section 5 concludes.

[9]Similar criminogenic effects of prison time have been found by Gaes and Camp (2009), while Green and Winik (2010), exploiting once again random assignment of judges, find that recidivism does not respond to incarceration. Starting with Kling (2006), researchers have also used the random assignment of judges to estimate the effect of incarceration length on the inmates' labor market prospects.

[10]Both, Raphael and Stoll (2009) and Neal and Rick (2014) show that the growth in admissions in mainly driven by changes in criminal justice policy towards more punitive sentencing rather than changes in criminal behavior.

2 The Quasi-experiment

To understand the sources of variability that will allow us to identify the causal effect of the "Bollate treatment" it is useful to start with a little background on the Bollate prison, and on the working of the Italian judicial and prison system.

2.1 The Bollate Prison

Inmates convicted to a prison sentence of less than three years and inmates waiting for their definitive sentence are typically incarcerated in jails (*Case Circondariali*), near the place where they reside, or, temporarily, near the place where they committed the crime.[11] Given that most incarcerations in the *Case Circondariali* tend to be short, these detention centers invest very little effort in trying to rehabilitate the inmates. If convicted to a prison sentence of at least three years, the inmates are transferred to a different type of prison, known as *Casa di Reclusione.*

The aim, in principle, is a) to separate serious convicted offenders from the other ones, and b) to focus rehabilitative efforts on those inmates who spend a sufficiently long time in prison. In practice, due to severe overcrowding and chronic lack of resources, the rehabilitative efforts in most *Case di Reclusione* are often rather limited.

We focus on inmates who spent at least part of their sentence in the "*Casa di Reclusione* Bollate" (near Milan; we will henceforth refer to this prison simply as Bollate). As we mentioned in the Introduction, Bollate was opened in late 2000, with the explicit goal of creating a rehabilitating prison, leaving ample room for a range of activities and establishing joint work/training programs with regional institutions and non governmental organizations. Inmates can go to school (up to secondary education), learn English and computer languages. They can train to become carpenters, electricians, cooks, welders, as well as work in or out of the prison for several agricultural and service cooperatives.

Differently from other prisons, security is not seen merely as a police concern but also educators, psychologists and even the inmates themselves are involved and given responsibilities.[12]

Table 1 presents the main characteristics of the prisons from which the Bollate prison draws most of its inmates. About 70 percent of inmates are transferred from the largest *Casa circondariale* in the Lumbardy region, San Vittore.

The first striking difference between Bollate and all other prisons is that in the former inmates are free to move out of their cells for most of the day (10 to 12 hours), while the majority of inmates in the other prisons spend only around 4 hours outside their cells (which represents the minimum time required by law).

Bollate is also the youngest prison. San Vittore was built in 1879, following Bentham's panopticon design. Opera, the other major *Casa di Reclusione* was built in 1980. These

[11]Individuals can be incarcerated before trial if caught in the act of committing an offence (*flagranza di reato*) or whenever there is a significant risk that they either pollute the evidence, recommit the same crime, or escape the judgment (upon decision of a special court, *Giudice per le indagini preliminari*).

[12]Inmates were asked to sign a "Responsibility Pact", committing to a responsible behavior lest being transferred to a different prison.

older prisons tend to be overcrowded: in 2009, at San Vittore, the ratio of inmates over official capacity was 142 percent, at Opera it was 128 percent (similar conditions are observed in all the other years of our sample). Bollate, instead, is always below its capacity. This contributes to better prison life, keeping suicides and attempted suicides, self-inflicted injuries, and hunger strikes at the lowest level compared to all the other prisons in Lumbardy.

Apart from the open cell policy and the lack of overcrowding, Bollate is special for its rehabilitation efforts, and in particular for those targeted to the future entry into the labour market of inmates. In most prisons, a fraction of the inmates (between 12 and 30 percent) work for the prison administration, cleaning, cooking, etc. These jobs are hardly useful for their future job chances outside the prison. At Bollate inmates have the opportunity to work for other employers than the prison administration, both inside and outside the prison. At a given point in time, about 30 percent of inmates are actively working for pay, either for employers that open a production line inside Bollate or for employers outside the prison. The fraction of inmates with similar arrangements is just 0.5 percent at San Vittore, 6.5 percent at Opera, and is never larger than 6.6 percent at other prisons in Lumbardy.

On top of this inmates in Bollate are more likely to be at school or at the university. For example, in 2009 in Bollate 8 inmates were enrolled at a university, against the 7 inmates at all the other prisons in Lumbardy combined. A remarkable feature of Bollate is that its running costs are much lower than the average prison in Italy. Table 2 shows, for two recent years, that the per-inmate daily cost of Bollate is about 65 euros, while the average for the whole country is about 130 euros. The difference is mainly due to the much lower wage cost, which in turn reflects the much lower number of guards and administrative staff, relative to inmates (the per capita wage of people working at Bollate is the same as in other prisons of the country). In 2009, in the Bollate prison, 470 prison guards and administrative staff dealt with 1032 inmates, a ratio of about 1/2. Nationwide the same year the total number of prison guards and administrative staff working inside penal institutions was 43,817 against a prison population of 63,983, a ratio of about 2/3.

2.2 The Treatment and the Identification Strategy

Inmates are selected into Bollate through two main channels. Either they apply to be sent there, or they are proposed by the administration of a different prison (usually in the same region) or by the Justice Department.[13] A third channel of access to Bollate, which does not involve an explicit selection process, is provided by displacement of inmates from nearby overcrowded prisons; we will considered displaced inmates later.

2.2.1 The Selected Inmates

For each request/proposal, the regional administration office for Lumbardy of the Ministry of Justice (the "*Provveditorato Regionale di Milano*") assesses, together with the Bollate

[13] A small number of inmates give up themselves directly to the Bollate prison, which we treat as if they applied to be sent to Bollate.

prison administration, whether the following criteria are satisfied. Inmates should, as a rule: have a residual sentence in the range 2 to 10 years; be in a good health status, and not be under methadone treatment; have a definitive sentence;[14] have shown propensity and active interest for rehabilitation programs (this is reflected in a positive assessment by a specialized team); have had a generally good behaviour in the previous prison; and, finally reside or have interests and relationships in the Lumbardy region. Once the assessment is completed, either the same regional office or a Department within the Ministry (the "*Dipartimento dell'Amministrazione Penitenziaria*") decree the transfer of the inmate.

Clearly, these criteria involve a good deal of selection.Still, among the selected inmates, the *time it takes* for the whole procedure to be completed and therefore, given the total sentence, the length of the residual sentence upon arrival at Bollate, can vary for a host of factors:

1. the initial request/proposal can be incomplete, and additional documents need to be obtained;

2. initially, some of the criteria might not be fully satisfied,or the people assessing them might not be fully convinced that they are satisfied, and the request/proposal is put on hold until they are;

3. there can be delays with which an inmate who satisfies the criteria submits the request or is identified by the administration of the current prison as eligible for the proposal;

4. if the inmate is considered a good prisoner worthwhile retaining, the administration of the prison of origin might potentially delay the process;

5. an inmate might be already involved in some activities or rehabilitation processes that is best not to interrupt;

6. the various administrative offices involved in the procedure can take different time to process the information and to reach a judgment, due to random variation of the backlog of other administrative tasks or of their efficiency;

7. whenever the conditions for the application of preemptive imprisonment ("*custodia cautelare*") apply, an inmate might have already served part of his/her sentence before the latter becomes definitive, depending on the number of appeals and on the speed with which they are settled. Since in principle Bollate only accepts inmates with a definitive sentence, any given sentence length can be associated with different lengths of the residual sentence;

[14] The Italian judicial system allows for up to two appeal courts. Depending on whether or not a given sentence is resisted, and up to which degree of appeal, the time elapsed before the sentence becomes definitive can vary by several years. Although in principle a convicted should not go to prison before the sentence is definitive, there can be a number of reasons why he/she is incarcerated even before the final appeal is decided.

The variability imparted by these factors might in principle be exploited to tease out the causal effect of the treatment – defined as the length of the residual sentence upon arrival at Bollate – on recidivism.

However, it might also be argued that the length of the delay itself reflects some selection. For example, for factors 1, 2 and 3 it could be argued that "better" inmates (more educated, with better labour skill, better behaviour, etc.) are more likely to be identified in a shorter time, so they would end up at Bollate earlier; as to factors 4 and 5, conversely, it could be argued that "better" inmates are more likely to be retained for longer by the prison of origin, so they would end up at Bollate later. Factor 6 is plausibly exogenous. A point worth stressing relates to factor 7. Conditional on the crime committed and on the criminal history, the speed with which a a given sentence becomes definitive often depends on the working efficiency of judges. As shown in Coviello et al. (2011) different judges can have very different levels of productivity.[15] Since judges are randomly assigned to cases, these differences lead to random variation of the timing of arrival to Bollate.

Unfortunately, it is impossible with the data at our disposal to weigh the importance of the different delays. However, we have a range of variables that characterize the selection mechanism of inmates (whether they applied or were proposed, where they were spending their previous prison time) and their previous criminal history, which are arguably a good proxy of the information set available to the people involved in the selection process. Our identification assumption, when using the entire sample of inmates, is that conditional on such variables, as well as on the total sentence length, the time it takes for the process to be completed – which translates into the residual sentence to be spent at Bollate when transferred – is as good as random.

Before moving to other sources of variability in the residual sentence, it is worth pausing to consider whether the latter is an appropriate measure of the treatment. Indeed, for about 2/3 of inmates the residual sentence upon arrival at Bollate represents also the actual sentence spent there, as they are never transferred again before their final prison release.

An inmate might however be transferred to another prison ahead of time if he misbehaves, or the treatment appears to be of little use, or conversely if his behaviour is so promising that he is given an early release (through non-custodial sentences). Clearly, both possibilities are the result of the inmate's behaviour, so the actual time spent at Bollate suffers from endogeneity.

The effect of the residual sentence upon arrival at Bollate, therefore, has the nature of an intention to treat effect. It might differ from the average treatment effect as the actual prison time, potentially shorter, is potentially endogenous. Despite this drawback, it could be considered a more appropriate measure of the treatment, since the residual sentence upon arrival might overstate the effective "dose" of the treatment received. This is a standard problem in policy evaluation studies: the intention to treat is cleaner, because it

[15] The judges in their data are also based in Milan, but deal with labor controversies. The judge with the lowest productivity would on average take 400 days to finish a trial, while the fasted ones would take less than half that time.

is more clearly exogenous, but overstates the measure of the administered treatment due to non-compliance.[16] We will present results for both measures of the treatment, using the potential time spent at Bollate as an instrument for the actual time.

2.2.2 The Displaced Inmates

As mentioned, not all inmates that are present at Bollate go through the admission procedure we have just described. Some inmates are sent there because nearby prisons are overcrowded and Bollate has spare capacity (which is very frequent). The Bollate administration has no control on which or when inmates are displaced there. Since almost all displacements originate from prisons within the same Lumbardy region, the "*Provveditorato Regionale di Milano*" collects the requests from the prisons having too many inmates, relative to their capacity, and distributes them in nearby prisons with spare capacity. For a number of years the inmates displaced to Bollate did not need to satisfy the requirements that we described before; only recently (post 2008) a looser version of the screening process has been introduced also for displaced inmates, but given that our sample stops in 2009 almost all the displaced inmates that we consider belong to the pre-screening period.

This implies that the delays directly affecting the explicit selection process (factors 1, 2, 3 above), which are more likely to imply that "better" inmates are selected earlier (increasing their residual sentence at Bollate), are shut down. These are for us the most worrying kind of delays, since speeding up the arrival of the most promising inmates, or delaying the arrival of the least promising ones, would generate a negative correlation between the residual sentence length and future recidivism, even in the absence of a real treatment effect. Thus, focussing on displaced inmates strengthen our identification strategy. Moreover, given that the displaced inmates are much more likely to be a random sample of the whole population of inmates, they provide an interesting comparison group to the inmates selected into Bollate, and one for which the external validity of our results is arguably stronger.

Focussing on displaced inmates, we are left with residual sentences that vary because, conditional on total sentence length, there is random variation in the time of arrest and conviction (similar to factor 7 above) and in the time when a given prison becomes overcrowded and a transfer takes place. [17] In passing, these sources of variability resemble the conditional exogeneity assumption used by Drago et al. (2009) and by Kuziemko (2013). In both studies the difference between the actual and the recommended sentence is not due to the timing of overcrowding at a specific prison facility, but rather due to the timing of a mass release.

[16] In studies where compliance cannot be observed, the intention to treat provides a sobering but perhaps more realistic assessment of the effects of the treatment, as a certain share of non-compliance is part and parcel of the treatment. In our case, in which any difference between the intention to treat and the actual treatment is under the control of the prison administration, perhaps the latter is in principle the most appropriate measure.

[17] moreover, an additional source of variability (admittedly, a limited one) is provided by possible delays in the administrative process matching the requests by overcrowded prisons with the available places in nearby prisons with spare capacity, similar to factor 6 above.

