Leave the Door Open? Prison Conditions and Recidivism

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Abstract

We estimate the effect on recidivism of replacing time served in a common closed-cell prison with time served in an open-cell one. We deal with the endogenous assignment of inmates to different prison regimes using variation that is driven by nearby prisons' overcrowding. Switching regimes for a year reduces recidivism by around 6 percentage points (or pp). The effects are largest for inmates with low levels of education and are weak for violent and for hardened criminals.

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Over recent decades most developed countries have witnessed high and often increasing rates of incarceration. In the United States, at the end of 2015, almost one per cent of the adult population was behind bars, with a sevenfold increase in the incarceration rate since the early 70s (Carson and Anderson, 2016). Over the last 15 years the total prison population has gone up by almost 20 percent, more than the corresponding growth rate of the world population, in spite of strong counteractive forces, like population aging (see Table 8 in Walmsley, 2016).

This process risks feeding 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. Addressing this "revolving door" problem is now a top priority for many policymakers: if societies were able to reduce reoffending, victimization and incarceration rates would be reduced as well, generating large economic and social benefits (see Raphael and Stoll, 2009, Kuziemko, 2013). Well-identified empirical evidence on crime desistence has also been the topic of a recent literature review (Doleac, 2019).

Since recidivating criminals have already spent time in prison, it is natural to ask whether, and if so how much, prison conditions affect subsequent recidivism. In broad terms, there are two alternative and opposite views on how prison conditions should be and on their impact on recidivism.

One view is that prison life should isolate inmates not just from the outside world: inmates should spend a large part of the day inside their cell, movements inside the prison should be regulated and monitored; discipline should be strict, with punishment for every deviation, and inmates should have little or no room to choose how their daily life is organized. We will call prisons of this kind *closed*. According to this view, the experience of harsh prison conditions is what deters current inmates from recidivating.

Another view maintains that punishment for criminal behaviour should amount to no more than the limitation of freedom. Within the prison walls life should be as normal as possible; inmates should spend most of the day outside their prison cell, working, studying, keeping personal relationships, in an environment that allows for movement around the prison premises with little supervision; self-responsibility is emphasized. We will call prisons of this kind *open*. According to this view, rehabilitation – rather than deterrence – is what curbs recidivism, and rehabilitation is only possible if inmates are given the possibility to make decisions and are asked to take responsibility for their choices.

These different approaches have been followed in different countries and at different times. In the U.S. the traditional and prevalent approach to criminal justice stressed the deterrence effect of harsh prison conditions. For a brief interlude, at the end of the 60's, concerns emerged that many correctional institutions were detrimental to rehabilitation. Some proposals were put forward, envisaging prison conditions preparing inmates for their successful re-entry into society, and some correction facilities were built according to those proposals. 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" when trying to rehabilitate prisoners. Hence, the U.S. went back to the emphasis on "tough-on-crime" policies, incapacitation and deterrence.

The open prisons model was instead championed by some European countries, and most notably by the Scandinavian ones, where open prisons started being built since the 70's.Recently, scholarly papers (e.g., Pratt, 2008, Ward et al., 2013) as well as the general press (e.g., Larson, 2013, Benko, 2015, The Economist, 2017) have brought the spotlight on the "Scandinavian model" of open prisons.[1]

It is difficult, however, to draw general lessons about the effect on recidivism of open prisons from the experiences of the Scandinavian ones. One obstacle is size: most of the existing open prisons house less than 100 inmates, and even the largest do not usually 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 given by the sizeable differences in the average time spent in prison, which is close to 3 years in the United States (Pew Center, 2012) and just three to six months in the Scandinavian countries (Aebi and Delgrande, 2002-2015). A further obstacle is cost: for example, spending in Scandinavian prison is in excess of 100 thousand dollars per inmate per year (Aebi and Delgrande, 2002-2015), compared with just 31 thousand dollars in the United States (Mai and Subramanian, 2017). A final obstacle is, of course, the selection problem, as inmates who are sent to the open

[1]Even a major private firm contractor as CoreCivic (former Correction Corp. of America), announced in 2014 a change in its business model, committing to "*play a leadership role in reducing recidivism... planning to expand the company's prison rehabilitation programs*," (Barrett, 2014, Mukherjee, forthcoming).

prisons are not a random sample of the population of inmates (neither would interact with a random group of inmates), so that any naive comparison of their recidivism rates with those of 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 the open prison model.

The main contribution of our paper is to fill this gap in a quasi-experimental setting. We use data from one of the largest detention centers in Europe, and the largest *open* prison in Italy, the *Bollate* prison, inaugurated at the end of 2000 near the city of Milan.[2] Besides being open, Bollate is *large* (about 1000 inmates), *costs no more* – if anything, less – than a traditional closed prison in the same country (more on this later), and features an average prison time that is close to the one in U.S. prisons. 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 years served – and exploit a variation in such margin that we show is as good as random. Hence we study the causal effect of varying the length of the sentence served in the open prison, holding the total time spent in prison constant.

Specifically, we focus on a subset of inmates who did not go through the standardized selection process into Bollate and were displaced there due to overcrowding of the prison in which they were serving their sentence (we will refer to them as "displaced inmates", while we will call "selected inmates" those transferred to Bollate after the screening process).[3] Our counterfactual prison experience therefore takes place in an overcrowded facility. But overcrowding tends to be the norm in Italy.[4] The median overcrowding rate is 147 percent in the prisons of origin of Bollate inmates for the years 2003-2009, not much higher than the 130 percent for the median Italian prison facility.

What is key for our purpose is that neither Bollate nor the sending prisons get to choose the inmates to be displaced or the time of displacement. The Regional branch of the Prison Administration (RPA) irregularly grants the overcrowded prisons in the Region permission to displace, towards one of the (few) undercrowded prisons, a given (variable) number of inmates. Each of the sending prisons then

[2]Bollate prison featured in 2003 in the New York Times article "*Italian inmates receive training in a Cisco computer program: Behind bars but learning to network.*"

[3]See Appendix A for more information on the screening process. The usefulness of focussing on the intensive margin of the treatment in connection with recidivism is noted and exploited by Di Tella and Schargrodsky (2013).

[4]It is also prevalent in Europe. According to the Council of Europe Penal Statistics about a third of countries covered in their survey have an overall prison population that exceeds overall capacity (Aebi and Delgrande, 2002-2015), including Italy, France, Germany, Spain, and the UK.

displaces that given number of inmates working its way down a list of displaceable inmates, on a "conveyor belt," first-in-first-out basis. Each inmate present in the sending prison enters that list, in chronological order, as soon as he receives his first conviction.[5]

Hence, we compare the recidivism of inmates who were serving the *same time spent in prison* in the *same prison* and became displaceable to the open prison after the *same length of time* since their incarceration, but whose residual sentences to be served there – which represent our measure of the treatment – differ in length because of *i*) differences in the number of inmates already in the list at the moment each inmate became eligible for displacement and *ii*) differences in the number and size of displacement opportunities granted by the RPA to the sending prison. Both differences are plausibly uncorrelated with the inmates' idiosyncratic propensity to recidivate.

The focus on displaced inmates offers two further advantages. First, since they do not go through any selection process, the external validity of our results is likely to be stronger. Second, they typically spend less time in Bollate than selected inmates; because of this, Bollate's management tends not to start with them (long lasting) training initiatives explicitly targeted to rehabilitation – for example, they are rarely given the opportunity to work outside the prison walls. This means that their experience is potentially able to tell apart the effects on recidivism of specific rehabilitation initiatives – such as working or training programs – and those simply due to prison conditions that require inmates to make decisions and take responsibility for their choices, within the boundaries set by the prison walls.

As we will document below, prison conditions in an open prison like Bollate are clearly more pleasant than those in a typical closed prison and generate a *treatment bundle*. The effect of this on recidivism is an empirical question, as in theory there are forces working in opposite direction. On the one hand, more pleasant prison conditions lower the disutility of prison and therefore reduce generic deterrence. Whether specific deterrence would also be reduced is less clear cut: since recidivating inmates are not readmitted into Bollate, for rational and forward looking criminals there should be no effect.[6] On the other hand, by improving the prospects of a profitable re-entry in the society, serving time in an open prison that offers training and working programs increases the opportunity

[5]Displaced inmates are all male, as there are no overcrowded female prisons.

[6]However, Bushway and Owens (2013) find that inmates whose sentence is shorter than expected are more likely to re-offend.

cost of reoffending. Moreover, even aside from participation in training or working programs, prison conditions that trust inmates to make decisions and ask them to take responsibility for their choices might, in and of themselves, influence the inmates' future behavior. A better prison treatment may also generate a sense of reciprocity, leading to better behavior both in prison and after release.

To briefly preview our results, we find that the opportunity to serve a given total time replacing one year in a traditional closed prison with one year in an open one reduces recidivism (over a three-year period) by about 6 pp (against an average three-year recidivism of about 40 percent). We find some heterogeneity across different categories of inmates: the reduction of recidivism is higher for inmates who are less educated, and therefore are less well equipped to deal with the challenges of a non criminal life. There is also evidence that violent inmates, as well as inmates with the highest ex-ante risk of recidivating (who tend to recidivate within a short period of time), do not respond much to the treatment.

It is not easy to reach neat conclusions on the mechanisms underlying the reduction in recidivism, since the open and closed prison models differ on a number of fronts – a different idea of punishment, freedom of movement inside the prison walls, self-responsibility, trust, rehabilitation programs, productive use of time, quality of the physical facilities, quality of the fellow inmates – and we have no detailed information on whether and how these potentially endogenous factors change and influence behavior with time served in prison. We do find that the longer inmates stay in 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 a potential driver of our results.

However, compared to selected inmates, displaced ones are less likely to be given access to (outside) work opportunities while in prison. Also, since they usually remain in Bollate for a shorter period, they are less involved in other activities more explicitly aimed at rehabilitation (like training programs). Yet we find that the treatment is at least as effective in reducing their recidivism.[7] We interpret this as indirect evidence that other aspects of the treatment are also likely to play a role. Indeed, entering the open prison displaced inmates experience a number of radical changes: a threefold

[7]Results for the sample of selected inmates are reported in Appendix A.

increase in the time spent outside their cell (from 4 to up to 12 hours), a shift from meticulous external control on their daily life to self-responsibility, from constrained idleness inside the cell to productive use of time. Our conjecture is that the longer displaced inmates face these differences, the more they produce a psychological turnaround that reduces recidivism.

The reduced recidivism might also result from weaker criminogenic role models observed while in prison: Bollate's management might use the selection to limit the arrival of "bad" fellow prisoners. 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 cell block to measure the effect on recidivism of being exposed to a larger group of "worse" inmates during an inmate's stay. We find no statistically robust evidence that such exposure increases recidivism. And while the counterfactual prison would have been a fairly overcrowded one (median overcrowding rates are close 150 percent), there is little evidence that overcrowding differences between Bollate and the prison of origin explain the reduction in recidivism.

Another challenge to the scalability of the open prison model comes from the possibility that what ensures a good behavior by the inmates serving their time is the threat to be transferred back to a closed prison.[8] If all prisons were like Bollate, that threat would lose its bite. And if restrained misbehavior during time served carries over to post-release, then a muted threat could also mute the effect on recidivism.[9] The relevance of this concern hinges, again, on whether it is the threat of being transferred that triggers, at least initially, the good behavior, or it is the nicer conditions in themselves that do not trigger the bad behavior. At present, we have no data to tell apart those two effects, and any policy intervention that were to scale up the open prison conditions would need to monitor them carefully.[10]

Relationship with the literature

Several studies have tried to identify the causal determinants of recidivism. Most of them focus on

[8] Between 3 and 4 percent of the displaced inmates are transferred to another prison before release.

[9] While this is certainly a possibility, the frequency and severity of antagonistic behavior by inmates may respond to worse prison conditions. Therefore, by scaling up the open prison conditions there would be two offsetting effects: the disciplining threat would be muted, but there would be less need for a disciplining threat.

[10] It is also the case that the scalability of the open prison conditions would face a natural limit in the need for high security facilities to deal with inmates belonging to criminal organizations, in which case more restrictive limits to their ability to interact are a necessity.

the impact on re-offending of receiving, or not receiving, a custodial sentence or analyze the impact of the incarceration length; only a few, and in particular Katz et al. (2003), Drago et al. (2011), Chen and Shapiro (2007), and Tobòn (forthcoming) take into account the conditions under which the sentence is served. The latter are the ones most closely related to our work. The first paper finds that harsher prison conditions (proxied by prison suicides) are associated with lower crime rates; the analysis is cross-sectional, however, it does not consider the recidivism of individual inmates and cannot identify causality. The other three papers show that worse conditions increase recidivism. Drago et al. (2011) use variation in prison assignment and measure prison conditions using the degree of prison overcrowding, deaths in prison, and degree of isolation. Chen and Shapiro (2007) exploit discontinuities in the assignment of federal prisoners to security levels, though their estimates are noisy due to a small sample problem. Tobòn (forthcoming) exploits quasi-random assignment to less crowded and higher service prisons in Colombia. None of these studies however compares outcomes for sharply different prison regimes, like we do for the open versus closed prison models.

There is more experimental evidence on the effects of post-release treatment programs for ex-inmates – for example, job training – on recidivism and employment, albeit with mixed results: some papers find that job training can be beneficial (Raphael, 2010, Redcross et al., 2010), other finds the opposite (Visher et al., 2005), or no effects (Cook et al., 2015). Job training programs are also part of the conditions that inmates experience in the open prison. In our case, however, these programs are only one of the aspects of the treatment, and they take place while inmates are still detained (possibly during day releases), while post-release job training, once inmates are out of prison, may compete with inmates' old delinquent habits.

