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ABSTRACT

Prison Work and Convict Rehabilitation[*]

I study the causal pathways that link prison work programs to convict rehabilitation, leveraging administrative data from Italy and combining quasi-experimental and structural econometric methods to achieve both a credible identification and the isolation of mechanisms. Due to competing channels, I find that work in unskilled prison jobs impacts convicts on longer or shorter terms differently. Increasing work time by 16 hours per month reduces by between 3 and 10 percentage points the reincarceration rate, within three years of release, of convicts on terms longer than six months – because prison work counteracts the rapid depreciation of earning ability experienced by these convicts. For those on shorter terms, the analogous increase leads instead to a re-incarceration rate that is up to 9 percentage points higher, because of a liquidity effect that weakens deterrence.

JEL Classification:	K42, J47
Keywords:	prison labor, prisoner rehabilitation, crime, recidivism, re-incarceration

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1 Introduction

Work programs for inmates under sentence are widespread, yet surprisingly little is known about whether or how these programs actually contribute to the rehabilitation of convicts. Although there is causal evidence regarding the effects of incarceration and prison conditions on recidivism (Chen and Shapiro, 2007, Cook et al., 2015, and Mueller-Smith, 2015 for the United States; Drago et al., 2011, and Mastrobuoni and Terlizzese, 2018, for Italy; Bhuller et al., 2020 for Norway) and some researchers have attempted to evaluate prison work programs (Maguire et al., 1988, Saylor and Gaes, 1997, Wilson et al., 2000, Bushway, 2003, Hopper, 2013, and Cox, 2016 for the US; Simon (1999) for Britain, Alós et al., 2015 for Spain; Gómez Baeza and Grau, 2017 for Chile), evidence for a causal impact and for pathways connecting prison work with rehabilitation remains elusive. Leveraging administrative data from Italy, I fill this research gap by adopting a dual-pronged empirical strategy that combines – in a mutually consistent way – a quasi-experimental approach, to achieve a credible identification, with structural econometrics to disentangle different effects.

Prison work consists of labor services provided by inmates during an incarceration term. Given the history in many countries of exploiting convict labor (e.g., Rubio, 2019) and of using work as a form of punishment, international principles were adopted after World War II to regulate the provision of such services. According to the United Nations' *Standard minimum rules for the treatment of prisoners*, first approved in 1957, all able inmates under sentence should work for pay in useful occupations – preferably in jobs created by the prison administration – that "must not be of an afflictive nature" so as "to keep prisoners actively employed for a normal working day" (United Nations, 1977, Article 71). These principles embody a threefold rationale that figures prominently in my analysis: (i) avoiding idleness and inactivity, which may favor criminogenic social interactions in prison (the *social effect* of prison work); (ii) earning money for oneself and one's dependents while incarcerated (the *liquidity effect*); and (iii) developing work habits and useful skills for a normal post-release life (the *training effect*).

Reality is far from these desiderata. Although prison work in most countries is formally organized in ways that implement the UN's *Standard minimum rules*, prison overcrowding and scarce funds for prison work programs typically result in the rationing

of work opportunities for inmates or in extremely low earnings (or both). According to the latest Census of State and Federal Correctional Facilities (U.S. Department of Justice, 2008), about 60% of inmates in US state prisons were participating in a work program at the end of 2005. These inmates earn hourly wages between $0.14 and $0.63 in regular prison jobs (compulsory institution work assignments), and between $0.33 and $1.41 in jobs at state-owned businesses. The corresponding rate for federal inmates ranges between $0.12 and $0.40.[1]

In Italy, hourly wages in prison jobs are much higher (currently about €7) and so work opportunities are more severely rationed because of the more stringent budget constraint faced by Italy's prison administration (as well as more prison overcrowding than in the United States). Statistics published by the Italian Department of Prison Administration (DPA) reveal that only 26.8% of inmates were employed in a prison job at the end of 2019, and the ratio of convict to prison jobs was 37.8% even though work is compulsory for all able convicts. Furthermore, just over 4% were participating in a training program. Hence, most inmates in Italy find prison time to be primarily idle time.[2] The re-incarceration rate – an important measure of convict rehabilitation – is correspondingly large. An analysis by Tagliaferro (2014) of flows in the DPA's inmates register indicates that about 33% of convicts (and 60% of all prisoners) had, at the end of 2014, been incarcerated in Italy before.[3]

Connecting these facts, in this paper I ask: Does replacing idle time with active time at work during custody reduce the re-incarceration rate? If so, why – but if not, then why not? An answer to these questions is required if we are to understand deterrence and convict rehabilitation policy, including the evaluation of whether prison work programs reduce future expenditures on enforcement, prosecution, and incarceration. The setting of my research is the Italian prison labor system, whose features provide me with the leverage needed to identify a causal effect. In order to maximize the number

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[1]See Sawyer (2017) and Federal Bureau of Prisons, work programs. Factory work programs managed by Federal Prison Industries pay higher wages in line with those at state-owned businesses, but they employ less than 10% of the federal prison population (Federal Prison Industries, Inc., 2017 Annual Report).

[2]In 2015 the Italian government implemented a reform of schooling programs in prison. As a result, in 2017/2018 about 20% of inmates were participating in a primary education program, about 10% in a secondary education program, and less than 2% in tertiary education (a convict may participate in both education and work programs). The post-reform period is outside the time frame of my sample.