We cannot rule out, however, that the prison of origin still cherry-picks the inmates to be displaced. Thus, some elements of selection might be present even when restricting the analysis to displaced inmates. A plausible conjecture, which is unofficially confirmed by prison operators and administrators, is that more trouble-making prisoners are more likely to be displaced (this point is akin to factors 4 and 5 above). If this were the case, in a sample that includes subsequent waves of displaced inmates from the same prison, more trouble-making prisoners would be displaced earlier, and would mechanically tend to have longer residual sentences. This would be a source of bias in our estimates, though one biasing the estimated effect of the treatment towards zero. If instead the less trouble-making prisoners were to be preferentially selected for displacement – as one could argue if the transfer to Bollate were to be used as a reward for good behaviour – we would observe the opposite bias.

Indeed, the evidence seems to support the first possibility: our sample of displaced inmates seems to be be negatively selected, as is apparent from their recidivism rates (Table 3). The difference in recidivism between displaced and actively selected inmates is 12.1 percentage points (39.7 against 27.8 percent), and is significant at the 1 percent level.

2.2.3 The Displaced Inmates, at a Point in Time

To address the concern about a possible selection of displaced inmates by the sending prisons, we focus on those inmates who were displaced *at the same time and from the same prison*. It is reasonable to assume that all inmates displaced at a given point in time were selected using the same criterion. For example, they might all be selected because their (unobserved by us, but observed by the sending prison) propensity to recidivate is high. Or because it is low. Whatever criterion is used, as long as it is common and not correlated with the residual sentence, the remaining variability in the latter comes from the random variation in the time of arrest, conditional on total sentence length. Intuitively, we identify the effect of the "Bollate treatment" by comparing the future recidivism of inmates who were displaced to Bollate at the same time, from the same prison, where they were serving the same sentence, but who had started serving it at different random times in the past, so that they are left with randomly different residual sentences to be served at Bollate and are therefore treated with randomly different "doses" of the treatment.

A bias might still be present, however, if the selection of the displaced inmates were to be based directly (also) on their residual sentence. This might be the case if, for example, the sending prison wanted to get rid of those inmates who were expected to generate the largest amount of trouble, which in turn is given by the product of their "per-period troublesomeness" – plausibly correlated with their "propensity to recidivate"– and the number of periods in which they would remain in the sending prison, if not displaced. In this case, the inmates with a short residual sentence would be displaced only if their per-period troublesomeness, and hence their propensity to recidivate, were particularly high, thereby generating a negative correlation between residual sentence and recidivism, independent on the effect of the treatment.

Our informal discussions with prison administrators do not lend much credence to such an hypothesis. Moreover, the residual sentence of displaced inmates is on average rather short, and is therefore a margin somewhat unlikely to be really relevant.

Still, we can control for the possibility that the selection of the inmates to be displaced were intentionally based (also) on their residual sentence.

The key observation is the following: if the sending prison observes inmates' propensities to recidivate and residual sentences and selects the inmates to be displaced based on some function of both, given that we observe the residual sentences any decision to displace some inmates and not displace others reveals information on their respective propensity to recidivate.

To see this in the starkest form, suppose that the propensity to recidivate can only take two values, high and low, that the sending prison displaces inmates with higher values of some function increasing in both, propensity to recidivate and residual sentence, and that at a given point in time inmate A is displaced and inmate B is not. Now, if the residual sentence of A is shorter than B's, then it must be that A's propensity to recidivate is larger. Hence B's propensity to recidivate must be low. Suppose we also observe inmate C who, similarly to B, was not displaced when A was displaced and had a residual sentence that is different from that of B but still longer than that of A. Then C has a low propensity to recidivate as well. Finally, suppose that, at some later date, both B and C get displaced. Since they have the same propensity to recidivate (both low), we can causally attribute to their different residual sentences any difference in actual recidivism that we were to observe.

Of course, this example is special, but its key insight generalizes: each of the displacement decisions made by the sending prison contains information on the propensity to recidivate of the inmates *not* displaced on that occasion. We will make this idea more precise in the following section, using a simple formal apparatus. In particular we will show that any two inmates who were not displaced during enough displacement episodes occurred during their tenure at the sending prison, with enough displaced inmates in each episode and enough variability in their residual sentences, are very likely to have the same propensity to recidivate. Hence, we can include as controls in the regression a vector of variables characterizing, for each inmate eventually displaced to Bollate, all the previous displacement episodes occurring during his presence at the sending prison.

2.2.4 A simple formal framework

To present the identification strategy in a formal way, consider the following definitions:

T_{ij}^{B}: time of transfer to Bollate of inmate i from prison j

T_{i}^{S}: starting time of the sentence of inmate i

S_i: length of the sentence of inmate i

$D_i = S_i - (T_{ij}^{B} - T_{i}^{S})$: residual time to be spent (potentially) at Bollate (this is our "intention to treat"). [18]

We postulate the model

$$R_i = \beta_0 + \beta_1 D_i + \beta_2 S_i + \gamma' X_i + \rho_i$$

where R_i is (future) recidivism of inmate i, X_i is a vector of covariates and ρ_i is the unobservable "per-period propensity to misbehave/recidivate".

The coefficient β_1 would have a causal interpretation under an assumption of conditional independence:

$$D_i \perp \rho_i | S_i, X_i. \tag{CIA}$$

Whether or not CIA holds hinges on the precise definition of the variable T_{ij}^B, since we control for S_i, and T_i^S is clearly independent on ρ_i.

Consider the case of an overcrowded prison j, near to Bollate, that at some (random) time τ is granted the possibility of displacing to Bollate n_τ^j inmates. Then $T_{ij}^B = \tau$ for all the n_τ^j displaced inmates, and a correlation between D_i and ρ_i (conditional on S_i) can only arise if they have been selected for displacement on the basis of both, D_i and ρ_i. Selection on ρ_i would not in itself be a problem, as the variability of D_i would only depend on factors independent on ρ_i. [19] If, instead, the selection of displaced inmates were to be based both on D_i and on ρ_i (assuming, of course, that the sending prison observes both), CIA would not be a reasonable assumption.

In particular, if the selection were based on a function of D_i and ρ_i, increasing or decreasing in both arguments, it would (on average) induce, among the group of displaced inmates, a negative correlation between these two variables. [20] If instead the selection were based on a function of D_i and ρ_i increasing in one and decreasing in the other argument, it would induce (on average) a positive correlation between the two variables. [21]

Clearly, a negative correlation between D_i and ρ_i among the inmates displaced to Bollate would spuriously boost the effect of the treatment (it would make the estimated value more negative); a positive correlation would instead underestimate the effect of the treatment.

Note that a selection based on an increasing function of both arguments would be consistent with the idea of the sending prison trying to get rid of its more troublesome

[18] Note, for future reference, the following: fix a value for T_{ij}^B, say τ; then the variable D_i also measures the residual time that inmate i would spend at prison j, from τ onwards, if not transferred to Bollate.

[19] The interpretation of the coefficient β_1 would need to take this into account, of course: rather than the causal effect of the treatment on the average displaced inmate (conditional on S_i, X_i), it would be the causal effect of the treatment on the displaced inmates with certain values of ρ_i (depending on the selection criterion, and again, conditional on S_i, X_i)

[20] This is most easily understood by thinking to the marginal inmate selected for displacement. Any change in one of the two variables that would switch the inmate from the displaced to the non displaced group would need to be compensated, for him to remain among the displaced, by a change in the opposite direction of the other variable.

[21] The argument in the previous footnote can be easily adapted to explain in this case the positive correlation.

inmates. If instead the sending prison wanted to reward its best inmates, the selection would likely be a decreasing function of ρ_i (displace inmates with low values of ρ_i) and an increasing function of D_i (displace inmates who can remain for longer at Bollate). A selection based on a decreasing function of both arguments is harder to rationalize.

Let us focus on the negative correlation case, which is for us the more troublesome, and consider a selection criterion based on an increasing function of both D_i and ρ_i (the argument to follow could be easily adapted to a decreasing function of both arguments). Suppose, for concreteness, that prison j displaces, at any time τ in which it is given the opportunity to do so, the inmates who are expected to generate more trouble, where the expected trouble is given by their per-period propensity to misbehave (ρ_i), times the length of time they are expected to remain at prison j if not displaced (D_i).[22] The prison would then rank all inmates on the basis of the product $\zeta_i \stackrel{def}{=} D_i \rho_i$, and displace the first n^j_τ in the ranking. Formally, inmate i is displaced at time τ if $\zeta_i \geq \zeta_{(N^j_\tau, N^j_\tau - n^j_\tau + 1)}$, where N^j_τ is the number of inmates present in prison j at time τ, n^j_τ is the number of inmates that prison j is allowed to displace at time τ and $\zeta_{(N,n)}$ is the $n-th$ order statistics out of a sample of size N (hence, $\zeta_{(N^j_\tau, N^j_\tau - n^j_\tau + 1)}$ is the smallest of the largest n^j_τ values of ζ among the N^j_τ present inmates). [23]

We want to show that for each displaced inmate i, the history of previous displacement episodes in which he had not been displaced (for short, the history of missed displacements) contains information on ρ_i, and in particular that it shifts the probability mass towards smaller values of ρ. Relatedly, we want to show that inmates who shared enough episodes of missed displacement are likely to have the same ρ. [24]

Assume that, for all inmates: ρ has a (discrete) prior distribution with M distinct values, $r_1, r_2 ... r_M$ (where $r_1 < r_2 < ... r_M$), with unconditional probabilities p_1, $p_2 ... p_M$ (all strictly positive); D has a prior distribution with H values, $d_1, d_2 ... d_H$ (where $d_1 < d_2 < ... d_H$), with probabilities $q_1, q_2 ... q_H$; ρ and D are independent.

These assumptions clearly imply the unconditional distribution of $\zeta_{(N^j_\tau, N^j_\tau - n^j_\tau + 1)}$ (henceforth, to simplify the notation, we will denote the latter as $\zeta_{(n)}$, unless there is ambiguity).

Consider first one single displacement episode. Using the information on the residual sentences of the n^j_τ displaced inmates, update the distribution of $\zeta_{(n)}$. Note that we do not know which is the marginal displaced inmate (i.e. the inmate who corresponds to $\zeta_{(n)}$), and therefore we cannot simply condition the distribution of $\zeta_{(n)}$ on the particular D of the marginal inmate. Rather, an efficient updating needs to exploit the information on the values of all the Ds among displaced inmates.[25].

[22] See footnote ...

[23] For simplicity we will neglect the possibility of ties for the marginally displaced inmate.

[24] For each inmate i who is eventually displaced to Bollate (from prison j) we observe: the number of previous episodes of displacement to Bollate that took place while i was at prison j; for each such episode, the number of inmates displaced to Bollate, their residual sentences at the time of displacement [and the total number of inmates present at j TRUE?]; the residual sentence of inmate i at the time of displacement.

[25] A proof of this claim is available upon request

This conditional distribution can now be used to update the prior distribution of ρ for the inmates not displaced. Indeed, for any inmate i who is present in prison j at time τ and is *not* displaced, it must be that $D_i\rho_i < \zeta_{(n)}$. Given that we observe D_i[26], we know that $\rho_i < \frac{1}{D_i}\zeta_{(n)}$, and we can compute the probability distribution of ρ_i conditional on such information, according to Bayes theorem:[27]

$$\Pr(\rho_i = r_k|\rho_i < \frac{1}{D_i}\zeta_{(n)}) = \frac{\Pr(\rho_i < \frac{1}{D_i}\zeta_{(n)}|\rho_i = r_k)p_k}{\sum_{m=1}^{M}\Pr(\rho_i < \frac{1}{D_i}\zeta_{(n)}|\rho_i = r_m)p_m}, \tag{1}$$

for $k = 1, 2...M$.

Note that

$$\Pr(\rho_i < \frac{1}{D_i}\zeta_{(n)}|\rho_i = r_k) \geq \Pr(\rho_i < \frac{1}{D_i}\zeta_{(n)}|\rho_i = r_{k+1}),$$

for $k = 1, 2...M-1$, as clearly the event $(\frac{1}{D_i}\zeta_{(n)} > r_k)$ includes the event $(\frac{1}{D_i}\zeta_{(n)} > r_{k+1})$. Therefore, if we define

$$\mu_k = \frac{\Pr(\rho_i < \frac{1}{D_i}\zeta_{(n)}|\rho_i = r_k)}{\sum_{m=1}^{M}\Pr(\rho_i < \frac{1}{D_i}\zeta_{(n)}|\rho_i = r_m)p_m},$$

we have

$$\begin{aligned} \mu_1 &\geq 1 \\ \mu_k &\geq \mu_{k+1}, \end{aligned} \tag{2}$$

for $k = 1, 2...M-1$.

Since (1) can be written as

$$\Pr(\rho_i = r_k|\rho_i < \frac{1}{D_i}\zeta_{(n)}) = \mu_k \Pr(\rho_i = r_k),$$

for $k = 1, 2...M$, (2) implies that, relative to the unconditional probability, conditioning on an episode of missed displacement unambiguously increases (at least weakly) the probability that $\rho_i = r_1$, the smallest possible realization of ρ, and that the conditional distribution of ρ_i is "smaller", in the first-order stochastic dominance sense, than the unconditional one (i.e. the unconditional distribution first-order stochastically dominates the conditional one). [28]

This then shows that an episode of missed displacement shifts the probability mass

[26] Whenever at a later date τ' inmate i is displaced to Bollate, we observe his residual sentence at date τ', and we can easily infer his residual sentence at date τ.