As to the literature that has analyzed the effect of imprisonment on recidivism, without distinguishing among different prison conditions, we note that there is no consensus on the sign of the effect, let alone its magnitude. A review by Nagin et al. (2009) concludes that "*As imprisonment is used in contemporary democratic societies, the scientific jury is still out on its effect on reoffending.*" Another insightful literature review by Ouss (2013) stresses the need for "*evidence-based economic contributions to addressing the relationship of incarceration to recidivism.*"

Most quasi-experimental studies have used the random assignment of judges (with different sanctioning preferences) to estimate the effect of incarceration and incarceration length on inmate's outcomes. Among these, Bhuller et al. (2020) use data from Norwegian prisons and find that spending more time in prison, some of which invest heavily in trying to rehabilitate inmates, lowers recidivism. Yet, as judges do not govern whether individuals end up in an open prison (and judge's stringency does not differentially affect whether an individual is sent to an open versus a closed prison), their analysis is silent about the causal effect of this prison model as such.[11]

Di Tella and Schargrodsky (2013), in a radically different prison context, leverage the same exogenous variation to show that Argentinean inmates who spend a larger fraction of their sentence under electronic monitoring, instead of ordinary imprisonment, have *lower* recidivism.[12]

Mueller-Smith (2015), using data from Harris County, Texas – another example of a harsh prison regime – finds that incarceration generates an increase in the likelihood of defendants reoffending after being released, while Loeffler (2013) finds no evidence that incarcerations changes recidivism.

Using a regression discontinuity design, Mueller-Smith and Schnepel (2017) measure similar criminogenic effects when offenders are sentenced to spending time in Texan prisons rather than be put on probation.[13] Interestingly, Kuziemko (2013) also uses a regression discontinuity design, exploiting changes in Georgia's parole-board guidelines, to show that an extra year in prison, but coupled with incentives to participate in rehabilitation efforts, leads to large reductions in recidivism.

Our results suggest a way to interpret these opposite findings. Prison time served by inmates in facilities with a radically different prison life and with different rehabilitation programs may lead to different recidivism behavior: it might reduce or increase recidivism, depending on whether it takes place in open prisons, like Bollate or prisons in Scandinavia, or in a harsher one, like typical Italian prisons, or prisons in Argentina and Texas.[14]

[11] Landersø (2015) studies a somewhat related issue, the effect of incarceration length on labor market outcomes, using data from Danish prisons (he focuses on short sentences, between one and two months). Sentencing conditions and imprisonment lengths in Scandinavian prisons have been extensively studied in the criminology and sociology literature, though the focus is not in identifying causal effects.

[12] Electronic monitoring has also been shown to work in New South Wales (Williams and Weatherburn, 2019), England and Wales (Marie, 2009), and France (Henneguelle et al., 2016).

[13] Criminogenic effects of prison time have been found by Gaes and Camp (2009), Mueller-Smith (2015), and Harding et al. (2017), while Dobbie et al. (2018) and Green and Winik (2010), exploiting again random assignment of judges, find that recidivism does not respond to incarceration.

[14] Admittedly, while we focus on the intensive margin some of the papers quoted consider the extensive margin. Our proposed reconciliation implicitly assumes that the effect of the treatment on recidivism has the same sign at both the

1 The Quasi-experiment

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

1.1 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.[15] Given that most incarcerations in the *Case Circondariali* tend to be short term, these detention centers invest very little effort in trying to rehabilitate the inmates. If convicted of a prison sentence of at least three years, the inmates are transferred to a prison, known as *Casa di Reclusione*.

The aim, in principle, is to separate offenders convicted of serious crimes from the other ones, and 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" (in the Lombardy region, near Milan; we will henceforth refer to this prison simply as Bollate). Bollate was opened at the end of 2000 with the explicit goal of creating an open prison with a rehabilitation program, leaving ample room for a range of activities and establishing joint work/training programs with regional institutions, firms, and non governmental organizations.

It is one of the few, and certainly the largest, open prison in Italy (as mentioned above, they are more common in Nordic countries and, to a lesser degree, in the United Kingdom).[16] Bollate prison cells are kept open during the day, and prisoners are trusted to serve their sentences with minimal

extensive and intensive margins.

[15] 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*).

[16] 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).

supervision: inmates are allowed to move freely around the prison with electronic badges. Inside the Bollate prison, inmates can go to school and university, and they have access to several job training programs. Some inmates work inside the prison for agricultural and service cooperatives. For about 5 percent of inmates even the prison walls are "open," as they get to work outside during day releases.[17]

Bollate has its own garden produce, grown by inmates. They run a restaurant, open to the public, and publish a magazine (every other month). 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, they can spend their time in dedicated play rooms that are nicely furnished and full of toys, and spouses are guaranteed some intimacy. Security is not merely seen as a police concern but also educators, psychologists and even the inmates themselves are involved and given responsibilities. Inmates are asked to sign a "Responsibility Pact," committing to responsible behavior lest they be transferred to a different prison. In such an environment, and possibly also thanks to the threat of transfer to an ordinary prison, violence is contained and fewer guards are needed, which keeps costs down.

Summing up, 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. Table 1 documents several features of Bollate and of the prisons from which Bollate draws most of its inmates (almost 70 percent of inmates in Bollate are transferred from the largest *Casa circondariale* in the Lombardy region, San Vittore).

The first striking difference between Bollate and these other prisons is that inmates are free to move within the prison walls for most of the day (10 to 12 hours), while inmates in most other prisons spend only around 4 hours outside their cells (which is the minimum time required by law). These differences in the time spent idle inside the cell can also be observed in prisons located in other countries. According to a recent survey carried out in the UK, in open prisons 54 percent of inmates can move freely inside the prison for 10 or more hours (HM Inspectorate of Prisons, 2017). In ordinary closed-cell UK prisons inmates spend most of their time inside their cell.[18]

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

[18]The UK HM Inspectorate of Prisons (2017), concerned about these numbers, recommends that inmates are given at

Bollate is also the youngest prison. San Vittore was built in 1879, following Bentham's panopticon design. Opera, the other major *Casa di Reclusione* in the region, was built in 1980. These 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. Table 1 suggests that 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 Lombardy.

Apart from the open cell policy and the lack of overcrowding, Bollate is special for its rehabilitation efforts, and in particular for those targeted at improving inmates' future labour market prospects. In most prisons, a fraction of inmates (between 12 and 30 percent) work for the prison administration in menial jobs with little or no specialization, which are unlikely to improve much their future employability. In Bollate, inmates have the opportunity to work for employers other than the prison administration, both inside and outside the prison, and to learn skills which will be useful in the labour market: carpenters, electricians, chefs, welders, ICT specialists, taylors, odontologists, etc. At any 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 of the prison walls. 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 Lombardy.

While one might think that all these efforts come with a hefty price tag, a remarkable feature of Bollate is that its running costs are much lower than the average prison in Italy. Appendix Table A1 shows that the per-inmate daily cost of Bollate was 65 euros (USD 28,000 per year), while the average for the whole country was 115 euros (USD 49,000 per year). The difference is mainly due to the lower wage bill for guards and administrators, in turn resulting from their lower number compared to the number of inmates (wages of prison staff do not vary across prisons). In 2009, in Bollate, 470 prison guards and administrative staff dealt with 1032 inmates, a ratio of less than one guard every two inmates. Nationwide such ratio was about 2/3.

least 10 hours of yard time. The report highlights also a series of studies on the behavioral issues that tend to emerge when inmates spend the whole day inside their cells.

As a rule, inmates present in Bollate are selected through a screening process from a pool that includes both, those who apply to be sent there and those who are proposed by the administration of a different prison (usually in the same region) or by the Justice Department.[19]The Regional branch of the Prison Administration for Lombardy, together with the prison administration of Bollate, assesses each transfer application to determine whether a number of criteria are satisfied. Broadly speaking, the selection process is aimed at identifying inmates more responsive to rehabilitation interventions (more information is provided in Appendix A). A third channel of access to Bollate, quantitatively more important in the first few years since the prison's opening, is provided by displacement of inmates from nearby overcrowded prisons.

Specifically, during the period that we considered, the RPA frequently granted overcrowded prisons in the Lombardy region permission to displace some of their inmates towards nearby prisons that had spare room. This occurred whenever overcrowding became particularly severe and there were enough empty cells in a nearby prison. Bollate, which opened in late 2000 with an availability of about 1000 prison beds, was often on the receiving end of these transfers (Appendix Figure A1 shows the size and timing of such episodes). Importantly, neither the management of Bollate nor that of the sending prison had control on which or when inmates were displaced there (see Section 1.3).

1.2 The Data

We worked with the Prison Administration ("*Dipartimento dell'Amministrazione Penitenziaria*") of the Italian Ministry of Justice, its regional administration office for Lombardy and the administration of the Bollate prison, to link different administrative records collected up until February 2013.

We were granted access to a large amount of information on inmates who spent some prison time in Bollate between December 2000, the opening month, and February 2013, the closing date of our analysis (Bollate Prison, 2013). 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 Dipartimento di Amministrazione Penitenziaria (2020).

[19]A small number of inmates hand themselves in directly to the Bollate prison (this does not guarantee that they will be accepted to Bollate). We treat these cases as if they applied to be sent to Bollate.

We restrict our sample to Italian (57 percent of inmates are foreigners), male (less than 30 inmates are female), non sex offenders. We exclude foreigners because of the difficulty in measuring recidivism for foreign offenders who, in more than 90 percent of the cases, [20] are illegal immigrants without any paperwork and are therefore able to hide their identity or leave the country after dismissal from prison. This introduces a large noise in the information about their recidivism, and we choose not to contaminate the data on the Italians. We also exclude 8 percent of inmates who are sex offenders, as they are subject to very specific incarceration rules. We focus on inmates who have served a definitive sentence.[21]

We measure recidivism through re-incarceration within three years from the end of the inmate's custodial term (though we also look at shorter time windows).[22] The choice of a three year measure of recidivism forces us to restrict the analysis on inmates released up to 2009.

In the end our sample includes each inmate who spent some time in Bollate between the end of 2000 and 2009, was released (from Bollate or from some other prison) at the latest by 2009 and is Italian, male, non sex-offender: in total we have 2308 people. [23] For each of them we have a complete prison history, with the number and the dates of previous prison spells (if any) and the relative crimes, the dates of the period spent in Bollate, the length of the total time served corresponding to the crime for which they spent time in Bollate, the kind of crime, the date of a possible new incarceration after Bollate (and up to February 2013), whether the release from the last prison was followed by a non-custodial sentence (e.g. home detention, monitored liberty, parole, etc.) or by liberty. We have information on a number of characteristics of the inmates: age, sex, marital status, presence of relatives, education, drug addiction.

We also have some information on the selection process to Bollate, as we can distinguish the prisoners displaced there due to overcrowding of nearby prisons (i.e. not selected), those transferred for

[20]Sample estimate contained in a report by Openmigration.org.

[21]This avoids considering as recidivating an inmate who is released from prison, pending the result of an appeal, and is then re-incarcerated once the final sentence is pronounced (without the occurrence of a new crime). Anyway, 90 percent of inmates receive a definitive conviction before release.

[22]Re-incarceration rates tend to be slightly higher than reconviction rates, though less than one percent of Bollate inmates get released due to an acquittal.

[23]The (Italian, male, non sex-offenders) inmates who were in Bollate in the period between 2000 and 2009 are 11,113; given that most of them have long sentences – as reported in Appendix A, a long enough sentence is one of the requirement in the selection process – requiring that they had been released not later than 2009 considerably narrows down our sample.

"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.

For the inmates displaced to Bollate from nearby overcrowded prisons we also know whether they were incarcerated after receiving a conviction and the date in which they were convicted, whenever the conviction occurred after their incarceration. Transfers are more likely to happen at the beginning of an inmate's incarceration, which skews the distribution of the fraction of time spent in Bollate to the left (see Appendix Figure A2).

The comparison between displaced inmates and selected ones is informative about the typical selection mechanism that takes place in open prisons. Table 2 shows the average recidivism, potential and actual time served in Bollate, and total time served, for groups of inmates identified by different reasons for entry: displaced from nearby prisons due to overcrowding (1,553 inmates), actively selected into Bollate (479, further distinguished according to the different reasons for entry mentioned above), and inmates for which the information on entry reason is missing (281). For each group the table also reports the fraction who ended up in the cell block 5, where inmates working outside the prison are housed.[24]

Differently from selected inmates (see footnote 23), displaced ones are not required to have a sufficiently long sentence, and therefore on average have shorter sentences (more on this later). Moreover, in the first few years since its opening, Bollate had considerable spare capacity and was often on the receiving end of displacements, which implies that many displaced inmates entered early into Bollate. For both these reasons, since we select our sample by requiring that inmates have been released at the latest by 2009, we end up oversampling displaced inmates over selected ones.[25]

Inmates displaced to Bollate serve on average shorter sentences (1.44 years, or 17 months) con-

[24]We observe the cell block in which inmates were at the moment in which they were released from Bollate.

[25]If we were to drop this requirement, the displaced would represent about 60 percent of all Bollate inmates (cumulated over the years). Since their inflow depends on prison overcrowding, the fraction of displaced inmates who entered Bollate drops after the 2006 collective pardon (which corresponds to the peak of overcrowding). The pardon led to the sudden release of about one third of the prison population (see Drago et al., 2009, Barbarino and Mastrobuoni, 2014), and the fraction of displaced inmates entering Bollate drops from 75 percent in 2006 to 60 percent in 2007, 2008 and 2009, 44 percent in 2010, and 24 percent in 2011.

siderably less than selected inmates (3.55 years, or 43 months); their average (potential) residual sentence upon arrival in Bollate is about 10 months (0.85 years) and is about 8 months shorter than that of the selected inmates.

