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Do better prisons reduce recidivism? Evidence from a prison construction program

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Do better prisons reduce recidivism? Evidence from a prison construction program*

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Abstract

From the US to Colombia, from India to Uganda, many inmates suffer from under-provision of services such as surveillance or rehabilitation in overcrowded prisons. Yet, we know little about how prison quality affects long-term inmate outcomes. I study a prison construction program in Colombia and find that quasi-random assignment of inmates to less crowded, and higher service facilities reduced recidivism. Criminal capital is an important mechanism. Less crowded and better service facilities are associated with a lower level of unsupervised criminal contact within prisons. The program led to substantial welfare gains, even when assuming a low social cost per crime.

JEL codes: D04, H41, J24, K14, K42

Keywords: crime, violence, recidivism, prison conditions, Colombia

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1 Introduction

Almost 11 million people worldwide are in prison. In roughly 60% of the countries the number of inmates exceeds the capacity of the prison system. In this context, many inmates have repeated, unsupervised contact with other criminals, and have poor or no access to health, education or rehabilitation services, clean water or food, or even enough physical space. The problem of space and resources is more pressing for developing rather than for developed countries. On average, developed countries have 16% of their prison system capacity not in use, while developing countries have an overcrowding level of 40%.[1]

In principle, prison time is expected to decrease the probability of recidivism, e.g., by deterring inmates with the threat of further punishment or improving their job skills through training and rehabilitation.[2] But what happens if prisons have no space or other resources? On the one hand, the punishment could be even more severe and have a stronger deterrent effect. Nonetheless, there may be countervailing concerns. For instance, unsupervised interactions between inmates may increase their criminal skills and network.[3] Empirical evidence on the causal effects of prison quality is scarce and relies on narrow proxies of prison conditions. In this paper, I study an extensive prison construction program in Colombia to examine the effects of the quasi-random assignment of inmates to less crowded, and higher service facilities on recidivism rates. To the best of my knowledge, this is the first study that exploits quasi-experimental assignment of inmates to prisons to study the effects of prison

[1] See Appendix A.

[2] These mechanisms are rooted in the economic theory of crime introduced by Becker (1968) and Ehrlich (1973), where crime is a gamble and individuals weigh the expected benefits and costs of crime to decide whether or not to engage in criminal activities. See for instance Abrams (2012); Drago et al. (2009); Ganong (2012); Hansen (2015); Helland and Tabarrok (2007); Kessler and Levitt (1999); Kuziemko (2013); Levitt (1996); Vollaard (2013) for empirical evidence on the deterrent effects of incarceration and punishment; or Barbarino and Mastrobuoni (2014); Buonanno and Raphael (2013); Levitt (1996); Lofstrom and Raphael (2016); Owens (2009) for empirical evidence on the incapacitation effects of the prison system. On the other hand, see Aizer and Doyle (2013); Bhuller et al. (2019); Dobbie et al. (2018); Grogger (1992, 1995); Kling (2006); Landerso (2015); Munyo and Rossi (2014); Schnepel (2017); Tuttle (2019); Yang (2017a,b) for empirical evidence on the effects of human capital, employment opportunities or public assistance of former inmates on recidivism.

[3] See for instance Bayer et al. (2007); Drago and Galbiati (2012); Cohn et al. (2015); Gaes and Camp (2009); Glaeser et al. (1996); Stevenson (2017).

quality—broadly measured to account for its many dimensions such as the surveillance or rehabilitation services—on recidivism.

Since the mid-1990s, sustained crises in the Colombian prison system led the Constitutional Court to declare the situation unconstitutional and call on other authorities to intervene. As a result, the government started an extensive construction program of ten new prisons in different parts of the country. The capacity of the Colombian prison system grew by approximately one-third in three years, creating large differences in the amount and quality of resources between the newer and older prisons.[4] Hence, the institutional setting offers a unique opportunity to test hypotheses regarding the effects of prison conditions on recidivism. For instance, by 2016, relative to the new prisons, the older prisons had overcrowding levels that were approximately six times larger, there were almost four times more inmates per prison guard, and 20% fewer inmates were enrolled in rehabilitation programs.[5]

To conduct the empirical analysis, I worked with the National Prison Institute of Colombia (INPEC) to access individual level data describing the universe of incarceration events for the 2009-2016 period. Each record includes an anonymous identifier that allows me to follow individuals over time, as well as information on the criminal records, legal situation and socioeconomic characteristics of the inmate.

I estimate causal effects between prison quality and recidivism by exploiting plausibly exogenous variation in prison assignment. The critical empirical challenge when estimating the effects of prison conditions is that unobservable individual characteristics could potentially determine prison assignment as well as postrelease criminal behavior.[6] In Colombia,

[4]In absolute numbers, the prison system went from having space for 55,000 inmates in February 2010 within prisons as old as 100 years, to having space for 75,000 inmates in January 2013. The prison population also grew during that period. It went from 78,000 inmates to 115,000. The disproportionate increase in prison population affected mostly older prisons rather than the new ones (as I show in Section 4 in detail).

[5]The Constitutional Court also documented extreme situations in the living conditions within old prisons, including the systematic underprovision of medical treatment and medicines, limitations in water supply, and poor sanitation and hygiene infrastructure. See sentence T-762/2015 from the Colombian Constitutional Court.

[6]Hence, a naïve comparison between inmates serving time in newer versus older prisons may not identify a causal effect. For example, if inmates who showed a lower risk of recidivism were "rewarded" with the assignment to a new prison, then comparing the average re-entry rates between inmates sent to newer versus older prisons would overestimate a negative relation between bad prison conditions and recidivism

prison assignment is determined at the level of the judicial district, following two criteria associated with the location of the judicial process and the family of the inmate. In all cases, however, more than one prison complies with these criteria. Hence, to distribute inmates evenly across facilities, prison authorities from the different judicial districts send inmates in small sequences to one prison and then to another on a rotating basis. On average, they switch the prison every six inmates. Qualitative evidence suggests that the assignment rule across the different judicial district is rather arbitrary, and consistent with this I show that observed characteristics do not predict a sequence break. In the main empirical analysis, I use data from the ten judicial districts where the new prisons were built, and compare outcomes between inmates sent to new versus old prisons.

I follow two main approaches. First, because the assignment mechanism is plausibly exogenous, I estimate mean differences in recidivism outcomes across inmates assigned to new and old prisons using ordinary least squares regressions. Second, since prison assignment is determined by the place in line of each inmate, then the assignment of inmate $n-1$ affects the assignment of inmate n. To the extent that inmate $n-1$'s location only affects recidivism of inmate n through the shift in assignment probabilities, I use $n-1$'s assignment as an instrumental variable.

I find similar results with both approaches, i.e., more severe prison conditions increase the risk of recidivism. I find that inmates assigned to the new prisons have a risk of returning to prison within one year that is 2.4 percentage points lower relative to that of inmates assigned to older prisons, using ordinary least squares. With a sample average of 7.3%, the magnitude of the difference is approximately 33%. The instrumental variables estimate produces a similar coefficient, i.e., a decrease in the recidivism risk of 2.9 percentage points, which is a 40% decline relative to the sample average.

I also follow these two main approaches to empirically assess the mechanisms. In particular, I study whether assignment to a new prison is associated with the number of people

(or underestimate a positive relation).

in the short range criminal network of each inmate (i.e., the number of people sharing the same prison cell with each inmate at the moment of entry). To build this outcome, I use data on the exact prison cell where inmates are assigned to. I also study if assignment to a new prison is associated with the probability of enrollment in rehabilitation programs within prison. This outcome is recorded in the main database I use in the analysis.

The results suggest that it is mainly the extent of unsupervised criminal contact—as opposed to the participation in rehabilitation programs—the relevant mechanism linking more severe prison conditions with recidivism outcomes. I find that assignment to new prisons is associated with a decrease of roughly 44 inmates (or 70% relative to the sample mean) in the short range criminal network, using ordinary least squares. The instrumental variable results are similar in magnitude but rather imprecise. On the contrary, I see no evidence that assignment to new prisons is associated with enrollment in rehabilitation programs.

In a secondary analysis to assess robustness, I study recidivism outcomes for inmates that were transferred from old to new prisons once the new prisons opened. More specifically, when each of the ten new prisons opened, many inmates were collectively transferred to each of these new facilities. Because these inmates had different amounts of time served upon transfer, and were scheduled for release at different times, they were exposed to different intensity levels of new versus old prisons. In this case, the empirical challenge is that unobservable individual characteristics could potentially determine an early transfer to a better facility as well as postrelease criminal behavior. The timing of the process suggests that these transfers were not scheduled based on individual characteristics of the inmates but rather on characteristics shared by the selected groups. Moreover, I test whether observed characteristics are similar for inmates with an early versus a late transfer to the new prison.

The results are also consistent with a negative association between prison conditions and recidivism outcomes. I find that an increase of one-standard deviation in the proportion of time served in a new prison (i.e., an increase of 25 percentage points in the total time served under better conditions), is associated with a decrease of 1.4 percentage points in the risk of returning to prison within one year. With an average recidivism risk of 9% in the sample, the magnitude of the difference is approximately 16%.

In a back-of-the-envelope welfare analysis, I estimate that investing in new prison with better services can lead to substantial welfare gains, even when assuming a relatively low social cost per crime. In particular, I estimate that the welfare gain per prison slot is positive if the average social cost per crime is $3,150, a value that is well below even the most conservative estimates for low-cost crimes, such as nonviolent thefts.

This paper addresses several gaps in the literature. First and foremost, it provides the first quasi-experimental evidence on the effects of prison quality—broadly measured—on recidivism. Perhaps the closest study on the subject is Drago et al. (2011), who make an initial attempt to examine the effects of prison conditions on recidivism using individual-level data from the Italian penal system. They focus on mortality rates, overcrowding levels, and the degree of isolation from society as proxies of prison quality. To identify the relationship between prison conditions and recidivism, the authors control for the primary sources of heterogeneity in prison assignment. Their results, although imprecisely estimated, suggest that inmates exposed to harsher prison conditions are more likely to recidivate.

Second and perhaps most obvious, this paper addresses the absence of studies on prisons and recidivism from developing countries, especially from Latin America. The recidivism of former inmates is a significant policy concern worldwide. In the US, France or the UK, for instance, more than half of all released inmates are reconvicted within five years of exiting prison (Fazel and Wolf, 2015). This problem is probably more pressing in Latin America, a region that hosts 43 of the 50 most dangerous cities in the world and accounts for more than one-third of the world's homicides with only 8% of the population.[7] Notwithstanding these problems with crime and violence, few studies on prisons and recidivism have focused on this region.[8] Indeed, to the extent that prison quality is less of a problem in developed economies,

[7]See Consejo Ciudadano para la Seguridad Pública y Justicia Penal and United Nations Office on Drugs and Crime Global Study on Homicide 2013.

[8]For instance, a recent systematic review of the impacts of incarceration on crime identified 34 different studies (Roodman, 2017). A total of 28 used data from the U.S., four used data from other developed

the paucity of studies on prison conditions is probably associated with the regional focus of this literature.

This paper is also related, more generally, to a broader literature on other dimensions of prison quality and recidivism. In particular, on the effects of alternatives to prison such as probation or electronic monitoring on the recidivism risk (Di Tella and Schargrodsky, 2013; Green and Winik, 2010; Henneguelle et al., 2016; Kuziemko, 2013); the general deterrent effects of prison conditions on crime rates (Bedard and Helland, 2004; Katz et al., 2003); and the effects of deliberate differences in prison conditions with varying security levels on postrelease criminal behavior (Chen and Shapiro, 2007; Gaes and Camp, 2009).

Additionally, this paper offers an opportunity to observe how "being soft on crime" may lead to positive social outcomes. Previous studies on the political economy of crime policy show how political parties that promote and implement policies that are arguably lenient and soft on criminals face electoral costs (Drago et al., 2018).[9] Also, that politicians perceive these costs and act consequently (Levitt, 1997; Huber and Gordon, 2004). Ultimately, the growing body of evidence on what does and does not work to prevent crime should contribute to shaping the political process differently.

Finally, recent literature suggests that incarceration leads to negative labor market outcomes for offenders in the US and positive labor market outcomes for offenders in Norway.[10] But, do prisons need to be as good as those in Norway to improve inmate outcomes or do modest improvements also help? The results on this paper suggest that modest improvements can indeed help in closing the gap.

countries and only one used data from a developing country: Argentina, which is arguably one of the few exceptions in Latin America's widespread crime and violence problem (Di Tella and Schargrodsky, 2013). The paucity of studies and data from Latin America would not even allow reliable country-level recidivism rates.

[9]See for instance Drago et al. (2018), who study how Italian voters "punished" the political party that implemented the collective clemency bill to release a large number of inmates.

[10]See Mueller-Smith (2015) for the case of the US and Bhuller et al. (2019) for the case of Norway.

2 Conceptual framework and qualitative observation

In this section, I introduce a model of the effects of harsher prison conditions on the recidivism of inmates, and discuss qualitative findings on the mechanisms resulting from fieldwork in both new and old Colombian prisons.

The basic setup is based on occupational choice models with both legal and criminal sectors.[11] I focus on the occupational choice of an individual released from prison and study how the model captures changes in recidivism when prison conditions are more severe. I highlight the basic intuition and results here and develop the formal model in Appendix B.