[27] For notational simplicity, the dependence on the displaced inmates'residual sentences of the distribution of $\zeta_{(n)}$ is left understood.

[28] The first claim is obvious. The second can be easily proved by contradiction (to simplify the notation, consider the case of support 3; the proof readily extends to any finite support). Suppose $p_1\mu_1 + p_2\mu_2 < p_1 + p_2$ (this is the only possibility that would contradict the claimed first-order stochastic dominance). Then $\frac{p_1}{p_1+p_2}\mu_1 + \frac{p_2}{p_1+p_2}\mu_2 < 1 \Rightarrow \mu_2 < 1$, since $\mu_1 \geq 1$. Moreover, since $\mu_3 \leq \mu_2$, it also follows that

towards lower values of ρ for all inmates who were not displaced. The size of the shift depends on the number of displaced inmates and their residual sentences – which update the distribution of $\zeta_{(n)}$ – and on the residual sentence of the inmate not displaced – as apparent from (1). A larger number of displaced inmates, with longer residual sentences, and a longer residual sentence of the inmate not displaced, all imply a larger leftward shift of the probability mass.[29] Clearly, any additional episode of missed displacement further shifts the probability mass in the same direction.

Consider now two inmates, say u and w, who both failed to be displaced in the same displacement episode. Following the above argument we can compute the distribution of ρ_u and ρ_w, conditional on the missed displacement, and we know that in both cases the conditional distributions are "smaller" than the (common) unconditional one. Intuitively, we might expect this to increase (relative to the unconditional case) [30] the probability that $\rho_u = \rho_w$, as for both variables a larger probability mass is now loaded on the lowest realizations.

It is easy to verify that this intuition is correct if the (common) unconditional distribution for ρ from which we start is discrete uniform. More generally, it can be proved that if the distributions of ρ_u and ρ_w before the missed displacement are both monotone decreasing (even if not necessarily identical), observing for both inmates a missed displacement episode (weakly) increases the probability that $\rho_u = \rho_w$.[31]

Clearly, if the distributions of ρ_u and ρ_w before the missed displacement are monotone decreasing, the updated distributions, conditional on the missed displacement, are also monotone decreasing, since they are first-order stochastically dominated by the unconditional ones. Hence, not being displaced again in a new displacement episode would further increase the probability that $\rho_u = \rho_w$.

It is important to note that the monotone decreasing condition on the distributions of ρ for the inmates not (yet) displaced is likely to hold when both inmates missed enough displacement episodes. Indeed, as shown before, observing any displacement leads to a conditional distribution on ρ, for the inmates not displaced, which is first-order stochastically dominated by the distribution prior to the observation. Therefore, any missed displacement shifts some of the probability weight on smaller values of ρ, making it more likely that the new distribution is monotone decreasing.

$\mu_3 < 1$. But then we could write:

$$\begin{aligned} 1 &= p_1\mu_1 + p_2\mu_2 + p_3\mu_3 \\ &= (p_1 + p_2)(\frac{p_1}{p_1 + p_2}\mu_1 + \frac{p_2}{p_1 + p_2}\mu_2) + p_3\mu_3 \\ &< 1 \end{aligned}$$

which is a contradiction.

[29] This is obvious for the number of displaced inmates and for the residual sentence of the inmate not displaced. For the remaining implication, note that longer residual sentences among the displaced inmates lead to a conditional distribution of $\zeta_{(n)}$ putting more probability weight on smaller values of ρ.

[30] In the unconditional case, $\Pr(\rho_u = \rho_w) = \sum_{m=1}^{M} p_m^2$

[31] A proof is provided in the Appendix D. Note that if the two inmates have different residual sentences, the distributions of their ρs conditional on a missed displacement are no longer identical. Therefore, the proof needs to allow for the possibility that the prior distributions are not identical

In view of the preceding analysis, for each inmate i eventually displaced, the characteristics of his missed displacements – how many, how many inmates where displaced, what were their residual sentences at the time of displacement, how did they compare with the residual sentence of inmate i at that time – provide information on his ρ_i (in particular, they shift the probability mass in the distribution of ρ_i towards its smaller values). Moreover, inmates who shared enough missed displacements are likely to have the same ρ.

Therefore, including in the regressions controls to characterize the episodes of missed displacements experienced by each inmate i is an indirect way of controlling for his (expected) ρ_i . We can also run regressions restricting the sample to inmates who shared several missed displacements, and compare the results as we vary the number of missed displacements shared.

Since these controls are proxies for the unobserved ρs, large movements of the coefficient on D would be a source of worry, especially if the coefficient were moving towards zero. If, instead, the coefficient turned out to be stable or were to become even more negative, it could be concluded that a more precise measure of ρ would not change the estimate or would move the coefficient further in the same direction (in which case our estimate would provide a lower-bound of the effect) (see Altonji et al., 2005, Oster, 2013).

Indeed, there are observable events that perfectly identify the value of ρ, under the (strong) assumption that the econometrician knows its support. To see this, consider again a displacement episode occurred at time τ, in which n_τ inmates were displaced and inmate i was not (inmate i, however, will be displaced to Bollate at a later date, so we can infer what was his residual sentence at time τ; let it be denoted by d_i). Then we know that $\rho_i < \frac{D_h}{d_i}\rho_h$ for all $h \in \Delta^j_\tau$, where Δ^j_τ denotes the set of inmates displaced from j at time τ. In particular, $\rho_i < \lambda\rho_{\underline{h}}$, where $\underline{h} = \arg\min_{h\in\Delta^j_\tau}(\frac{D_h}{d_i})$ and $\lambda = \frac{D_{\underline{h}}}{d_i}$. According to Bayes rule:

$$\Pr(\rho_i = r_1 | \rho_i < \lambda\rho_{\underline{h}}) = \frac{\Pr(\rho_i < \lambda\rho_{\underline{h}} | \rho_i = r_1)p_1}{\sum_{m=1}^{M}\Pr(\rho_i < \lambda\rho_{\underline{h}} | \rho_i = r_m)p_m}.$$

Consider the case $\lambda r_M < r_2$.[32] Then $\Pr(\rho_i < \lambda\rho_{\underline{h}} | \rho_i = r_m) = \Pr(r_m < \lambda\rho_{\underline{h}}) = 0$ for all $m \geq 2$. This is because $\lambda\rho_{\underline{h}} \leq \lambda r_M < r_2 < r_m$ for all $m > 2$. Hence, $\Pr(\rho_1 = r_1 | \rho_1 < \lambda\rho_{\underline{h}}) = 1$.

We could now consider the ideal comparison of two inmates who have different residual sentences but the same level of ρ: consider inmates u and w, with the same total sentence, present at date τ in prison j, who were not displaced at τ, when someone with residual sentence d_h was displaced, and it is true that both $\frac{d_h}{d_u} < \frac{r_2}{r_M}$ and $\frac{d_h}{d_w} < \frac{r_2}{r_M}$; then we would know that $\rho_u = \rho_w = r_1$, and if at a later date τ' both u and w were displaced to Bollate, we could interpret the difference in their (future) recidivism as being causally due to the difference in their residual sentence spent at Bollate.

To implement such a comparison the econometrician is supposed to know the value $\frac{r_2}{r_M}$. Such a precise knowledge is, of course, an exacting requirement.

[32] Assume also that $\lambda r_m > r_1$, to avoid zero-probability conditioning events.

Even an approximate assessment would however be useful to narrow down the range of possible values of ρ. For example, observing that both $\frac{d_h}{d_u}$ and $\frac{d_h}{d_w}$ are both less than, say, 20%, then we would know that both ρ_u and ρ_w are less than 20% of ρ_h. If the highest level of the propensity to misbehave is unlikely to exceed 5 times its lowest level, we would be rather confident that ρ_u and ρ_w are both very close to the minimum.

2.3 The Data and the Randomization Tests

2.3.1 Prison Records and Sample Selection

We collaborated with the "*Dipartimento dell'Amministrazione Penitenziaria*" of the Italian Ministry of Justice, its regional administration office for Lumbardy, the "*Provveditorato Regionale di Milano*" and the administration of the Bollate prison to link different administrative records collected up to February 15, 2013.

We were granted access to a large amount of information on inmates who spent some prison time in Bollate between 2001, the opening year, and 2013, the closing date of our analysis. The information includes the entire history of incarcerations, dating as far back as 1971, and of incarcerations following their release from Bollate (if occurring before 2013). Starting in 2006 we can also measure transitions inside the Bollate prison across different sections, which will allow us to provide direct evidence about the treatment mechanisms (as different sections correspond to different activities inside and outside the prison).

As mentioned, we restrict our sample to Italian (57 percent of inmates are foreigners), male (less than 30 inmates are female), inmates that are not sex offenders. We excluded foreigners because of the difficulty of measuring recidivism for foreign offenders, who most of the time are illegal immigrants without any paperwork and are therefore able to hide their identity or leave the country after dismissal from prison. We excluded the 8 percent of inmates who are sex offenders because they are subject to specific incarceration rules.

There are many possible definitions of recidivism. From a legal viewpoint, recidivism occurs when a release after a definitive conviction [33] is followed by another definitive conviction. We will maintain the first requirement and weaken the second, by considering as recidivist any inmate who, having served a definitive conviction, is re-incarcerated within three years from the end of his custodial and non-custodial (e.g. home detention, monitored liberty, etc.) sentence. We are not requiring that the last imprisonment corresponds to a definitive conviction because the latter would force us to keep a very long window of observation after the inmate release, given the three levels of appeal in the Italian judicial system. Implicitly, we therefore prefer false positives (a re-incarcerated inmate who is later acquitted) to false negatives (a re-incarcerated inmate who is definitively convicted only past the three year window). Given that conviction rates for re-incarcerated criminals tend to be high, the likelihood of false negatives is likely to be negligible, and unrelated to the residual sentence in Bollate.

[33] Inmates who by the time of dismissal had a definitive conviction are 90 percent of the total number of inmates. Restricting to a definitive conviction before the release avoids that a re-incarcerated is due to the final conviction for the same crime

Having chosen a three year measure of recidivism, this forces us to restrict our analysis on inmates released up to 2009.

In the end we have, for each (Italian, male, not sex-offender, serving a definitive sentence) released inmate who spent some time in Bollate between 2001 and 2009 (about 2300 people) a complete "prison history," with the number and the dates of previous prison spells (if any), the dates of the period spent in Bollate, the date of a possible new incarceration after Bollate (and up to February 2013). We have information on a number of characteristics of the inmates as well as on the crimes for which they had been imprisoned. We also have some information on the selection process into Bollate, as we can distinguish the prisoners displaced there due to overcrowding of nearby prisons, those transferred for "treatment" reasons, those assigned there when their request has been approved, those assigned there by the Justice Department without mentioning "treatment", and those transferred for other reasons (mainly transfers from the Central Government or arrests by Bollate officers). This kind of information is missing for 12 percent of the sample.

2.3.2 Summary Statistics and Randomization Tests

Our main measure of the "Bollate treatment" is the length of the residual sentence to be spent in Bollate (we will always condition on the total sentence served). Figure 1 shows the distribution of the ratio between the residual and the total sentence, namely the fraction of the total sentence served at Bollate. The left panel is for the entire sample, the right one for the sample of displaced inmates. Transfers are more likely to happen at the beginning of an inmate's incarceration, which skews the distribution to the left, and this is true even when focussing on displaced inmates.

The average sentence and average residual sentence served at Bollate by entry reason are shown in Table 3. Inmates displaced to Bollate have an average total "served" sentence (1.268 years, or 15 months) that is lower than the three years minimum sentence that inmates typically need to be at Bollate. Thus their average residual sentence upon arrival is also low (9 months), 6 months shorter on average than that of the selected inmates.

One third of the times the actual sentence served in Bollate is shorter than the potential one (this is true also for displaced inmates). This happens either because inmates are transferred to other prisons or because they are given non-custodial sentences at the end of their stay in Bollate. The different entry reasons is associated with different treatment strategies. Table 3 show that only a handful of displaced inmates finish their incarceration in Section 5 – the section from which inmates spend daytime working outside the Bollate prison – while for the other inmates the proportion varies from 10 to 25 percentage points. Recidivism patterns are also strikingly different. Inmates selected to be sent at Bollate have on average a recidivism rate much lower, by 12 percentage points, than inmates displaced there. Among the selected inmates, those who applied to be transferred and those transferred by the Justice department and the Central Government (other entry reasons) have the lowest recidivism rates.

Summary statistics for all the additional variables that describe the inmates and their crimes and that are later used as regression controls are shown in Table 4 (for the entire sample, inclusive of the displaced inmates, on the left panel and for the sample of only the displaced inmates on the right one). We already described the recidivism patterns. The second variable in Table 4, *Art. 4 bis* (*Divieto di concessione dei benefici e accertamento della pericolosit sociale dei condannati per taluni delitti*), restricts the applicability of prison benefits (day releases, outside work, non-custodial sentences) for a series of crimes (e.g. terrorism, organized crime, slavery, sex trade, kidnapping with extortion, etc.). Twelve percent of all inmates are subject to such restrictions, while the fraction goes down to 6 percent for displaced inmates. On average an inmate is 38 years old, single (60 percent), not addicted to drugs (70 percent), with a secondary schooling degree (50 percent), and with an unknown employment status. He has an average of 3.3 previous incarceration spells, has committed either a theft (30 and 33 percent for the full sample and the displaced one), a drug-related crime (29 and 22 percent), or a robbery (24 and 19 percent).