[3]For the United States, Durose et al. (2014) report that 28.2% of inmates released from state prisons in 2005 received a new prison sentence within three years of release (49.7% if including technical violations; 36.2% if including jail sentences).

of convicts who work, prison wardens implement an elementary work-sharing mechanism: inmates "take turns" holding prison jobs. This mechanism has two components: (i) a deterministic (*de jure*) component, whereby the assignment order is legally tied to the duration of inmates' unemployment spells in prison; and (ii) a discretionary (*de facto*) component, whereby the warden can override the *de jure* ranking if certain convicts are deemed unreliable or unfit for work. Although this discretionary component complicates the analysis by introducing nonrandom variation in work shares, the deterministic component provides an instrument for such shares in a *within-cohort design*.

To understand this design, consider two inmates who belong to the same cohort – by which I mean that they were admitted to prison in the same year and were also released in the same year. These two inmates were admitted on two consecutive days and served an incarceration term of identical duration (so that they were also released in two consecutive days). Moreover, they were convicted for the same type of offenses, served their sentence in the same facilities, and have similar individual characteristics. Therefore, the fractions of the respective prison terms that these two inmates spent at work should also be similar. If this is not the case, then it is either (i) because one of them was admitted a day earlier than the other, thus acquiring (for essentially random reasons) higher *de jure* priority at any stage of a rotation process over imperfectly divisible work shifts; or (ii) because of the warden's discretion. My identification is based on the former account: the variation in work shares that is due to entry dates within cohorts of similar inmates who were incarcerated for the same time and who experienced similar prison conditions during the term. In principle, such an instrument allows for identifying the parameters of both the reduced-form model and the structural model.[4]

The empirical analysis exploits unique administrative data that contain the universe of about 125,000 convicts released from 209 correctional facilities in Italy between 2009 and 2012, hours worked and earnings from prison jobs, and post-release re-incarceration records for three years. At a first level of empirical analysis, I use two-stage least squares (2SLS) to identify the local average treatment effect (LATE) of prison work on the probability of being re-incarcerated following release, which applies to those who are not affected by warden's discretion (i.e., "compliers"). First-stage results confirm that the in-

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[4]Lewbel (2019) argues that "good reduced-form instruments are generally also good structural model instruments" (p. 862). A discussion of the integrated use of reduced-form and structural methods, as I pursue here, may also be found in Low and Meghir (2017).

struments generated by the deterministic component of the allocation mechanism have the expected effect. Second-stage results indicate that an increase of 1 standard deviation (SD) in average monthly hours spent working in a prison job (i.e., 16.6 hours per month in prison, which is tantamount to tripling the average work time of 8.4 hours) reduces the re-incarceration rate of ex-convicts who were imprisoned for at least six months by about 8–9 percentage points (p.p.) in the year after release – a persistent effect that increases to 10–11 p.p three years from the release date. Thus the re-incarceration rate of these ex-convicts would be reduced by a third within three years of release. A simple calculation shows that the short-term internal rate of return on marginal funds allocated to prison work programs implied by these estimates was *at least* 10.5% at the time to which the data refer, but is much lower at the current prison wage.

To put the magnitude of these effects into perspective, consider Mastrobuoni and Terlizzese's (2018) result that replacing one year spent in an ordinary prison in Italy with one year in an open-cell prison reduces the re-incarceration rate by 6 percentage points three years after release; or Bhuller et al.'s (2020) finding, for Norway, that imprisonment, in comparison with alternative sentences that lack a training component, reduces the likelihood of new criminal charges by 11 p.p. within five years of release. For convicts who spent less than six months in prison, I find instead a positive treatment effect: a 1-SD increase in average monthly hours spent working in a prison job during a short sentence *increases* the re-incarceration rate within three years of release by up to 9 p.p.

At a second, deeper level of analysis, I investigate underlying mechanisms by building and estimating a simple dynamic model of prison work and crime that enables me (a) to decompose the contribution of the liquidity, social, and training effects to the overall, reduced-form causal effects; (b) to explain the OLS–2SLS gap and treatment effect heterogeneity; and (c) to perform counterfactual policy experiments. After deriving the model's solution, I apply the generalized method of moments (GMM) to identify parameters directly, via the same orthogonality conditions that identify the reduced-form model's parameters. This approach to structural estimation allows me to provide a transparent identification and to obtain reduced-form and structural estimates that can be meaningfully compared. Simulating the model with the same policy shock implicitly used in the reduced-form analysis, I can estimate the average treatment effect (ATE), which turns out to be a reduction in the re-incarceration rate of about 3 p.p, within

three years of release. When restricting to plausible compliers, the model replicates the reduced-form LATE quite accurately. It is intriguing that, when I estimate the structural model via GMM using the OLS orthogonality conditions, the results are similar to those obtained via the 2SLS conditions. This similarity stands in sharp contrast to the reduced-form setting, where OLS and 2SLS estimates diverge considerably, and suggests that the OLS conditions contain sufficient identifying information in a *nonlinear* model. So, in the absence of (excluded) instrumental variables, structural estimation would have been well suited to reveal the causal effect of prison work on re-incarceration.