For both groups, the actual sentence length served in Bollate is on average about 80 percent of the potential one (the two measures coincide for about 2/3 of inmates). This happens because inmates might be transferred to other prisons.[26]

Only a handful of displaced inmates finish their incarceration in cell block 5, while for the selected inmates the proportion is on average 15 percent (and can be as high as 25 percent for some subgroups). Consistently with the screening process which the selected inmates went through, their recidivism rate is on average much lower than that of displaced inmates (by 12 pp). Among the selected inmates, those who applied to be transferred and those transferred by the Justice department have the lowest recidivism rates. The group of inmates whose entry reason is unknown is difficult to characterize: they show recidivism rates similar to those of the displaced inmates, total and potential residual sentence length similar to those of selected inmates, actual residual sentence length similar to those of displaced inmates. In the following we will group them together with the selected inmates, so as to keep the sample of displaced inmates as cleanly defined as possible. Other differences between the two groups of inmates are shown in Table 3.

Displaced inmates are on average younger[27] and are less likely to have a stable relationship, are less educated, more likely to be drug addicted; their criminal profile is more skewed towards petty crimes, as is the case with the typical inmate in Italian prisons.[28] All these differences are statistically

[26]Only 3.5 percent of displaced inmates have been transferred to another prison before release. The fraction is considerably larger for the selected inmates (35 percent of them are transferred to other prisons prior to release). This is likely due to the longer stay in Bollate, the more violent background of the selected inmates – induced by the selection based on the length of the residual sentence – and, possibly, the stronger scrutiny selected inmates are subject to compared to displaced ones.

[27]The average age is considerably higher than in the United States, though is roughly in line with the average age of inmates in Italian prisons, which is close to 42 (Ristretti Orizzonti, 2014).

[28]As documented in Appendix A, one of the criteria in the screening process is a sufficiently long sentence, which is obviously correlated with the severity of the crime. The selection is therefore meant to identify, *among serious criminals*, those more likely to respond positively to the rehabilitation interventions.The difference in the criminal profiles of the two groups is consistent with the difference observed for the variable *Art. 4 bis*. The latter identifies the cases where the applicability of prison benefits (day releases, outside work, non-custodial sentences) is restricted. This occurs for a series of serious crimes (e.g. terrorism, organized crime, slavery, sex trade, kidnapping with extortion, etc.). 20 percent of selected inmates are subject to such restrictions, while the fraction goes down to 7 percent for displaced inmates.

highly significant.

1.3 The Identification Strategy

We assume that the recidivism probability of inmate i, R_i, is a (linear) function of the total time to be served (regardless of the type of prison), of the prison conditions, as measured by the times served in the open and in the traditional, closed prisons, of a vector of covariates capturing the characteristics of inmate i and his previous prison history, and of an unobserved error, capturing the idiosyncratic propensity to recidivate of inmate i:

$$R_i = \alpha_0 + \alpha_1 S_i + \alpha_2 S_i^O + \alpha_3 S_i^C + \gamma' X_i + \varepsilon_i, \tag{1}$$

where S_i is the total years served, $S_i^O > 0$ and S_i^C are the parts of the total years served in the open prison and in a traditional, closed prison, respectively, X_i is a vector of covariates and ε_i is the unobservable propensity to recidivate. Given that S_i^O is always positive, we only exploit variation at the intensive level. All inmates are "treated" with an open prison, but with different "doses."

We allow for a direct role of total time in prison because the time away from the family and the social network, the chance to mature and grow older, while having no opportunity to commit crime, are all factors that might affect the inmate's future behavior. Our main interest is on the effect of prison conditions, and in particular of the residual sentence spent in the open prison S_i^O as opposed to the one spent in a traditional closed prison S_i^C; in theory, besides the length of time spent in each of the two prison regime, also the sequence in which the two regimes are experienced might matter. In our sample, however, it never happens that the time spent in Bollate precedes the time spent in the closed prisons, so we will not consider this possibility.

Since $S_i = S_i^O + S_i^C$, we cannot estimate separately α_1, α_2 and α_3. We therefore rewrite the model as

$$R_i = \beta_0 + \beta_1 S_i^O + \beta_2 S_i + \gamma' X_i + \varepsilon_i, \tag{2}$$

where $\beta_1 = \alpha_2 - \alpha_3$ and $\beta_2 = \alpha_1 + \alpha_3$. The equation makes clear that our coefficient of interest, β_1, reflects the difference between the effect on recidivism of the time served in the open and in the closed prison. Equivalently, β_1 captures the effect on recidivism of increasing in equation (1) S_i^O by one year and simultaneously reducing S_i^C by one year, leaving S_i unchanged.

Disregarding for now that inmates may be transferred away from Bollate before the end of the sentence for reasons that might be correlated with recidivism, the estimated coefficient β_1 would have a causal interpretation under an assumption of conditional independence:[29]

$$S_i^O \perp \varepsilon_i | S_i, X_i. \tag{CIA}$$

We will argue that, given the institutional features governing the displacement of inmates from overcrowded prisons, with an appropriate choice of the vector of covariates X_i, condition (CIA) is likely to hold in the sample of displaced inmates.[30]

Recall that all the inmates in overcrowded prisons become potentially displaceable as soon as they receive a conviction.[31] At that moment they enter a (prison-specific) list, chronologically ordered. Whenever an overcrowded prison is granted by the Regional Prison Administration the permission to displace to Bollate (say) n inmates, it will simply pick the first n in the list, following a first-in-first-out rule (with possible exceptions due to the composition of the displacement opportunities, better explained below).

For a given sentence length, S_i, the amount of time inmate i will spend in Bollate, S_i^O, is larger the sooner he gets displaced there. In turn, other things equal, the latter occurs:

a) the sooner inmate i in prison j receives his first conviction;

b) the fewer inmates there are at that moment ahead of him on the list of displaceable inmates formed at prison j;

c) the larger (in number and/or in size) the opportunities to displace inmates towards Bollate

[29] In a linear model the weaker conditional uncorrelatedness suffices.

[30] If the link between ε_i and the conditioning variables were non linear, condition (CIA) might not be enough. In a robustness check we will control for the conditioning variables in a flexible way (through a rich set of fixed effects).

[31] As mentioned, in Italy inmates might be incarcerated before receiving a conviction.

granted to prison j by the (Lombardy) RPA from the moment in which inmate i entered the list.

Condition (b) is plausibly uncorrelated with inmate i's propensity to recidivate.[32]

The same holds for condition (c). However, inmates of different age groups, and inmates addicted to alcohol or drugs, sleep at Bollate in different, dedicated cell blocks (inmates who sleep in different cell blocks will nevertheless meet while performing different activities). Prison j might thus not always be able to pick the first n in its chronological list. For example, when Bollate's spare capacity in the cell block dedicated to, say, young inmates (less than 30 years old) is smaller than the number of young inmates among the first n in the list of the displaceable inmates, some of those with the lower ranking in the list would be skipped and replaced by inmates with rank lower than n but not young.

Since we do not observe the detailed breakdown of the available places in Bollate into different cell blocks, we might detect some deviations from the first-in-first-out rule, correlated with inmate's age or addiction. These exceptions are relatively rare and can be seen in Figure 1, which compares, for the inmates eventually displaced to Bollate, the predicted order of displacement from a given prison of origin based on the date of conviction with the actual order of arrival; the correlation between the two orderings is close to 1.[33] Since we observe the age of displaced inmates and whether they are addicted to alcohol or drugs, we can include these variables in the vector of covariates X_i and therefore condition the correlation between recidivism and treatment intensity on such observables.[34]

The third factor determining the timing of an inmate's transfer to Bollate is the speed with which, after the incarceration, his conviction was meted out (condition (a)). This speed might be correlated with his propensity to recidivate. However, since we observe for each displaced inmate the date of conviction, we can compute the delay between incarceration and first sentence and simply condition

[32] A potential challenge to this claim would arise if the length of the queue were strongly linked to overcrowding, and overcrowding influenced criminal tendencies. We will show that our result remain unchanged when we control for overcrowding in the prison of origin.

[33] We will see that the results are robust to conditioning on the occasional differences between the predicted and the actual ordering of displacement.

[34] There is some flexibility in the definition of young, so we simply include age fixed effects. We use age at exit fixed effects, though very similar results are obtained when including age at entry or age at transfer fixed effects. We cannot include two of these measures, as together they would be collinear with the time spent in Bollate or time spent in the prison of origin.

on it. Table 3 shows that the time from incarceration to the first sentence is fairly short (slightly longer than one month on average).[35]

Controlling for such delay, total time served, age and addiction, the only sources of variability of the residual sentence to be spent in Bollate would then be differences in the number and dimension of displacement opportunities towards Bollate granted by the RPA to the prison of origin at different moments and differences in the backlog of displaceable inmates at the time of inclusion in the list.

To put it differently, we identify the effect of time spent in the open prison on recidivism by comparing two hypothetical inmates who were serving the same sentence length in the same (closed) prison, had the same age and drug addiction, received their definitive sentence after being imprisoned with the same delay (possibly nil), but at different points in time. At one of those times (say the first), the prison had a bigger backlog of inmates waiting to be displaced, or was authorized by the RPA to displace a smaller number of inmates, or both. As a result, the inmate present in the prison on the first of the two times had to wait longer before being displaced to the open prison, and therefore had a shorter residual sentence to be spent there.

In Appendix A we show that potential time spent in Bollate is likely to be as good as random. Specifically: i) conditional on total time served, the other controls cannot predict potential time served; ii) potential time served does not predict a pre-determined index of recidivism that is based on the same controls (i.e. age, previous time served, etc.).

We still need to consider the potential for endogeneity of the actual residual sentence. Indeed, for about 2/3 of the displaced inmates the actual residual sentence upon arrival at Bollate also represents the potential 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 if the treatment appears to be of little use. Clearly, these possibilities are the result of the inmate's behaviour, so the actual time spent in Bollate suffers from endogeneity.

To tackle this endogeneity we will use potential residual sentence upon arrival at Bollate as either our main variable of interest, in which case we will estimate an intention to treat effect, or as an instrumental variable for the actual time spent in Bollate. As usual the intention to treat may be more

[35]For about half of the displaced inmates such time is zero, as they are incarcerated at the time of their first sentence.

policy relevant, as compliance cannot be relied upon, but overstates the measure of the administered treatment due to non-compliance.

2 Results

2.1 Non-parametric Evidence

The information on the exact time of re-incarceration allows us to construct non-parametric Kaplan-Meier cumulative failure (recidivism) functions to compare displaced inmates who spent different fractions of their sentence in Bollate. As in the rest of the analysis inmates are followed for three years after the end of their prison time.

Figure 2 plots failure functions for two groups of inmates, depending on whether they served in Bollate less than 1/3 or more than 2/3 of their total time served, having excluded from the sample inmates with a fraction of time served in Bollate between 1/3 and 2/3 (to compute these ratios we always use the potential time spent in Bollate, to avoid any endogenous interruption of the treatment). It is important to control for the total time served, since Bollate opened at the end of 2000 and, by construction, longer sentences will be negatively correlated with the fraction of time spent in Bollate. For this reason we produce separate plots, for inmates with total time served above and below 1.5 years (a figure which is close to the median and the mean). [36]

In both cases, the differences in recidivism up to a year after release are negligible. This likely captures inmates whose unobserved "propensity to recidivate" is strong enough to be unaffected by treatment efforts and quick to materialize. It also suggests that liquidity constraints at the time of release are not driving the effects (Munyo and Rossi, 2015).

The inmates who do not recidivate for at least a year seem to be more responsive to the Bollate

[36]The 1.5 years cutoff is a coarse control for total time spent in prison and might leave some residual imbalance in the covariates. We use the predicted recidivism computed in Appendix A to assess whether this is the case. Regressing predicted recidivism on a dummy equal 1 when the potential time spent in Bollate is less than 1/3 of total time, and controlling for total time served being above or below 1.5 years, we find a *negative* coefficient (-2.3 pp, s.e. 1.2 pp). Hence, inmates who (potentially) spend a lower fraction of their sentence in Bollate tend to have pre-treatment characteristics predicting a lower recidivism. In turn this means that the coarse control used in the figure leaves some correlation between the treatment intensity and the pre-treatment covariates that, if anything, implies that the figure underestimate the reduction in (actual) recidivism due to the treatment.

treatment. After the first year, the cumulative differences in recidivism start growing, reaching about 10 pp at the end of the recidivism window. The differences between the failure functions are more striking when the total time served is above 1.5 years, meaning that the more treated inmates spend at least 9 months in Bollate. In relative terms these are large differences. Next we use regression models to better control for total time served, for additional regressors, as well as to assess the statistical significance of these differences.

2.2 Main Results

We estimate the intention to treat effect by ordinary least squares with a linear probability model (later we will show that Probit models as well as hazard models lead to similar results). The unobserved errors are allowed to be correlated among inmates who were released during the same week and spent their final prison time in Bollate in the same cell block (there are 5 cell blocks). This is to address concerns highlighted by Bayer et al. (2009) and Drago and Galbiati (2012), who find evidence of peer effects among inmates who have spent prison time together and who have been released at the same time. Alternatively, in the Appendix Table A5, we use a spatial lag error model that allows errors to be correlated among inmates whose detention in one of the cell blocks has overlapped, even if their release has happened at different times. Finally, one could argue that Bollate inmates form relationships when they arrive, no matter the cellblock. This would also be a clustering that mimics the variation of our instrument. All methods to compute the standard errors deliver similar results, and in the rest of the analysis we use the first one.

When estimating the (local) average treatment effect, we run instead two-stage least squares regressions (2SLS), using the potential time served in Bollate as an instrument for the actual time served. 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 the inmates are transferred to other prisons before the end of their prison spell. These are clearly endogenous outcomes. While the exogenous variability of potential time served in Bollate makes it a good instrument, a caveat is in order in interpreting the results of the 2SLS regressions, since the local average treatment effects are driven by the compliers, and these might be those who respond more strongly to the improved prison conditions.