Next to the mean and the standard deviation we show the coefficients on the residual sentence in regressions where the dependent variables are, one at the time, those listed in the first columns. The purpose is to formally check the quasi-random nature of our treatment, by comparing the expected value of each covariate conditional on different levels of the residual sentence. Each regression also controls for the total years spent in prison. This is key, since residual and total sentences are strongly positively correlated. Without conditioning on the total sentence, inmates with longer residual sentences are associated with more serious crimes, tend to be older, etc. We can only hope to verify the quasi-random assignment of the residual sentence once we condition on the total sentence.

Ideally, we would not want any of the coefficients in these regressions to be statistically significant, with the obvious exception of that associated with the first variable (recidivism). Indeed, most are not, but there are some observable characteristics that are different for inmates with different potential treatment levels. In particular, inmates whose residual sentence in Bollate is higher are more likely to have secondary schooling, and show a few significant differences in the types of crimes committed. While of course we will control for these (and other) variables in our main regressions, this casts some doubts on the random nature of the residual sentence assignment. For this reason, we will restrict our sample of analysis in the attempt to isolate the variability of the residual sentence that can more confidently be judged as random.

However, we will later show that, when assessing the effect of the treatment on recidivism, whether or not we control for these differences (e.g. we also control for a full set of age fixed effects) makes little difference. This is reassuring, as it implies that even if there were some selection at work in the treatment assignment, it does not seem to be very predictive of recidivism.

The coefficients on the right panel of Table 4 represent the balance check for the displaced sample, with (columns 9 and 10) and without (columns 7 and 8) controls for prison of origin times week of transfer fixed effects. Controlling for these fixed effects we are essentially comparing inmates who were displaced at the same time and from the same prison. Hence, we are treating each overcrowding event as a separate experiment where the selection process, if present, is common to all transferred inmates. Almost all the coefficients are now statistically insignificant. The few that remain significant consistently suggest, if anything, a negative selection. Displaced inmates with longer residual sentences are more likely to be "worse:" more likely to be drug addicts and not being able to describe their employment condition, less likely to be employed. This kind of selection, if present, would impart a bias towards zero to our estimates of the effect of the treatment on recidivism.

Overall, recidivism is the only variable that is consistently associated with residual sentences. This represents a first indication that the two might indeed be causally linked to each other.

3 Results

3.1 Non-parametric Evidence

Having information on the exact time of re-incarceration we can use non-parametric Kaplan-Meier cumulative failure (recidivism) functions to compare inmates who spent most of their time in Bollate with those who spent little time in Bollate. As in the rest of the analysis inmates are followed for three years after the total sentence has been served.

Figure 2 plots failure functions for inmates who served less than 1/3 of their total time at Bollate against inmates who spent at least 2/3 of their total time at Bollate. To compute these ratios we always use the potential time spent at Bollate to avoid any endogenous interruption of the Bollate treatment. As it is important to control for the total time served (otherwise a lower fraction of time spent in Bollate would also be associated with a longer sentence), we produce a plot for each quartile of total time served. The quartiles are 0-6 months, 6-14 months, 14-30 months and 30 and more months. This means that more or less treated inmates who are in the first quartile have either spent between 4 and 6 months or less than 2 months in Bollate. While there are negligible differences up to a year after release, after that the cumulative differences in recidivism start diverging and reach a 10 percent difference after 3 years. The differences between the failure functions are more striking and start earlier when the total time served is above the median (14 months), meaning that more treated inmates spend at least 9 months in Bollate. For the third and fourth quartile the relative differences in recidivism are about 40 and 55 percent. These are massive differences. Next we use regression models to be able to better control for total time served, to control for additional regressors, as well as to asses the significance of these differences.

3.2 Main Results

We estimate the intention to treat effect by ordinary least squares with a linear probability model (later we will see that probit models as well as hazard models lead to similar results).

For individual i, transferred in week $\tilde{t}$ from prison j, and released at time t, recidivism is a function of the total years served (TOT_YRS), potential years served at Bollate

(POT_BOL_YRS), as well as other controls (X):[34]

$$RECID_i(j,t) = \beta_1 TOT\_YRS_i + \beta_2 POT\_BOL\_YRS_i + \gamma' X_i + \epsilon_i,$$

where

$$\epsilon_i = \begin{cases} \alpha_{j,\tilde{t}} + \varepsilon_i(s,t), & \text{if displaced;} \\ \alpha_j + \delta_t + \varepsilon_i(s,t), & \text{otherwise;} \end{cases}$$

The unobserved errors $\varepsilon_i(s,t)$ are allowed to be correlated across inmates released during the same week who spent their final prison time in Bollate in the same section $s \in 1, ..., 5$. Alternatively, in the Online appendix Table 12 we use a spatial lag error model that allows errors to be correlated between inmates whose detention in the prison section has overlapped. Both methods to compute the standard errors deliver similar results, which is why in the rest of the analysis we use the easier to compute clustered ones.

When estimating the average treatment effect we run a two-stage least squares regressions (2SLS), using the potential time served at Bollate as an instrument for the actual time served.

Table 5 shows both kind of regressions for the whole sample and table 6 does the same, distinguishing between the sample of displaced inmates and the sample of those actively selected. Time served at Bollate (both potential and actual) is measured in years (days divided by 365). Looking first at the whole sample, and focussing on the intention to treat, one extra (potential) year at Bollate (and therefore one less year spent at a "normal" prison, given that the regression controls for the total length of the sentence) reduces recidivism by 5.2 percentage points when controlling only for the total time served in prison (as in the previous balance test table), and by 5.5 percentage points when controlling also for the possible causes of entry and for all the additional variables listed in the summary statistics table (see Table 4). In addition, we also control for year times quarter of release, to capture labor market conditions inmates face when they exit prison, and prison of origin fixed effects, to control for differential treatments there. The reduction in recidivism is highly statistically significant and sizeable. In relative terms, one more year at Bollate, as opposed to any of the prisons of origin, reduces recidivism by 16 percent of the average recidivism rate.

The sign of the other covariates is in line with expectations. A previous history of recidivism, proxied by the number of previous incarcerations, is highly predictive of future recidivism. Interestingly, the total time spent in prison increases recidivism, even though the effect is statistically significant only when other controls are present. This criminogenic effect of prison time at ordinary prisons is in line with the results reported by Nagin et al. (2009). Our result show, however, that merely looking at the time spent in prison can be highly misleading. The way in which the prison time is spent is of crucial importance, and a good use of that time actually reduces recidivism. The causes of entry into Bollate that reflect a conscious choice (by the inmates and by the officials assessing the requests) are highly significant and are associated with a sizeable reduction

[34]Later we are going to test for non-linear effects.

in recidivism, confirming that the selection process is effective in screening inmates with a lower recidivism potential. Finally, drug addiction significantly increases recidivism, a well known result.

We also control for marital status, three education dummies, three employment dummies, and nine crime dummies. As mentioned, the estimated effect of the treatment is little affected by the inclusions of the controls. If anything the point estimate is somewhat larger, which together with the raising R-squared, suggests that controlling for unobserved selection would be unlikely to turn around the results (see Altonji et al., 2005, Oster, 2013).

The IV regression gives similar results. The effect of the treatment, when measured by the actual time spent in Bollate, is about 10 percentage points when only the total sentence length is controlled for, and 9.5 percentage points when also all the other controls are included. The larger effect is expected, as the residual sentence upon arrival overestimates the length of the actual prison stay: in the first stage regression the coefficient on the length of the first is always close to 50 percent, with a t-statistic of about 15, and an F-statistic of about 200. A visual representation of the first stage is shown in Figure 3. For about 2/3 of inmates actual and potential days spent in Bollate coincide (they correspond to points on the 45 degree line in the figure). The rest of inmates is either transferred to other prisons or is given alternative sentences, and these are clearly endogenous outcomes.

The result for the sample of displaced inmates suggests that selection is unlikely to explain these large treatment effects. Table 6 shows that for displaced inmates the estimated intention to treat effects (Columns 2 to 4) and average treatment effects (Columns 6 to 8) are not only highly significant, but even larger, at least in the levels, than for the selected inmates (Columns 1 and 5, respectively).

The difference between the columns 2 and 3 (and between columns 6 and 7) reflects the inclusion of some variables controlling for the possibility that the prisons of origin select inmates to be displaced based on their dangerousness.

In particular, a set of prison of origin times week of release fixed effects makes sure that we are comparing inmates that have been displaced from the same institution around the same time, and thus are subject, if anything, to the same selection criteria. This controls for the potential bias induced by a selection of the inmates to be displaced based on their dangerousness or trouble-making potential (be it positive or negative). In this way we are left comparing inmates whose only difference is the moment in which they started serving their original sentence. It should be noted that when we control for the week of transfer we cannot anymore control for the quarter of exit, since these two variables would implicitly fix the residual time spent at Bollate. This is why the quarterly unemployment rate in Northern Italy and the quarterly youth unemployment rate are added as a proxy for the labor market conditions inmates face when released.

As mentioned , one residual concern could be that the selection of displaced inmates, while being common, is based on the residual sentence itself. We appease this concern by using a revealed preference measure of selection. Following the formal discussion in Section 2.2.4, for each inmate, we control for the number of episodes in which each inmate was not displaced, the number of inmates that were displaced in his stead, moments of the distribution of their residual sentence, relative to the residual sentence of the not (yet) displaced inmate; intuitively, the larger the number of missed displacements, the lower must have been the urge of getting rid of him perceived by the prison administrators, as revealed by their own choices (assuming that there was any such urge).

In Figure 4 we provide visual evidence of the absence of correlation between several of these revealed preference statistics and recidivism. While this is reassuring, there might still be a correlation conditional on all other covariates.

Yet, in Columns 4 and 8 we find no evidence that more dangerous or trouble-making inmates are displaced sooner (or later): the coefficient on the revealed preference index is not statistically different from zero, and its inclusion among the controls does not significantly change the estimated effect of the treatment. If anything controlling for selection the coefficient on the residual sentence tends to become more negative.

Summing up, even controlling for just the total time served, as shown in Table 4, the intention to treat effect on displaced inmates is 6.8 percentage points, or 17 percent relative to their average recidivism rate (40 percent). Adding a large number of controls increases the estimate by about 1 percentage point. In particular, while displaced inmates tend to be more dangerous (more prone to recidivism) we find no evidence that they were selected on the basis of their residual sentence length. The variability of the latter, therefore, can be taken as a near-random variability that identifies the causal effect of the treatment length.

3.3 Robustness Checks

In Table 7 we run several robustness checks for all inmates (conditional on the cause of entry), and for the displaced ones. All regressions control for the usual set of variables, including prison of origin and year times quarter of exit fixed effects. For brevity we focus on the intention to treat (first set of columns) and on the average treatment effects (second set of columns).

The baseline intention to treat effects were 5.5 percent for the entire sample (Table 5) and 8.3 percent for the displaced sample (Table 6). The first two rows of Table 7 show that excluding the few inmates that have one definitive conviction but also an ongoing trial at the time of release does not alter the results.[35] The second set of regressions shows that the intention to treat is only slightly lower when we exclude the 652 inmates who have shown some addiction to drugs, showing that the rehabilitation effects are not driven by such inmates. Despite the much smaller sample size, focussing on recent years also does not alter the results. Shortening the horizon within which we measure recidivism from 3 to 2 year lowers the treatment effects, indicating that long term effects might be larger than short term ones.

The results are also robust to using a probit model instead of a linear model (next two rows). In the Appendix Table 13 we also show that a hazard model delivers the same results. Adding demeaned squared terms for the total time served and the time served in Bollate makes little difference for the overall sample, while for the displaced sample it

[35] These inmates might end up in prison again when their ongoing trial is settled with a definitive sentence. Their new incarceration, therefore, would reflect an older crime.

lowers the size and the significance of the reported coefficients (last two rows). Yet the corresponding joint tests of significance can all be rejected at the 5 percent level. Finally, the results for displaced inmates could potentially be biased if some of the inmates whose cause of entry is unknown were also displaced inmates, and if such "item non response" were correlated with recidivism. In row 13 we report results obtained by adding those inmates to the sample of displaced inmates. Comparing these results with those of the second and sixth Column of Table 5 we see that there are almost no differences.

4 The Mechanism

Our results show that spending more time at Bollate, and correspondingly less time at one of the other traditional prisons, reduces recidivism by a statistically significant and economically meaningful amount. What is not clear is the mechanism underlying this effect: is it merely the passing of time, leading to a larger dose of the same treatment? Or is the passing of time just the gateway for qualitative differences in the treatment, which are the true causes of the observed effect on recidivism? While we will not be able to conclusively answer these questions, in this Section we will make a first attempt at identifying the underlying mechanism.

4.1 Heterogeneity of the Effects

We can learn something about the mechanisms by trying to identify the circumstances in which the treatment is most effective. We will therefore explore whether the effects across different groups of inmates are heterogeneous. The Table 8 reports, for various subgroups of inmates having or not having a certain characteristic in the total sample and in the sample of displaced ones, the intention to treat effect and the (instrumented) average treatment effect. The first four rows in the Table (rows 1 to 4) refers to inmates who have or do not have committed economically motivated crimes.