I use the model to decompose this effect, and establish that, for convicts on sentences longer than six months, the training effect accounts for virtually all of the rehabilitating impact of prison work because it counteracts the fast depreciation of expected labor market earnings during custody. The social effect is also a contributor but has little relevance. And the liquidity effect goes in the opposite direction; that is, it favors re-incarceration by increasing the value of being in prison relative to being free – thereby weakening deterrence. The primacy of the training effect revealed by this mechanism decomposition is consistent with Bhuller et al. (2020), who find that the positive effect of incarceration on rehabilitation in Norway is driven by inmates who were not employed prior to incarceration, as well as with a large literature (reviewed in Chalfin and McCrary, 2017) that documents how the larger expected earnings induced by less labor market tightness or higher wages tend to exert a deterrent effect. Among more recent contributions, Yang (2017), Agan and Makowsky (2018), Siwach (2018), and Schnepel (2018) report large-scale evidence from the US that higher wages or more job opportunities appreciably reduce the likelihood of returning to prison. Finally, the training effect's leading role is consistent with evidence from randomized employment-oriented prisoner reentry programs (Redcross et al., 2012; Cook et al., 2015), a context in which the social effect is absent and the liquidity effect is limited. For convicts on short incarceration spells, I find instead that the liquidity effect drives a detrimental effect of prison work and that the social and training effects are statistically insignificant.

My results imply that the mandatory prison work programs adopted in Italy (and elsewhere) could be quite effective for inmates who are removed from society for a sufficiently long time but not for those on short sentences. However, my analysis also suggests that the optimal prison work program does *not* feature the relatively high wage

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rate currently observed in Italy.[5] In addition, the self-productivity of labor market and criminal skills implies that the optimal program assigns new convicts to work as soon as possible, which is at odds with Italy's current waiting list-system. Counterfactual policy experiments illustrate these points.

This paper makes both an empirical and a methodological contribution. The *empirical* contribution consists of using new administrative data to study a research question that is new in economics; in criminology, the question is not new but does not have a satisfactory answer yet. There are notable gaps in the study of training and work programs as rehabilitation tools, and I aim to fill them. In reviews of research addressing reentry, deterrence, and desistance from crime, Raphael (2011), Chalfin and McCrary (2017), and Doleac (2019) discuss econometrically identified studies of work and income support programs offered *after* release; however, analogous studies of work programs during custody are not mentioned. I am aware of only indirect causal evidence that prison work improves post-release outcomes. The aforementioned studies by Mastrobuoni and Terlizzese (2018) and Bhuller et al. (2020) focus on, respectively, a model prison in Italy and the Norwegian prison system, where work and training opportunities are at center stage in the rehabilitation process and are available to most inmates. However, those contexts are special in many respects and facilitate rehabilitation via a bundle of favorable prison conditions, of which work is just one component. In this sense they offer only indirect evidence.

Some attempts have been made to obtain direct causal evidence by using an instrumental variables strategy: Hopper (2013) studies the Prison Industry Enhancement Certification Program in Indiana and Tennessee, and Gómez Baeza and Grau (2017) examine the Chilean prison labor system. In both cases the instrument is based on the prisons where an inmate served his sentence.[6] Despite such prisons being determined solely by the crime's location, this identification is problematic because – even if one assumes that crimes are committed in random locations – the particular prison where one is incarcerated affects rehabilitation in many ways and not only through prison work (a

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[5]This conclusion is consistent with Polinsky's (2017) analysis of a static economic model of deterrence via prison work. The optimal mandatory work program actually features *zero* compensation because the absence of earnings maximizes the deterrent effect of incarceration.

[6]Since prison populations consist almost entirely of men and since female prisoners are excluded from my analysis (see Section 3), masculine pronouns are used (throughout) when referring to individual prisoners. I will instead use feminine pronouns when referring to a prison warden.

case in point is the open-cell prison studied by Mastrobuoni and Terlizzese, 2018). An additional complication highlighted by my analysis is that the LATE and the ATE may differ. Also, none of these studies offers an explicit theoretical framework that could be used to decompose the contribution of different mechanisms.

Empirical research in criminology has investigated prison labor programs extensively, but these studies typically lack a research design capable of establishing causality. Assignment to prison work is highly selective. Wilson et al. (2000) undertake a meta-analysis of more than 30 studies in the United States, and find that, when researchers attempt to correct for selection-bias, the correlations are substantially altered. However, like in Saylor and Gaes's (1997) evaluation of the Post-Release Employment Program (PREP) in the US, such correction relies on observables (unconfoundedness assumption). A subsequent review by Bushway (2003) and more recent work by Alós et al. (2015) are similarly inconclusive from a causal viewpoint.

My *methodological* contribution consists of demonstrating empirically that, in the absence of quasi-experimental variation, structural empirical analysis can go a long way toward identifying causal effects – an exercise in the spirit of LaLonde (1986). Moreover, by combining reduced-form and structural methods I can both identify the causal effect of prison work and perform a mechanism decomposition. There is no conflict between the two methods. Low and Meghir (2017) discuss the advantages of an empirical methodology that validates a structural model by comparing its predictions to reduced-form estimates derived from experimental variations. My structural and reduced-form estimates are connected in an even stronger sense because there is an *exact* correspondence (up to the difference between structural and reduced-form errors) between the respective identification conditions: the different versions of the method of moments that I use in these cases are based on the same moment conditions. Lewbel (2019) provides an excellent discussion of how combining the best features of causal and structural methods allows researchers to compensate for the shortcomings of each approach.

The rest of this paper proceeds as follows. Section 2 describes the Italian prison labor system and illustrates how its features can be exploited to identify the causal effect of prison work on re-incarceration. The data are presented in Section 3. I carry out the empirical analysis in Section 4 at the reduced-form level and in Section 5 at the structural level. Taking stock of the results, Section 6 concludes.