The top panel in Table 4 shows the reduced form (intention to treat) regressions, the panel in the middle shows the 2SLS results, and the bottom panel shows the first stage. All measures of time served are in years (days divided by 365).

Consider first the intention to treat regressions (the top panel). In the first column, to provide a benchmark, we estimate the effect of the treatment in the simplest possible specification, without any controls, while in Column 2 we add total time served. Without controls one extra (potential) year in the open prison reduces recidivism by 5.4 pp (with a significance level of less than 1 percent). When we control for total time served the reduction of recidivism caused by one extra year spent in the open prison (and therefore, given the total time served, one less year spent in an ordinary closed prison) increases to 7.3 pp. The smaller effect in Column 1 is due to total time served in prison being positively correlated with both recidivism and time spent in Bollate.

Following the argument presented in Section 1.3, in Column 3 we include also the time from incarceration to first sentence,[37] drug addiction and age at exit fixed effects as controls.[38] The estimated intention to treat effect is slightly reduced, to 6.3pp, still highly significant. This confirms that the variability associated with the delay in receiving the conviction and with the capacity constraints in Bollate is unlikely to selectively affect recidivism. In Column 4, we further add the other covariates listed in the central panel of Table 3 (capturing demographics and the criminal history), prison of origin and year by month of transfer to Bollate fixed effects, exploiting both the variability within prisons and within month of transfer. Adding prison of origin times year by month of transfer fixed effects is implicitly controlling for overcrowding in the prison of origin at the time of transfer.

The estimated intention to treat effect is unchanged and still highly significant. Finally, in Column 5, we also add the interaction between the year by month of transfer to Bollate fixed effects with the prison of origin fixed effect, to use only the variability among inmates who were displaced at the same

[37] Adding the time to the first sentence we lose 15 observations, for which this information, which had to be hand collected from the judicial files, could not be found.

[38] Results are unchanged had we controlled for age at transfer or age at entry fixed effects (see Section 2.3).

time from the same prison. The estimated intention to treat effect is again unchanged.[39] It is worth noting that in all specifications the time from incarceration to the first sentence, meaning the delay in receiving the sentence, does not predict recidivism.

Moving now to the 2SLS results (second panel), the average treatment effects are about 4 pp larger than the corresponding intention to treat effects. 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 is always close to 60 percent, with a t-statistic of about 15, and an F-statistic of about 200.

Taking Column 4 as our preferred specification, an extra year spent in Bollate, as opposed to any of the prisons of origin, reduces recidivism by 10.5 pp, i.e. by about 27 percent of the average recidivism rate (39.6 percent). The signs of the other covariates (shown in the Appendix Table A6) are in line with expectations. In particular, a previous history of recidivism, proxied by the number of *previous* incarcerations (i.e. excluding incarcerations that depend on future recidivism), is highly predictive of future recidivism.

Interestingly, the total time served increases recidivism, even though the effect is not statistically significant. Different forces would drive this coefficient to be positive, for example, building criminal capital (Chen and Shapiro, 2007), or unobserved criminal attitude that is observed to the judge, while specific deterrence would lead to a negative coefficient (see Nagin et al. (2009) for a review of the literature on specific deterrence). Our result show, however, that any inference on the effect of time served on recidivism must take into account the way in which the prison time is spent.

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 virtually unaffected by the inclusions of these controls. This, together with the rise in the R-squared, suggests that controlling for unobserved selection would be unlikely to have a large effect on the results (see Altonji et al., 2005, Oster, 2013).

The Appendix Table A8 presents the result of a similar analysis conducted on the inmates ex-

[39] In columns 4 and 5 the observations for which the fixed effects perfectly predict the outcome are dropped, in order to get correct standard errors.

plicitly selected to Bollate (see Appendix A).[40] We find that also for the selected inmates more time in Bollate reduces recidivism, with similarly sized coefficients. While this may seem at odds with a selection mechanism aimed at choosing the most promising inmates, if the most promising inmates are those with the lowest expected recidivism – and not those with the largest expected *reduction* in recidivism – the selection may, somewhat paradoxically, reduce the potential *gains* from spending time in Bollate. Moreover, one of the criteria for the selection is the residual sentence length, which should be sufficiently long to allow a meaningful treatment. This implies that, among the selected inmates, violent criminals are, on average, over-represented. These, as we will show, are less likely to respond to the treatment, providing another reason why the effect we find for the selected sample is not larger than the one for the displaced.

2.3 Robustness Checks

In Table 5 we run several robustness checks. All regressions control for the set of variables included in our preferred specification (Column 4 of Table 4), including prison of origin and year times month of displacement fixed effects. For the sake of space we only report the intention to treat effects (those estimated through 2SLS are larger across the board, but paint a very similar picture).

Since we are controlling for the time of displacement, we cannot also control for the time of exit, since jointly the two variables are collinear with the potential time spent in Bollate. Instead, we control for the labor market conditions that inmates face at the time of release. In Column 1 we add quarterly unemployment rate in Northern Italy and the quarterly youth unemployment rate in the country.[41] The estimated intention to treat effects is almost unchanged (-6.6 pp against -6.4 pp).

In column 2, rather then controlling for age at exit fixed effects, which are more likely to be the relevant age measure but may depend on the inmates behavior while in prison, we control for age at entry fixed effects. The intention to treat effect are little changed (-6.8 pp).

Another control that may depend on the inmate's behavior while in prison is the time served in

[40] In this case we are less confident that we identify the causal effect of the treatment: if the most promising inmates are more quickly transferred to Bollate, our estimate would overstate the causal effect

[41] The quarterly data on unemployment can be downloaded from the Italian Statistical Office data archive (ISTAT, 1961-1995).

prison. Inmates may be granted some early release, through automatic sentence reductions, collective pardons, home detention, monitored liberty or other forms of non-custodial sentence.[42] Rather than simply excluding time served from the regression, as we did in Column 1 of Table 4, in Column 3 of Table 5 we control for total initial sentence (we obtained this variable from the Bollate prison). The correlation between total sentence and time served is 93 percent, but total sentence is less correlated with potential time served in Bollate when compared to total time served (67 percent against 72 percent). When substituting time served with total sentence the intention to treat effect is slightly reduced (-5 pp), and is still significant at the one percent level.[43] If instead we control for total sentence as well as total time served, the effect is almost the same as in our preferred specification (-6.6 pp). And, interestingly, conditional on time served, total sentence is negative (possibly due to deterrence effects), while time served is positive and becomes significant, indicating a criminogenic effect of prison time in the prisons of origin. But given the lack of exogenous variation we need to stress that these results have to be taken with a grain of salt.

In columns 5, 6 and 7 we change the sample composition. In column 5 we add inmates with unknown entry reasons to the displaced, which reduces the absolute value of the coefficient by about 1 pp. In Column 6 we exclude the few inmates who have one definitive conviction but also an ongoing trial at the time of release (for which they might have to face some time in prison). The (absolute value of the) estimated intention to treat effect is again slightly smaller (-5.6 pp). The baseline results are roughly unchanged when we restrict to inmates who were transferred up until 2008, since starting from 2009 Bollate was allowed to provide some feedback about inmates who were supposed to be displaced there (Column 7). The results are also robust to using different functional forms. In Columns 8 we use a probit model instead of the linear probability one. This increases the (absolute value of the) marginal effects, from 6.3 to about 9 pp.[44] In the Appendix Table A9 we also show that a semi-parametric hazard model delivers similar results.

[42]The conditions for an early release via a non-custodial sentence (parole requirements) are not dependent on the type of prison where the inmate was serving his sentence.

[43]The IV treatment effect, not shown in the table, is -8.3 pp (s.e. 3.2 pp). If, instead, we instrument time served with total sentence the treatment effect is -9.2 pp (s.e. 4.1 pp).

[44]Adding a cubic term in potential years treated leads to similar marginal effects. The coefficients on the squared and cubic term for potential years treated 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.

In Column 1 of Appendix Table A4 we control for the occasional differences between the predicted and the actual order of transfer shown earlier in Figure 1. The coefficient on time served in the open prison is basically unchanged and the coefficient on the difference between the two orderings is not statistically different from 0. This confirms that the difference, that is driven by the availability of prison beds in different prison sections, is as good as random.[45] In the following columns we address another potential identification issue. We control for total time served and delay in receiving the sentence in a flexible way, by including fixed effects corresponding to the length in quarters or months of the conditioning variables, to take care of the possibility that the relation between them and the unobserved propensity to recidivate be non-linear. The regressions presented in Columns 2 and 3 only exploit the variability among inmates whose total time served has the same number of quarters or months (respectively); the regression in Column 4 further controls in a flexible way for the time from incarceration to first sentence. Adding these more flexible controls, if anything, strengthens the results.

3 The Mechanism

Our results show that spending more time in an open prison, and correspondingly less time in a traditional, closed one, 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 mechanisms.

[45] Mukherjee (forthcoming) has a similar identification strategy to instrument whether inmates are assigned to private prisons, the availability of prison beds.

3.1 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 explore whether the effects across different groups of inmates are heterogeneous by simply interacting the time spent in Bollate (actual or potential) as well as the total time served with various observable characteristics. These are all coded as dummies: whether the inmate has committed a violent crime, whether his prison of origin overcrowding rate (the ratio between inmates and prison capacity) was above the median (above 147 percent), whether it is the first incarceration, whether the inmate is in a relationship, whether he has a drug addiction, whether his educational attainment is above secondary education, whether his age is below median.[46] We also include the interaction with the measure of recidivism risk (predicted on the basis of observables) used in Appendix Table A3, and in particular we consider whether such a measure is in the top quartile.

As before, the top panel of Table 6 measures intention to treat effects while the bottom one measures local average treatment effects. In the description we focus on the 2SLS results.

Column 2 shows that for inmates with observables corresponding to a predicted recidivism risk in the top quartile of the distribution the effect of the treatment is reduced to about 2 pp.[47] This result would be consistent with the non-parametric evidence presented in Section 2.1 if these high risk offenders were also the ones recidivating soon after release. This is indeed the case. Recidivism risk is strongly negatively correlated (-33% (t-stat=10.1)) with the time it takes recidivating inmates to be back in prison.

Similarly, criminals who have committed violent crimes show a small reduction in recidivism (the effect of the treatment is -3 pp; Column 3). A stark difference between violent and non-violent crimes can also be found when looking at the kind of future crimes recidivating inmates commit. The vast majority (68 percent) of recidivating inmates do not change their attitude towards the use of violence. Appendix Table A10 Column 1 replicates the last Column of Table 4, while in Column 2 and 3

[46]To measure overcrowding we collected data on prison capacity and prison population on the universe of Italian prison (these data are available on the Ministry of Justice web site (Dipartimento di Amministrazione Penitenziaria, 2020)) starting from the year 2003, so we loose two years of data).

[47]For inmates with observables corresponding to a level of predicted recidivism risk in the top 50 percent the effect is roughly half that for inmates in the bottom 50 percent.

recidivism takes value one only if a violent or a non-violent crime is committed when recidivating, respectively. The effect of the treatment on recidivism of future violent criminals is small, and is not statistically different from zero. Column 3 confirms that a reduction in non-violent crimes is driving the results. This in line with the findings in Bhuller et al. (2020), where non-violent crimes are driving the decrease in the number of crimes of Norwegian inmates, whose prisons are often "open."

The other significant heterogeneity is by educational attainment (Column 7 of Table 6). The benefit for inmates with education above secondary level (6.6 percent have a college degree and 52 percent have a secondary level degree) is considerably smaller than for inmates with lower levels of education. This points to a 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.

All other interaction terms are not statistically different from zero. Interestingly, this include overcrowding, which seems to rule out that the reduction in recidivism is significantly driven by the avoidance of time spent in overcrowded prisons.[48]

Though imprecisely estimated, two other dimension of heterogeneity are worth noting. The almost 1/3 of inmates with a drug addiction seems to have their recidivism reduced by a large amount from spending time in Bollate (Column 1). Large reductions are also observed for inmates at their first incarceration, compared to inmates with previous incarceration spells. This suggests that rehabilitation efforts are most successful when applied earlier in the criminal career.

3.2 Direct and Indirect Evidence on the Mechanism

In Section 1.1 we highlighted that spending prison time in the open prison as opposed to any other closed prison in Lombardy can be very different.

Compared to the "panopticon-style" of prison life that is the norm in most prisons in the world, the conditions in the open prison are indeed a momentous change, and it is reasonable to conjecture not only that they can influence the inmates' recidivism, but also that such influence is increasing in

[48]For the 12 percent of inmates coming from prisons without overcrowding, the treatment effects are indeed slightly smaller (in absolute terms), but the difference is not significant. We get similar results when we use overcrowding rates to measure heterogenous effects.

the duration of their stay in the open prison, as it takes time for them to take hold in the psychology of inmates used to being treated harshly and to being denied self-determination. The increasing effectiveness of these conditions, however, cannot be empirically tested, since they start to apply to all Bollate inmates as soon as they are transferred there, and we have no measures of their increasing intensity.

There is however one important aspect of the treatment that is unevenly assigned and whose time variability is measurable: work outside of the open prison. Inmates who work outside of Bollate are transferred to cell block 5, and Bollate keeps track of the day releases, most of which are related to work. Using this margin of variation we can provide direct, albeit only suggestive evidence of one aspect of the mechanism underlying our result. Since day-releases are only allowed when inmates have demonstrated good behavior, it allows us to measure whether time in Bollate influences such behavior.