The intention to treat effects are -5.7 and -8 percent, significantly different from zero, for the subset of the total sample of inmates and of the sample of displaced ones, respectively, who have committed economically motivated crimes (e.g., theft, burglary, robbery, drug dealing, fraud), while they are close to zero for those in prison due to non-economically motivated and mostly violent crimes. This suggests that inmates who were committing crimes for a living are more likely to respond favorably to the Bollate rehabilitation efforts.

The second set of results (rows 5 to 8), shows that the treatment response is considerably larger (in absolute terms) among inmates who are at the first prison experience, especially relative to their lower recidivism. For example, average treatment effects for "rookies" displaced inmates are equal to -17 percentage points, while their average recidivism is just 36.5 percent. Yet, even inmates who have been in prison before are responding positively to the treatments. This suggests that rehabilitation efforts are most successful when applied earlier in the criminal career.

The third set of results (rows 9 to 12) show that the effects tend to be larger (in absolute terms) for inmates who have a family, in particular when we consider displaced inmates. Though we do not have information about the presence of children, these results are consistent with a positive role in reducing recidivism being played by the presence of better visiting facilities for children and partners at Bollate, compared to other prisons. Rehabilitation efforts seem to be more fruitful, therefore, when they interact with family relationships.

Looking separately at inmates who have, or have not, at least secondary education, the fourth set of results (rows 13 to 16), shows that the treatment is more effective for inmates with lower levels of education. This points at greater effectiveness of rehabilitation efforts on those inmates who are less well equipped to cope with the challenges of a non-criminal life and who would be more likely to struggle once released.

The final set of regressions (rows 17 to 20) considers separately inmates who are, or are not, prohibited from accessing alternative sanctions by a previous judge order. There is no evidence that the effect of the treatment is significantly different across these two groups.

According to most of the measures of prison conditions shown in Table 1, the San Vittore prison stands out as probably the harshest prison in Lombardy, which makes the comparison with the conditions at Bollate starkest. For this reason we might conjecture that the effect of the "Bollate treatment" be larger for inmates that are transferred from the San Vittore prison. Table 9 shows that the treatment effects are indeed larger (in absolute terms) when looking at inmates displaced from San Vittore, but such differences are not statistically different from zero (given that only 12 percent of the displaced inmates are transferred from a prison that is not San Vittore, the statistical power to detect treatment differences across prisons is limited).

4.2 Direct Evidence of the Mechanism

In Section 2.1 we highlighted that spending prison time at Bollate as opposed to San Vittore or any other prison in Lombardy can be a very different experience. This is the result of several differences between Bollate, on the one hand, and other prisons, on the other. The first, and perhaps the most striking, is that at Bollate inmates spend two to three times more hours outside their cells. The significance of this difference becomes even more salient when we consider that, as shown in Table 1, San Vittore, Opera, Monza, and Busto Arsizio – the prisons from which more than 80 percent of transferred inmates come – are regularly overcrowded, which translates into more inmates per cell and thus less space than the 9 square meters (100 square feet) each inmate is supposed to have under normal circumstances. Another important difference is the "Responsibility Pact" that inmates sign when entering Bollate. They are offered the opportunity to actively participate in their rehabilitation program (work, education, the interior design of their prison, etc.)in exchange of peaceful behavior (and cheaper supervision).

Compared to the "panopticon-style" of prison life that is the norm in most prisons in the world, these humanizing prison conditions are indeed a momentous change, and it is reasonable to conjecture both, that they can influence the inmates' recidivism, and that such influence is increasing in the duration of their stay at Bollate. This however cannot be empirically tested, since those conditions equally apply to all Bollate inmates as soon as they are transferred there.

There is however one important aspect of the treatment that is unevenly assigned and is measurable: work outside of the Bollate prison. Inmates who work outside of Bollate are transferred to Section 5. And once they are in Section 5, Bollate keeps track of the day releases.[36] For each inmate (not just the ones that were released) we computed a dummy equal to one if an inmate has ever been transferred to Section 5. For selected inmates (left columns), the likelihood to be transferred during an incarceration is 27 percent. For displaced inmates is only 7.8 percent.

Regressing this dummy on the potential years served at Bollate, as well as the usual controls, we get that each potential year increases the likelihood to be transferred to Section 5 by 8 percentage points (30 percent) for the selected inmates, and by 2 percentage points (25 percent) for the displaced ones (though for the displaced inmates the coefficient is not significantly different from zero). Regressing the dummy on the actual years spent at Bollate (instrumented with the potential ones) shows that an additional year increases the chances of transfer by 18 percentage points for the selected inmates, and by 7.5 percentage points (again without reaching statistical significance) for the displaced ones.

The fraction of days spent in day releases (typically corresponding to work outside Bollate) can be used in a similar manner to understand the mechanisms. During their entire stay, selected inmates can spend on average 1.44 percent of their days outside of prison; displaced inmates only 0.24 percent. Yet, an additional potential year in Bollate increases such fraction by 1.43 percentage points (almost 100 percent) for the selected inmates, and by 0.21 percentage points (87 percent) for the displaced ones. Both intention to treat effects are significantly different from zero, and the same is true for the average treatment effects, which are more than twice as large.

It obviously stands to reason that having the possibility to work outside, while being in prison, is an important ingredient of rehabilitation, and is therefore a driver of the estimated effects of the treatment. It is moreover consistent with the finding that the largest changes in recidivism are for economically motivated crimes.

At the same time, the larger effects found for the displaced inmates, who are less exposed to outside work, suggest that other mechanisms might be important as well: as mentioned before, freedom of movement, responsibility, conditions respectful of human dignity, productive use of time, all these might positively affect the post release behavior of inmates.

4.3 Negative Spillovers

One additional mechanism that might be at play is provided by peer effects.[37] By selecting "better" inmates Bollate might in fact simply minimize negative peer influences. Since more time spent at Bollate is equivalent to spending more time with more positively selected inmates, this could explain our results.

[36] Since 2006 Bollate keeps track of all transfers across the different Sections in Bollate.

[37] See Chen and Shapiro (2007) and Bayer et al. (2009)) for evidence on peer effects in prison.

We try to test whether this is a relevant mechanism underlying our results by using the presence of displaced peers. The idea is that displaced inmates are negatively selected (as shown in Section 2.2.2), and therefore, the higher the presence of displaced inmates among ones' peers, the less effective a mechanism based on the influence of positively selected inmates should be. We measure the presence of displaced peers by computing the fraction of "prisoner days" spent together with displaced inmates: at Bollate (first measure); in the final prison Section (second measure);in the final cell (third measure). While the last two measures might be endogenous (Bollate might redistribute displaced inmates to reduce negative peer effects), they are also more precise.

In Table 11 we control for such "exposure" to displaced inmates, and also interact it with the potential time served in Bollate. Overall there is no evidence that the effect on recidivism is significantly affected by the "exposure" to potentially "worse" peers. Given the result that the effect of the treatment is larger for displaced inmates as compared to the actively selected ones, this suggests that a less exacting selection process would generate a larger marginal effect on recidivism.

5 Conclusions

This paper has shown that, when trying to reduce recidivism, *something works*: following the recommendation of the Council of Europe (2006), that is offering *prison conditions which do not infringe human dignity and which offer meaningful occupational activities and treatment programmes to inmates, thus preparing them for their reintegration into society*, seems effective in curtailing recidivism. Conversely, traditional prison conditions seem to be criminogenic. This is good news for those countries (Italy being a notable example) whose laws, often neglected, mandate prison conditions in line with the Council of Europe recommendation: by doing the "right thing" they would also reap the economic and social benefits of a fall in recidivism. It should provide instead cause for thought to those countries that primarily rely on the deterrence provided by harsh prison conditions, as their policy might backfire due to increased recidivism.

More work needs to be done to understand the mechanisms underlying our results. We find evidence that one such mechanism involves offering inmates, while in prison, opportunities to work outside, thus making it easier their entry into the labour market when released. Offering such opportunities might be difficult, however, particularly when there is substantial slack in the labour market. Therefore, policies aimed at reducing recidivism by "making prison work," while sensible and effective, might be hard to implement and are largely outside the control of prisons' administrators.

We find evidence that even for inmates who are not involved in outside work being exposed to prison conditions that emphasize responsibility and guarantee freedom of movement, conditions respectful of human dignity, productive use of time, are effective in reducing recidivism. Policies to that effect seem easier to implement, and are almost surely cost effective.

Finally, we do not find robust evidence that peer effects are an important driver of our results. This suggests that scaling up the experience of Bollate, even by weakening somewhat the selection criteria, and adopting similar standards in other prisons, might not risk undermining the positive results so far observed.

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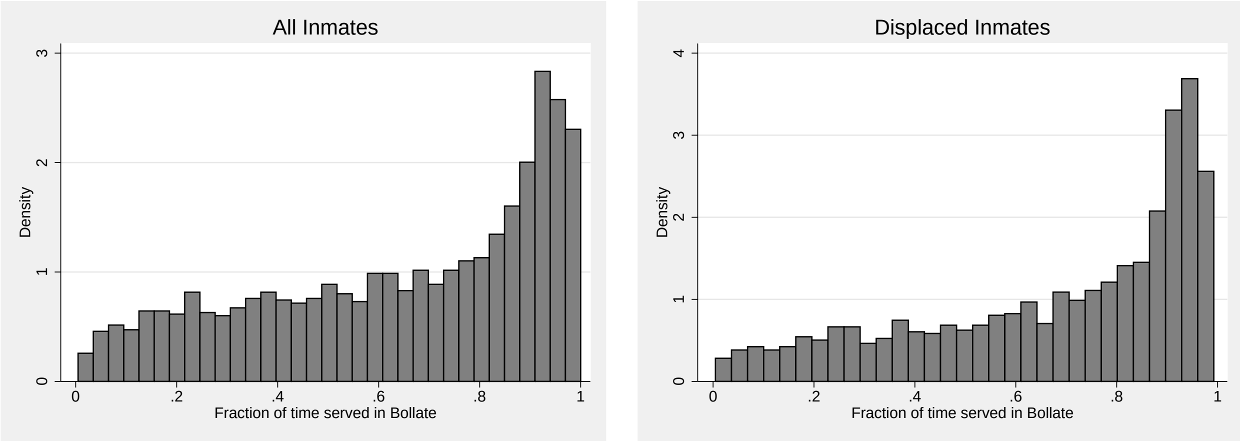

Figure 1: Histogram of the Fraction of Time Spent in the Bollate Prison

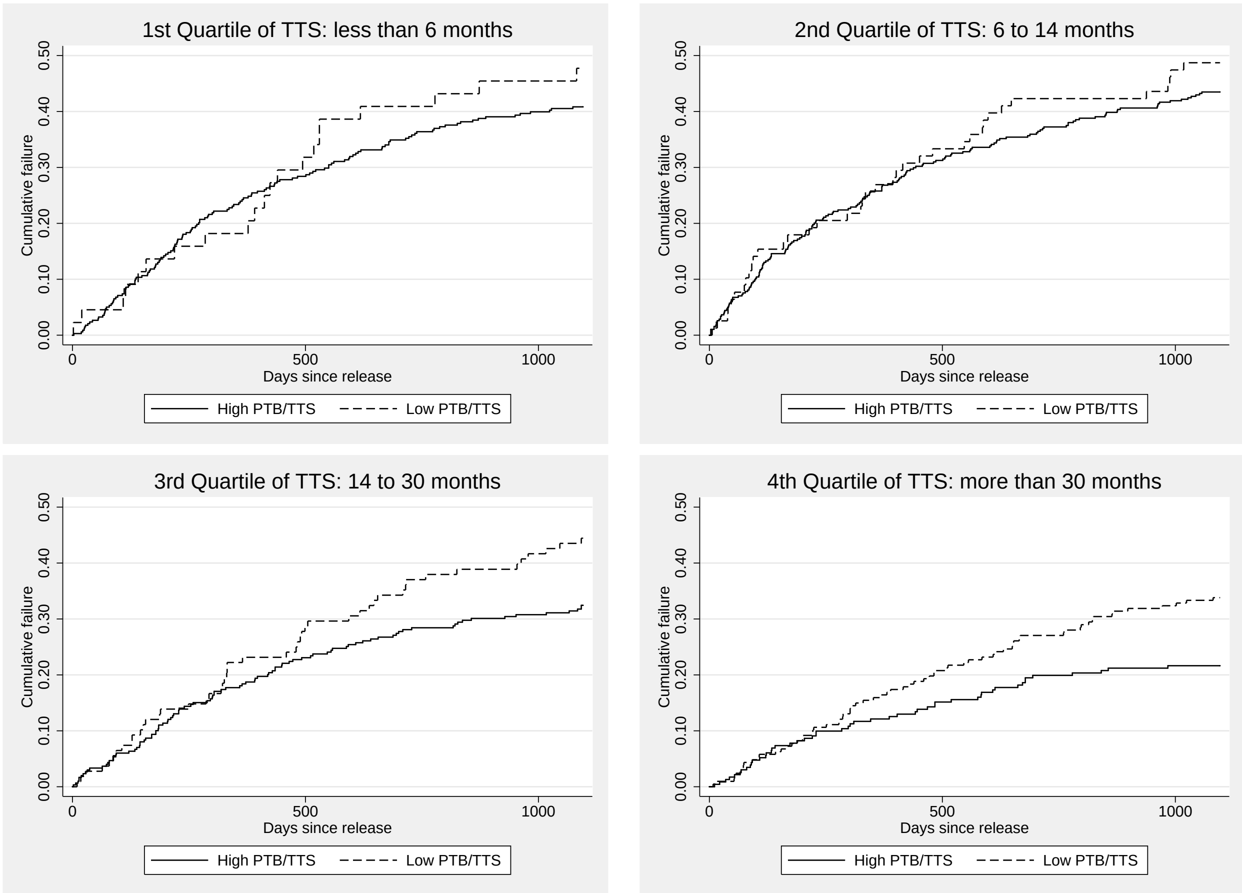

Figure 2: Kaplan-Meier Cumulative Failure (Recidivism) Functions

Notes: PTB and TTS stand for Potential Time in Bollate and Total Time Served. Failure (recidivism) is truncated at 3 years, or 1095 days. The "High PTB/TTS" group has served at least 2/3 of the total time in Bollate, a "Low PTB/TTS" group has served less than 1/3 of the time in Bollate.