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2 Institutional setting and research design

2.1 The Italian prison labor system

Prison work in Italy is regulated by the Penitentiary Code (PC), a set of norms that govern the organization and functioning of correctional facilities as well as incarceration alternatives such as community service and house arrest.[7] The PC stipulates that work is compulsory for all convicts (i.e., for all inmates with a final guilty verdict), and work can be refused by an inmate only for health reasons approved by the prison warden.

Types of jobs: Two types of jobs are available for convicts. The first are jobs created directly by the DPA, which I refer to as *prison jobs*. These account for about 85% of all work positions held by inmates, all convicts are eligible for them, and they are the focus of this paper. The vast majority of prison jobs (about 90% of the total) consist of unskilled jobs for daily prison functioning and upkeeping – referred to as "domestic jobs" – such as cleaning, doing the laundry, cooking and serving food, personal assistance, shopping and delivering, and ordinary maintenance of the prison building. All newly admitted inmates receive basic training to perform any of these tasks, in expectation of assignment to a domestic job at some point in the incarceration term. About 5% of prison jobs are more skilled and originate mainly from small manufacturing activities managed directly by the DPA with the primary purpose of serving correctional facilities; examples include carpentry, typography, blacksmithing, weaving, tailoring, and shoemaking. Finally, about 3% of prison jobs originate at prison farms, and a residual minority of inmates are employed by the DPA at external jobs.[8] Because most prison jobs consist of low-ability tasks, they contribute little to labor market skills strictly defined. However, I shall argue that such jobs might contribute greatly to so-called soft labor market skills and to mental health. The second type of jobs are *external jobs* created by private-sector employers and performed by convicts either inside or outside the prison. This work accounts for the remaining 15% of inmates' jobs. Only a highly selected minority of convicts are eligible for external jobs so I do not consider them in the analysis.

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[7]"Penitentiary Code" is my translation of *Ordinamento Penitenziario*

[8]These figures refer to averages between 2000 and 2019 and are calculated by the author using statistics published by the DPA at the Italian Ministry of Justice website.

Earnings: According to the PC, prison work should mimic an ordinary employment relationship. This means, in particular, that all employed inmates must receive monetary compensation. For prison jobs, the wage rate is set by a committee appointed by the DPA, and it must be at least two thirds of the compensation determined by national collective agreements for the corresponding occupation. The real wage for prison jobs has been sharply reduced between 1995 and 2017 because the committee never met in this period after fixing, in 1994, nominal hourly wages that averaged €3.5. In October 2017, new wage rates averaging about €7 came into effect. Each year, the Italian Ministry of Justice allocates financial resources to the total wage fund for prison jobs; the DPA then splits that fund among correctional facilities in proportions determined by the number of convicts held in each facility. The total wage fund in fiscal year 2019 was about €110 million (see Figure 1).

For external jobs, in contrast, employers pay the full market wage rate. However, since fiscal year 2000 they have received a tax credit and an 80% reduction in the social security contributions they must make for each hired convict. As much as two thirds of a convict's earnings (from either prison or external jobs) can be withheld by the DPA to pay for personal maintenance costs in prison and outstanding debts related to compensating victims and other legal expenses. The maintenance cost (which is set by the Ministry of Justice) is currently about €6 per day, but exemptions are often granted in consideration of economic conditions and good behavior. A convict's net earnings are paid into a prison-based personal account, which yields modest interest, that he can use to purchase consumption goods at the prison's outlet (extra food, typically) or to transfer money to dependents. Upon release, the prisoner cashes in his outstanding balance.

Job scarcity: The DPA is required by the PC to ensure all convicts a job as part of their rehabilitation. However, this is a nonbinding provision because the PC conditions this requirement with an "unless otherwise impossible" exception. In practice, an impossibility arises because the two thirds wage floor (relative to market wages) renders the aggregate wage fund for prison jobs insufficient to employ all convicts; hence work opportunities are strictly rationed. As shown in Figure 1, the number of prison jobs per convict normally ranged between 0.3 and 0.4 between 2000 and 2019.[9] The figure also

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[9]The 2006/2007 "blip" in this trend reflects a collective pardon that led to the early release of more than half of all convicts.

shows that the number of prison jobs per convict is directly affected by the total wage fund earmarked by the government. The reason is that prison wardens cannot transfer any part of a prison's share of the wage fund across fiscal years. This fact is critical to understanding the identification logic that I illustrate. Finally, Figure 1 indicates that the average external job/convict ratio was less than 0.07 between 2000 and 2019.

Figure 1: Jobs per convict and total wage fund
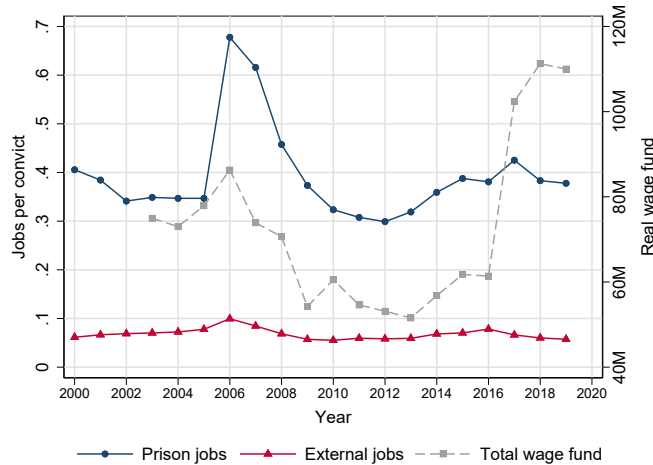
Notes: This figure plots the ratio between the number of prison jobs (offered by the DPA and performed by inmates inside correctional facilities) or external jobs (offered by private-sector employers and performed either inside or outside prison) and the number of convicts (inmates with a final guilty verdict) in Italian correctional facilities between 2000 and 2019; also reported is the total annual wage fund for prison jobs (in millions of euros at 2019 prices). *Source*: Author calculations from statistics published by the DPA.