While we observe information on the day-releases for all inmates, transfers across sections are only observed for a subset of years. In Table 7, Columns 1 to 4, we regress a variable that equals one if the inmates has been transferred to Section 5 at least once (26.9 percent of selected inmates and 7.9 percent of displaced ones have spent some time in Section 5) on potential time served in the open prison, as well as the usual controls. Each additional potential year increases the likelihood by, respectively, 13.49 and 3.95 pp, which in relative terms is close to 50 percent. In Columns 5 to 8 as outcome we use the fraction of days spent in day releases. Each additional potential year in Bollate increases the fraction by 0.687 pp (48 percent of the average)[49] for the selected inmates, and by 0.137 pp (56 percent of the average) for the displaced ones.[50] Hence, good behavior and the probability to work outside, while being in the open prison, increases with the length of their stay (the intensity of the treatment). While this does not establish a causal link between working opportunities outside the prison and our rehabilitation result, it is consistent with the conjecture that the former is one of the mechanisms underlying the latter.

The differential intensity with which additional time spent in the open prison translates into the

[49]During their entire stay, selected inmates spend on average 1.44 percent of their days outside of prison; displaced inmates only 0.24 percent.

[50]Since we do not require 3 years to compute recidivism, the sample size is slightly larger.

probability to work outside for displaced and selected inmates also offers indirect, supporting evidence for the role of other aspects of the open prison. Appendix A argues that the treatment effect for selected inmates has a similar size as that for displaced inmates. Since at the same time the latter are less likely to be exposed to outside work, even as their stay in Bollate lengthens, their strong response to the treatment suggests that other aspect characterizing prison life in the open prison – the possibility to make decisions, being treated as adults, and the stress on self-responsibility – are also important and increase in importance as time goes by.

3.3 Negative Role Models

With the exception of the displaced, all inmates transferred to Bollate go through a screening process, described in Appendix A, aimed at identifying those more likely to react positively to the rehabilitation efforts. By selecting these "better" inmates Bollate might in fact simply minimize the presence of negative role models. Since more time spent in Bollate is equivalent to spending more time with positively selected inmates, and less time in other prisons with inmates who are more likely to exert negative role models, and if on average inmates interact with other inmates in proportion to the time spent together, this could explain our results.

We test whether this is a relevant mechanism underlying our results by using the prevalence of displaced inmates among each inmate's fellow prisoners. Differently from selected inmates, displaced ones do not go through the screening process. Therefore, if our results were driven by the composition of one's fellow prisoners, we would expect that a higher prevalence of displaced peers would weaken the effect of the treatment.[51] It is important to highlight that our goal is to test a mechanism based on the composition of the environment, we do not aim at measuring or identifying potential peer effects.[52] While peer effects result from actual interactions, the mechanism we have in mind only relies on imitative behavior, irrespective of actual interaction. More specifically, the dimension of heterogeneity at which we look concerns the number of (displaced) fellow prisoners each inmate

[51] We consider displaced inmates as "worse" peers precisely because they did not go through the screening process, which aims at identifying inmates more receptive of rehabilitation treatments.

[52] See Chen and Shapiro (2007), Bayer et al. (2009) and Stevenson (2017) for evidence on peer effects in prison and a full-fledged peer effect analysis.

can potentially interact with, and this is not necessarily proportional to the number of peers each inmate interacts with, as peers may match based on several dimensions, for example age, education, birthplace, criminal experience, etc.

We measure the prevalence of negative role model among one's fellow prisoners by computing for each inmate the ratio between the total number of displaced present during his prison time and the total number of all his fellow prisoners,[53] both weighted by the days of overlap, in Bollate (first measure); in the final cell block (second measure); in the final cell (third measure). While the last two measures might be endogenous (Bollate might redistribute displaced inmates to reduce negative role models), they are arguably more precise.

In Table 8 we control for the prevalence of displaced inmates (the variable is measured in deviation from its mean, which is 35 percent when fellow prisoners are computed at the cell level), both on its own and interacted with potential time treated in Bollate (we measure also this variable in deviation from its mean). If the observed reduction in recidivism were the result of a reduced presence of negative role models, we would expect the effect of the potential time served in Bollate to be closer to zero when inmates face a larger fraction of displaced fellow prisoners, i.e. we would expect the coefficient on the interaction term to be positive. This is in fact the case (the coefficient on the interaction is 0.043, for the displaced fellow prisoners computed at the cell level), but the effect is not significantly different from zero, while the main effect of potential time served in the open prison is almost unchanged and still significant.[54]

Disregarding the lack of statistical significance of the coefficient on the interaction term and assuming that our linear specification continues to hold for values very different from those in the sample, we can compute how much of the reduction in recidivism would be lost if Bollate were to avoid any selection at entry. In this case Bollate would still have a composition of inmates that in-

[53]Departing from the sample selection adopted in other analyses, we include all inmates when computing this measure, including foreigners and those who are not released before 2009.

[54]Given that the relevant variables are demeaned, the level effect of the prevalence of displaced inmates (evaluated at the average potential time treated in Bollate) can be read directly from the coefficient on displaced inmates, and is negative (though it is only marginally significant, and only when computed at the cell level), i.e. it reduces recidivism of displaced inmates. We interpret this result as follows. Given that selected inmates absorb the larger fraction of the resources devoted to rehabilitation, when their share is smaller (i.e. when the fraction of displaced is larger), more rehabilitation efforts can be devoted to displaced inmates, generating positive investment externalities in rehabilitation.

cludes both types, the "better" ones – now identified through the selection at entry – and the others – now represented by the displaced – but in different proportions. Under the conservative assumption that all the "better" inmates in the region are currently absorbed by Bollate, we can estimate that in a random, non-selected sample of inmates in the region there would be about 24 percent of "better" inmates.[55] Therefore, in the hypothetical case of no selection, the share of "worse" inmates, approximated by the displaced, would go to 76 percent (thus increasing the demeaned fraction by 41 pp); this would dampen the effect on recidivism, as the total effect would be (for the case of displaced in the same final cell) $-0.036(= -0.054 + 0.41 \times 0.043)$. However, considering the lack of statistical significance of the estimated coefficient and the extrapolation way out of sample, this calculation should be taken with a grain of salt. It suggests that scaling up the Bollate experience through a less exacting selection process might weaken its rehabilitation capacity, but the evidence that this would happen is far from conclusive and, given the potentially large gains in curbing recidivism, the issue should be further investigated, possibly with experimental methods, before reaching conclusions for prison policies.

4 Conclusions

The questions of whether and how different prison conditions affect recidivism are very important ones in designing a prison system, along with questions about the relative costs of providing different prison conditions and about their effects on general deterrence. This paper offers a clear and robust affirmative answer to the "whether," some tentative answers to the "how," and briefly touches on the cost issue. It remains silent on the question of general deterrence, as the latter concerns the ex-ante impact of the threat of punishment on the public at large, while we only deal with inmates who have already experienced some form of punishment.

On the "whether" question, we showed that prison conditions offered in an open prison, with meaningful training and occupational activities, aimed at improving inmates' reintegration into society, are effective in curtailing recidivism. Admittedly, Bollate is starkly different from the average

[55] The estimate considers only inmates who would go to a *Casa di Reclusione*.

Italian prison, which might contribute to the positive rehabilitation effects that we find. At the same time, we find evidence that rehabilitation has limited effects on violent criminals and on inmates with the highest risk of recidivating, meaning that some targeting might be beneficial. Since these inmates are the first ones recidivating, there is also little evidence of treatment effects when the period of analysis is shorter than a year. For this reason it is important to measure recidivism over a sufficiently long period of time.

More data, particularly on the post release earnings and opportunities, would be needed to fully understand the mechanisms underlying our results, i.e. to answer the "how" question. We find evidence that one such mechanism involves offering inmates, while in prison, opportunities to work outside, thus making their entry into the labour market when released easier. 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 prison administrators.

We also find evidence that, even for inmates who are scarcely involved in outside work, prison conditions emphasizing responsibility and respect of basic human rights are effective in reducing recidivism. Policies to that effect seem easier to implement, and are almost surely cost effective.

Indeed, we showed that the running costs of an open prison need not be larger, and are in fact considerably smaller, than those of a traditional closed prison, thanks to the fewer guards needed, in turn a positive pay-off of the emphasis on inmates' self-responsibility and of prison conditions that do not trigger antagonistic behavior, or of the disciplinary effect of the threat to be sent back to a harsh, closed prison. These two reasons would play out differently if open prison conditions were to become more widespread – with the former being largely unaffected and the latter being muted – and any policy move in that direction would need to monitor carefully the effects on costs.

Finally, we do not find robust evidence that the composition of fellow prisoners drive of our results. This should appease another possible concern about scaling up the experience of Bollate (by weakening somewhat the selection criteria), since worsening the ex-ante average quality of the selected inmates seems not to undermine the positive effects on recidivism. However, we do not know to what extent the post release behavioral changes caused by serving the sentence in an open prison need, as initial trigger, the positive shock experienced by moving to a nicer prison from an harsher one, or whether learning to behave well may require an initial period of “forced attention,” in turn sustained by the threat of being kicked out of the former and sent back to the latter. If these were the case, expanding the number of open prisons might mute the positive shock or weaken the threat, and thereby dilute the learning process. This may explain why Scandinavian prison systems tend to operate open and close prisons in parallel, with inmates spending the last part of their sentence in the open one (keeping the threat of transfer alive).

Yet another concern on the scalability of the open prison conditions lies in the possible weakening of specific deterrence: offenders who substitute time served in a harsh closed prison with time served in a nicer, open one might conclude that the criminal justice system’s bark is worse than its bite. However, preventing a new access to an open prison to a recidivating inmate, as it is the case at Bollate, should mitigate the negative effect on specific deterrence. More generally, the impact of expanding the number of open prisons on general deterrence has to be carefully considered, to make sure that the reduction in recidivism were not offset by an increase in the number of first time offenders, due to a lower expected cost of punishment. More work and possibly experimentation are needed to assess these possible general equilibrium effects.

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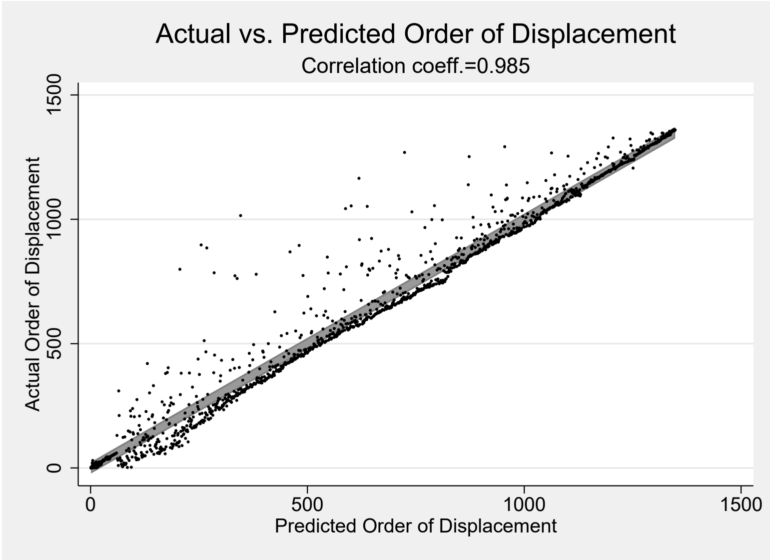

Figure 1: Actual vs. Predicted Order of Displacement

Notes: The figure plots the association between the predicted and the actual order of displacement. The former is the chronological order in which all inmates eventually displaced to Bollate received their first conviction, the latter is the actual chronological order of displacement.

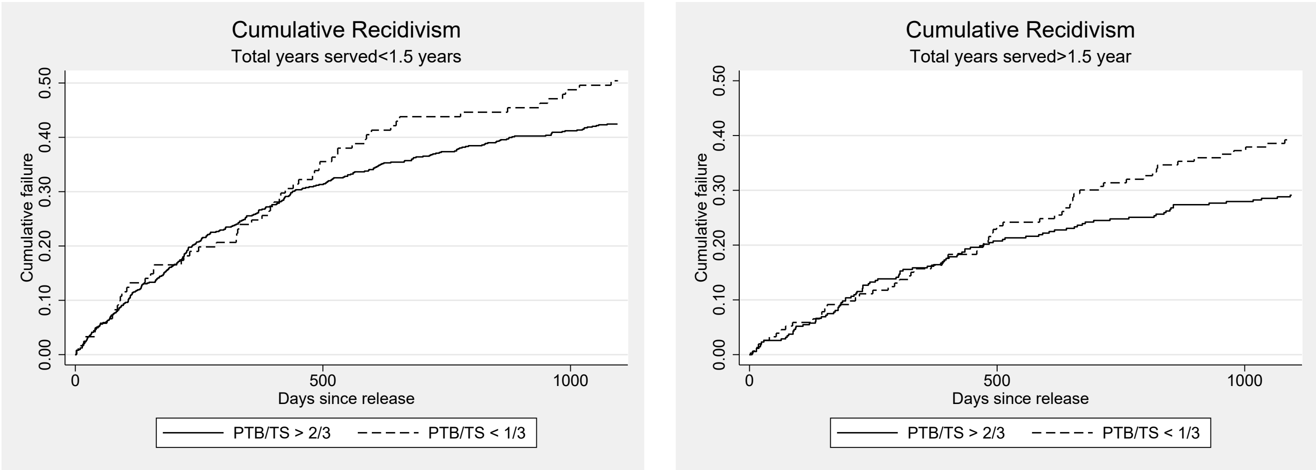

Figure 2: Kaplan-Meier Cumulative Failure (Recidivism) Functions

Notes: The figure plots, for each days since their release, the fraction of inmates who recidivated by that day. The solid and dashed lines refer, respectively, to those inmates for whom the ratio of the potential years treated in Bollate (PTB) and the total time served (TS) exceeds 2/3 or fall short of 1/3. The left and the right panels refer, respectively, to inmates whose total time served is shorter or longer than 1.5 years. Failure (recidivism) is truncated at 3 years, or 1095 days.