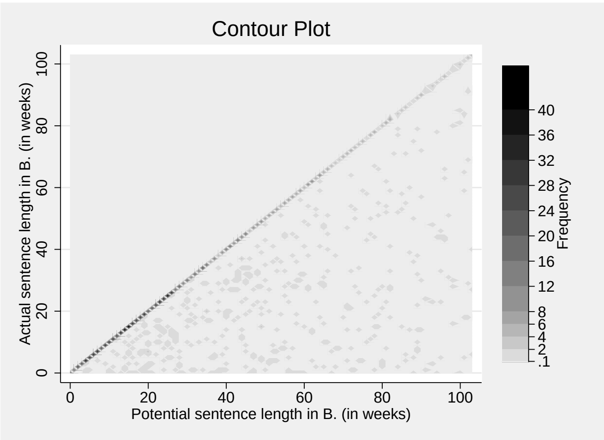

Figure 3: First Stage Relationship

Notes: Actual time in Bollate against potential time expressed in semesters to highlight the distribution (truncated at 100 weeks). For about 2/3 of inmates the two durations coincide.

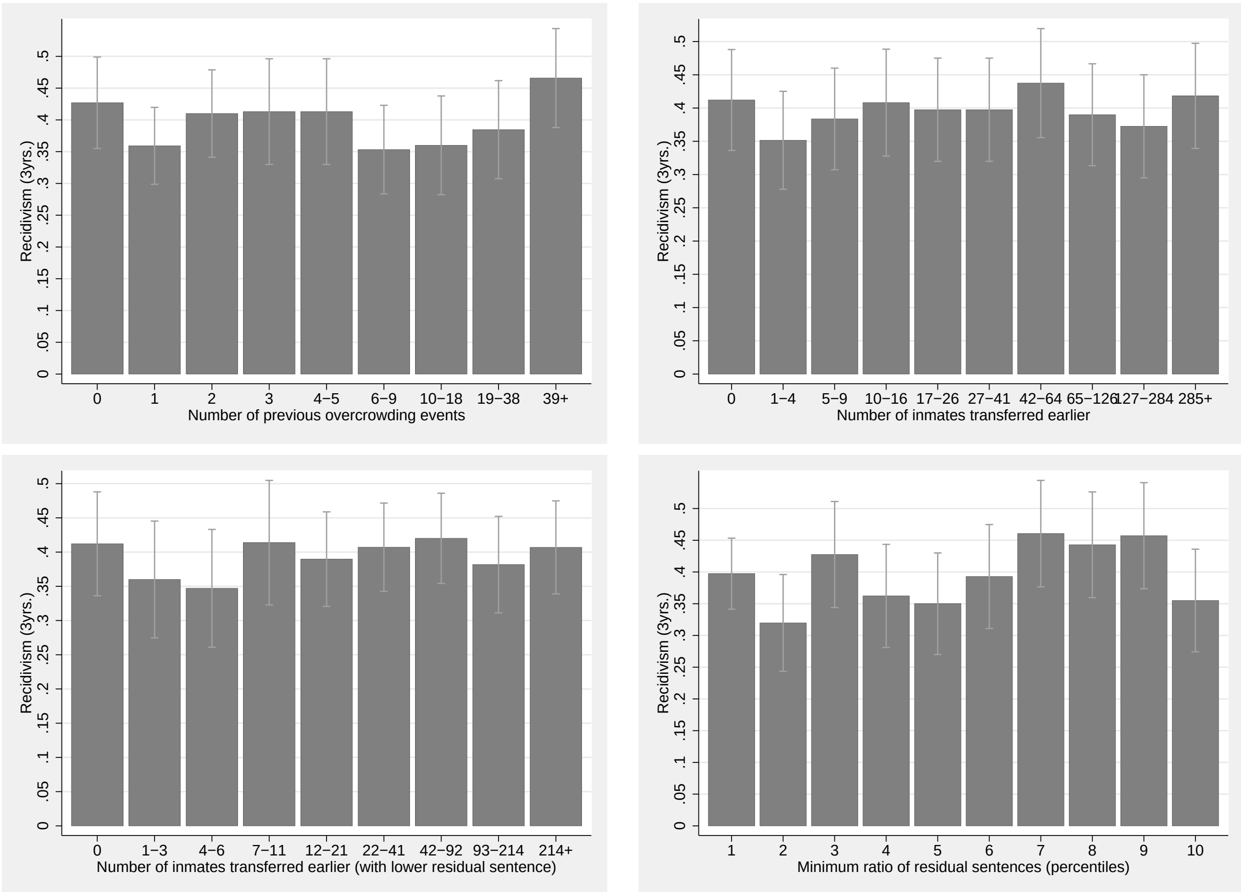

Figure 4: Revealed Choice Measure for Displaced Inmates

Notes: Vertical lines indicate 95 percent confidence intervals.

Table 1: Prison conditions in different prisons

Admission prison	N	Fraction	Type	Open Hours	Establ.	Capacity	Inmates	Overcrowd.	Suicides	Self-inf. inj.	Hunger str.	Prison Work	Indep. Work
Milano San Vittore	1584	68.4%	Mainly closed c.	4	1879	1127	1596	42%	1.3%	9.6%	7.3%	17.5%	0.5%
Milano Opera	130	5.6%	Closed cells	4	1980	973	1246	28%	0.2%	0.8%	7.4%	28.3%	6.5%
Monza	114	4.9%	Closed cells	4	1992	741	775	5%	0.5%	5.9%	3.0%	22.7%	6.6%
Busto Arsizio	66	2.8%	Closed cells	4	1982	297	425	43%	0.0%	3.3%	5.4%	23.3%	0.0%
Como	65	2.8%	Closed cells	5.5	1980	606	546	-10%	0.7%	3.1%	3.8%	14.5%	1.8%
Bergamo	29	1.3%	Closed cells	4	1978	511	497	-3%	2.0%	13.9%	5.4%	12.7%	4.0%
Varese	13	0.6%	Closed cells	5	1886	99	135	36%	0.7%	4.4%	6.7%	12.6%	5.9%
Others	317	13.7%	Closed cells	by law min. 4h									
Milano Bollate	**-**	**-**	Open cells	10 or 12	2000	1311	1032	-21%	0.0%	0.7%	2.3%	22.6%	27.2%

Notes: Suicides and attempted suicides, self-inflicted injuries, inmates in hunger strikes, prison work, and independent work are measured in 2009 and per-inmate, dividing by the number of inmates at the end of 2009.

Table 2: Running costs at Bollate and on average

	Year 2012			Year 2013		
	Bollate		Whole country	Bollate		Whole country
Budget item	Total cost	Cost per inmate	Cost per inmate	Total cost	Cost per inmate	Cost per inmate
Goods and services	3,798,587	9.17	10.57	2,814,203.63	6.75	8.89
Labor costs	20,316,848	49.04	104.82	20,732,849	50.05	103.86
Inmate living, assistance, rehabilitation, and transport costs	2,927,871	7.07	8.56	2,856,439	6.85	9.37
Investments	44,159	0.11	3.75	51,063	0.12	7.37
Total:	27,087,465	65.39	128.01	26,454,555	63.76	129.49

Notes: The costs per inmate are daily.

Table 3: Recidivism and Treatment Intensity by Entry Reason

	Recidivades (3 yrs.)	Released from Section 5	Potential Time in Bollate	Actual Time in Bollate	Total Time Served	Nobs.
Transferred to be treated	0.316	0.148	1.492	1.200	3.727	196
Applied to be treated	0.246	0.106	1.467	1.164	3.529	199
Transferred by the Justice Dep.	0.254	0.254	1.311	0.906	3.015	63
Other entry reasons	0.286	0.190	2.050	1.444	3.614	21
Total selected sample	0.278	0.146	1.482	1.157	3.546	479
Transferred due to overcrowding	0.396	0.024	0.853	0.685	1.441	1557
Entry cause unknown	0.416	0.046	2.240	0.793	4.045	281

Table 4: Summary Statistics and Balance Test

	Whole sample, N=2,317				Displaced sample, N=1,557					
	Statistics		Coefficient on potential years served		Statistics		Coefficient on potential years served		Coefficient on potential years served	
Dependent vars.:	mean	sd	beta	se	mean	sd	beta	se	beta	se
Recidivist	0.37	0.48	-0.052***	(0.012)	0.40	0.49	-0.072***	(0.019)	-0.066**	(0.030)
Art. 4 BIS	0.12	0.32	-0.004	(0.010)	0.07	0.26	-0.000	(0.017)	0.049**	(0.023)
Age	38.12	10.81	0.423	(0.281)	37.46	10.66	0.517	(0.433)	0.744	(0.704)
Drug addiction	0.28	0.45	0.014	(0.014)	0.30	0.46	0.033	(0.022)	0.062***	(0.019)
Total number of incarcerations	3.34	2.73	-0.073	(0.065)	3.42	2.74	0.020	(0.114)	0.076	(0.152)
In a relationship	0.29	0.45	0.003	(0.011)	0.26	0.44	0.004	(0.019)	0.001	(0.031)
Separated or divorced	0.09	0.29	0.011	(0.007)	0.09	0.28	0.019*	(0.011)	0.032*	(0.017)
College degree	0.07	0.25	0.007	(0.006)	0.05	0.22	-0.002	(0.008)	0.007	(0.014)
Secondary schooling	0.52	0.50	0.038***	(0.011)	0.51	0.50	0.012	(0.021)	0.011	(0.033)
Primary schooling	0.19	0.39	-0.014	(0.013)	0.18	0.38	-0.006	(0.020)	0.007	(0.030)
Unknown education	0.00	0.02	-0.000	(0.000)	0.00	0.03	-0.000	(0.000)	0.001	(0.001)
Employed	0.11	0.32	0.000	(0.010)	0.07	0.26	-0.022	(0.015)	-0.025	(0.023)
Unemployed	0.08	0.28	-0.010	(0.008)	0.06	0.24	-0.017	(0.012)	-0.014	(0.016)
Employment unknown	0.79	0.41	0.008	(0.013)	0.86	0.35	0.047**	(0.019)	0.045*	(0.024)
Homicide	0.03	0.18	-0.023***	(0.007)	0.01	0.11	-0.023*	(0.012)	-0.018	(0.021)
Assault	0.15	0.36	0.016	(0.010)	0.13	0.33	0.013	(0.016)	-0.002	(0.027)
Sex-related crime	0.01	0.11	0.005	(0.004)	0.00	0.03	-0.002	(0.002)	-0.002	(0.002)
Theft	0.30	0.46	-0.006	(0.012)	0.33	0.47	-0.010	(0.020)	0.020	(0.028)
Robbery	0.24	0.43	0.013	(0.012)	0.20	0.40	0.001	(0.020)	0.005	(0.029)
Extortion	0.05	0.22	0.007	(0.008)	0.04	0.19	0.015	(0.011)	0.030*	(0.017)
Possesion of stolen goods	0.21	0.41	0.047***	(0.012)	0.16	0.37	0.060***	(0.020)	0.089***	(0.030)
Drug-related crime	0.29	0.45	0.056***	(0.014)	0.24	0.43	0.060**	(0.025)	0.061*	(0.031)
Other crime	0.17	0.38	-0.026***	(0.007)	0.20	0.40	-0.029**	(0.012)	-0.026	(0.022)

Notes: The "Statistics" columns show the mean and the standard deviation of the variables listed across the different rows. Each of these variables is used as a dependent variable in regressions where the right-hand-side variables are the potential years spent in Bollate (shown in the Table) and the total time served. The last set of balance tests (the last two columns) control for weeks of entry times prison of origin fixed effects.