Assignment to scarce jobs: Inmates assigned to external jobs are selected by prison wardens and employers in a highly discretionary manner that reflects the special nature of this type of prison labor. Yet for prison jobs the PC set up a rationing mechanism by establishing four priority criteria that prison wardens must apply when assigning inmates to work: (i) the duration of the unemployment spell during custody; (ii) the presence of dependents; (iii) an inmate's skills and experience; and (iv) the work activity that an inmate may undertake upon release. In practice, the first criterion is given the most weight because it is the only objective rule on the list. Information about dependents, skills, and experience is self-reported and therefore difficult to verify, especially in the case of foreign-born inmates. So in order to avoid unfair treatment, these priority criteria are rarely applied by prison wardens; hence the duration of the unemployment spell while in custody is the criterion on which this rationing mechanism pivots – a mechanism that consists of a simple work-sharing system. The common practice is to

place new convicts at the bottom of a waiting list and to assign them a temporary prison job (typically for a few weeks) when their turn comes. At the end of that work period, they are placed back at the bottom of the waiting list and the process starts over.[10] The waiting list is determined by a ranking that reflects the number of days a prisoner has been jobless. Inmates who are in a longer unemployment spell (either because they were never assigned to a prison job since being admitted to prison or because they were last assigned to a prison job long before) are ranked higher. Given this ranking, the assignment mechanism has two components: a deterministic (*de jure*) component, whereby the warden simply follows the order determined by the ranking; and a discretionary (*de facto*) component whereby the ranking can be overridden if, for instance, the warden deems a convict to be unreliable, unfit for work owing to mental or physical conditions, or already busy in other activities such as employment at external jobs.

2.2 The identification problem and its solution

The assignment mechanism's *discretionary* component is the source of the identification problem when one seeks to establish a causal relation between prison work and convict rehabilitation. More specifically, the time spent at work during an incarceration term reflects unobserved individual characteristics that are probably correlated with the unobserved (to the econometrician) propensity to re-engage in criminal activities after release. However, the *deterministic* component of the assignment mechanism offers a solution. Recall that the wage fund for prison jobs is allocated to correctional facilities at the beginning of every fiscal year and must be spent by wardens before the end of that period. It follows (absent warden discretion) that if two inmates entered the same prison in the same year for an incarceration term of identical duration, then the one who was admitted earlier will always have higher priority in assignment to work at any stage of the rotation process and so will spend a larger fraction of the prison term working. Thus, within data cells defined in terms of entry-by-release years ("cohorts") and if the days spent in prison are kept constant, differences in work time must reflect either war-

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[10]This practice was acknowledged and endorsed in a 2016 Report of the Minister of Justice: "Prison wardens, in order to maintain a sufficient level of employment among inmates, tend to reduce working hours per inmate and to implement turnover. Ensuring work opportunities to inmates is strategically important . . . to limit and manage the hardships of prison life, tensions, and protests." (p. 5, my translation from *Relazione sullo svolgimento da parte dei detenuti di attività lavorative o di corsi di formazione professionale*).

den discretion or entry dates. The latter are determined by the timing of apprehension and judicial decisions and so they reflect *only* the timing of arrest and the duration of the judicial procedure. I therefore claim that entry dates can be viewed as randomly assigned within cohorts, which yields an exogenous source of variation in the share of the incarceration term that a convict spent at work.

The examples in Figure 2 illustrate this logic by considering a facility that offers one prison job. This position is divided into quarterly work shifts, and a convict is assigned to a shift based on a ranking determined by his number of days spent in prison without working. Assume that the warden does not override this ranking. In the figure's Example 1, convict A is the only prisoner at the beginning of year 1 and so is assigned to that year's first work shift. During the year's first quarter (q1:**1**), convicts B and C join the prison in two consecutive weeks and form a job waiting list in that order. When A's turn is over, he is placed at the bottom of the waiting list and B is assigned to the job. The rotation process continues until B and C are released – again in two consecutive weeks – at the beginning of the second quarter of year 2, after spending an equal number of days (4.5 quarters) in prison. Convicts B and C constitute *cohort 1,2* (admitted in year 1, released in year 2), and the convict admitted even a short time earlier ends up working more than the other. In this example, an inmate is not assigned to a job in the quarter during which he is due for release (I will later show that this assumption is supported by the data); however, the conclusion would be the same if a shift could be divided further. The key point is that convict B has an advantage over C at any assignment point (unless B has just completed a work shift, as at the end of q2:**1**) and so ends up working more.

Consider next the slightly more complex situation in Example 2, where there are two cohorts. Convicts A and F belong to cohort 0,2 and convicts B, C, D and E belong to cohort 1,2. Within each cohort, inmates spend an equal number of days in prison (7 quarters for cohort 0,2; 3.5 quarters for cohort 1,2). In cohort 0,2, convict A was admitted earlier than F and thus ends up working three shifts while F works only two. In cohort 1,2, convicts B and C similarly work one shift each while D and E never work because they never reach the top of the waiting list during the their respective terms of incarceration. So within cohorts, convicts who were admitted earlier work some fraction of their incarceration terms that is no smaller – and possibly larger – than the corresponding fraction for convicts admitted later.