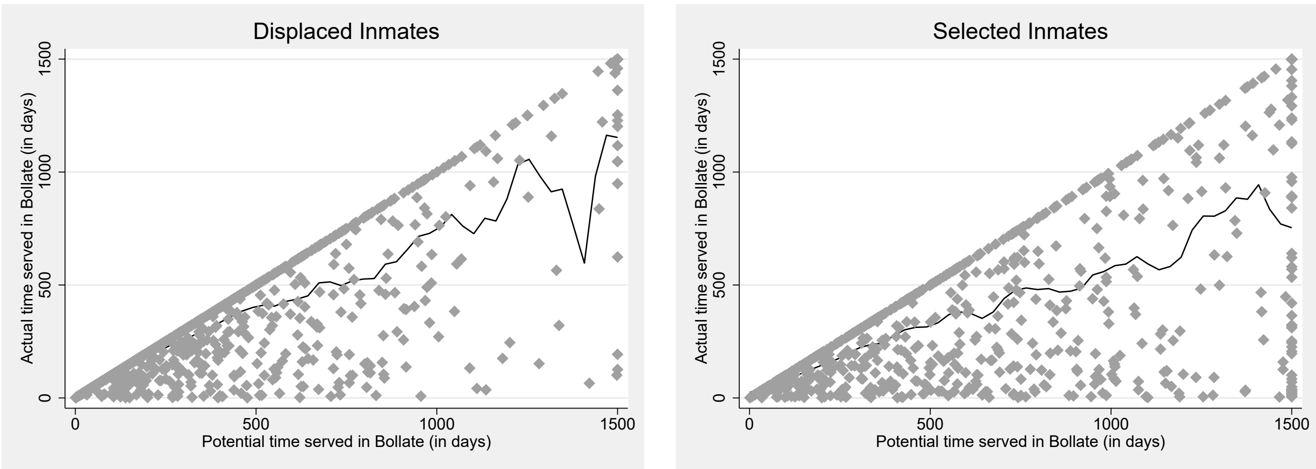

Figure 3: First Stage Relationship

Notes: The figure plots the association between potential and actual time served in Bollate (truncated at 1500 days). The latter can be shorter than the former whenever inmates transferred to Bollate are later transferred again to another prison. The left and right panels refer, respectively, to displaced and selected inmates. The solid line in each panel is a local linear regression. For about 2/3 of inmates the two durations coincide.

Table 1: Prison conditions in different prisons (2009)

Admission prison (year built)	Hours	Capacity	Overcrowding rate	Suicides	Self-inflicted Injuries	Hunger strikes	Prison Work	Independent Work
Milano San Vittore (1879)	8-21 vs. 4h	1127	42%	1.3%	9.6%	7.3%	17.5%	0.5%
Milano (1980)	9-11,18-19	973	28%	0.2%	0.8%	7.4%	28.3%	6.5%
Monza (1992)	9-11,13-15	741	5%	0.5%	5.9%	3.0%	22.7%	6.6%
Busto Arsizio (1982)	9-11, 13-15	297	43%	0.0%	3.3%	5.4%	23.3%	0.0%
Como (1980)	9-11, 13-15, 16.30-18	606	-10%	0.7%	3.1%	3.8%	14.5%	1.8%
Bergamo (1978)	9-11, 13-15	511	-3%	2.0%	13.9%	5.4%	12.7%	4.0%
Varese (1886)	8.45-11.30, 13.30-15.45	99	36%	0.7%	4.4%	6.7%	12.6%	5.9%
Milano Bollate (2000)	9-19, 8-20	1311	-21%	0.0%	0.7%	2.3%	22.6%	27.2%

Notes: Suicides (including 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. Overcrowding is the ratio between Inmates and Capacity (both head counts), minus 1 and multiplied by 100. Hours is the number of hours inmates are allowed to spend outside their cell.

Table 2: Recidivism and Treatment Intensity by Entry Reason

	Recidivism (3 yrs.)	Released from Cell block 5	Potential Years Treated	Actual Years Treated	Total Years Served	Nobs.
Transferred to be treated	0.32	0.15	1.49	1.20	3.73	196
Applied to be treated	0.25	0.11	1.47	1.16	3.53	199
Transferred by the Justice Dep.	0.25	0.25	1.31	0.91	3.02	63
Other entry reasons	0.35	0.00	2.05	1.44	3.61	21
Total selected sample	**0.28**	**0.15**	**1.48**	**1.16**	**3.55**	**479**
Entry cause unknown	0.42	0.05	2.24	0.79	4.05	281
Selected and unknown	0.33	0.11	1.76	1.02	3.73	760
Displaced	**0.40**	**0.02**	**0.85**	**0.68**	**1.44**	**1553**

Notes: The table presents some relevant variables for groups of inmates defined by the reason with which they were transferred to Bollate: whether displaced or selected, and among the latter further distinguishing by different types and responsibilities for the transfer. “Recidivism” and “Released from Cell block 5 ” are variables measured as the fraction of inmates for which the corresponding condition applies; “Potential years treated,” “Actual years treated” and “Total years served” are measured in years.

Table 3: Summary Statistics

	Selected/Unknown (I)		Displaced Inmates (II)		II-I	
	mean	sd	mean	sd	mean	se
Recidivism (3 yrs.)	0.329	0.470	0.395	0.489	0.066	0.023
Potential years treated	1.762	1.396	0.852	0.885	-0.91	0.058
Total years served	3.731	3.279	1.441	1.707	-2.29	0.116
Drug addiction	0.245	0.430	0.297	0.457	0.053	0.025
Art. 4 bis	0.209	0.407	0.072	0.259	-0.137	0.017
Total number of incarcerations	3.182	2.704	3.421	2.742	0.24	0.135
In a relationship	0.336	0.472	0.262	0.440	-0.073	0.020
Separated or divorced	0.099	0.298	0.089	0.285	-0.01	0.013
College degree	0.096	0.295	0.052	0.221	-0.045	0.012
Secondary schooling	0.546	0.498	0.511	0.500	-0.035	0.024
Primary schooling	0.218	0.413	0.178	0.382	-0.041	0.019
Homicide	0.083	0.276	0.014	0.118	-0.069	0.011
Fraud	0.104	0.305	0.057	0.233	-0.047	0.013
Threat of violence	0.114	0.319	0.040	0.196	-0.075	0.012
Drug-related crime	0.383	0.486	0.243	0.429	-0.139	0.025
Assault	0.138	0.345	0.110	0.313	-0.028	0.014
Theft	0.425	0.495	0.429	0.495	0.004	0.023
Robbery	0.370	0.483	0.219	0.414	-0.151	0.020
Crimes against the State	0.283	0.451	0.227	0.419	-0.056	0.022
Crimes against the Public Health	0.408	0.492	0.253	0.435	-0.155	0.025
Other crime	0.074	0.261	0.121	0.326	0.047	0.013
Age at exit	41.207	11.261	38.325	10.741	-2.881	0.553
Time from incarceration to first sentence			0.103	0.261		

Notes: The table presents the summary statistics for the covariates used in the analysis, for the sample of selected and displaced inmates. With the exception of "Potential years treated" in Bollate, "Total years served", "Age at exit" (all measured in years), and "Total number of incarcerations" (a natural number), all other variables are dummy equal to 1 when the corresponding characteristic is present. The type of crime dummies are not exclusive, so they need not sum to 1. The sample of selected inmates include 281 inmates whose reason of entry is unknown. The standard errors in the last column are clustered by cell block and week of release, for a total of 392 clusters: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect of the Treatment for Displaced Inmates (dependent variable: inmate recidivates within 3 years (0/1))

	(1)	(2)	(3)	(4)	(5)
	Panel A: Reduced Form Model(d.v. Recidivates)				
Potential years treated	-0.054	-0.073	-0.063	-0.064	-0.063
	(0.014)	(0.019)	(0.020)	(0.021)	(0.023)
Total years served		0.014	0.015	0.025	0.023
		(0.012)	(0.014)	(0.017)	(0.017)
Drug addiction			0.117	0.156	0.148
			(0.030)	(0.039)	(0.042)
Time from incarceration to first sentence			0.011	0.047	0.051
			(0.053)	(0.055)	(0.064)
R-squared	0.010	0.011	0.093	0.255	0.264
	Panel B: 2SLS Model (d.v. Recidivates)				
Actual years treated	-0.079	-0.119	-0.102	-0.105	-0.102
	(0.023)	(0.033)	(0.035)	(0.037)	(0.040)
Total years served		0.020	0.019	0.028	0.025
		(0.014)	(0.015)	(0.018)	(0.019)
Drug addiction			0.114	0.165	0.155
			(0.031)	(0.040)	(0.042)
Time from incarceration to first sentence			0.015	0.055	0.061
			(0.055)	(0.056)	(0.065)
R-squared	-0.005	-0.014	-0.003	0.109	0.107
	Panel C: First stage (d.v. Actual years treated)				
Potential years treated	0.684	0.616	0.618	0.606	0.612
	(0.040)	(0.048)	(0.045)	(0.043)	(0.047)
R-squared	0.695	0.701	0.704	0.741	0.745
Age at exit FE			√	√	√
Other Xs				√	√
Prison FE				√	√
Year/Month FE				√	√
Prison × Year/Month FE					√
Observations	1,553	1,553	1,538	1,527	1,494
F-stat on the excluded instrument	293.8	165.3	187.8	195.7	172.7

Notes: The average recidivism rate is 39.5 percent. A flag on the variables in the bottom part of the Table signals inclusion in both, reduced form and 2SLS regressions. The "Other Xs" are all the covariates included in the central panel of Table 3. Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 5: Robustness Regressions for Displaced Inmates (dependent variable: inmate recidivates within 3 years (0/1))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Additional controls				Sample selection			Probit
	Labor market conditions	Age at entry	Total sentence		Adding the unknowns	No ongoing trials	Year of entry $\leq$ 2008	Marginal effects
Potential years treated	-0.066***	-0.068***	-0.050***	-0.066***	-0.056***	-0.056**	-0.063***	-0.090***
	(0.021)	(0.021)	(0.018)	(0.021)	(0.016)	(0.025)	(0.021)	(0.026)
Total years served	0.025	0.024		0.045**	0.027***	0.018	0.025	0.031*
	(0.017)	(0.015)		(0.022)	(0.010)	(0.019)	(0.016)	(0.018)
Total sentence			0.005	-0.023				
			(0.013)	(0.018)				
Time from incarceration to first sentence	0.045	0.055	0.093*	0.057		0.019	0.043	0.064
	(0.055)	(0.054)	(0.049)	(0.053)		(0.069)	(0.055)	(0.066)
Unemployment rate in Northern Italy	-0.040							
	(0.057)							
Youth unemployment rate	0.017							
	(0.015)							
Observations	1,527	1,527	1,526	1,526	1,813	1,374	1,508	1,520
R-squared	0.255	0.259	0.258	0.260	0.241	0.260	0.255	
Mean dep. variable	0.395	0.395	0.395	0.395	0.399	0.379	0.379	0.395

Notes: Only the reduced form regressions are shown. All regressions control for the additional covariates and fixed effects included in Column 4 of Table 4. The Probit results represents marginal effects computed at mean values, and are estimated by maximum likelihood. Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Heterogeneity of the Effects for Displaced Inmates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Displaced inmate recidivates within 3 years (0/1)							
	Panel A: Reduced Form Model							
	Drug addicted	Above 75th perc. in risk index	Violent crimes	Above median overcrowding	First incarceration	In a relationship	Above secondary school	Below median age
Potential years treated	-0.047	-0.078	-0.081	-0.067	-0.051	-0.057	-0.103	-0.087
	(0.019)	(0.019)	(0.024)	(0.026)	(0.022)	(0.023)	(0.026)	(0.023)
Interaction	-0.056	0.062	0.056	0.022	-0.033	-0.021	0.070	0.051
	(0.040)	(0.049)	(0.033)	(0.038)	(0.034)	(0.037)	(0.034)	(0.034)
Interaction variable	0.084	0.110	-0.139	-0.020	-0.055	0.021	-	-
	(0.045)	(0.055)	(0.062)	(0.041)	(0.040)	(0.039)	-	-
R-squared	0.195	0.199	0.198	0.198	0.196	0.194	0.196	0.195
	Panel B: 2SLS							
Actual years treated	-0.074	-0.133	-0.153	-0.093	-0.083	-0.088	-0.179	-0.137
	(0.031)	(0.034)	(0.049)	(0.036)	(0.037)	(0.037)	(0.055)	(0.039)
Interaction	-0.099	0.112	0.121	0.015	-0.054	-0.056	0.129	0.078
	(0.072)	(0.067)	(0.058)	(0.063)	(0.062)	(0.070)	(0.064)	(0.058)
Interaction variable	0.083	0.093	-0.159	-0.020	-0.054	0.030	-	-
	(0.047)	(0.056)	(0.063)	(0.044)	(0.042)	(0.045)	-	-
Observations	1,538	1,537	1,537	1,506	1,537	1,537	1,537	1,537
R-squared	0.112	0.112	0.113	0.120	0.112	0.111	0.110	0.111
First stage F-stat	28.74	75.05	43.28	48.87	69.32	41.01	32.33	158.7

Notes: All regressions control for the additional covariates and fixed effects included in Column 4 of Table 4. In each column, the "Interaction" refers to the variable obtained multiplying "Potential years treated" (or "Actual years treated") as well as "Total years served" times the variable listed in the heading of the column. The recidivism risk is the predicted recidivism used in Appendix Table A3, Index 1 (results using Index 2 are almost identical). Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Mechanism: work opportunities (dependent variable: fraction of days spent working outside ($\times$100))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Transferred to Section 5 ($\times$100)				Fraction of Days Spent in Day-releases ($\times$100)			
Sample	Selected	Displaced	Selected	Displaced	Selected	Displaced	Selected	Displaced
	Reduced Form		2SLS		Reduced Form		2SLS	
Potential years treated	13.493	3.952			0.687	0.137		
	(5.424)	(3.629)			(0.315)	(0.075)		
Actual years treated			34.609	13.210			1.890	0.224
			(15.026)	(10.869)			(0.992)	(0.124)
Total years served	2.375	1.418	1.557	0.877	-0.029	0.122	-0.070	0.114
	(1.368)	(2.085)	(1.308)	(2.353)	(0.068)	(0.081)	(0.095)	(0.086)
Observations	461	580	461	580	1,161	1,807	1,161	1,807
R-squared	0.420	0.295	0.189	0.152	0.156	0.219	-0.087	0.047
Mean dep. var.	26.89	7.903	26.89	7.903	1.440	0.243	1.440	0.243
First stage F-stat			42.31	363			42.31	363

Notes: All regressions control for the additional covariates and fixed effects included in Column 4 of Table 4. The sample of selected inmates includes those inmates whose entry reason is unknown. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Mechanism: Negative Role Models or Treatment?