Table 5: Recidivism and Treatment Intensity

	(1)	(2)	(3)	(4)
	Recidivates (0/1)			
	Reduced Form		Instrumental Var.	
Potential years served in Bollate	-0.052***	-0.055***		
	(0.012)	(0.012)		
Actual years served in Bollate			-0.102***	-0.095***
			(0.023)	(0.020)
Total years served	0.006	0.024***	0.008	0.025***
	(0.005)	(0.007)	(0.006)	(0.007)
Transferred to be treated		-0.073		0.009
		(0.050)		(0.050)
Applied to be treated		-0.112**		-0.033
		(0.048)		(0.047)
Transferred due to overcrowding		-0.069*		-0.001
		(0.037)		(0.039)
Transferred by the Justice Dep.		-0.210***		-0.144**
		(0.065)		(0.066)
Art. 4 BIS		0.052		0.065
		(0.044)		(0.043)
Drug addiction		0.079***		0.092***
		(0.027)		(0.026)
Total number of incarcerations		0.048***		0.048***
		(0.004)		(0.004)
Other Xs	No	Yes	No	Yes
First stage F-stat			222.0	313.4
Observations	2,317	2,317	2,317	2,317
R-squared	0.011	0.230	-	-

Notes: Potential years served in Bollate and total years served are expressed as days over 365. The other Xs are four educational dummies, three previous employment dummies, 9 crime dummies, 37 age dummies, prison of origin and year times quarter of exit dummies. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Recidivism and Treatment Intensity by Type of Entry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Recidivates (0/1)							
	Reduced Form				Instrumental Variables			
	Selected	Displaced			Selected	Displaced		
Potential years served in Bollate	-0.035	-0.068***	-0.060**	-0.083***				
	(0.025)	(0.018)	(0.024)	(0.030)				
Actual years served in Bollate					-0.054**	-0.108***	-0.096***	-0.137***
					(0.027)	(0.029)	(0.034)	(0.045)
Total time served	0.018*	0.033***	0.021	0.028*	0.018**	0.037***	0.024*	0.032**
	(0.010)	(0.012)	(0.015)	(0.017)	(0.008)	(0.013)	(0.014)	(0.016)
Art. 4 BIS	0.096	-0.002	-0.016	-0.001	0.095	-0.007	-0.019	-0.005
	(0.070)	(0.050)	(0.065)	(0.068)	(0.059)	(0.050)	(0.055)	(0.058)
Drug addiction	-0.058	0.143***	0.144***	0.145***	-0.060	0.150***	0.154***	0.159***
	(0.060)	(0.035)	(0.043)	(0.043)	(0.050)	(0.034)	(0.037)	(0.038)
Total number of incarcerations	0.041***	0.050***	0.051***	0.051***	0.039***	0.051***	0.051***	0.051***
	(0.011)	(0.005)	(0.006)	(0.006)	(0.010)	(0.005)	(0.005)	(0.005)
Unemployment rate in Northern Italy			-0.085	-0.092			-0.107*	-0.125*
			(0.074)	(0.074)			(0.064)	(0.065)
Youth unemployment rate			0.030	0.032*			0.026	0.027
			(0.019)	(0.019)			(0.017)	(0.017)
OtherXs and prison FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Week of release by prison FE			Yes	Yes			Yes	Yes
Revealed Preference Measures				Yes				Yes
First stage F-stat					479	1,557	1,557	1,557
Observations	479	1,557	1,557	1,557	0.424	0.224	0.402	0.398
R-squared	0.418	0.242	0.412	0.414	187.5	187.2	144.1	81.56

Notes: The additional Xs are all those included in Column 2 of Table 5. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Robustness Regressions

	Robustness regressions:	Sample:	Potential time in Bollate		Actual time served in Bollate		Obs.	Mean dep. variable
(1)	Inmates without ongoing trials	all	-0.059***	(0.012)	0.026***	(0.007)	2,035	0.356
(2)		displaced	-0.073***	(0.018)	0.023*	(0.013)	1,393	0.380
(3)	Inmates without drug addictions	all	-0.052***	(0.014)	0.017**	(0.007)	1,666	0.346
(4)		displaced	-0.066***	(0.020)	0.021*	(0.012)	1,092	0.354
(5)	Inmates released after 2006	all	-0.051***	(0.015)	0.026***	(0.009)	1,146	0.362
(6)		displaced	-0.089***	(0.026)	0.051**	(0.021)	696	0.408
(7)	Two-year recidivism	all	-0.037***	(0.012)	0.017***	(0.006)	2,317	0.322
(8)		displaced	-0.046***	(0.017)	0.016*	(0.010)	1,557	0.339
(9)	Probit	all	-0.210***	(0.043)	0.083***	(0.023)	2,267	0.374
(10)		displaced	-0.244***	(0.061)	0.111***	(0.038)	1,545	0.396
(11)	With in addition a demeaned squared	all	-0.072***	(0.018)	0.026**	(0.011)	2,317	0.374
(12)	terms of time (Total and Bollate)	displaced	-0.050*	(0.028)	0.006	(0.018)	1,557	0.396
(13)	Including inmates with an unknown cause of entry	displaced	-0.061***	(0.015)	0.031***	(0.010)	1,838	0.396

Notes: All regressions control for the additional Xs used in Column 2 of Table 5. The probit results are estimated by maximum likelihood. The corresponding marginal effects at the average for the reduced form regressions are -0.0670 and -0.0742, while for the 2SLS they are -0.108, and -0.125. The coefficients on the squared terms for potential or actual time spent in Bollate are precisely estimated to be close to zero and all the corresponding joint tests of significance can be rejected at less than the 5 percent level. Clustered standard errors (by prison section and week of release) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Heterogeneity of the Effects

	Heterogeneity split:		Sample:	Potential time in Bollate		Actual time served in Bollate		Obs.	Mean dep. variable
(1)	Committed economically motivated crimes	Yes	all	-0.057***	(0.013)	-0.098***	(0.023)	1,871	0.395
(2)			displaced	-0.080***	(0.020)	-0.132***	(0.034)	1,235	0.419
(3)		No	all	-0.036	(0.039)	-0.052	(0.049)	446	0.287
(4)			displaced	-0.013	(0.052)	-0.016	(0.055)	322	0.311
(5)	In prison for their first time	Yes	all	-0.072***	(0.022)	-0.130***	(0.036)	608	0.229
(6)			displaced	-0.110***	(0.037)	-0.170***	(0.051)	401	0.262
(7)		No	all	-0.057***	(0.016)	-0.095***	(0.025)	1,709	0.426
(8)			displaced	-0.066***	(0.024)	-0.106***	(0.039)	1,156	0.443
(9)	In a relationship at the time of arrest	Yes	all	-0.046*	(0.025)	-0.088**	(0.043)	662	0.319
(10)			displaced	-0.103**	(0.046)	-0.198**	(0.083)	407	0.342
(11)		No	all	-0.064***	(0.015)	-0.109***	(0.024)	1,655	0.396
(12)			displaced	-0.065***	(0.021)	-0.099***	(0.033)	1,150	0.416
(13)	Secondary education and above at the time of arrest	Yes	all	-0.037**	(0.016)	-0.066**	(0.027)	1,363	0.365
(14)			displaced	-0.031	(0.024)	-0.048	(0.034)	875	0.398
(15)		No	all	-0.096***	(0.021)	-0.161***	(0.038)	954	0.388
(16)			displaced	-0.123***	(0.029)	-0.209***	(0.053)	682	0.394
(17)	Below median age (36)	Yes	all	-0.072***	(0.020)	-0.131***	(0.038)	1,161	0.450
(18)			displaced	-0.064**	(0.030)	-0.103**	(0.049)	817	0.469
(19)		No	all	-0.041***	(0.015)	-0.068***	(0.023)	1,156	0.298
(20)			displaced	-0.077***	(0.023)	-0.122***	(0.035)	740	0.316
(21)	Subject to ART. 4 BIS (no alternative sanctions)	Yes	all	-0.090**	(0.039)	-0.131***	(0.044)	271	0.373
(22)			displaced	-0.081	(0.085)	-0.133*	(0.078)	112	0.402
(23)		No	all	-0.052***	(0.014)	-0.090***	(0.023)	2,046	0.374
(24)			displaced	-0.066***	(0.020)	-0.102***	(0.030)	1,445	0.396

Notes: All regressions control for the additional Xs used in Column 2 of Table 5. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Heterogeneity of the Effects by Prison of Origin

	(1)	(2)	(3)	(4)
	Recidivates (0/1)			
Potential years served in Bollate (PYB)	-0.066***	-0.079***		
	(0.017)	(0.020)		
PYB × Not transferred from San Vittore	-0.042**	-0.027		
	(0.017)	(0.039)		
Actual years served in Bollate (AYB)			-0.130***	-0.132***
			(0.034)	(0.034)
AYB × Not transferred from San Vittore			-0.060**	-0.035
			(0.027)	(0.052)
Total years served (TYS)	0.033***	0.033**	0.037***	0.010
	(0.010)	(0.013)	(0.011)	(0.022)
TYS × Not transferred from San Vittore	0.017***	0.029	0.017**	-0.010
	(0.007)	(0.018)	(0.007)	(0.022)
Not transferred from San Vittore	0.022	0.054	0.032	0.063
	(0.042)	(0.062)	(0.044)	(0.060)
Observations	2,317	1,557	2,317	1,557
R-squared	0.203	0.226	0.187	0.206
First stage F-stat			68.91	66.31

Notes: All regressions control for the additional Xs used in Column 2 of Table 5. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Mechanism: Evidence of Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Transferred to Section 5 (×100)				Fraction of Days Spent Working Outside (×100)			
Sample	Selected	Displaced	Selected	Displaced	Selected	Displaced	Selected	Displaced
	Reduced Form		2SLS		Reduced Form		2SLS	
Potential years served in Bollate	8.090***	2.061			1.428*	0.209*		
	(1.990)	(2.478)			(0.800)	(0.114)		
Actual years served in Bollate			17.931***	7.580			3.519*	0.425*
			(3.945)	(8.214)			(1.895)	(0.230)
Total years served	1.967**	1.187	1.721**	0.609	-0.400	0.097	-0.435	0.074
	(0.929)	(1.826)	(0.789)	(2.244)	(0.450)	(0.074)	(0.437)	(0.081)
Observations	595	661	595	661	1307	1914	1307	1914
Mean dep. var.	26.89	7.867	26.89	7.867	1.440	0.242	1.440	0.242
R-squared	0.370	0.208	0.389	0.265	0.227	0.143	0.204	0.104
First stage F-stat			62.91	22.38			95.48	164.5

Notes: All regressions control for the additional regressors used in Column 2 of Table 5, including the prison of origin, and year times quarter fixed effects. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Mechanism: Peers or Treatment?

	(1)	(2)	(3)	(4)	(5)	(6)
			Recidivates (0/1)			
Sample:	*Full*	*Displaced*	*Full*	*Displaced*	*Full*	*Displaced*
Peers measured using the:	*Whole prison*		*Section*		*Individual cell*	
Potential time served in Bollate	-0.061***	-0.072***	-0.050***	-0.074***	-0.050***	-0.076***
	(0.014)	(0.021)	(0.014)	(0.021)	(0.014)	(0.021)
Fraction of displaced peers	-0.146	-0.096	0.007	-0.070	-0.035	-0.099*
	(0.140)	(0.203)	(0.065)	(0.079)	(0.048)	(0.058)
Potential time served in Bollate	-0.038	0.006	-0.021	0.005	0.009	0.009
$\times$ Fraction of displaced peers	(0.054)	(0.077)	(0.046)	(0.055)	(0.031)	(0.049)
Total time served	0.024***	0.033***	0.024***	0.033***	0.023***	0.024*
	(0.007)	(0.012)	(0.007)	(0.012)	(0.008)	(0.013)
OtherXs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,317	1,557	2,317	1,557	2,123	1,460
R-squared	0.227	0.242	0.226	0.242	0.232	0.249

Notes: All regressions control for the additional regressors used in Column 2 of Table 5, including the prison of origin, and year times quarter fixed effects. The squared terms are evaluated net of the mean. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Online Appendix

A Photographic Evidence

Figure 5: Pictures taken in Bollate

Notes: The pictures have been taken from `http://www.carcerebollate.it/`. From left to right and top to bottom they show the visitors' center for children, a cell and a corridor.

Figure 6: Pictures taken in Bollate

Notes: Most pictures have been taken from `http://www.carcerebollate.it/`. From left to right and top to bottom they show the horses, the library, the garden, the music sound room, and the glass laboratory.

Figure 7: Pictures taken in Bollate

Notes: Most pictures have been taken from `http://www.carcerebollate.it/`. From left to right and top to bottom they show the school, the carpentry, the computer laboratory, the kitchen, the garden produce, and the cell phone laboratory.

B Spatial Lag Error Model for the Standard Errors

In this Section we use an alternative specification for the standard errors. Until now errors were clustered by week of exit and prison section. Instead of just clustering in a different way, we use a spatial lag error model to model the standard errors. The following model allows errors of inmates who spent at least one day together in the same section to be correlated with each other:

$$RECID = \beta_1 TOT\_YRS + \beta_2 POT\_BOL\_YRS + \gamma' X + \lambda W \epsilon + \epsilon$$

The element r c of the adjacency matrix is positive when inmate r and c have spent at least one day in the same section, and equal to zero otherwise. The exact value depends on whether the full, or the standardized adjacency matrix are used. Under the full the positive values are equal to one, meaning that the composite error term is allowed to depend on the *sum* of all the peers' errors. With the standardized version the adjacency matrix is rescaled so that the rows sum up to one. In this case the composite error term is allowed to depend on the peers' *average* errors. While there is some evidence that the composite error term depends positively on the sum of the peers' errors, the standard errors are almost identical to the clustered standard errors.