Figure 2: Prison job rotation and the within-cohort design
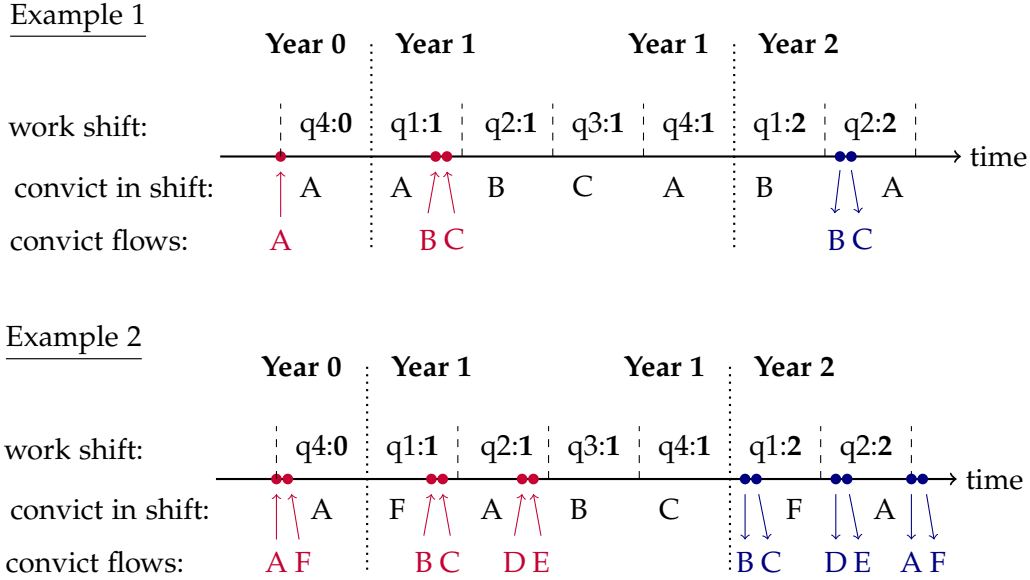
Notes: This figure illustrates a correctional facility that offers one prison job divided into quarterly work shifts. Inward- and outward-pointing arrows represent prison admissions (inflows) and releases (outflows), respectively. Convicts take turns working, in an order determined by the unemployment spell's duration at the start of each quarter (longer duration translates into higher priority). An inmate is not assigned to a job in the quarter when he is due for release. In Example 1, convicts B and C form cohort $1, 2$ (admitted in year 1, released in year 2); in Example 2 convicts A and F form cohort $0, 2$ while B, C, D and E form cohort $1, 2$. Within each cohort, prison terms have the same duration, and those admitted earlier tend to work more than do those admitted later.

This mechanism's footprints are clearly visible in the data. Using the universe of convicts released between 2009 and 2012 from all Italian prisons (as Section 3 describes in more detail), I report in Figure 3 the within-cohort effect of entry week on the monthly hours in a prison job during an incarceration term – along with the associated 95% confidence interval. That effect is estimated by way of the following regression model,

$$H_{i,I,O,\mathbf{p}} = \alpha_H + \sum_{w=1}^{51} \beta_w Z_{i,w} + \gamma_H D_i + \tilde{\delta}_I + \tilde{\delta}_O + \tilde{\delta}_{I,O} + \tilde{\delta}_{\mathbf{p}} + \varepsilon_i. \tag{1}$$

Here $H_{i,I,O,\mathbf{p}}$ is the average number of monthly hours spent working at a prison job during the term by inmate i, who was admitted to prison in year I, was released in year O (i.e., belongs to the I, O cohort), and served his sentence in prison $\mathbf{p}$ (possibly a set of different facilities). On the right-hand side (RHS) of equation (1), $Z_{i,w}$ is a dummy variable that is equal to 1 if i was admitted to prison in week w of year I (and set to 0 otherwise), D_i is the duration of the incarceration term in days, $\tilde{\delta}_I + \tilde{\delta}_O + \tilde{\delta}_{I,O}$ represents entry-by-release year effects (i.e., the coefficients for fully interacted entry-by-release year

dummies, thus yielding within-cohort estimates), $\tilde{\delta}_{\mathbf{p}}$ denotes prison effects, and the ε_i are residual unobservables.

Equation (1) is a version of the first-stage regression of the 2SLS model that I employ in the reduced-form analysis. Under the assumption that, within entry-by-release year cells, entry week in the year is uncorrelated with the unobservable determinants of work time during the incarceration term, the OLS estimand of β_w identifies the average within-cohort causal effect of being admitted in week w on monthly work hours during the term, keeping constant the number of days spent in prison. Figure 3 shows that convicts who entered prison in the first two weeks of the respective admission year spent an average of more than 2 extra hours at work every month (about 30% of the mean) as compared with to those admitted in the last week of the same year – again, for a given number of days spent in prison. Consistently with the examples in Figure 2, this effect is reduced by passing entry weeks until the work advantage approaches zero toward the end of the admission year.