Relative to some form of benchmark prison conditions, more severe prison conditions could influence the occupational choice of released inmates through four main ways. First, severe prison conditions can affect the expected punishment by inmates, who may inform their expectations based on their prior prison experience (e.g., Becker, 1968; Ehrlich, 1973; Katz et al., 2003). Second, harsher prison conditions could entail a deterioration (or lack of improvement) in human capital, that enters the individual's production function. For instance, in more severe prisons it may be more difficult to participate in education or job training programs, get treatment for drug abuse, or any other investments in human capital (e.g., Aizer and Doyle, 2013; Ehrlich, 1975; Grogger, 1995). Third, severe prison conditions can affect the individual's attitudes toward society in general (i.e., a change in the intrinsic preferences over illegal occupations). For example, a bad experience could trigger a retaliatory behavior against society, while a positive experience may result in more cooperative reciprocal tendencies (e.g., Fehr and Gächter, 2000; Murton, 1976; Selke, 1993). Finally, changes in prison conditions and services can change the individual's criminal network and skills, a form of human capital (or criminal capital for ease of exposition) that enters the individual's criminal production function. For instance, an inmate could improve his criminal opportunities due to easier unsupervised contact with other criminals, which can be

[11] I adapt the class of models introduced by Blattman et al. (2017b) and Blattman and Annan (2016), who develop their analysis extending traditional models of criminal behavior. See for instance Draca and Machin (2015).

common in overcrowded prisons (e.g., Bayer et al., 2007; Drago and Galbiati, 2012); or ease to join criminal gangs that foster crime in the streets (e.g., Dooley et al., 2014; Lessing, 2017; Skarbek, 2012).

2.1 Impacts of worsening prison conditions

Under some benchmark prison conditions, released offenders engage in the criminal sector if the expected returns from crime are higher than the highest possible marginal rate of substitution between leisure and consumption that they can obtain without engaging in crime. Generally, choosing crime will be more likely for people with low productivity in the legal sector, more criminal capital, a lower perception of the severity of punishment if convicted, and a lower disutility from crime.

If prison conditions are more severe: (i) productivity and the disutility of crime decrease, and criminal capital rises, these three effects increase the likelihood of choosing the criminal sector; and (ii) the expected severity of punishment increases, which lowers the likelihood of choosing the criminal sector. The direction of the effect is ultimately an empirical question. If the relationship between more severe prison conditions and the risk of recidivism is positive, the data would mainly reinforce theories of human capital, criminal capital, and reciprocities on the motives for criminal behavior. Otherwise, it would bolster theories of specific deterrence.[12]

2.2 Qualitative observation in Colombian prisons

To understand the mechanisms that could link more severe prison conditions with recidivism outcomes, I conducted roughly two years of fieldwork in two Colombian prisons. Interviewees included inmates and prison guards, and I visited inmate cells, facilities for rehabilitation programs, as well as any surveillance infrastructure. The first is an old prison known as

[12]Finally, note that more severe prison conditions should not induce any change in the probability of detection, arrest, and sanction by the criminal justice system. Hence recidivism, which is unobservable in practice, can be indirectly measured by other means such as to prison re-entry or new convictions.

"Bellavista," located in Medellín. This prison was built in 1976. By 2016, it hosted about 6,000 inmates, although it only had the capacity to host 2,400 (i.e., there was roughly one prison slots for every six inmates). The second is a new prison known as "Pedregal," also in Medellín. This prison opened in 2011 with an installed capacity to host 2,400 inmates, although it hosted about 3,400 inmates in 2016 (i.e., there were roughly two prison slots for every three inmates). I chose these prisons because they are both in Medellín, Colombia's second largest city. This implies they broadly receive similar support from the city budget. However, they have widely different infrastructures and receive different levels of funding from the National Prison Institute of Colombia (INPEC).[13]

There are two salient differences between both prisons that directly link to transmission mechanisms. On the one hand, inmates in the "Bellavista" prison seem to largely improve their criminal capital. This results from repeated, unsupervised contact with other inmates, as well as the need to engage with other criminals to comply with informal prison rules. Inmates in this prison have literally no supervision.[14] On the contrary, inmates in the "Pedregal" prison have full time surveillance in all wings, all are assigned a specific space, and all have specific times for restroom use or access to other prison services.

On the other hand, inmates in the "Bellavista" prison have very limited opportunities to join rehabilitation programs and, if they are able to enter, the programs lack content and personnel to reasonably lead to rehabilitation. There is always an over-demand for programs and prison authorities need to either reject entry or design fast, easy and unstructured programs for inmates to join. Prison authorities have the legal duty to allow access

[13]In other major cities there is a similar situation. For instance, in both Bogotá and Cali (the first and third largest cities) there is also a new and an old prison. In Bogotá, the new prison is known as "La Picota," while the old one is known as "La Modelo." In Cali, the new prison is known as "Jamundí," while the old prison is known as "Vistahermosa."

[14]For instance, the largest two prison wings in "Bellavista" host more than 1,000 inmates each, even though they have the capacity to host roughly 250-300 inmates. As a result of this situation, prison guards do not enter the wings but rather leave them to be regulated by senior inmates linked to organized crime. Inmates in those wings usually need to work inside (e.g., selling drugs, providing surveillance, or selling other goods) because either they are part of a criminal organization (hence it is their job to comply with those duties), or they need to earn money to pay for space inside, restroom time, or virtually any scarce resource. Eventually, most inmates engage directly with criminal organizations and develop contacts and criminal capital that is valuable once they exit prison.

to rehabilitation programs to every inmate that wants to enter, hence there is a trade-off between supply of programs and program quality. This trade-off gets more complex as the supply shrinks.[15] As opposed to the "Bellavista" prison, the "Pedregal" prison had very structured rehabilitation programs. Inmates received intense training in personal finance, entrepreneurship, non-cognitive skills management and many other skills. The supply of rehabilitation programs in the prison generally matched its demand.

My fieldwork in Colombian prisons is consistent with the hypotheses that recidivism may be increase in more severe prisons because of an improvement in criminal capital (networks and skills), or a potential productivity loss associated with the deterioration of human capital and skills valuable in the legal labor market.

3 Data

I use administrative records from the database of the Colombian prison system (SISIPEC). This database is a centralized information system fed by each prison continuously, as events happen. I obtained the data from the Information Technology (IT) department of the National Prison Institute of Colombia (INPEC).[16] The database consists of the stock of in-

[15] For instance, one prison guard at the "Bellavista" prison was running all programs for roughly 300 inmates. These were all music programs, offering either dance or instrument playing classes. The prison guard did not have any music experience but rather was appointed because he was younger than most guards and presumably understood better the music interests of inmates. The prison was offering these programs because a private company donated many instruments. Another example is a relatively comprehensive drug treatment program. The program is run by a professional psychologist and includes components of cognitive behavioral therapy, which have been proven successful to rehabilitate criminals (e.g., Blattman et al., 2017a). In this case, the problem is related to supply. The capacity of the program is to host up to 20 inmates while the demand in 2018 was over 400.

[16] The process to obtain and clean the information spanned for about two years, and took several steps. First, this data is protected by law and internal policies, preventing the use of personal information by third parties (e.g., Law 1266/2008, Law 1581/2012 and the Policy on the Treatment of Personal Information from INPEC). I obtained permission to use the data from the Ministry of Justice after full disclosure of the scope of this research project. Second, the structure of the database follows from specific statistical reports that are regularly produced by INPEC. To retrieve the information, IT representatives from INPEC developed and implemented additional queries over several months until they met the data needs precisely. Finally, SISIPEC is a relatively new database that started to operate at the end of 2009, and quality controls on the decentralized feeding process are still under development (see the SISIPEC Web technical reference. for further details). As a result, the raw data had input errors of different kinds (e.g., nonstandardized crime types or inconsistencies with dates of entry and exit). I cleaned and organized the information in coordination with IT representatives from INPEC in a process that took about one year.

mates for the end of 2009 and every in or outflow onwards until September 2016. The initial database comprises information from all 137 national prisons and includes a total of 466,037 incarceration events corresponding to 413,769 different individuals. I restricted the information to the relevant cases in the ten judicial districts where the new prisons are located.[17] The final database comprises information from 57 prisons and includes a total of 74,050 eligible incarceration events corresponding to 70,858 different individuals.[18]

3.1 Information

For each incarceration event I have information on four broad sets of characteristics. The first set consists of data on the characteristics of the event. This includes an anonymous identifier for the inmate, the date of arrest and release, the last prison where the individual was, and the date of entry to the last prison. The second set consists of legal situation controls. I observe two variables. The first is an indicator of whether the inmate has any previous conviction. This variable is not restricted to the time frame for which the data is available but to the complete history of the Colombian prison system. The second variable is an indicator of whether the inmate was convicted or not during the current incarceration event. The third set consists of crime controls. I recode crimes up into three categories. The first is violent crime and includes homicide, assault, sexual assault and other violent crimes such as torture or family violence. The second category is property crime and includes crimes as all forms of theft and fraud, as well as conspiracy.[19] The third category is drug

[17]Data lost during the cleaning process correspond to 4% of the total records. These were incarceration events for which the IT department from INPEC had no explanation. Hence no solution was available to prevent data loss. The distribution of lost records is generally similar to the distribution of records across prisons, age ranges or crime types. Consequently, there is no reason to consider that data quality may affect the analysis.

[18]I focus on males, as only three of the ten new prisons that provide variation in prison conditions house both males and females. I also focus on inmates in any of these ten judicial districts that were incarcerated after the new prisons opened, as those have a positive probability of assignment to new prisons. The information includes data on any arrested individual subject to a judicial order requiring confinement in prison, be it while on trial or convicted, that effectively entered a prison.

[19]Crime data in the U.S. defines robbery as a particular form of theft mediated by the use of violence. Hence robberies could be classified as violent rather than property crimes. However, crime data in Colombia do not have the same classification criteria, and therefore I consider any theft as a property crime. For details on the definitions in U.S. crime data see the Unified Crime Reports.

crime and is related to cases of drug possession, trafficking or manufacturing. The fourth set consists of socio-economic characteristics, and include: age at release; indicator variables for having finished primary, secondary or tertiary education at the moment of entry; an indicator variable for having minor children; and the location of the family.

3.2 Measuring recidivism with reincarceration

Previous studies on recidivism use a wide range of proxies for recidivism and criminal activity, such as re-arrests, new charges, new appearances in court, reconvictions and reincarcerations.[20] The data I have allows me to use two different measures. First, I measure recidivism by looking at whether or not inmates return to prison. I use the anonymous identifier for each inmate to create an indicator variable. Second, since I observe the conviction outcome in each incarceration event, I can also focus on new convictions. This alternative measure, however, entails less variation (as incarceration and conviction imply incarceration). I use reconvictions to conduct sensitivity tests.

A second issue in measuring recidivism is the time frame. Some studies look at some months after inmates are released while others consider longer periods of up to three or more years. The trade-off is to include more data (as shorter periods imply observing the total time frame for more incarceration events) or to have more variation in recidivism rates (as recidivism is cumulative and longer periods imply more inmates would recidivate). For simplicity, I balance the trade-off by looking at one year periods in the baseline analysis and assess the sensitivity of the results using other time frames. I start the clock to measure recidivism on the day the inmates are released.[21]

[20] See for instance Roodman (2017).

[21] Green and Winik (2010) raise a concern regarding the starting date to measure recidivism. They focus on comparing prison time with parole. If more prison time implies less parole time and less prison time implies more parole time, starting the clock at the day of release may be problematic. Consequently, they measure recidivism starting with the date of arrest. I use an equivalent alternative to account for this problem by controlling for the total time served. Hence, for simplicity, I always focus on time frames starting at the date of release.

3.3 Summary statistics

Table 1 presents summary statistics. Columns (1) and (2) describe the universe of eligible incarceration events. I do not use this sample in any regression, but it is the baseline sample from which I draw the empirical applications. About 22% of the inmates had a prior conviction, 26% had a current conviction for violent crimes, 67% for property crimes, and 18% for drug crimes. The average inmate served 398 days in prison, and 8.1% returned to prison within one year after release. Columns (3) and (4) present the sample I use in the main empirical applications. This is the set of eligible incarceration events where inmates were convicted and released, and I observe the post-incarceration year. About 24% of these inmates had a prior conviction, 13% had a current conviction for violent crimes, 73% for property crimes, and 17% for drug crimes. The average inmate served 453 days in prison, and 7.3% returned to prison within one year after release.

4 Setting and treatment description

The National Prison Institute of Colombia (INPEC) manages the Colombian prison system, which holds about 120,000 inmates distributed in 137 prisons. For more than two decades, the prison system has been in a sustained crisis. Indeed, the Constitutional Court declared this situation unconstitutional on several occasions, e.g., 1998, 2013, and 2015. These declarations were extraordinary measures used by the judicial power to demand the attention of other authorities and formally ask them to intervene. The most relevant situations observed by the Constitutional Court were the lack of space and resources, the inability to provide security for inmates and oversee their interactions, the joint confinement of convicted individuals and inmates awaiting trial, and the the inability to run rehabilitation programs.

As a response to the crisis, the Colombian government decided to build new prisons and support their operations with larger budgets relative to older prisons. The construction was commissioned in 2004 and resulted in ten new prisons that opened between 2010 and 2013. The evolution of average overcrowding levels for old and new prisons is depicted in

Table 1: Summary statistics

	Universe of eligible events *(N=74,050)*		Sample of events in empirical analysis *(N=14,962)*	
	Mean	S.D.	Mean	S.D.
Inmate characteristics	(1)	(2)	(3)	(4)
Pre-incarceration:				
Recidivist = 1	0.223	0.416	0.243	0.429
Violent crime = 1	0.257	0.437	0.133	0.340
Property crime = 1	0.671	0.470	0.727	0.446
Drug crime = 1	0.181	0.385	0.168	0.374
Age at entry	32.935	11.804	35.087	11.743
Primary education = 1	0.613	0.487	0.612	0.487
Secondary education = 1	0.312	0.463	0.307	0.461
Tertiary education = 1	0.050	0.219	0.055	0.227
Has minor children = 1	0.798	0.402	0.827	0.379
Post-incarceration:				
Age at release	34.226	11.836	36.315	11.624
Days served	397.709	375.799	453.277	382.517
New prison = 1	0.320	0.466	0.458	0.498
Returned within 1 year = 1	0.081	0.272	0.073	0.260

Notes: Columns (1) and (2) report summary statistics for all eligible incarceration events. Columns (3) and (4) report summary statistics for the sample of events where the inmate was convicted and released, and I observe post-incarceration year.