	(1)	(2)	(3)
	Displaced inmate recidivates within 3 years (0/1)		
Peers measured using the:	*Whole prison*	*Section*	*Individual cell*
Potential years served	-0.060	-0.061	-0.054
	(0.019)	(0.020)	(0.021)
Fraction of displaced peers	-0.121	-0.086	-0.075
	(0.086)	(0.057)	(0.041)
Potential years served	0.062	0.042	0.043
$\times$ Fraction of displaced peers	(0.073)	(0.055)	(0.049)
Total years served	0.021	0.020	0.008
	(0.015)	(0.015)	(0.017)
OtherXs	Yes	Yes	Yes
Observations	1,537	1,537	1,440
R-squared	0.195	0.196	0.199

Notes: All regressions control for the additional covariates and fixed effects included in Column 4 of Table 4. Columns 1 to 3 correspond to different neighborhoods within which the presence of other displaced peers is measured. Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

A Online Appendix of "Leave the Door Open? Prison Conditions and Recidivism," by Giovanni Mastrobuoni and Daniele Terlizzese

Selection into Bollate

The Regional branch of the Prison Administration for Lombardy (the "*Provveditorato Regionale di Milano*", RPA), together with the prison administration of Bollate, assesses each transfer application according to the following criteria. The inmates selected should: have a residual sentence in the range of 2 to 10 years (the upper limit has later been removed); be in good health, and not be under methadone treatment; have a definitive sentence;[56] have shown propensity and active interest for rehabilitation programs (this is reflected in a positive assessment by a specialized team, that drafts a psychological profile of each applying inmate); have had generally good behaviour in the previous prison(s); and, finally, reside or have interests and relationships in the Lombardy region.[57] Once the assessment is completed and the various criteria deemed satisfied, the transfer of the inmate to Bollate is finalized.

Clearly, these criteria involve a good deal of positive selection: inmates are explicitly screened to identify those who would be more receptive of the rehabilitation efforts, and it is therefore highly likely that their intrinsic propensity to recidivate be lower than that of the average inmate. [58] Therefore, a naive comparison between their recidivism and that of the average inmate would almost surely overstate the causal effect on recidivism of serving the sentence in an open prison.

Focussing on the intensive margin of the treatment – the length of the residual sentence upon arrival to Bollate – might help to sidestep the selection problem. The time it takes for the screen-

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

[57] This aspect is not peculiar to Bollate. In general, convicts are sent to prisons geographically close to their area of residency and interest.

[58] By average inmate we actually mean "average among those inmates with similarly long sentences". A long sentence, by itself, would likely induce negative selection.

ing procedure to be completed and therefore, given the total time served, the length of the residual sentence upon arrival to Bollate, can vary for a host of factors (incomplete requests, bureaucratic delays in handling applications, number and speed of appeal trials...). The variability imparted by these factors might in principle be exploited to tease out the causal effect of the treatment on recidivism. However, the length of the delay itself might reflect some selection. For example, "better" inmates (more educated, with better labour skills, better behaviour, etc.) might be identified more quickly, so they would end up in Bollate earlier; or, conversely, "better" inmates might be retained for longer by the prison of origin, so they would end up in Bollate later.

Unfortunately, we are not able to weigh the importance of the different delays, and we cannot control for all the variables that belong to the information set relevant for the selection process of inmates (we only know whether they applied or were proposed, where they were spending their previous prison time and their previous criminal history).

Randomization and Balance Tests

Appendix Table A2 presents a test of the random assignment of our main measure of the treatment (potential years served in the open prison). The aim is to test the ability of observables to predict the intention to treat. We control for the total time served, the delay in receiving the sentence, and the variable "age," as these are mechanically linked to the time spent in Bollate.[59]

Columns 1 and 2 show that for the sample of displaced inmates the observed covariates are jointly unable to predict the intention to treat (the F test for the joint significance of all the covariates has a tail probability of 26 percent). Even taken one by one, only the coefficient on the homicide dummy is significantly different from zero, and only at the 10 percent level.

In Columns 3 and 4 we repeat the exercise without controlling for the time from incarceration to first sentence and for age. Two more dummies become significant, again only at the 10 percent level, but the tail probability of the F test is in fact even higher (34 percent), suggesting that the variability imparted by the delays in meting out the conviction or by the constraints due to the com-

[59]The previous discussion would suggest conditioning also on the variable "drug addiction;" conservatively, Appendix Table A2 includes this variables among the covariates whose significance gets tested, but the results would be unchanged had we conditioned also on "drug addiction."

position of available cells in Bollate is not generating selection. While in our baseline regression we remain cautious and exploit only the variability among inmates with equal conviction delay, age and drug addiction, we will show that our results are essentially unchanged when not imposing such restrictions.[60]

The test for the random assignment of the treatment fails, instead, when we consider the sample of selected inmates (this is true also if we exclude from the selected those whose entry reason is unknown[61]). Several covariates are statistically significant, and the F test of their joint insignificance has a tail probability of only 0.1 percent. This was expected, since the delays in the selection process – which is the variability we exploit when we consider the selected sample – are potentially correlated with the inmates' individual characteristics, and we are unable to control for all the information available to the people doing the selection.

An alternative way to test for random assignment of the treatment is presented in Appendix Table A3. We first construct a measure of recidivism risk by regressing recidivism on all the pre-treatment characteristics listed in the upper part of Appendix Table A2, together with age fixed effects and (possibly) prison of origin and year by month of transfer to Bollate fixed effects. We thus exclude from this regression total time served, time from incarceration to first sentence and potential time spent in Bollate.[62] Next, we regress this measure of predicted recidivism on potential time spent in Bollate, total time served and time from incarceration to first sentence. A negative and significant coefficient on potential time spent in Bollate would mean that low risk inmates – as predicted on the basis of pre-treatment characteristics – tend to spend more time in Bollate, and would thus falsify the random assignment of the treatment. Appendix Table A3 shows that potential time spent in Bollate is uncorrelated with predicted recidivism (the point estimate is not significantly different from 0 and, if anything, is slightly positive).

[60]We will always control for the total time served. This is key, since residual and total time served are strongly positively correlated. Without conditioning on the total time served, inmates with longer residual sentences are associated with more serious crimes.

[61]For brevity we do not show these results, which are available upon request.

[62]The R-squared in this first regression is around 20 percent.

Results for the Selected Inmates

Appendix Table A8 shows how time spent in Bollate reduces recidivism for the selected group of inmates, replicating for this group the estimate of equation (2) in the main text (we use here the same definitions of variables). The first two columns include also inmates for whom the cause of entry is unknown while the following two columns restrict the analysis only to inmates who are known to have been screened.

When analyzing selected inmates we exploit the variability in the timing of transfer to Bollate arising from differences in the speed with which the request to be transferred to Bollate was submitted (either by the inmate himself, or by the prison of origin) and in the length of time it took to screen the applications of inmates and grant their request. If our vector of controls were to include all the variables observed by the people involved in the selection process, then we could conclude that condition (CIA) in the main text holds.

If, however, the people doing the screening had access to a larger information set, we would not be able to rule out the possibility that the transfer to Bollate occurs earlier for inmates with lower ε_i (for example, it might be that less problematic inmates are more quickly identified), thus inducing a negative correlation between ε_i and S_i^O, which would spuriously magnify the (negative) effect of the treatment and would challenge the causal interpretation of the results. For this reason we use the estimates on the sample of selected inmates only to help interpreting the results for the displaced inmates and understanding the mechanism underlying those results.

Spatial Lag Error Model for the Standard Errors

In the main text errors were clustered by week of exit and cell block. In this Section, to assess the robustness of that modelling choice, we model the errors as following a spatial structure (i.e. we use a spatial lag model). In particular, we allows the errors of inmates who spent at least one day together in the same cell block to be correlated with each other:

$$R_i = \beta_0 + \beta_1 D_i + \beta_2 S_i + \gamma' X_i + \lambda W \varepsilon_i + \varepsilon_i, \tag{A1}$$

where W is an adjacency matrix whose element (i, j) is positive when inmates i and j have spent at least one day in the cell block , and equal to zero otherwise. The adjacency matrix can be specified in a dichotomous or in a standardized way. The value of the (i, j) entry will be 1 in the former case, so that the composite error term is allowed to depend on the *sum* of all the peers' errors. With the standardized version the adjacency matrix the value of the (i, j) entry is normalized, 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 the spatial lag model seems supported by the data (the loading λ is statistically significant), the standard errors are almost identical to the clustered standard errors used in the man text.

Figures

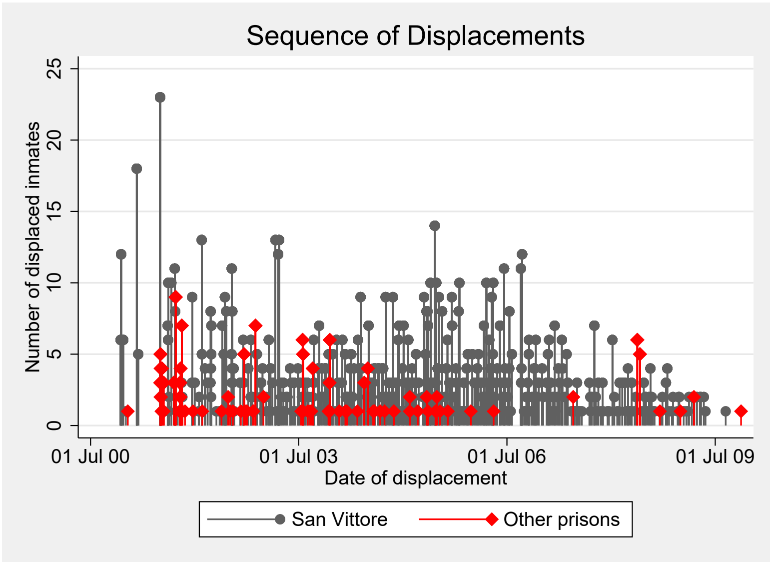

Figure A1: Sequence of Displacements

Notes: The figure plots the daily number of inmates displaced to Bollate from the San Vittore prison and from all the other prisons.

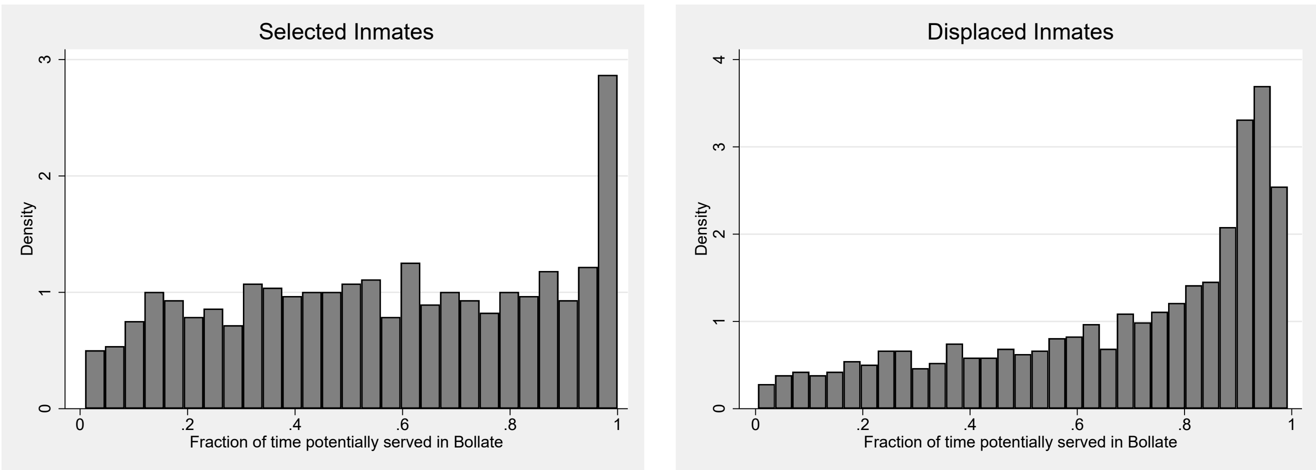

Figure A2: Distribution of the Fraction of Time Potentially Served in Bollate

Notes: The figure plots the distribution of the fraction of the total time that remains to be served when the inmate is transferred to Bollate. The left panel refers to selected inmates, the right one to the displaced.

Tables

Table A1: Running costs for Bollate and the average prison

	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	92.02	20,732,849	49.70	90.88
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	115.21	26,454,555	63.41	116.87

Notes: All costs are in euro, at current prices of the year. The costs per inmate are per day in prison. To increase the comparability between the costs for Bollate and for the average prison we excluded from the latter a (rough) estimate of the central administration costs.