However, entry week is unrelated to covariates. In analogy with the balancing test that a researcher would perform to verify random assignment in a randomized experiment, Figure 4 reports the estimated $\boldsymbol{\beta}_w$ from the following linear probability model,

$$Z_{i,w} = \alpha_w + \mathbf{X}_i \boldsymbol{\beta}_w + \gamma_w D_i + \hat{\delta}_I + \hat{\delta}_O + \hat{\delta}_{I,O} + \hat{\delta}_{\mathbf{p}} + \varepsilon_{i,w}, \tag{2}$$

where $\mathbf{X}_i$ is a $1 \times K$ vector of covariates and $\boldsymbol{\beta}_w$ is a $K \times 1$ vector of coefficients. For this exercise, I include in $\mathbf{X}_i$ the nine covariates associated with the panels of Figure 4. For each covariate, the figure reports coefficients estimated from equation (2) for $w = 1, \ldots, 51$ as well as the 95% confidence intervals. Figure 4 reveals that, unlike average monthly work hours, covariates do not systematically predict entry week – an outcome that renders the latter more credible as an instrument for prison work. Estimated coefficients are close to zero even in the few instances where they are statistically significant. The p-values from the test of $H_0 : \boldsymbol{\beta}_w = 0$ are below 5% in 14 instances out of 51, and their average is 0.29.

I report in the online appendix the distribution of entry week in the admission year by conviction offenses. These distributions look essentially uniform, which suggests the absence of any relevant seasonality. In Section 4 I discuss other possible threats to this identification strategy and I provide a formal discussion of the identifying assumptions and of the parameter that these assumptions allow me to identify and estimate.

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Figure 3: Within-cohort effect of entry week on monthly work hours, given term length
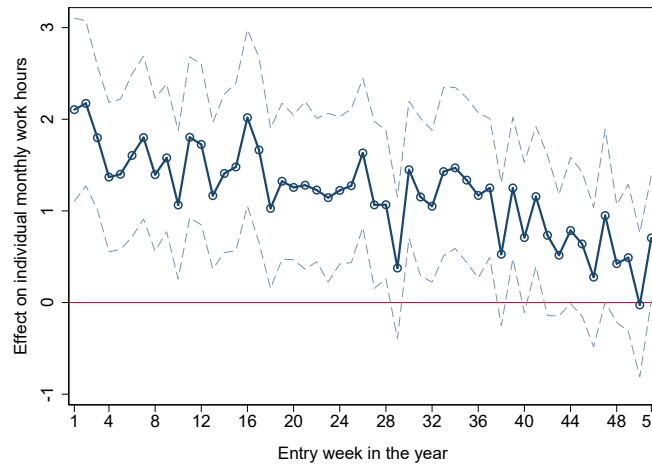
Notes: Open circles mark the OLS estimates of coefficients β_w for the entry-week dummies in equation (1), whose dependent variable is the average number of monthly hours spent at work during the prison term. The dashed lines connect the respective extremes of the 95% confidence intervals, and standard errors are clustered at the release-prison level. Sample: universe of 125,670 convicts released between 2009 and 2012, at the end of their sentence, from 209 correctional facilities in Italy.

Figure 4: Within-cohort effect of covariates on entry week, given term length
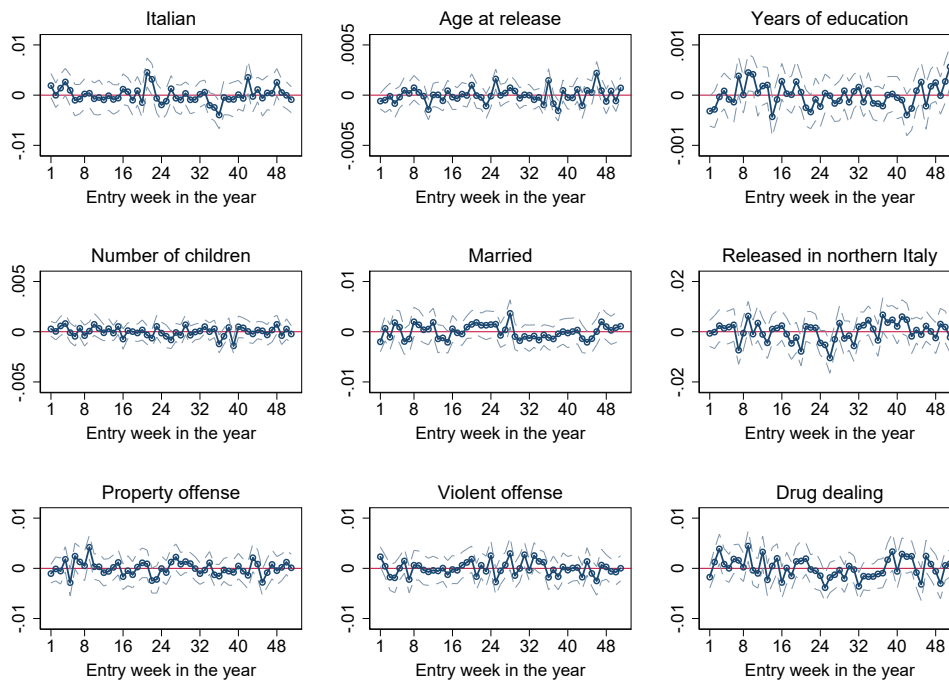
Notes: The circles are the OLS estimates of coefficients β_w on covariates $\mathbf{X}_i$ in equation (2), estimated for $w = 1, \cdots, 51$, where the dependent variables are entry week dummies. The dashed lines connect the respective extremes of the 95% confidence intervals. Standard errors are clustered at the release prison level. Sample: universe of 68,408 convicts released between 2009 and 2012, at the end of their sentence, from 209 correctional facilities in Italy and with nonmissing covariates.