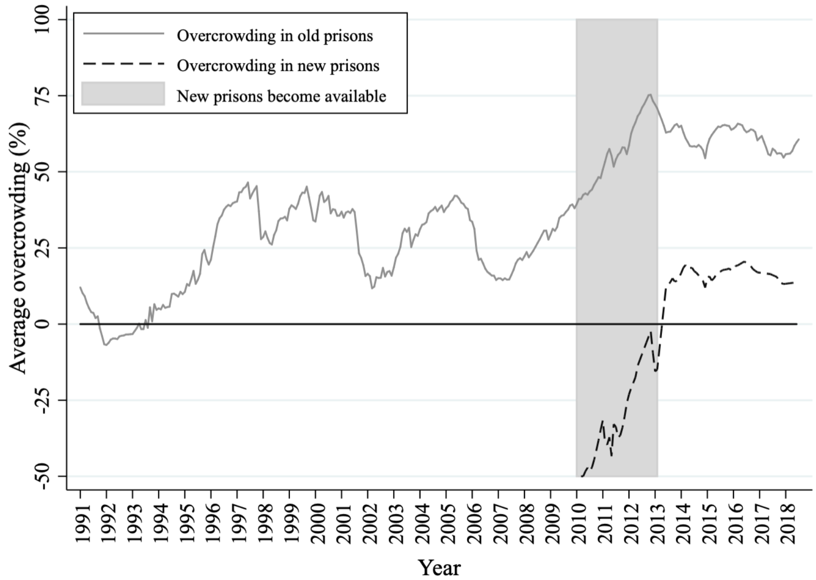
Figure 1. Shaded in gray is the period of improvements in prison capacity resulting from the construction program. Since 1993, old prisons have been overcrowded.[22] Between 2007 and 2013 there is a sustained increase in average overcrowding levels for old prisons. Average overcrowding in new prisons follows a similar pattern between 2010 and 2013. [23] Generally, inmates in new prisons have lower overcrowding levels.

Overcrowding levels proxy for prison quality, more broadly. Table 2 presents summary

[22]Note there are two drops in average prison overcrowding for old prisons before the opening of the new prisons. In 2000 a new penal code was issued with Law 599/2000, and in 2005 a reform introduced with Law 906/2004 created the oral accusatory system. In both cases, the overall prison population dropped.

[23]This general increase in the overcrowding levels in the system is explained by a burst upwards in prison population resulting from several different law changes. In particular: Law 975/2005 implemented the peace process between the Colombian government and paramilitary groups, Law 1142/2007 introduced changes related to citizen security and interpersonal violence, and Law 1453/2011 introduced further modifications to foster citizen security.

Figure 1: Overcrowding in old and new Colombian prisons



Notes: The figure presents the evolution of the overcrowding level of the national prison system, by type of prisons. Overcrowding is measured as the proportion of inmates exceeding the prison capacity. In each case, I aggregate separately new and old prison slots and inmates. 0 overcrowding implies the aggregate number of slots (per type of prison) matches the aggregate number of inmates.

statistics on different characteristics as of September 2016. New prisons include the ten prisons built after 2010, while the remaining 127 prisons are in the group of old prisons. Some of the oldest prisons in this group date back to the early 1900s. The average overcrowding level for old prisons is 60%, while new prisons have overcrowding levels averaging 12%. There are 55 inmates per prison guard in old prisons, while the number of inmates per prison guard in new prisons is 14. About 20% more inmates have access to rehabilitation programs in new prisons. Other quality measures follow a similar pattern.[24]

[24]Moreover, a qualitative assessment from the National Planning Department covering all prisons points to major problems with infrastructure conditions and services in old prisons. In particular, the report indicates that old prisons have largely restricted access to clean water and food, medicines and medical supplies while new prisons meet most technical requirements for proper operation. See the Policy Brief 3828/2015 from the National Planning Department.

Table 2: Comparison of means: Old versus new prisons

Prison characteristics	Old prisons (1)	New prisons (2)	Diff. (2)-(1) (3)	Diff. p-value (4)	Obs. (5)
Overcrowding (pop. - capacity / capacity) × 100	60.5	11.7	-48.8	0.008***	137
Number of inmates per prison guard	54.7	14.1	-40.6	0.006***	137
Share of inmates in any rehabilitation program	0.646	0.772	0.126	0.022**	137
Share of inmates who died in prison (2009-2016)	0.007	0.006	-0.001	0.682	137
Share of inmates who receive visits	0.585	0.687	0.103	0.005***	137

Notes: Columns (1) and (2) report unconditional means for prison characteristics in old and new prisons. Column (3) reports the mean differences with percentage changes in parenthesis. Column (4) reports p-values for a t test on the equality of means. There are 127 old prisons and 10 new prisons included in the comparison. Data is for September 2016.

5 Effects of prison conditions on recidivism

The conceptual framework I outlined in Section 2 suggests that prison conditions could affect recidivism through several mechanisms. Some mechanisms tend to decrease recidivism and others to increase it. For instance, the deterrent effect of a severe prison experience should reduce recidivism, but its adverse effect on human capital may increase it. The final effect is ultimately an empirical question. One way to address this problem is to compare inmates assigned to prisons of different quality. To do this, however, I have to control for the selection problem. For instance, if inmates who show a lower risk of recidivism are "rewarded" with an assignment to a prison with better conditions and services, a simple comparison of average re-entry rates between inmates sent to these versus other (more severe) prisons would overestimate a negative association between severe prison conditions and recidivism (or underestimate a positive relation).

Recent empirical work on the effects of incarceration on crime and recidivism addresses this problem mainly through randomized experiments (e.g. Gaes and Camp, 2009) or natural experiments resulting from random judge assignment (e.g. Di Tella and Schargrodsky, 2013; Green and Winik, 2010; Kling, 2006), mass releases (e.g. Buonanno and Raphael, 2013; Drago et al., 2009) or sharp discontinuities in assignment policies (e.g. Chen and Shapiro, 2007; Kuziemko, 2013).[25] In the context of this paper, the critical selection problem is related to the decision to assign inmates to one prison or another. I address the problem similarly to studies focusing on random judge assignment. In those cases, random assignment of judges ensures that sending a defendant to prison or electronic monitoring, for instance, is quasi-random (more punitive judges tend to prefer prison, while more lenient judges tend to prefer electronic monitoring).[26] In my setting, the main difference is that prison allocation is not decided by a judge but rather by a prison official that is not randomly assigned. However, the decision taken by the prison official, as I explain below, mimics a quasi-random process.

5.1 How are inmates assigned to prisons?

When a judicial authority determines that some individual needs to be confined in prison, be it while the trial is taking place or once the person is convicted, the decision on facility assignment falls on the corresponding regional director of INPEC, advised by a board that reviews the specific information for each case. The decision is taken on a one-by-one basis, driven by two main criteria.[27] First, on trial defendants should be in prisons located within the same judicial district where the case is.[28] Second, convicted individuals should be in prisons located within the same judicial district where the inmate's family lives. Transfers follow the same criteria.[29]

[25] See Roodman (2017) for a discussion on the identification strategies used in previous studies.

[26] See Di Tella and Schargrodsky (2013) for further details on the specific example.

[27] These criteria are specified in Law 65/1993, modified by Law 1709/2014.

[28] In principle, inmates on trial should go to either regional or municipal jails rather than national prisons. However, this does not happen as there is a large capacity deficit in regional and municipal jails. See Law 65/1993, modified by Law 1709/2014. Hence both inmates on trial or convicted are sent to national prisons.

[29] Some inmates are in prison while on trial. In this case, the assignment process usually meets the first criterion mechanically. In particular, a judicial authority—from where the case is—decides on the preventive confinement of the defendant. Then, the regional director of INPEC (in the same jurisdiction of the judicial authority) decides on the allocation to one of the prisons within that judicial district. After the verdict, prison authorities may transfer inmates to meet the second criteria if that was not the case. Inmates for which the two criteria match usually stay in the same prison since the arrest. Other inmates are free while the judicial process takes place. In this case, the assignment process usually meets the second criterion mechanically. After the verdict, convicted offenders go to a prison in the same judicial district where their families live.

Since all judicial districts have more than one prison and most prisons can house both low and high-risk individuals, several prisons meet the criteria for the allocation of a given inmate. In these situations, prison officials send inmates in small sequences to one prison and then to another on a rotating basis.[30] This happens within each judicial district in an independent process. The idea is to distribute inmates evenly so that no specific prison goes through extreme changes in their prison population in the short run.[31] On average, conditional on judicial district, I observe a sequence break every six inmates (i.e., every sixth inmate there is a change in the prison where inmates go). As a result of this informal rule, the place in line that each person occupies within a given judicial district determines their final allocation. Note this setting parallels a randomized control trial with block randomization. In this case, individuals are (quasi) randomly assigned to treatment within judicial districts. Hence, as I explain below, I use judicial district (block) fixed effects in all empirical applications.

5.2 Evidence on the quasi-random allocation process

The ten new prisons are in ten different judicial districts. Hence, in judicial districts with new prisons, regional directors of INPEC decide on the allocation of inmates to either one new prison or one of several old ones.

To provide evidence on the quasi-random allocation process I study whether breaks in each sequence seem to follow a pattern. To do this, I sort incarceration events chronologically within each judicial district and create an indicator variable for inmates breaking the

[30] In particular, I interviewed prison officials in Regional Noroeste and Regional Central. Regional Noroeste ranks third among regional offices of INPEC according to the prison population, while Regional Central is the largest one. In both cases, the argument pointed to the establishment of the same ad-hoc rules that were easy to follow and implement.

[31] Of course, there is always the possibility that some allocation decisions are deliberate. As prison officials report, this usually happens in two cases. First, inmates have specific health requirements and need to go to prisons that are close enough to a high complexity hospital. In these cases, inmates usually go to one of the prisons in large cities (all of which have more than one prison). Second, with high profile inmates. For instance, top leaders of criminal organizations could sometimes go to prisons outside their family region. The intention in such cases is to prevent their continuous involvement in organized crime activities. In these cases, inmates usually go to a prison in a large city outside their family region. When any of these situations happen, however, the allocation follows a similar quasi-random process in the new judicial district where the inmates go. Hence I do not expect this situation to introduce bias in the empirical analysis.

sequence, i.e., those inmates sent to a different prison than the previous inmate within the same judicial district.[32] I conduct two tests. On the one hand, I run a regression of the indicator variable for breaking the sequence on pre-incarceration characteristics and judicial district (block) fixed effects, and test the null hypothesis that the covariates do not jointly predict a sequence break. Table 3 presents the results using the universe of 74,050 incarceration episodes regardless of the legal situation of the inmates and whether the relevant period to observe recidivism is available. The p-value for the F test is not significant at conventional levels for any of the regressions. Also, with the only exception of the dummy variable for property crimes—which is marginally significant, observable pre-incarceration characteristics do not seem to be correlated with sequence breaks. In Appendix C.1 I replicate this test using the 14,962 incarceration episodes included in the main empirical analysis, where I use only cases for convicted inmates where I observe the recidivism outcome. Results are generally similar.

On the other hand, I compare observed characteristics between inmates who did not break the sequence and those who broke it. The comparison of means is presented in Table 4. Column (1) presents the unconditional mean for each observed characteristic for inmates who did not break the sequence. I want to make comparisons that take into account the level of quasi-randomization as well as observed pre-incarceration characteristics. One way to present this, following Aizer and Doyle (2013) and Di Tella and Schargrodsky (2013), is to include in column (2) the mean of the predicted values resulting from a regression of each characteristic on an indicator variable for breaking the sequence, judicial district (block) fixed effects, and the pre-incarceration fixed effects.[33] Column (3) presents the differences in levels and percentages, and column (4) presents the p-values of the differences. The sample includes all events regardless of the legal situation of the inmate or whether the

[32]When conducting these tests I include data on all incarceration events in the ten districts where the new prisons are located, regardless of the legal situation (convicted or not, released or not) or whether the relevant period to observe recidivism is available.

[33]In particular, I include fixed effects for family location, year of entry and the interaction between the location of the family and year of entry.

Table 3: OLS regressions: Effect of pre-incarceration characteristics on prison allocation decisions (N=74,050)

	Dependent variable: Inmate broke the sequence = 1		
	(1)	(2)	(3)
Recidivist = 1	0.006	0.006	0.005
	[0.004]	[0.004]	[0.004]
Violent crime = 1	0.008	0.007	0.007
	[0.005]	[0.005]	[0.005]
Property crime = 1	0.008	0.008*	0.008*
	[0.005]	[0.005]	[0.005]
Drug crime = 1	0.007	0.007	0.006
	[0.005]	[0.005]	[0.005]
Age at entry	-	0.0004	0.0007
		[0.0006]	[0.0006]
Age at entry ^{2}	-	-4.16e-6	-7.09e-6
		[7.18e-6]	[7.09e-6]
Primary education = 1	-	-	-0.006
			[0.007]
Secondary education = 1	-	-	-0.003
			[0.007]
Tertiary education = 1	-	-	-0.010
			[0.011]
Has minor children = 1	-	-	-0.005
			[0.006]
Family location FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes
Family location × Entry yr. FE	Yes	Yes	Yes
p-value of F test	0.393	0.521	0.367

Notes: OLS regressions. The dependent variable is an indicator that equals one if the inmate changed the sequence on prison assignment and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust standard errors are reported in brackets. The null hypothesis in the F tests that the reported covariates (excluding the fixed effects) do not jointly predict a sequence break. All regressions include a non-reported constant. The sample includes all incarceration episodes regardless of the legal situation (convicted or not, released or not) or whether the relevant period to observe recidivism is available.