Table 12: Recidivism and Treatment Intensity Controlling for Revealed Preference Measures of Selection

	(1)	(2)	(3)	(4)	(5)	(6)
	Recidivates (0/1)					
	Whole Sample				Displaced	
Adjacency matrix:	Dichotomic		Standartized		Dichotomic	Standartized
Potential years served in Bollate	-0.054***	-0.057***	-0.052***	-0.057***	-0.073***	-0.074***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.020)	(0.020)
Total years served	0.007	0.024***	0.006	0.024***	0.015	0.014
	(0.005)	(0.006)	(0.005)	(0.006)	(0.010)	(0.010)
Other Xs		Yes		Yes		
Observations	2317	2317	2317	2317	1557	1557
λ	0.19	0.18	0.00	0.00	0.14	0.00
log-likelihood	-1592	-1302	-1593	-1303	-1087	-1088
p-value LR test $\lambda = 0$	0.0995	0.197	0.913	0.665	0.208	0.498

Notes: The additional Xs are all those included in Column 2 of Table 5. "Spatially" lagged standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The distance matrix allows inmates who have potentially interacted in prison for at least one day to have correlated errors.

C Hazard Model

Table 13: Logit Hazard Model

	(1)	(2)	(3)	(4)
	Recidivates (0/1)			
	Whole Sample		Displaced	
Potential years served in Bollate	-0.232***	-0.215***	-0.232***	-0.215***
	(0.054)	(0.070)	(0.054)	(0.070)
Total years served	0.086***	0.091***	0.086***	0.092***
	(0.025)	(0.034)	(0.025)	(0.034)
Quartic in time	Yes	No	Yes	No
Month/Year fixed effects	No	Yes	No	Yes
Observations	63,342	42,326	61,931	41,394
Number of individuals	2278	1549	2278	1549
pseudo-R2	0.0786	0.0783	0.0822	0.0830

Notes: We construct monthly panel data and use a logit hazard model (inmates are followed up to when they recidivate or 3 years past release, whatever comes first. All regressions control for the additional regressors used in Column 2 of Table 5. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

D Revealed Preference Measures of Selection

Claim: Let ρ_u and ρ_w be independently distributed on the same support $r_1 < r_2 < ...r_M$, with prior probabilities denoted p_k and $q_k, k = 1, 2...M$, respectively. Suppose that, conditional on a particular observation, the probability mass in both probability distributions get shifted to the left; more specifically, suppose that, conditional on that observation, the new probabilities are $\mu_k p_k$ and $\lambda_k q_k$, $k = 1, 2...M$, for some μ_k and λ_k such that

$$\begin{aligned} \mu_1 &\geq 1, \mu_k \geq \mu_{k+1} \\ \lambda_k &\geq 1, \lambda_k \geq \lambda_{k+1}, \end{aligned} \tag{3}$$

with

$$\sum_{k=1}^{M} \mu_k p_k = 1 \tag{4}$$

$$\sum_{k=1}^{M} \lambda_k q_k = 1. \tag{5}$$

Assume that both initial probabilities are monotone decreasing, i.e assume, for $k = 1, 2...M - 1$,

$$\begin{aligned} p_k &\geq p_{k+1} \\ q_k &\geq q_{k+1}. \end{aligned} \tag{6}$$

Then

$$\sum_{k=1}^{M} \mu_k \lambda_k p_k q_k \geq \sum_{k=1}^{M} p_k q_k$$

where $\sum_{k=1}^{M} p_k q_k$ is the probability that $\rho_u = \rho_w$ before the observation and $\sum_{k=1}^{M} \mu_k \lambda_k p_k q_k$ is the probability that $\rho_u = \rho_w$ conditional on the observation.

Proof. To prove this, notice that, from (4) and (5), we have:

$$(\sum_{k=1}^{M} \mu_k p_k)(\sum_{k=1}^{M} \lambda_k q_k) = 1$$

which we can rewrite as

$$\sum_{k=1}^{M} \mu_k \lambda_k p_k q_k + \sum_{k=1}^{M} \mu_k p_k \sum_{s \neq k} \lambda_s q_s = 1.$$

Therefore,

$$\sum_{k=1}^{M} \mu_k \lambda_k p_k q_k \geq \sum_{k=1}^{M} p_k q_k$$

if and only if

$$1 - \sum_{k=1}^{M} p_k q_k \geq \sum_{k=1}^{M} \mu_k p_k \sum_{s \neq k} \lambda_s q_s. \tag{7}$$

Consider the RHS in (7). Using (4) and (5) we can write it as

$$\begin{aligned}
& \sum\nolimits_{k=1}^{M} \mu_k p_k \sum\nolimits_{s\neq k} \lambda_s q_s \\
= \;& \sum\nolimits_{k=1}^{M} \mu_k p_k (1-\lambda_k q_k) \\
= \;& \sum\nolimits_{k=1}^{M-1} \mu_k p_k (1-\lambda_k q_k) + \mu_M p_M (1-\lambda_M q_M) \\
= \;& \sum\nolimits_{k=1}^{M-1} (\mu_k p_k - \mu_k \lambda_k p_k q_k) + (1-\sum\nolimits_{k=1}^{M-1} \mu_k p_k)(\sum\nolimits_{s=1}^{M-1} \lambda_s q_s) \\
= \;& \sum\nolimits_{k=1}^{M-1} (p_k \mu_k + q_k \lambda_k - 2 p_k q_k \mu_k \lambda_k) - \sum\nolimits_{k=1}^{M-1} \mu_k p_k \sum\nolimits_{s=1, s\neq k}^{M-1} \lambda_s q_s .
\end{aligned}$$

Consider the LHS in (7). We can write it as

$$\begin{aligned}
& 1 - \sum\nolimits_{k=1}^{M} p_k q_k \\
= \;& \sum\nolimits_{k=1}^{M} p_k - \sum\nolimits_{k=1}^{M} p_k q_k \\
= \;& \sum\nolimits_{k=1}^{M-1} (p_k - p_k q_k) + p_M (1-q_M) \\
= \;& \sum\nolimits_{k=1}^{M-1} (p_k - p_k q_k) + (1-\sum\nolimits_{k=1}^{M-1} p_k)(\sum\nolimits_{s=1}^{M-1} q_s) \\
= \;& \sum\nolimits_{k=1}^{M-1} (p_k + q_k - 2 p_k q_k) - \sum\nolimits_{k=1}^{M-1} p_k \sum\nolimits_{s=1, s\neq k}^{M-1} q_s .
\end{aligned}$$

Therefore,

$$\sum\nolimits_{k=1}^{M} \mu_k \lambda_k p_k q_k \geq \sum\nolimits_{k=1}^{M} p_k q_k$$

if and only if

$$\begin{aligned}
\sum\nolimits_{k=1}^{M-1} (p_k + q_k - 2 p_k q_k) - \sum\nolimits_{k=1}^{M-1} p_k \sum\nolimits_{s=1, s\neq k}^{M-1} q_s \;\; \geq \\
\sum\nolimits_{k=1}^{M-1} (p_k \mu_k + q_k \lambda_k - 2 p_k q_k \mu_k \lambda_k) - \sum\nolimits_{k=1}^{M-1} \mu_k p_k \sum\nolimits_{s=1, s\neq k}^{M-1} \lambda_s q_s .
\end{aligned} \tag{8}$$

Clearly, if $\mu_k = \lambda_k = 1$ for all k we have that in (8) RHS=LHS. Consider a Taylor first-order approximation of the RHS, around $\mu_k = \lambda_k = 1$ for all k. We have

$$
\begin{aligned}
& \sum\nolimits_{k=1}^{M-1} (p_k\mu_k + q_k\lambda_k - 2p_kq_k\mu_k\lambda_k) - \sum\nolimits_{k=1}^{M-1} \mu_k p_k \sum\nolimits_{s=1,s\neq k}^{M-1} \lambda_s q_s \\
\simeq\ & \sum\nolimits_{k=1}^{M-1} (p_k + q_k - 2p_kq_k) - \sum\nolimits_{k=1}^{M-1} p_k \sum\nolimits_{s=1,s\neq k}^{M-1} q_s + \\
& \sum\nolimits_{k=1}^{M-1} (p_k - 2p_kq_k - p_k \sum\nolimits_{s\neq k}^{M-1} q_s)(\mu_k - 1) + \sum\nolimits_{k=1}^{M-1} (q_k - 2p_kq_k - q_k \sum\nolimits_{s\neq k}^{M-1} p_s)(\lambda_k - 1) \\
=\ & \sum\nolimits_{k=1}^{M-1} (p_k + q_k - 2p_kq_k) - \sum\nolimits_{k=1}^{M-1} p_k \sum\nolimits_{s=1,s\neq k}^{M-1} q_s + \\
& \sum\nolimits_{k=1}^{M-1} (1 - q_k - \sum\nolimits_{s\neq k}^{M-1} q_s - q_k)p_k(\mu_k - 1) + \sum\nolimits_{k=1}^{M-1} (1 - p_k - \sum\nolimits_{s\neq k}^{M-1} p_s - p_k)q_k(\lambda_k - 1) \\
=\ & \sum\nolimits_{k=1}^{M-1} (p_k + q_k - 2p_kq_k) - \sum\nolimits_{k=1}^{M-1} p_k \sum\nolimits_{s=1,s\neq k}^{M-1} q_s + \\
& \sum\nolimits_{k=1}^{M-1} (q_M - q_k)p_k(\mu_k - 1) + \sum\nolimits_{k=1}^{M-1} (p_M - p_k)q_k(\lambda_k - 1).
\end{aligned}
$$

Therefore, up to an approximation of higher order, (8) holds if

$$
\sum\nolimits_{k=1}^{M-1} (q_M - q_k)p_k(\mu_k - 1) + \sum\nolimits_{k=1}^{M-1} (p_M - p_k)q_k(\lambda_k - 1) \leq 0. \tag{9}
$$

We now have

$$
\begin{aligned}
\sum\nolimits_{k=1}^{M-1} (q_M - q_k)p_k(\mu_k - 1) + \sum\nolimits_{k=1}^{M-1} (p_M - p_k)q_k(\lambda_k - 1) &\leq \\
(q_M - q_{M-1}) \sum\nolimits_{k=1}^{M-1} p_k(\mu_k - 1) + (p_M - p_{M-1}) \sum\nolimits_{k=1}^{M-1} q_k(\lambda_k - 1) &\leq 0,
\end{aligned}
$$

where the last inequality follows from (6), which implies that $(q_M - q_{M-1}) \leq 0$ and $(p_M - p_{M-1}) \leq 0$, and from (3), which implies that

$$
\begin{aligned}
\sum\nolimits_{k=1}^{M-1} p_k\mu_k &\geq \sum\nolimits_{k=1}^{M-1} p_k \Leftrightarrow \sum\nolimits_{k=1}^{M-1} p_k(\mu_k - 1) \geq 0 \\
\sum\nolimits_{k=1}^{M-1} q_k\lambda_k &\geq \sum\nolimits_{k=1}^{M-1} q_k \Leftrightarrow \sum\nolimits_{k=1}^{M-1} q_k(\lambda_k - 1) \geq 0.
\end{aligned}
$$

□

Table 14: Recidivism and Treatment Intensity Controlling for Revealed Preference Measures of Selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Recidivates (0/1)							
	Reduced Form				Instrumental Variables			
Potential years served in Bollate	-0.057**	-0.081***	-0.062**	-0.083***				
	(0.024)	(0.028)	(0.026)	(0.030)				
Actual years served in Bollate					-0.091***	-0.133***	-0.101***	-0.137***
					(0.034)	(0.042)	(0.037)	(0.045)
Total years served	0.018	0.032**	0.021	0.028*	0.020	0.036**	0.024*	0.032**
	(0.015)	(0.016)	(0.015)	(0.017)	(0.014)	(0.016)	(0.014)	(0.016)
Minimum ratio of residual sentences			0.002	-0.006			0.003	-0.005
			(0.024)	(0.025)			(0.021)	(0.021)
Number of previous overcrowding instances	-0.363			-0.277	-0.386			-0.308
over sentence in prison of origin	(0.369)			(0.370)	(0.309)			(0.309)
No overcrowding instances	-0.051			-0.066	-0.048			-0.065
	(0.074)			(0.077)	(0.063)			(0.066)
Number of preferred inmates		-0.006		-0.006		-0.007*		-0.007*
		(0.005)		(0.005)		(0.004)		(0.004)
Number of preferred inmates		0.001		0.001		0.001		0.001
with lower residual sentence		(0.001)		(0.001)		(0.000)		(0.000)
First four moments of the ratio			0.820	0.749			0.765	0.688
of residual sentence (p-value)								
Observations	1,557	1,557	1,557	1,557	1,557	1,557	1,557	1,557
R-squared	0.412	0.413	0.412	0.414	0.403	0.398	0.401	0.398
First stage F-stat					145.5	106.0	110.8	81.56

Notes: The additional Xs are all those included in Column 2 of Table 5. All regressions control for prison of origin times week of entry fixed effects. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1