Table A2: Randomization Test

	(1)	(2)	(3)	(4)	(5)	(6)
	Displaced Inmates				Selected Inmates	
	Potential years treated		**Potential years treated**		**Potential years treated**	
	coef	se	coef	se	coef	se
Art. 4 BIS	0.164	0.110	0.053	0.113	-0.062	0.117
Total number of incarcerations	-0.005	0.005	-0.001	0.006	-0.030	0.016
In a relationship	-0.031	0.038	-0.019	0.040	-0.203	0.107
Separated or divorced	0.045	0.062	0.060	0.065	-0.173	0.167
College degree	0.004	0.066	-0.001	0.071	0.347	0.184
Secondary schooling	0.013	0.038	0.034	0.040	0.333	0.133
Primary schooling	-0.006	0.052	0.005	0.057	0.117	0.180
Homicide	-0.714	0.399	-0.660	0.358	-0.297	0.253
Fraud	0.059	0.066	0.118	0.064	0.214	0.159
Threat of violence	0.119	0.134	0.109	0.133	0.026	0.146
Drug-related crime	0.292	0.185	0.233	0.185	-0.004	0.234
Assault	0.047	0.056	0.087	0.056	0.289	0.145
Theft	0.068	0.054	0.085	0.051	0.220	0.089
Robbery	0.076	0.060	0.067	0.061	0.077	0.100
Crimes against the State	0.048	0.043	0.048	0.044	-0.086	0.085
Crimes against the Public Health	-0.127	0.189	-0.048	0.188	0.235	0.234
Other crime	0.054	0.067	0.081	0.064	0.016	0.165
Drug addiction	0.039	0.046	0.045	0.048	0.027	0.122
Time from incarceration to first sentence	*-0.816*	*0.203*				
Total years served	*0.429*	*0.045*	*0.360*	*0.031*	*0.235*	*0.023*
Age fixed effects	√				√	
Observations	1,538		1,553		760	
R-squared	0.586		0.555		0.434	
F-statistic for joint test	1.192		1.112		2.432	
p-value	0.264		0.338		0.001	

Notes: Columns 1, 3 and 5 show the coefficients of a regression where "Potential years treated" in Bollate is regressed on the variables listed in the first column, with or without age fixed effects. Columns 1 to 4 refers to the sample of displaced inmates, columns 5 and 6 to the sample of selected inmates. The latter includes 281 inmates whose reason of entry is unknown. The F-test at the bottom for the joint significance of these regressors excludes the variables which are expected, a priori, to affect the timing of transfer to Bollate (see Section 1.3; these are the variables below the continuous line, in italics; including or not drug addiction among them does not alter the results). Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Balancing Test based on Predicted Recidivism (displaced inmates)

	(1)	(2)	(3)	(4)
	Recidivism index			
	Index 1	Index 2	Index 1	Index 2
Potential years treated	0.005	0.000	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Total years served	-0.007	-0.004	0.001	0.000
	(0.004)	(0.004)	(0.004)	(0.004)
Time from incarceration to first sentence	-0.027	-0.032	-0.052	-0.054
	(0.016)	(0.017)	(0.015)	(0.016)
Age fixed effects	√	√	√	√
Prison Fixed effects			√	√
Year/Month fixed effects			√	√
Observations	1,538	1,531	1,527	1,527
R-squared	0.406	0.381	0.489	0.515

Notes: We construct a measure of predicted recidivism (recidivism risk) by regressing actual recidivism on all observable characteristics listed in the upper part of Table A2 plus age fixed effects (denoted Index 1, in Columns 1 and 3) and prison of origin fixed effects (denoted Index 2 in Columns 2 and 4). "Potential years treated" in Bollate, "Total years served" and "Time from incarceration to first sentence" are, therefore, excluded from this first step. The table presents the second step regression, in which predicted recidivism is regressed on "Potential years treated," "Total time served" and "Time from incarceration to first sentence". Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A4: Regressions with Additional Identification Conditions

	(1)	(2)	(3)	(4)
	Recidivates within 3 years			
Potential years treated	-0.064	-0.065	-0.076	-0.077
	(0.024)	(0.028)	(0.036)	(0.037)
Total years served	0.024			
	(0.018)			
Time from incarceration to first sentence	0.051	0.066	0.071	
	(0.064)	(0.083)	(0.099)	
Rank in the Delay of Displacement	-0.000			
	(0.002)			
Total sentence FE (trimesters)		√		
Total sentence FE (months)			√	√
Time from incarceration to first sentence FE (months)				√
Observations	1,494	1,485	1,462	1,454
R-squared	0.264	0.276	0.294	0.311

Notes: Only the reduced form regressions are shown. All regressions control for the additional covariates and fixed effects included in Column 4 of Table 4. Clustered standard errors (by prison section and week of release) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Recidivism and Treatment Intensity with "Spatially" Lagged Errors (Displaced inmates) (dependent variable: inmate recidivates within 3 years (0/1))

	(1)	(2)	(3)	(4)
Adjacency matrix:	Dichotomic		Standartized	
Potential years treated	-0.073	-0.065	-0.073	-0.069
	(0.019)	(0.019)	(0.019)	(0.019)
Total years served	0.013	0.024	0.014	0.023
	(0.011)	(0.014)	(0.011)	(0.014)
lambda	0.437	0.486	0.411	0.486
	(0.017)	(0.003)	(0.029)	(0.003)
Other Xs		√		√
Observations	1,537	1,537	1,537	1,537
log-likelihood	-1072	-903.5	-1071	-894

Notes: The adjacency matrix allows inmates who have potentially interacted in prison for at least one day to have correlated errors.The "Other Xs" are all the additional covariates and fixed effects included in Column 4 of Table 4. "Spatially" lagged standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Complete Regression Table 4 of the Reduced Form (dependent variable: inmate recidivates within 3 years (0/1))

	(2)	(3)	(4)	(5)
	Displaced inmate recidivates within 3 years (0/1)			
Potential years treated	-0.073	-0.063	-0.064	-0.063
	(0.019)	(0.020)	(0.021)	(0.023)
Total years served	0.014	0.015	0.025	0.023
	(0.012)	(0.014)	(0.017)	(0.017)
Drug addiction		0.117	0.156	0.148
		(0.030)	(0.039)	(0.042)
Time from incarceration to first sentence		0.011	0.047	0.051
		(0.053)	(0.055)	(0.064)
Art. 4 bis			-0.038	-0.024
			(0.053)	(0.054)
Total number of incarcerations			0.053	0.053
			(0.005)	(0.005)
In a relationship			0.016	0.013
			(0.029)	(0.030)
Separated or divorced			0.034	0.039
			(0.045)	(0.046)
College degree			-0.012	-0.012
			(0.062)	(0.062)
Secondary schooling			-0.019	-0.016
			(0.034)	(0.035)
Primary schooling			-0.021	-0.022
			(0.040)	(0.041)
Homicide			-0.086	-0.100
			(0.094)	(0.100)
Fraud			-0.019	-0.018
			(0.056)	(0.059)
Threat of violence			0.088	0.083
			(0.059)	(0.063)
Drug-related crime			0.217	0.217
			(0.101)	(0.104)
Assault			0.018	0.012
			(0.043)	(0.044)
Theft			0.085	0.095
			(0.028)	(0.030)
Robbery			0.027	0.036
			(0.039)	(0.040)
Crimes against the State			0.005	0.004
			(0.031)	(0.031)
Crimes against the Public Health			-0.209	-0.201
			(0.097)	(0.100)
Other crime			0.031	0.037
			(0.044)	(0.044)
Age at exit FE		√	√	√
Prison FE			√	√
Year/Month FE			√	√
Prison × Year/Month FE				√
Observations	1,553	1,538	1,527	1,494
R-squared	0.011	0.093	0.255	0.264

Notes: Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A7: Complete Regression Table 4 of the First Stage (dependent variable: Actual Years in Bollate)

	(1)	(2)	(3)	(4)	(5)
	Panel C: First stage (d.v. Actual years treated)				
Potential years served in Bollate	0.684	0.616	0.618	0.606	0.612
	(0.040)	(0.048)	(0.045)	(0.043)	(0.047)
Total years served		0.049	0.041	0.028	0.021
		(0.013)	(0.014)	(0.017)	(0.022)
Drug addiction			-0.027	0.081	0.072
			(0.024)	(0.030)	(0.030)
Time from incarceration to first sentence			0.041	0.075	0.100
			(0.069)	(0.078)	(0.088)
Art. 4 bis				-0.024	-0.041
				(0.074)	(0.078)
Total number of incarcerations				0.007	0.005
				(0.004)	(0.004)
In a relationship				-0.038	-0.035
				(0.025)	(0.025)
Separated or divorced				-0.028	-0.023
				(0.049)	(0.052)
College degree				-0.015	-0.007
				(0.046)	(0.047)
Secondary schooling				-0.010	-0.004
				(0.029)	(0.030)
Primary schooling				-0.037	-0.040
				(0.038)	(0.040)
Homicide				0.087	0.104
				(0.132)	(0.134)
Fraud				0.010	-0.008
				(0.057)	(0.056)
Threat of violence				0.049	0.026
				(0.089)	(0.094)
Drug-related crime				0.048	0.009
				(0.086)	(0.089)
Assault				0.068	0.080
				(0.040)	(0.041)
Theft				0.062	0.072
				(0.029)	(0.030)
Robbery				0.093	0.087
				(0.042)	(0.044)
Crimes against the State				-0.002	0.002
				(0.029)	(0.030)
Crimes against the Public Health				-0.034	0.011
				(0.086)	(0.091)
Other crime				0.040	0.050
				(0.040)	(0.040)
Constant	0.101	0.089	0.101	0.032	0.030
	(0.025)	(0.024)	(0.025)	(0.040)	(0.041)
Age at exit FE			√	√	√
Prison FE				√	√
Year/Month FE				√	√
Prison × Year/Month FE					√
Observations	1,553	1,553	1,538	1,527	1,494
R-squared	0.695	0.701	0.704	0.741	0.745

Notes: Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A8: Effect of the Bollate Treatment for Selected Inmates (dependent variable: inmate recidivates within 3 years (0/1))

	(1)	(2)	(3)	(4)
Sample:	Selected and unknowns		Selected inmates	
	Panel A: Reduced Form Model			
Potential years treated	-0.043	-0.052	-0.074	-0.050
	(0.015)	(0.019)	(0.019)	(0.028)
Total years served	0.007	0.024	0.012	0.027
	(0.007)	(0.009)	(0.007)	(0.014)
Applied to be treated	-0.143	-0.097	-0.071	-0.098
	(0.039)	(0.058)	(0.050)	(0.074)
Transferred by the Justice Dep.	-0.138	-0.192	-0.068	-0.111
	(0.051)	(0.060)	(0.056)	(0.078)
R-squared	0.027	0.378	0.034	0.492
	Panel B: 2SLS Model			
Actual years treated	-0.095	-0.129	-0.101	-0.072
	(0.032)	(0.051)	(0.026)	(0.039)
Total years served	0.009	0.025	0.013	0.027
	(0.007)	(0.009)	(0.007)	(0.014)
Applied to be treated	-0.104	-0.043	-0.071	-0.105
	(0.040)	(0.058)	(0.049)	(0.074)
Transferred by the Justice Dep.	-0.117	-0.158	-0.082	-0.123
	(0.051)	(0.062)	(0.057)	(0.082)
Other Xs		√		√
Prison FE		√		√
Year/Month FE		√		√
Age at exit FE		√		√
Observations	760	726	479	445
R-squared	0.025	0.110	0.021	0.180
F-stat	78.17	44.19	249.7	135.2

Notes: The average recidivism is 28 percent for selected inmates, 33.1 when also inmates with unknown entry reason are included. A flag on the variables in the bottom part of the Table (below the double continuous line) signals inclusion in both, reduced form and 2SLS regressions. The "Other Xs" are all the covariates included in the central panel of Table 3. Clustered standard errors (by cell block and week of release, for a total of 339 clusters) in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A9: Logit Hazard Model (dependent variable: inmate recidivates within 3 years (0/1))

	(1)	(2)
	Recidivates	
Potential years treated	-0.240	-0.240
	(0.074)	(0.074)
Total years served	0.017	0.017
	(0.049)	(0.049)
Time from incarceration to first sentence	0.001	0.001
	(0.001)	(0.001)
Quartic in time	√	
Time fixed effects		√
Observations	42,237	41,304
Number of individuals	1538	1538
pseudo-R2	0.0464	0.0516

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 covariates and fixed effects included in Column 4 of Table 4. Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A10: Effect of the Treatment for Displaced Inmates by Type of Future Crime

Recidivism based on ... crimes:	(1) all	(2) violent	(3) non-violent
	Panel A: Reduced Form Model		
Potential years treated	-0.063	-0.011	-0.052
	(0.023)	(0.015)	(0.022)
Total years served	0.023	0.007	0.016
	(0.017)	(0.011)	(0.017)
Observations	1,494	1,494	1,494
R-squared	0.264	0.225	0.194
	Panel B: 2SLS Model		
Actual years treated	-0.102	-0.017	-0.085
	(0.040)	(0.025)	(0.038)
Total years served	0.025	0.008	0.017
	(0.019)	(0.012)	(0.018)
Age at exit FE	√	√	√
Other Xs	√	√	√
Prison FE	√	√	√
Year/Month FE	√	√	√
Prison × Year/Month FE	√	√	√
Observations	1,494	1,494	1,494
R-squared	0.107	0.067	0.065
F-stat on the excluded instrument	172.7	172.7	172.7

Notes: The average recidivism rate is 39.5 percent. For violent crimes it is 14.2 percent. A flag on the variables in the bottom part of the Table (below the double continuous line) signals inclusion in both, reduced form and 2SLS regressions. The “Other Xs” are all the covariates included in the central panel of Table 3. Clustered standard errors (by cell block and week of release, for a total of 392 clusters) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$