Table 4: Comparison of means: Inmates who broke the sequence versus Inmates who did not (N=74,050)

Inmate characteristics	Did not break the sequence (1)	Broke the sequence (2)	Diff. (2)-(1) and (% change) (3)	p-value (4)
Pre-incarceration:				
Recidivist = 1	0.238	0.220	-0.018 (-8%)	0.123
Violent crime = 1	0.234	0.262	0.028 (12%)	0.641
Property crime = 1	0.740	0.657	-0.082 (-11%)	0.310
Drug crime = 1	0.143	0.189	0.046 (32%)	0.917
Age at entry	33.397	32.843	-0.554 (-2%)	0.871
Primary education = 1	0.590	0.617	0.027 (5%)	0.344
Secondary education = 1	0.331	0.308	-0.023 (-7%)	0.292
Tertiary education = 1	0.064	0.048	-0.016 (-26%)	0.591
Has minor children = 1	0.785	0.801	0.016 (2%)	0.373

Notes: Column (1) reports the predicted value from an OLS regression of each characteristic on an indicator variable for breaking the sequence, and fixed effects for: judicial district, family location, year of entry and the interaction between location of the family and year of entry. Column (2) reports the unconditional mean for inmates who broke the sequence (inmates who were sent to a different prison than the last incarcerated individual within the judicial district). Column (3) presents mean differences with percentage changes in parenthesis. Column (4) reports p-values for the indicator variable for breaking the sequence, with standard errors clustered at the sequence level (inmates sent to the same prison consecutively form a cluster). The sample includes all incarceration episodes regardless of the legal situation (convicted or not, released or not) or whether the relevant period to observe recidivism is available.

relevant period to observe recidivism is available. Observables are generally similar. I also replicate this test in Appendix C.1 using the 14,962 incarceration episodes included in the main empirical analysis (i.e., convicted inmates where I observe the recidivism outcome). Results are again broadly similar.[34]

[34] One additional (though rather implausible) threat would be if the government scheduled the construction and exact opening dates based on any characteristic of the transferred inmates. In Appendix C.2 I provide evidence ruling out this possibility.

5.3 Estimation and sample

To investigate the effects of prison conditions on recidivism, I estimate equation (5.1) using ordinary least squares (OLS):

$$Y_{id} = \beta^{OLS} N_{id} + \gamma_d + \Theta X_{id} + \varepsilon_{id} \tag{5.1}$$

where Y is the outcome for inmate i. N is an indicator variable that takes the value 1 if the inmate was in a new prison. γ is a vector of judicial district (block) fixed effects. X is a vector of controls and additional fixed effects that I vary to test the robustness of my results to different specifications. In general, X includes controls for the legal situation of the inmate, his criminal profile, age and days served in prison.[35] It also includes fixed effects for the family location, year of entry and release, and fixed effects for two interactions: family location and year of entry, and judicial district and year of release. ε is an error term. Note the specification allows me to control for factors such as social norms in the family region that may affect criminality, the criminal market where the inmate was released, or the ability of the criminal justice system in the year of release at the criminal market where the inmate was released, among other possible confounders. The coefficient of interest is β^{OLS}.

I restrict the analysis to the sample of inmates arrested after the construction program, allocated to either a new or an old prison. Columns (3) and (4) in Table 1 present summary statistics on all the observed characteristics of these inmates.[36] Note the sample shrinks from 74,050 to 14,962 inmates, as it only includes convicted males that served their time in one of the ten judicial districts where the new prisons are, who were incarcerated after the new prison in the judicial district opened. In particular, I consider those inmates for which the time frame between arrest and entry to the prison does not exceed one month, which is about

[35] Release dates may be affected by the treatment (which in this context is the assignment to a new prison) because inmates get time off for rehabilitative activities, and these are disproportionately available in new prisons as I show in Table 2.

[36] A few inmates were incarcerated more than once after the opening of the new prisons: 206 were in prison twice, and seven were in prison three times. For simplicity, I treat each incarceration event as if it were associated with a different inmate (i.e., each spell is treated as a separate incarceration event).

the average time an individual spends at police stations or temporary detention places before formal incarceration.[37] I focus on inmates in any of the ten judicial districts with new prisons that were incarcerated after the new prisons opened, as those have a positive probability of assignment to new prisons.

5.4 Results

Table 5 presents the results from estimating equation (5.1). The dependent variable is an indicator that takes the value 1 if the inmate returned to prison within one year after being released. The relevant independent variable that provides estimates for β^{OLS} is an indicator variable that takes the value 1 if the inmate was assigned to a new prison.

The coefficients are the differences in the probability of returning to prison between inmates assigned to new and old prisons, in percentage points. Column (1) includes all controls but no fixed effects. Column (2) adds judicial district (block) fixed effects and fixed effects for family location. Column (3) adds fixed effects for the year of entry and release, as well as the interactions between family location and year of entry, and judicial district and year of release. Generally, the results suggest a negative association between assignment to a new prison and the risk of returning to prison. The coefficient is negative and statistically significant at the 1% level in all regressions. In the fully specified regression reported in Column (3), the difference between inmates serving their sentence in new versus old prisons is 2.4 percentage points. Relative to the average risk of prison re-entry for the sample (see Table 1), the difference is equivalent to a reduction of 33%.[38]

[37]This information was provided in interviews with prison officials and confirmed in additional interviews with police agents from Bogotá and Medellín.

[38]See Appendix C.3 for further analyses on changes in the specification. In particular, I specify three alternatives. First, I include additional information on imprisonment and socio-economic characteristics of the inmates (e.g., being allowed supervised release at some point). Second, I change the outcome variable. Instead of using an indicator for returning to prison, I use an indicator for returning to prison and receiving a new conviction. Third, I include both convicted and non-convicted inmates in the sample (hence sample size almost doubles). The results are consistent with a negative association between prison conditions and recidivism.

Table 5: OLS regressions: Prison conditions and recidivism

	Dependent variable: Inmate returned to prison within 1 year = 1		
	(1)	(2)	(3)
Assigned to new prison = 1	-0.030***	-0.025***	-0.024***
	[0.005]	[0.007]	[0.007]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
District FE	No	Yes	Yes
Family location FE	No	Yes	Yes
Entry year FE	No	No	Yes
Release year FE	No	No	Yes
Family location × Entry yr. FE	No	No	Yes
District × Release yr. FE	No	No	Yes
Adjusted R2	0.122	0.123	0.127
Observations	14,962	14,962	14,962

Notes: OLS regressions. The dependent variable is an indicator that equals one if the inmate returned to prison within 1 year, and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Standard errors clustered at the sequence level in brackets (inmates sent to the same prison consecutively form a cluster). Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. All regressions include a non-reported constant.

5.5 Effect of prison conditions on recidivism over different time frames

I also examine the effect of prison conditions on recidivism using different time frames. This analysis has two purposes. First, to check the robustness of the baseline results to the ad hoc decision on the time frame of one year. As I discuss in Section 3, there is a trade-off in this decision. Less time implies a larger sample with less variation within the sample, and otherwise. Second, to see whether the effect of prison conditions on recidivism vary over time. I expect some differences due to the trade-off on sample and variation. In particular, it is implausible to observe any effect within just a few days. However, from the conceptual framework in Section 2, there can be different forces at play in the medium to long run. For instance, there could be some time frame within which an individual is willing to expect a legal job before turning back to crime.

Figure 2 reports the point estimates of β^{OLS} across 36 different regressions. Each case is equivalent to the regression results reported in Column (3) of Table 5, but I change the time frame to measure prison re-entry. Note that these time frames are cumulative. For instance, if an inmate returned to prison in month three, he would be counted as a recidivist from month three onwards. The x-axis reports the time frame and the sample size in each case. The y-axis measures the difference between inmates serving their sentence in new and old prisons, in percentage points. The lines for each coefficient denote 95% confidence intervals.

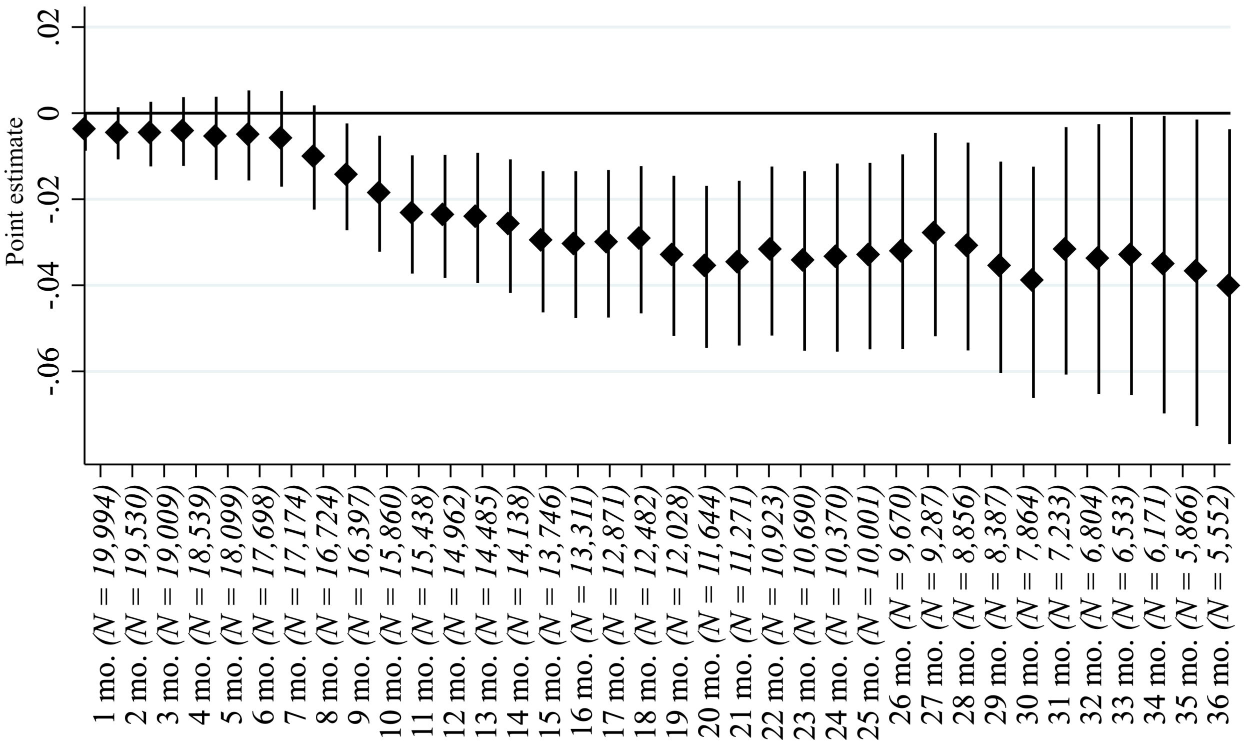
All the coefficients are negative. The results suggest the effect of prison conditions on recidivism is not different from zero over the first six months (something that could be explained by the lack of variation within the sample), then it increases for five months and remains relatively constant afterward. These results are consistent with an effect that is not transitory, which is merely affected by the lack of variation in the outcome within the first months. As expected, the decrease in sample size entails less precision (see how confidence intervals widen over time).

6 Effects of prison conditions on recidivism using instrumental variables

The selection process I illustrate in Section 5, alongside the empirical evidence supporting its quasi-randomness, suggest that a reasonable interpretation of the OLS estimate of β^{OLS} in equation (5.1) is that it is the causal effect of sending an inmate to a new prison on the risk of recidivism. Nonetheless, the setting allows me to explore a different local treatment effect using an instrumental variables approach.

Since the place in the line that an inmate occupies within the judicial district determines his prison assignment, the assignment of inmate $n-1$ to a new prison affects the assignment of inmate n. To the extent that inmate $n-1$'s location only affects recidivism of inmate n through the change in assignment probabilities, I instrument assignment to a new prison

Figure 2: The effect of prison conditions on recidivism for different time frames



Notes: The figure presents the point estimates for the ordinary least squares regression of an indicator variable that takes the value 1 if the inmate returned to prison after different time frames (each point estimate is for a different time frame measured in months, as noted in the labels on the x-axis), on a dummy variable for new prison, controls and fixed effects (see Section 5 for further details). The lines denote 95% confidence intervals.

with an indicator variable that takes the value 1 if the assignment of inmate $n-1$ corresponds to a new prison.

I explore the relevance of the instrument with the first stage presented in Table 6.[39] Columns (1) through (3) report the outcome of a regression of an indicator that takes the value 1 if the inmate was in a new prison on the instrument and a set of controls—which I vary across specifications. Overall, these results suggest that the instrument is highly correlated with the final assignment. In the complete specification that accounts for all controls and fixed effects, the probability of being assigned to a new prison if inmate $n-1$ in the same judicial district was in a new prison increases by 32 percentage points. The sample

[39]In the tests on the relevance and exogeneity of the instrument I use the actual sample I use in the analysis. This is, the 14,962 convicted inmates in the ten judicial district where the new prisons are located for which I observe at least one year after the inmate was released. See columns (3) and (4) in Table 1.

Table 6: OLS regressions: First stage for assignment to new prisons

	Dependent variable: Inmate was assigned to a new prison = 1		
	(1)	(2)	(3)
Last inmate in new prison = 1	0.636***	0.326***	0.319***
	[0.033]	[0.051]	[0.050]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
District (block) FE	No	Yes	Yes
Family location FE	No	Yes	Yes
Entry year FE	No	No	Yes
Release year FE	No	No	Yes
Family location × Entry yr. FE	No	No	Yes
District × Release yr. FE	No	No	Yes
Adjusted R2	0.469	0.654	0.666
Observations	14,962	14,962	14,962

Notes: OLS regressions. The dependent variable is an indicator that equals one if the inmate was assigned to a new prison, and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Standard errors clustered at the sequence level in brackets (inmates sent to the same prison consecutively form a cluster). Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. All regressions include a non-reported constant.

mean is 46%; hence the difference amounts to an increase of about 70%.

Regarding the exogeneity assumption, in principle, there is no reason to believe that there is a direct effect of the instrument (assignment of inmate $n-1$) on the risk of recidivism of the individual of interest (inmate n) in any other way than the shift in assignment probabilities. Perhaps the case that poses a major threat to the exclusion restriction is when, for instance, two individuals who know each other are arrested. However, even then, the probability of returning to prison for inmate n should be independent of the allocation decision taken by prison officials over the inmate $n - 1$. As an indirect test of the exclusion restriction, I compare observed characteristics between inmates whose predecessor was in an old prison and those whose predecessor was in a new prison. The comparison of means is presented in Table 7. Column (1) presents the unconditional mean for inmates whose predecessor was in an old prison. Column (2) presents the mean of the predicted values from a regression of each characteristic on the instrument, judicial district (block) fixed effects, and the pre-incarceration fixed effects.[40] Column (3) present the p-values of the differences. Again, observables are remarkably similar. These results suggest there is no effect of the instrument on observables, hence no effect on the dependent variable running through observables. Of course, I cannot test unobservables, but with observables being so similar there is no reason to believe that unobservables would pose a threat to the exclusion restriction.

Finally, the timing of the decision taken by prison officials on the allocation of inmates and the risk of recidivism make it unlikely for the dependent variable to have any reverse effect on the instrument.

6.1 Estimation and sample

To investigate the effects of prison conditions on recidivism using an instrumental variables approach I estimate equation (6.1):

$$Y_{id} = \beta^{IV} N_{id} + \gamma_i + \Theta X_{id} + \varepsilon_{id} \tag{6.1}$$

where I instrument N_i with an indicator variable that takes the value 1 if inmate $n-1$ incarcerated in the district was in a new prison. The sub-indices and controls are the same as in equation (5.1). The coefficient of interest is β^{IV}. Since the use of the instrument follows from the same setting and allocation decisions I describe in Section 5 for the OLS estimation, I use the same sample of 14,962 inmates for the IV estimation.

The institutional setting underlying the selection process and the use of the instrumental variable suggests the IV estimate also uncovers a causal relationship. The main difference is that β^{OLS} identifies the average treatment effect on the whole population of 14,962 inmates,

[40] As in other the comparison for inmates who did not break the sequence and those who did, I include family location, year of entry and the interaction between the location of the family and year of entry.

Table 7: Comparison of means: The previous inmate was in an old prison versus the previous inmate was in a new prison (N=14,962)

Inmate characteristics	The previous inmate to old prison (1)	The previous inmate to new prison (2)	Diff. (2)-(1) and (% change) (3)	p-value (4)
Pre-incarceration:				
Recidivist = 1	0.240	0.244	0.004 (2%)	0.242
Violent crime = 1	0.140	0.129	-0.011 (-8%)	0.449
Property crime = 1	0.770	0.700	-0.070 (-9%)	0.542
Drug crime = 1	0.114	0.200	0.086 (75%)	0.452
Age at entry	36.650	34.131	-2.519 (-7%)	0.524
Primary education = 1	0.598	0.621	0.023 (4%)	0.430
Secondary education = 1	0.316	0.301	-0.015 (-5%)	0.649
Tertiary education = 1	0.068	0.046	-0.022 (-32%)	0.459
Has minor children = 1	0.841	0.818	-0.023 (-3%)	0.749

Notes: Columns (1) reports the unconditional mean for individuals for which the inmate incarcerated before (within the judicial district) was sent to an old prison. Column (2) reports the predicted value from an OLS regression of each characteristic on the instrument and fixed effects for: judicial district, family location, year of entry and the interaction between location of the family and year of entry. Column (3) presents mean differences with percentage changes in parenthesis. Column (4) reports p-values for the indicator variable for breaking the sequence, with standard errors clustered at the sequence level (inmates sent to the same prison consecutively form a cluster).

while β^{IV} identifies the average treatment effect on the compliers—that is, inmates sent to new (old) prisons if and only if their predecessor was sent to a new (old) prison.

6.2 Results

Columns (1) through (3) in Table 8 present the baseline instrumental variables (IV) estimates. Column (1) includes all controls and no fixed effects. Column (2) adds judicial district (block) fixed effects and fixed effects for family location. Column (3) adds the rest of the fixed effects. The instrument is an indicator variable that takes the value 1 if inmate $n-1$ in the judicial district was in a new prison.

Again, the results point to a negative and statistically significant association between assignment to a new prison and the risk of recidivism. Importantly, the magnitudes are generally similar to the ordinary least squares estimates. In the complete specification reported in Column (3), the coefficient suggests that assignment to a new prison is associated with a decrease of 2.9 percentage points in the recidivism risk, or 40% relative to the sample mean. The coefficient is significant at the 5.7% level (p-value not reported in the table).[41] I interpret these estimates (see Subsection 6.1 for details) as a different local treatment effect than the one reported in Section 5.

7 Effects of prison conditions on recidivism using transfers

The prison construction program offers another opportunity to overcome the selection problem and identify a causal relationship between prison conditions and recidivism. When each of the ten new prisons opened, many inmates were simultaneously transferred from old to new prisons. These inmates had different amounts of time served upon transfer and their release was scheduled at different times. Hence they were exposed to different intensity levels of confinement in new prisons (relative to the total incarceration time). In this setting, it is possible to estimate the effect of a marginal increase in the share of prison time served in the new prison.

I examine the effects of prison conditions on recidivism using inmate transfers in Appendix D. Consistent with the previous specifications, the results suggest a negative association between the time served in a new prison and the risk of recidivism. In the fully specified regression reported in Column (3) of Table D.4.1, a one-standard deviation increase in the proportion of time served at a new prison is associated with a decrease of 1.4 percentage points in the risk of recidivism. The coefficient is marginally significant at conventional

[41] See Appendix C.4 for further analyses on changes in the specification for the instrumental variables strategy. These changes follow from the robustness analysis for the ordinary least squares estimates. First, I include additional information on imprisonment and socio-economic characteristics of the inmates. Second, I use re-conviction as the outcome variable. Finally, I include both convicted and non-convicted inmates in the sample. The results are also consistent with a negative association between prison conditions and recidivism.

Table 8: IV regressions: Prison conditions and recidivism

	Dependent variable: Inmate returned to prison within 1 year = 1		
	(1)	(2)	(3)
Assigned to new prison = 1	-0.030***	-0.029**	-0.029*
	[0.009]	[0.015]	[0.015]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
District (block) FE	No	Yes	Yes
Family location FE	No	Yes	Yes
Entry year FE	No	No	Yes
Release year FE	No	No	Yes
Family location × Entry yr. FE	No	No	Yes
District × Release yr. FE	No	No	Yes
Adjusted R2	0.122	0.123	0.127
Observations	14,962	14,962	14,962

Notes: IV regressions. The dependent variable is an indicator that equals 1 if the inmate returned to prison within one year, and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Assignment to a new prison is instrumented with a dummy variable that equals 1 if the last incarcerated inmate within the district was sent to a new prison. Standard errors clustered at the sequence level in brackets (inmates sent to the same prison consecutively form a cluster). Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. All regressions include a non-reported constant.

levels (the p-value is 0.065). Relative to the sample means (see Table D.1.1), an increase of 25 percentage points in the proportion of time served in a new prison is associated with a decrease of 16% in the risk of returning to prison within one year.[42]

8 Prison conditions, criminal contact, and rehabilitation programs

In the previous sections I use a reduced form estimation strategy to examine the relationship between prison conditions and recidivism. Since I can observe criminal contact of inmates

[42] See Appendix D.5 for further analyses on the robustness of these results on changes in the specification.

within prisons as well as enrollment in rehabilitation programs, in this section I focus on the identification of these specific mechanisms linking prison conditions with the extent of unsupervised criminal contact, as well as inmate participation in rehabilitation programs.

As I discuss in Section 2, criminal capital can increase recidivism (e.g., Bayer et al., 2007; Dooley et al., 2014; Drago and Galbiati, 2012; Lessing, 2017; Skarbek, 2012). Columns (1) and (2) of Table 9 examine the relationship between assignment to new prisons and the number of inmates that share the prison cell with each inmate at the moment of entry (or the short range criminal network). I build this measure using data on the specific prison cell that each inmate occupies. Note I do not observe this information for all 14,962 inmates included in the analysis of sections 5 and 6 but for 13,883.[43] Prison cells are relatively large spaces designed to host between 20 to 25 inmates, in general. In the sample of 13,883 inmates, the average number of inmates in the cell once an inmate enters prison is 63.

In Column (1) I estimate the effect of prison conditions on the size of the short range criminal network using ordinary least squares (leveraging solely on the plausible exogeneity of prison assignment as discussed in Section 5). The results suggest that, if an inmate is assigned to a new prison, the size of the short range criminal network decreases by almost 44 inmates, or 70% relative to the sample average. In Column (2) I estimate the effect of prison conditions on the short range criminal network using the instrumental variables strategy discussed in Section 6. The results suggest that assignment to new prisons is associated with a decrease of roughly 32 inmates in the short range criminal network (51% relative to the sample average). This latter result, however, is imprecisely estimated (the p-value is 0.195).

Moreover, as I argue in Section 2, enrollment in rehabilitation programs can also determine recidivism outcomes (e.g., Aizer and Doyle, 2013; Ehrlich, 1975; Grogger, 1995). Columns (3) and (4) of Table 9 examine the relationship between assignment to new prisons and an indicator variable for whether the inmate enrolled in a rehabilitation program. In

[43] This is a relatively large sample, hence I do not have reasons to believe that the data loss is correlated with assignment to new prisons. Indeed, if I run a regression of assignment to new prisons on data loss on the size of short range criminal networks, coefficient is 0.001 with a p-value of 0.936.

the relevant sample, roughly 60% of the inmates are enrolled in rehabilitation programs.

Generally, I find no significant association between assignment to new prisons and enrollment in rehabilitation programs. In Column (3) I estimate the effect of prison conditions on rehabilitation leveraging on the plausible exogeneity of prison assignment. In Column (4) I estimate this relationship using the instrumental variables strategy. Both results, however, are well above conventional levels of statistical significance. The magnitude of the OLS result is 3 percentage points or 5% relative to the sample average (the p-value is 0.243), and the magnitude of the IV result is 2 percentage points or 4% relative to the sample average (p-value of 0.688). Overall, these results favor the extent of unsupervised criminal contact—as opposed to the participation in rehabilitation programs—as the relevant channel that explains the link between less crowded and higher service facilities with recidivism outcomes.

9 Welfare analysis

Since better prison conditions imply the need for investments in infrastructure and committing to additional expenditures in security, management or rehabilitation personnel as well as other services, in this section, I introduce a back-of-the-envelope welfare analysis based on the previous work by Di Tella and Schargrodsky (2013). They compare prison with electronic monitoring. I compare new and old prisons, which proxy for prison quality.

As in their case, this analysis leaves aside potentially relevant aspects. For instance, the general benefits for a society that treats its inmates better, the externalities on the families of incarcerated offenders or victims, the wages from legal labor markets that former offenders would obtain if they decide not to continue their criminal activities or, importantly, the possible general deterrence effects of a harsher prison system.

Table 9: Mechanisms: Prison conditions, short range criminal network, and rehabilitation in enrollment programs

	DV: Size of short range criminal network		DV: Inmate is enrolled in rehab programs = 1	
	OLS strategy	IV strategy	OLS strategy	IV strategy
	(1)	(2)	(3)	(4)
Assigned to new prison = 1	-43.957***	-31.947	0.030	0.022
	[11.355]	[24.668]	[0.026]	[0.055]
Legal situation controls	Yes	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes	Yes
District (block) FE	Yes	Yes	Yes	Yes
Family location FE	Yes	Yes	Yes	Yes
Entry year FE	Yes	No	Yes	Yes
Release year FE	Yes	No	Yes	Yes
Family location × Entry yr. FE	Yes	No	Yes	Yes
District × Release yr. FE	Yes	No	Yes	Yes
Adjusted R2	0.650	0.649	0.396	0.396
Observations	13,883	13,883	14,962	14,962

Notes: OLS and IV regressions. In columns (1) and (2) the dependent variable is the number of inmates that share the cell with a specific inmate at the moment of entry. In columns (3) and (4) the dependent variable is an indicator for whether the inmate enrolled in rehabilitation programs. In columns (1) and (3) I run OLS regressions (see Section 5). In columns (2) and (4) I run IV regressions (see Section 6). * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Standard errors clustered at the sequence level in brackets (inmates sent to the same prison consecutively form a cluster). Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. All regressions include a non-reported constant.

9.1 A Simple Model

I start by defining the expected value of prison as $EV_i = -c_i - \delta r_i nK$, where $i = \{N, O\}$ denote a new or old prison, respectively. I define the expected value for two periods of different length. In the first period, the individual is in prison and in the second period he is released. The expected value of sending an inmate to prison depends on: (i) the fiscal cost of the prison slot and the services that need to be provided to the inmate during the first period (c_i); and (ii) a monetary equivalent of the cost of all crimes committed by the released offender during the second period ($\delta r_i nK$), where r_i is the proportion of inmates who recidivate, n is the average number of crimes committed per offender and K is the average social cost per crime, discounted by a factor δ.

The change in welfare for sending one individual to a new relative to an old prison is $\Delta W = EV_N - EV_O$. I assume that the fiscal cost of a prison slot is larger in a new prison and that the difference stems from a lump sum invested in the slot and larger maintenance expenditures. Hence the fiscal cost of a prison slot in a new prison could be defined as $c_N \equiv \theta + sc_O$, where θ is a lump sum invested in the prison slot, and $s > 1$ represents the larger cost for maintaining the infrastructure and providing services to the inmate in a new, relative to an old prison. For instance, θ could be the construction cost per slot (note I assume both the lump sum and the maintenance expenditures realize during the same period, for simplicity). I also define $\Delta r = r_N - r_O$ as the difference in the proportion of inmates in good versus bad prisons that recidivate.

Replacing for the expected values, the change in welfare is $\Delta W = -\theta + c_O (1 - s) - \delta (\Delta r) nK$. Note that Δr is equivalent to the difference in percentage points in the risk of recidivism for offenders confined to bad and good prison conditions.

9.2 Welfare Estimates

I focus on the ordinary least squares estimates (see Section 5.4). Hence the length of the first period is 453 days (see Table 1) and the length of the second period is 365 days (the time window that I use to measure recidivism). The length of both periods implies this is a short run welfare analysis (which makes any concern on possible general deterrence effects of a harsher prison system less relevant).

The parameter $\beta^{OLS} = -0.024$ I estimate in equation (5.1) is an empirical approximation of Δr (see column (3) of Table 5).[44] On the other components of the welfare change, I do the following. First, I approximate the lump sum investment for a new prison slot (θ) to \$582, which I obtain from the total construction cost of a prison slot under some simplifying assumptions (all prices in the welfare estimates are in 2017 U.S. dollars).[45] Second, I approximate the cost of maintenance and services for a prison slot in an old prison (c_O) to \$5,352 using data on the yearly budget on operation and maintenance from the National Prison System in Colombia before the new prisons opened.[46] Third, following Di Tella and Schargrodsky (2013), I assume a discount factor $\delta = 1$. Fourth, I approximate the average number of crimes committed by an offender (n) to 15, using the number of crimes committed per detected offender.[47] Fifth, I assume a prison slot in a new prison has a maintenance and operation budget that is 10% larger than the regular expenditures for a prison slot in an old prison, so that s is 1.1.[48]

[44] Note that β_1^{OLS} is an estimate of the difference in the detected recidivism rate rather than the true recidivism rate. For simplicity, I assume that both are equivalent, i.e., that the measurement error is the same for inmates serving time in either type of prison.

[45] To estimate this value, I take the total construction cost for each prison slot in the ten new prisons in Colombia, which is equivalent to \$24,241. To get the final number, I use a straight line depreciation formula over 50 years with no salvage value. Data on the original construction values are in Policy Brief 3575/2009.

[46] For details on the yearly budget on operation and maintenance from INPEC see this 2010 brief from the Ministry of Justice. I approximate the cost per slot by dividing the yearly budget by the average number of inmates in 2009 and then adjusting for 1.24 years. Note I cannot use current budgets because they are not desegregated by prison, and the aggregation includes both new and old prisons. Note also that I focus on the number of inmates rather than the number of actual prison slots to estimate the average cost per slot. I do this as the maintenance budget is mainly driven by the costs resulting from the inmate rather than an empty slot (e.g., food, water or health services).

[47] I use data for 2016 as a reference. The total number of reported crimes in 2016 was 1,077,183, of which 12,343 were homicides (including involuntary homicide). The average reporting rate in Colombia for 2016 was 29%; hence I adjust the number of crimes (except homicides) with the average reporting rate. The number of arrests in 2016 in Colombia was 260,541. Data on reported crimes and arrests are from the Annual Report from National Police. Data on the average reporting rate is from the Citizen Security Survey of the National Department of Statistics.

[48] There is no data available to make a precise estimation of the additional maintenance expenditures in new prisons. However, prison officials (from two different regional offices of INPEC that have both new and old prisons) suggested an approximately 10% difference.

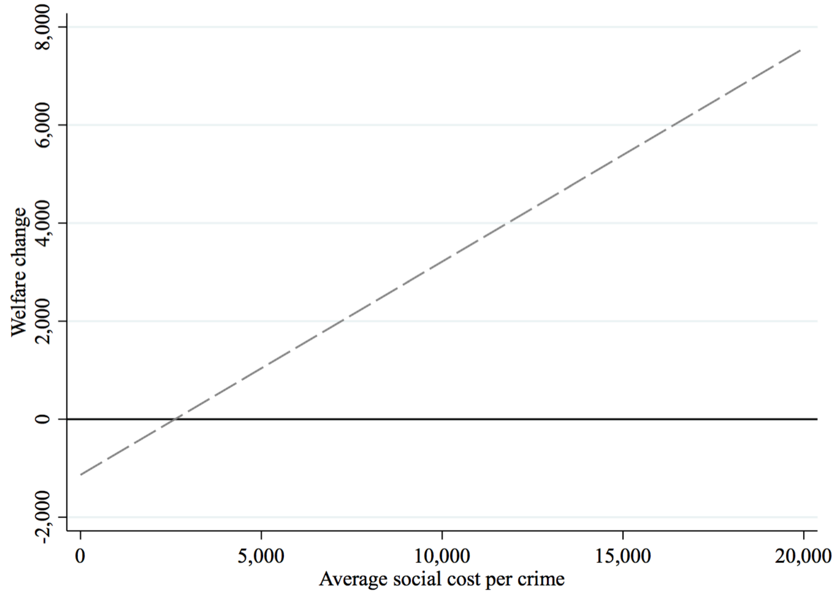
The final component to estimate the welfare change is the average cost per crime. Figure 3 depicts the welfare change for different values on the average cost per crime. It is straightforward to observe that, under the set of assumptions of this welfare analysis, the social gain for confining an inmate to a prison slot in a new prison becomes reasonably large as the average cost per crime grows. After about $3,150 per crime, the welfare gains become positive. Some estimates in the US for individual crimes suggest the cost of one homicide can be as high as $9 million and even nonviolent thefts have a social cost of about $8,000 (McCollister et al., 2010).[49] It is inherently impossible, however, to estimate a perfect monetary equivalent to the average social cost per crime for the specific setting I study. However, Table 1 provides some insights about the types of crimes potentially prevented. Column (3) presents summary statistics for the sample of inmates I use to estimate the effects of prison conditions on recidivism using ordinary least squares. About 13% committed violent crimes. It seems reasonable to conclude that, at least in the context of this prison construction program (and considering all the limitations of this analysis), the prison expansion program led to substantial welfare gains.

10 Discussion and conclusions

This study provides evidence that prison conditions affect postrelease criminal behavior, by showing that incarceration in lower quality prisons is associated with higher recidivism rates and more unsupervised criminal contact. In most of the world, many inmates suffer from underprovision of services such as surveillance or rehabilitation in overcrowded prisons. However, we have a limited understanding on how prison quality affects long-term inmate outcomes. The limited evidence results partly from identification challenges. For instance, prison quality is correlated with the strength of law enforcement agencies, hence simple comparisons between inmates assigned to prisons of different quality is subject to many endogeneity problems. I circumvent this problem by studying an extensive prison con-

[49]See also Anderson (1999), who estimates the aggregate burden of crime in the US to exceed $1 trillion (1997 US dollars) or more than 12% of the GDP.

Figure 3: Welfare change per prison slot



Notes: The figure depicts the relation between the average cost per crime in the horizontal axis (K) and the welfare change per prison slot in the vertical axis (ΔW). The exact equation is $\Delta W = -\theta + c_B\,(1-s) - \delta\,(\Delta r)\,nK$, where values for $\theta, c_B, s, \delta, \Delta r$ and n are defined in Section 9. All prices are in 2017 U.S. dollars.

struction program in Colombia that, given the institutional setting, led to the quasi-random assignment of inmates to new, less crowded and higher service prisons.

I find that the probability of returning to prison within one year for inmates assigned to new prisons is between 33 to 40% lower, relative to other inmates. The results statistically significant at conventional levels, and robust to a number of specifications and different identification strategies. The effects are not transitory. Indeed, the probability of returning to prison within three years for inmates assigned to new prisons is about 29%, relative to other inmates.

I also provide evidence suggesting that criminal capital may be the mechanism linking prison quality with recidivist behavior. More specifically, I find that inmates assigned to new prisons share their prison cell with fewer inmates. Moreover, I find no evidence of a difference in the probability of enrollment in rehabilitation programs for inmates assigned to new facilities. Overall, these findings bolster theories of criminal capital on the motives for criminal behavior.

These findings favor at least three different policy efforts. First, and more directly linked to the results, the construction of new prisons. Investing in additional prison infrastructure might potentially lead to substantial welfare gains. These gains depend, of course, on the type of crimes prevented as a result of the decrease in recidivism rates. These welfare gains grow with the prevention of more costly crimes. There are probably decreasing returns to investing in prison infrastructure, but it is still unknown over which ranges of variation. Second, and perhaps more generally, interventions aiming at the provision of improved services in prisons. These efforts may imply a wide range of actions directed at improving surveillance and space. Finally, a less costly way to provide better conditions to inmates is by releasing those with a lower recidivism risk. The ones that remain would enjoy better services. Kleinberg et al. (2018) provide insights on how to improve the selection process. This alternative is especially important in settings where budget constraints leave fewer policy levers for governments, or where institutions make it too difficult to implement broader changes in the prison system (as building new prisons).

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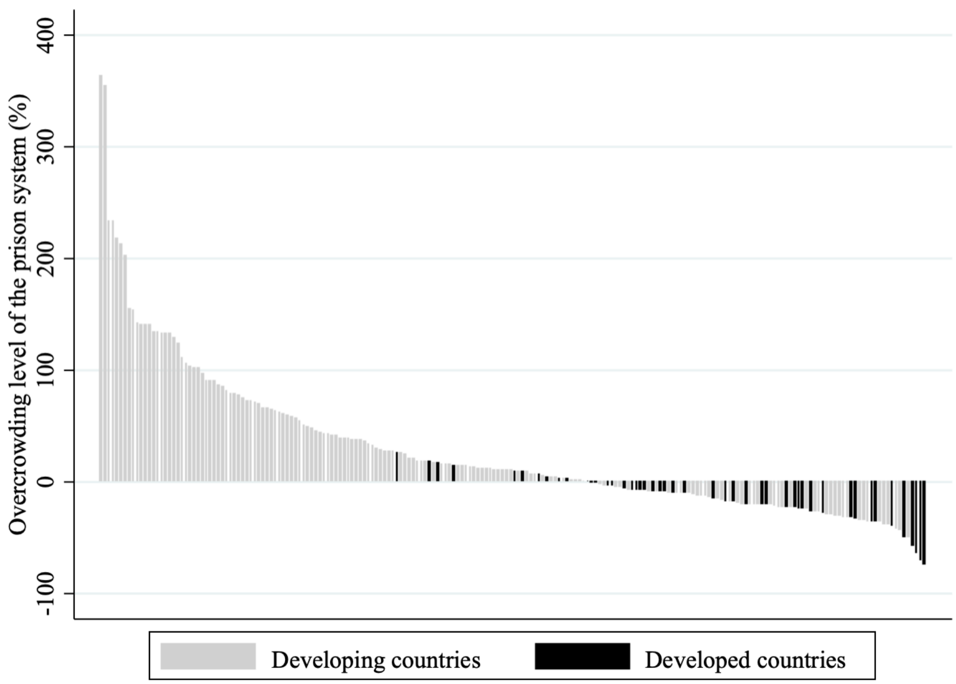
Appendix for online publication

A Data on prison overcrowding across countries

Figure A.1 illustrates prison quality for 204 countries around the world, proxied with the prison system overcrowding levels as estimated by Coyle et al. (2016). In approximately 60 percent of these countries the number of inmates exceeds the capacity of the prison system. As the figure illustrates, the problem is more pressing for developing countries as opposed to developed countries. On average, developed countries have free prison space, while developing countries have an overcrowding level of 40 percent.

Figure A.1: Prison overcrowding levels for 204 countries



Notes: The figure presents the overall overcrowding level of the prison system for 204 countries. An overcrowding level of exactly 0 implies that the prison system is at full capacity. Data on occupancy levels are from Coyle et al. (2016). Developed countries are those considered to be advanced economies by the International Monetary Fund in the World Economic Outlook.

B Formal model

This setup is based on occupational choice models with both legal and criminal sectors.[1] In this case, I focus on the occupational choice of an individual that has been released from prison.

The individual has a time endowment of $\overline{L}$ to split between l, b and h, that denote hours devoted to leisure, legal work or business and criminal activities, respectively. Legal business produces output according to a production function $F(\theta_t(\eta_{t-1}), b_t)$, where θ is productivity.[2] The individual's productivity in the current period is a function of prison quality in the previous period, represented by $\eta \geq 0$ (a larger η implies prison conditions are harsher). Prison quality could, for instance, determine access to rehabilitation programs in the form of education or job training, or opportunities to get treatment for drug abuse. Improvements in human capital by participating in these programs would increase productivity and the expected output from the legal sector.

Criminal activities produce output according to a production function $Q(\lambda_t(\eta_{t-1}), h_t)$, where λ is the extent of criminal capital (which entail criminal networks, contacts or skills, for instance). The individual's criminal capital in the current period also depends on prison quality in the previous period. For instance, if low quality implies more contact with other inmates—which can happen in overcrowded prisons—peer effects would improve the criminal network and skills of the individual.

Crime also entails a cost $\rho f_t(\eta_{t-1})h_{t-1}$, where ρ is the probability of apprehension and conviction, and $f_t(\eta_{t-1})h_{t-1}$ represents the penalty. The penalty is a linear function of criminal work in the previous period so that, for instance, more crime can imply a larger sentence. The penalty also depends on prison quality, as harsher conditions imply a more

[1] In particular, I adapt the class of models developed by Blattman et al. (2017) and Blattman and Annan (2016). See also Draca and Machin (2015) for a broader discussion of these models.

[2] Note I do not consider capital in the production function for two reasons. First, it is not necessary in the analysis. Second and perhaps more important, the labor market for former inmates in Colombia usually restricts to formal or informal activities that do not require any capital (as working in informal construction as a craftsman that works in construction).

severe punishment. Since the individual does not know exactly what prison conditions he would face if convicted, his best guess is prison quality experienced in the previous period.

Finally, the individual has a utility function $U(c_t, l_t, \sigma_t(\eta_{t-1})h_t)$, where c denotes consumption and $\sigma_t(\eta_{t-1})h_t$, with $\sigma > 0$, stands for a direct disutility from engaging in crime. As introduced by Blattman et al. (2017), this can be interpreted as shame or some other forms of social penalties or reciprocal behavior towards society. This parameter also depends on prison quality in the previous period. If prison quality was good, for instance, the parameter changes to reflect more cooperative reciprocal tendencies than otherwise. If prison quality was bad it may reflect a more retaliatory behavior than otherwise.

For the utility and production functions, I assume that $U'_c \geq 0, U'_l \geq 0, U'_{\sigma h} \leq 0, U''_{cc} < 0, U''_{ll} < 0, \partial^2 U/\partial h^2 \leq 0,\ F'_\theta \geq 0, F'_b \geq 0, F''_{\theta\theta} < 0, F''_{bb} < 0,\ F''_{\theta b} \geq 0,\ Q'_\lambda > 0, Q'_h > 0, Q''_{\lambda\lambda} < 0, Q''_{hh} < 0$ and $Q''_{\lambda h} \geq 0$. With respect to the individual's productivity, his criminal capital, the severity of punishment and the parameter on direct disutility from engaging in crime, I assume that $\theta' < 0, \theta'' < 0, \lambda' > 0, \lambda'' < 0, f' > 0, f'' < 0, \sigma' < 0, \sigma'' < 0$. For simplicity, I assume the individual has a discount factor between periods of $\delta > 0$.[3]

The individual's problem is:

$$
\begin{aligned}
\max_{c_t>0, l_t\geq 0, b_t \geq 0, h_t \geq 0} \quad & \sum_{t=0}^{\infty} \delta^t U(c_t, l_t, \sigma_t(\eta_{t-1})h_t) \\
\text{s.t.} \quad & c_t = F(\theta_t(\eta_{t-1}), b_t) + Q(\lambda_t(\eta_{t-1}), h_t) - \rho f_t(\eta_{t-1})h_{t-1},\ \forall t \\
& \overline{L} \equiv l_t + b_t + h_t,\ \forall t
\end{aligned}
$$

And the set of optimality conditions are:

[3]The main predictions remain unchanged when I assume the individual has quasi-hyperbolic preferences (β, δ), when I introduce financial markets with credit constraints or when I assume both quasi-hyperbolic preferences and financial markets with credit constraints simultaneously.

$$\frac{U_l'(t)}{U_c'(t)} = F_b'(t) \qquad \text{if } b_t > 0 \tag{B.1}$$

$$\frac{U_l'(t)}{U_c'(t)} - \sigma_t(\eta_{t-1})\frac{U_{\sigma h}'(t)}{U_c'(t)} = Q_h'(t) - \frac{U_c'(t+1)}{U_c'(t)}\rho f_{t+1}(\eta_t) \qquad if\, h_t > 0 \tag{B.2}$$

$$c_t = F(t) + Q(t) - \rho f_t(\eta_{t-1})h_{t-1} \tag{B.3}$$

where I use $U(t)$ to denote $U(c_t, l_t, \sigma_t(\eta_{t-1})h_t)$, $F(t)$ to denote $F(\theta_t(\eta_{t-1}), b_t)$ and $Q(t)$ to denote $Q(\lambda_t(\eta_{t-1}), h_t)$ for ease of notation.

As Blattman et al. (2017), I'm interested in the marginal conditions for engaging in each sector. To find those, I first consider the case where the criminal sector is not available. Note from the optimality condition (B.2) that the criminal sector has a discounted income associated with the probability of apprehension and the severity of punishment on the one hand, and the marginal rate of substitution between present and future consumption on the other hand. The criminal sector would not be available if this discount is large enough, so that $Q_h'(t) \ll U_c'(t+1)\rho f_{t+1}(\eta_t)/U_c'(t)$. In this scenario, the individual decides to engage in legal work depending on his levels of productivity. I denote consumption and labor in the legal business with $\hat{c}$ and $\hat{b}$ for this case. At each period t, the individual chooses $\hat{c}_t$ and $\hat{b}_t$ to satisfy $U_l'(\hat{c}_t, \overline{L} - \hat{b}_t, 0)/U_c'(\hat{c}_t, \overline{L} - \hat{b}_t, 0) = F_b'(\theta, \hat{b}_t)$. Hence, taking $\hat{c}$ and $\hat{b}$ as given, the individual will engage in the criminal sector if and only if:

$$Q_h'(t) - \frac{U_c'(t+1)}{U_c'(t)}\rho f_{t+1}(\eta_t) \geq \frac{U_l'(\hat{c}_t, \overline{L} - \hat{b}_t, 0)}{U_c'(\hat{c}_t, \overline{L} - \hat{b}_t, 0)} - \sigma_t(\eta_{t-1})\frac{U_{\sigma h}'(t)}{U_c'(t)} \tag{B.4}$$

which implies that the expected returns from crime (including both the marginal returns to time devoted to criminal activities and the discount) are higher than the highest possible marginal rate of substitution between leisure and consumption that the individual can obtain without engaging in crime. If the critical condition (B.4) is satisfied, then the individual will engage in both legal business and criminal activities, and will choose the levels b and h that meet conditions (B.1) and (B.2).

This setting outlines four mechanisms through which prison conditions would affect criminal involvement. Take for instance an increase in η, so that prison conditions are harsher. First, harsher conditions in the current period would induce an increase in the severity of punishment the individual expects in the next period. This would decrease hours devoted to crime. That is a specific deterrence mechanism. Second, harsher conditions in the current period would induce a decrease in productivity in the next period, hence the expected marginal returns to capital would be lower (and so the opportunity cost of crime would be lower) and time devoted to crime would increase. That is a human capital mechanism. Third, harsher conditions in the previous period would decrease the individual's direct disutility from engaging in crime, resulting in more hours devoted to the criminal sector. That is a reciprocities mechanism. Finally, harsher prison conditions would trigger a closer contact with peers, including affiliation with prison gangs, for instance. This would improve the individual's criminal network, resulting in more time devoted to crime. That is a criminal capital mechanism. Note the direction of these four mechanisms is different, hence the effect of an increase in η on criminal involvement is ambiguous and depends on the magnitude of the change for each specific mechanism.

C Additional data and robustness analyses

C.1 Additional balance tests

Table C.1.1 presents the results of a regressions of the indicator variable for breaking the sequence on pre-incarceration characteristics and fixed effects, and test the null hypothesis that the covariates do not jointly predict a sequence break. The sample includes the 14,962 incarceration episodes of the main analysis. These results suggest that sequence breaks do not seem to follow a pattern.

Table C.1.2 presents the comparison across observed characteristics between inmates who

Table C.1.1: OLS regressions: Effect of pre-incarceration characteristics on prison allocation decisions (N=14,962)

	Dependent variable: Inmate broke the sequence = 1		
	(1)	(2)	(3)
Recidivist = 1	0.010	0.010	0.009
	[0.007]	[0.007]	[0.007]
Violent crime = 1	-0.016	-0.016	-0.016
	[0.016]	[0.016]	[0.016]
Property crime = 1	-0.002	-0.002	-0.001
	[0.016]	[0.016]	[0.016]
Drug crime = 1	-0.015	-0.015	-0.016
	[0.016]	[0.016]	[0.016]
Age at entry	-	-0.001	-0.001
		[0.001]	[0.001]
Age at entry ^{2}	-	1.74e-5	1.22e-5
		[1.66e-5]	[1.68e-5]
Primary education = 1	-	-	0.003
			[0.014]
Secondary education = 1	-	-	0.005
			[0.015]
Tertiary education = 1	-	-	-0.017
			[0.019]
Has minor children = 1	-	-	-0.012
			[0.008]
Family location FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes
Family location × Entry yr. FE	Yes	Yes	Yes
p-value of F test	0.148	0.218	0.265

Notes: OLS regressions. The dependent variable is an indicator that equals one if the inmate changed the sequence on prison assignment and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust standard errors are reported in brackets. The null hypothesis in the F tests that the reported covariates (excluding the fixed effects) do not jointly predict a sequence break. All regressions include a non-reported constant. The sample includes all incarceration episodes regardless of the legal situation (convicted or not, released or not) or whether the relevant period to observe recidivism is available.

did not break the sequence and those who broke it. Column (1) presents the unconditional mean for each observed characteristic for inmates who did not break the sequence. Column (2) presents the mean of the predicted values resulting from a regression of each characteristic on an indicator variable for breaking the sequence, judicial district (block) fixed effects, and the pre-incarceration fixed effects.[4] Column (3) presents the differences in levels and percentages, and column (4) presents the p-values of the differences. The sample includes the 14,962 incarceration episodes of the main analysis. Again, these results generally suggest that sequence breaks do not seem to follow a specific pattern.

C.2 Additional evidence on the quasi-random allocation process

An additional—rather implausible—threat on the quasi-randomness of the selection process is related to the availability of new prisons in allocation decisions: When did the new prisons become available? Is it possible that the government scheduled the opening dates foreseeing a shock in the demand for prison slots? Could particular criminal profiles drive that shock? For instance, by inmates with a lower risk of recidivism? Official documents on the process suggest otherwise, as the construction schedule and the funding strategy were changed several times due to external factors. All prisons were initially scheduled to open in 2006, but the effective opening dates ranged from March 2010 through January 2013.[5] The reasons for rescheduling the construction program varied from case to case and included budget constraints, delays from public utility companies, problems with construction and environmental permits, and work delays because of intense rains in some regions.[6] Table

[4] In particular, I include fixed effects for family location, year of entry and the interaction between the location of the family and year of entry.

[5] The exact locations for new prisons were chosen based on the availability of government-owned land plots, the technical specifications of these plots and regional capacity deficits.

[6] The original construction and funding strategy was made public in March 2004 with a plan to build 21,200 prison slots. The plan suggested these new slots should be across regional offices of INPEC in order to cover current space deficits. The plan did not describe precisely where the new prisons were expected to open, but it did specify December 2006 as the expected date of operation for all. This plan was updated two times. First in 2006 and then in 2009. In March 2006 the government made public the final locations for 11 new prisons. Also, after realizing that the funding strategy was insufficient and the construction dates were unrealistic, the government updated both budgets and opening dates. In March 2009 the government

Table C.1.2: Comparison of means: Inmates who broke the sequence versus Inmates who did not (N=14,962)

Inmate characteristics	Did not break the sequence (1)	Broke the sequence (2)	Diff. (2)-(1) and (% change) (3)	p-value (4)
Pre-incarceration:				
Recidivist = 1	0.237	0.244	0.007 (-3%)	0.112
Violent crime = 1	0.115	0.137	0.022 (20%)	0.135
Property crime = 1	0.808	0.709	-0.099 (-12%)	0.029**
Drug crime = 1	0.098	0.183	0.085 (86%)	0.100
Age at entry	36.029	34.888	-1.140 (-3%)	0.567
Primary education = 1	0.592	0.616	0.024 (4%)	0.841
Secondary education = 1	0.330	0.302	-0.028 (-9%)	0.559
Tertiary education = 1	0.064	0.053	-0.011 (-17%)	0.156
Has minor children = 1	0.818	0.828	0.010 (1%)	0.189

Notes: Column (1) reports the predicted value from an OLS regression of each characteristic on an indicator variable for breaking the sequence, and fixed effects for: judicial district, family location, year of entry and the interaction between location of the family and year of entry. Column (2) reports the unconditional mean for inmates who broke the sequence (inmates who were sent to a different prison than the last incarcerated individual within the judicial district). Column (3) presents mean differences with percentage changes in parenthesis. Column (4) reports p-values for the indicator variable for breaking the sequence, with standard errors clustered at the sequence level (inmates sent to the same prison consecutively form a cluster). The sample includes all incarceration episodes regardless of the legal situation (convicted or not, released or not) or whether the relevant period to observe recidivism is available.

Table C.2.1: Scheduled and effective opening dates of new prisons

Prison	Original plan	2006 update	2009 update	Actual opening date
Florencia	December 2006	December 2007	December 2009	February 2011
Bogotá	December 2006	June 2008	June 2010	July 2011
Guaduas	December 2006	December 2007	May 2010	August 2011
Acacías	December 2006	December 2007	December 2009	May 2010
Yopal	December 2006	December 2007	August 2009	March 2010
Jamundí	December 2006	June 2008	February 2010	January 2013
Cúcuta	December 2006	December 2007	July 2009	January 2013
Medellín	December 2006	June 2008	August 2010	May 2011
Puerto Triunfo	December 2006	December 2007	October 2009	July 2010
Ibagué	December 2006	June 2008	April 2010	May 2011
Cartagena	December 2006	June 2008	August 2010	Not finished

Notes: All dates were published by the National Planning Department through three policy issues: Policy Brief 3277/2004, Policy Brief 3412/2006 and Policy Brief 3575/2009.

C.2.1 presents details on the original, updated and actual opening dates for each prison.

C.3 Robustness analyses (Ordinary least squares)

Table C.3.1 further examines the robustness of the ordinary least squares baseline results to different specifications. In column (1) I include additional information on imprisonment and socio-economic characteristics of the inmates (being allowed supervised release at some point, having minor children, and the educational attainment of the inmate). In column (2) I change the outcome variable. Instead of using an indicator for returning to prison, I use an indicator for returning to prison and receiving a new conviction. Finally, in column (3) I include both convicted and non-convicted inmates in the sample (note sample size almost doubles). All columns include the complete set of controls and fixed effects. The results are consistent with a negative association between prison conditions and recidivism.

argued that due to lack of fulfillment of technical specifications from public utility companies, delays with the issuing of construction permits from local authorities, delays with the issuing of environmental permits, and work delays because of intense rains in some regions, the construction plans had to be updated again. In the end, the Cartagena prison was not finished.

Table C.3.1: OLS regressions: Robustness for the effect of prison conditions on recidivism

	Additional socio-economic controls	Outcome is: receiving a new conviction	Sample includes non-convicted inmates
	(1)	(2)	(3)
Assigned to new prison = 1	-0.023***	-0.017**	-0.013***
	[0.007]	[0.007]	[0.004]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Family location FE	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes
Release year FE	Yes	Yes	Yes
Family location × Entry yr. FE	Yes	Yes	Yes
District × Release yr. FE	Yes	Yes	Yes
Adjusted R2	0.132	0.097	0.130
Observations	14,962	14,962	28,217

Notes: OLS regressions. The dependent variable is an indicator that equals one if the inmate returned to prison (in columns 1 and 3) or was reconvicted (in column 2) within 1 year, and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Standard errors clustered at the sequence level in brackets (inmates sent to the same prison consecutively form a cluster). Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. The additional socioeconomic controls in column (1) are indicator variables being allowed supervised release, having minor children, and finishing primary, secondary or tertiary education. All regressions include a non-reported constant.

C.4 Robustness analyses (Instrumental variables)

In Table C.4.1 I examine the robustness of the instrumental variables results by introducing changes in the specification, sample and outcome variables. Column (1) includes additional information on imprisonment and socio-economic characteristics of the inmates. In column (2) the dependent variable is an indicator variable for receiving a new conviction. In column (3) I include both convicted and non-convicted inmates in the sample. All columns include the full set of controls and fixed effects. In general, the main results remain unchanged—both direction and statistical significance. The only exception is in Column (2), where the outcome variable is an indicator for receiving a new conviction within one year after being released. This outcome mechanically entails less variation, as it not only implies returning to prison but receiving a new conviction. Hence the loss in precision is generally expected.

D Effects of prison conditions using transfers

D.1 Data

Table D.1.1 presents summary statistics on the sample of events where inmates were transferred from old to new prisons when the new prisons opened. Columns (1) and (2) describe the means and standard deviations, respectively. This is the set of eligible incarceration events where inmates were transferred, and I observe the post-incarceration year. About 21 percent of these inmates had a prior conviction, 36 percent had a current conviction for violent crimes, 62 percent for property crimes, and 23 percent for drug crimes. The average inmate served 1,694 days in prison, and 9 percent returned to prison within one year after release. On average these inmates served 38 percent of their time in a new prison.

Table C.4.1: IV regressions: Robustness for the effects of prison conditions on recidivism (*New Inmates-IV*)

	Additional socio-economic controls	Outcome is: receiving a new conviction	Sample includes non-convicted inmates
	(1)	(2)	(3)
Assigned to new prison = 1	-0.027*	-0.011	-0.019**
	[0.015]	[0.013]	[0.009]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Family location FE	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes
Release year FE	Yes	Yes	Yes
Family location × Entry yr. FE	Yes	Yes	Yes
District × Release yr. FE	Yes	Yes	Yes
Adjusted R2	0.132	0.097	0.130
Observations	14,962	14,962	28,217

Notes: IV regressions. The dependent variable is an indicator that equals 1 if the inmate returned to prison within one year, and zero otherwise, except in column (2) where the dependent variable is an indicator that equals 1 if the inmate received a new conviction. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Assignment to a new prison is instrumented with a dummy variable that equals 1 if the last incarcerated inmate within the district was sent to a new prison. Standard errors clustered at the sequence level in brackets (inmates sent to the same prison consecutively form a cluster). Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. The additional socioeconomic controls in column (1) are indicator variables being allowed supervised release, having minor children, and finishing primary, secondary or tertiary education. All regressions include a non-reported constant.

Table D.1.1: Summary statistics

	Sample of events in empirical analysis *(N=4,844)*	
	Mean	S.D.
Inmate characteristics	(1)	(2)
Pre-incarceration:		
Recidivist = 1	0.212	0.409
Violent crime = 1	0.357	0.479
Property crime = 1	0.616	0.486
Drug crime = 1	0.233	0.423
Age at entry	31.282	10.657
Primary education = 1	0.617	0.486
Secondary education = 1	0.314	0.464
Tertiary education = 1	0.025	0.155
Has minor children = 1	0.667	0.471
Post-incarceration:		
Age at release	35.929	10.768
Days served	1,694.310	983.918
Share of time served in new prison	0.380	0.246
Returned within 1 year = 1	0.090	0.287

Notes: Columns (1) and (2) report summary statistics for the sample of inmates incarcerated before the new prisons opened, that were transferred to the new prisons after. These are all convicted inmates, and for which the year after release is observable in the data.

D.2 Identification strategy

As I describe in Section ??, the prison construction program offers another opportunity to identify a causal relationship between prison conditions and recidivism. When the ten new prisons opened, many inmates were simultaneously transferred to them (and all where previously in old prisons). These inmates had different amounts of time served upon transfer and were scheduled for release at different times. This implies that, relative to total incarceration time, they were exposed to new prisons with different intensities. In this setting, it is possible to estimate the effect of a marginal increase in the share of prison time served in new prisons.

The identifying assumption to estimate a causal effect in this setting is that, conditional on the observed characteristics of the inmates and fixed effects, the relative exposure to better prison conditions is orthogonal to unobservables that affect the recidivism risk. For instance, if inmates with a low risk of recidivism were "rewarded" with an early transfer to a new prison—relative to their sentences, an estimate of the effect of exposure to new prisons on the probability of returning to prison would overestimate a negative association between serving time in severe prison conditions and recidivism (or underestimate a positive relation).

The empirical evidence suggests this is not the case. In particular, I follow a similar approach as Drago et al. (2009) and compare pre-incarceration characteristics between inmates who are below and above the median of the proportion of time spent in the new prison, relative to the overall incarceration period. Table D.2.1 presents the comparison of means. As in Section ??, I want to make comparisons that take into account observed pre-incarceration characteristics. Column (1) presents the unconditional mean for inmates whose proportion of time in the new prison falls below the median. Column (2) presents the mean of the predicted values from a regression of each characteristic on an indicator variable for being above the median, the total incarceration days and the pre-incarceration fixed effects.[7] Columns

[7]Note the variable I use to split the sample (proportion of time spent in the new prison) is potentially

Table D.2.1: Comparison of means: Inmates below and above the median of the proportion of time spent in the new prison

Inmate characteristics	Inmates below the median (1)	Inmates above the median (2)	Diff. (2)-(1) and (% change) (3)	p-value (4)	Obs. (5)
Pre-incarceration:					
Recidivist = 1	0.175	0.250	0.075 (43%)	0.005***	4,844
Violent crime = 1	0.446	0.268	-0.178 (-40%)	0.187	4,844
Property crime = 1	0.608	0.624	0.017 (3%)	0.629	4,844
Drug crime = 1	0.200	0.266	0.067 (33%)	0.049**	4,844
Age at entry	30.680	31.886	1.206 (4%)	0.194	4,844
Primary education = 1	0.612	0.621	0.009 (1%)	0.329	4,844
Secondary education = 1	0.320	0.309	-0.012 (-4%)	0.286	4,844
Tertiary education = 1	0.023	0.027	0.004 (19%)	0.474	4,844
Has minor children = 1	0.664	0.670	0.006 (1%)	0.292	4,844

Notes: Columns (1) reports the unconditional mean for inmates below the median of the proportion of time spent in the new prison, relative to the overall imprisonment period. Column (2) reports the predicted value from an OLS regression of each characteristic on an indicator variable for being above the median, total incarceration days and fixed effects for: prison, family location, year of entry and the interaction between location of the family and year of entry. Column (3) presents mean differences with percentage changes in parenthesis. Column (4) reports p-values for the indicator variable for being above the median, with robust standard errors. Column (5) reports sample sizes.

(3) and (4) present the p-values of the differences and the sample size, respectively. This comparison is equivalent to a pre-treatment balance test. Observables are generally similar, with two exceptions that are significant at conventional levels. On average, inmates who served a larger proportion of the sentence in a new prison had more prior convictions and more convictions for drug crimes in the current incarceration event. These differences, especially the difference in prior convictions, would bias the estimates positively (i.e., at baseline, inmates serving more time in new prisons seem to recidivate more).

affected by the opportunities to enroll in rehabilitation programs in new prisons. Hence I control for total incarceration days when I make these comparisons (and when I conduct the main analysis, as shown below in the estimating equation).

D.3 Estimation and sample

To examine the effects of prison conditions on recidivism using inmate transfers, I estimate equation (D.1) using ordinary least squares (OLS).

$$Y_i = \beta_1^T R_i + \Theta X_i + \varepsilon_i \tag{D.1}$$

where Y is the outcome for inmate i. R is the proportion of time spent by the inmate in the new prison, relative to the overall imprisonment period of that inmate. X is a vector of controls and fixed effects that I vary across specifications. In general, X includes controls for the legal situation of the inmate, his criminal profile, age and days served in prison; and fixed effects for the prison and family location, year of entry and release, as well as for two interactions: family location and year of entry, and prison and year of release.[8] ε is an error term. As in other specifications, the full set of fixed effects allows me to control for several factors. For instance, social norms in the family region, the criminal market where the inmate is arrested or released, or the ability of the criminal justice system in the year of arrest and release at the criminal market where the inmate is arrested or released, respectively. The coefficient of interest is β^T.

I restrict the analysis to the sample of inmates that were transferred when the new prisons opened, for whom I observe the post-incarceration year (see Table D.1.1).[9]

D.4 Results

Columns (1) through (3) in Table D.4.1 present the results from estimating equation (D.1). The dependent variable is an indicator that takes the value one if the inmate returned to prison within one year after being released. The relevant independent variable that provides

[8]Note that, in this case, the judicial district fixed effects are collinear with the prison fixed effects. This situation happens because the sample only includes inmates transferred to new prisons and each new prison is in a different judicial district.

[9]In particular, I consider inmates for which the time frame between the opening of the new prison and the transfer does not exceed one month, which is about the average time for the transfer logistics to be implemented. I received this information from prison officials at Regional Central and Regional Noroeste.

estimates for β^T is a z-score for the relative time served by the inmate in the new prison. The coefficients are the effects of a one-standard deviation increase in the proportion of total incarceration time served in a new prison. Column (1) includes all controls, but no fixed effects, Column (2) adds fixed effects for the family location and prison, and Column (6) adds all other fixed effects.

Generally, the results suggest a negative association between the time served in a new prison and the risk of recidivism. In the fully specified regression reported in Column (3), a one-standard deviation increase in the proportion of time served at a new prison is associated with a decrease of 1.4 percentage points in the risk of recidivism. The coefficient is marginally significant at conventional levels (the p-value is 0.065). In other words (see Table D.1.1 for the average recidivism risk and the standard deviation of the proportion of time served in a new prison), an increase of 25 percentage points in the proportion of time served in a new prison is associated with a decrease of 16 percent in the risk of returning to prison within one year.

D.5 Robustness analyses (Transferred inmates)

In Table D.5.1 I explore the robustness of the results using inmate transfers by introducing changes in the specification. Column (1) includes additional controls for the imprisonment conditions and socio-economic characteristics. In column (2) the dependent variable is an indicator variable for receiving a new conviction. In column (3) I include both convicted and non-convicted inmates. All columns include the full set of controls and fixed effects. The results generally point in the same direction, supporting the baseline findings. In Column (3), where I pool convicted and non-convicted inmates, I find a negative association but rather imprecise. One possible explanation is that non-convicted inmates add unnecessary noise to the measure of recidivism, as they may be entering and exiting the prison system while on-trial.

Table D.4.1: OLS regressions: Prison conditions and recidivism using inmate transfers

	Dependent variable: Inmate returned to prison within 1 year = 1		
	(1)	(2)	(3)
Relative time in new prison (z-score)	-0.009**	-0.008*	-0.014*
	[0.004]	[0.007]	[0.008]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
Family location FE	No	Yes	Yes
Prison FE	No	Yes	Yes
Entry year FE	No	No	Yes
Release year FE	No	No	Yes
Family location × Entry yr. FE	No	No	Yes
Prison × Release yr. FE	No	No	Yes
Adjusted R2	0.134	0.136	0.130
Observations	4,844	4,844	4,844

Notes: IV regressions. The dependent variable is an indicator that equals 1 if the inmate returned to prison within one year, and zero otherwise. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust standard errors reported in brackets. Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. All regressions include a non-reported constant.

Table D.5.1: OLS regressions: Robustness for the effects of prison conditions on recidivism using inmate transfers

	Additional socio-economic controls	Outcome is: receiving a new conviction	Sample includes non-convicted inmates
	(1)	(2)	(3)
Relative time in new prison (z-score)	-0.018**	-0.012*	-0.007
	[0.02]	[0.095]	[0.007]
Legal situation controls	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes
Age at release and time served	Yes	Yes	Yes
Family location FE	Yes	Yes	Yes
Prison FE	Yes	Yes	Yes
Entry year FE	Yes	Yes	Yes
Release year FE	Yes	Yes	Yes
Family location $\times$ Entry yr. FE	Yes	Yes	Yes
Prison $\times$ Release yr. FE	Yes	Yes	Yes
Adjusted R2	0.139	0.086	0.131
Observations	4,844	4,844	5,228

Notes: IV regressions. The dependent variable is an indicator that equals 1 if the inmate returned to prison within one year, and zero otherwise, except in column (2) where the dependent variable is an indicator that equals 1 if the inmate received a new conviction. * Significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust standard errors reported in brackets. Legal situation controls refer to the recidivist status. Crime controls are dummies for violent crime, property and calculation crime, and drug crime. The additional socioeconomic controls in column (1) are indicator variables being allowed supervised release, having minor children, and finishing primary, secondary or tertiary education. All regressions include a non-reported constant.

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