3 Data

The data for this study were obtained from the DPA, which maintains an internal database known as the *Sistema Informativo Amministrazione Penitenziaria*–Automatic Fingerprint Identification System (SIAP–AFIS) for the management of prisoners. This is the comprehensive information system used by the DPA for administrative purposes. The data extract made available to me contains the universe of 125,670 adult convicts who were unconditionally released – at a rate of 30k–32k per year – between 2009 and 2012, after completing their prison term, from 209 different correctional facilities in Italy. These convicts correspond to 114,002 distinct individuals, which means that some 9.3% of inmates in this universe were released and then re-incarcerated at least once during the 2009-2012 period. The data set excludes inmates released while awaiting trial and also convicts released into alternative detention states (e.g., parole, house arrest, or community service) because they face different crime incentives than do unconditional releasees. The data contain demographic and socioeconomic characteristics, work records for prison jobs (work hours and earnings in each year), the crimes for which prisoners were convicted (conviction offenses), and post-release re-incarceration records for three years following discharge from prison. The correct linkage of individuals across different sections of the database and over time is ensured by a fingerprint identification system, which generates the unique individual identifier in my data.

The final sample results from three restrictions on this universe. First, because female convicts account for only 6.1% of the total, they are excluded. Second, because electronic work records in prison jobs are available only after 2004, convicts admitted to prison before 2005 (3.1% of the male sample) are also excluded. Finally, because the model employed for my structural analysis addresses only those crimes that are economically motivated, I discard observations whose set of conviction offenses does not contain at least one such crime (12.3% of the male sample admitted after 2004).[11] The resulting final sample consists of 100,350 convicts (91,417 distinct individuals). Table 1 reports summary statistics for the universe and the final sample; it also gives the *p*-values from tests of the null hypothesis that the mean of each variable is equal in these two groups.

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[11]I define the following as economically motivated criminal offenses: larceny, burglary, motor vehicle (MV) theft, robbery, drug dealing, forgery, fraud, counterfeiting, embezzlement, receiving stolen goods, exploiting prostitution, perjury, criminal association, menacing, and extortion.

Table 1: Descriptive statistics

Variable	Universe (N = 125,670)		Final sample (N = 100,350)				
	Mean	SD	Mean	SD	Min	Max	p-val
1. Individual characteristics							
Male	0.939	0.239	1	0	1	1	0.00
Italian	0.586	0.493	0.571	0.495	0	1	0.00
Moroccan	0.087	0.282	0.096	0.295	0	1	0.00
Romanian	0.072	0.259	0.074	0.262	0	1	0.14
Tunisian	0.055	0.228	0.062	0.240	0	1	0.00
Albanian	0.031	0.174	0.033	0.178	0	1	0.04
Age at release	36.8	11.1	36.0	10.7	18.0	88.0	0.00
Age 18-24	0.140	0.347	0.152	0.359	0	1	0.00
Age 25-31	0.249	0.432	0.262	0.440	0	1	0.00
Age 32-38	0.235	0.424	0.237	0.425	0	1	0.17
Age 39-45	0.181	0.385	0.175	0.380	0	1	0.00
Age 46 or older	0.195	0.396	0.174	0.389	0	1	0.00
Number of children	0.72	1.30	0.62	1.18	0	17	0.00
Nonmissing marital status	0.882	0.323	0.873	0.333	0	1	0.00
Married	0.280	0.449	0.268	0.443	0	1	0.00
Never married	0.536	0.499	0.556	0.497	0	1	0.00
Divorced or separated	0.076	0.265	0.070	0.256	0	1	0.00
Nonmissing edu info	0.565	0.496	0.540	0.498	0	1	0.00
Years of education	7.02	3.07	7.05	3.00	0	16	0.12
No education	0.097	0.295	0.093	0.291	0	1	0.06
Elementary school	0.217	0.412	0.207	0.405	0	1	0.00
Middle school	0.589	0.492	0.607	0.488	0	1	0.00
High school	0.082	0.275	0.080	0.271	0	1	0.07
College	0.015	0.120	0.012	0.111	0	1	0.00
2. Admission, release, and re-incarceration							
Year entered prison	2008.9	2.3	2009.1	1.55	2005	2012	0.00
Year released	2010.5	1.1	2010.5	1.11	2009	2012	0.00
Prison term (years)	1.66	2.07	1.44	1.25	0.04	7.82	0.00
Released northern Italy	0.408	0.492	0.407	0.492	0	1	0.64
Released southern Italy	0.399	0.490	0.401	0.490	0	1	0.32
Re-incarcerated by 1 year	0.172	0.378	0.183	0.386	0	1	0.00
Days out	161.5	103.0	160.7	102.8	0	365	0.44
Re-incarcerated by 2 years	0.254	0.435	0.268	0.443	0	1	0.00
Days out	279.5	199.9	277.4	199.5	0	730	0.20
Re-incarcerated by 3 years	0.301	0.459	0.317	0.465	0	1	0.00
Days out	375.8	292.9	373.0	292.6	0	1095	0.21

Variable	Universe (N = 125,670)		Final sample (N = 100,350)				
	Mean	SD	Mean	SD	Min	Max	*p*-val
3. Conviction offenses							
Number of offenses	1.71	1.16	1.72	1.10	1	12	0.10
Drug dealing	0.362	0.480	0.410	0.492	0	1	0.00
Larceny/burglary/MV	0.266	0.442	0.296	0.457	0	1	0.00
Assault	0.193	0.394	0.161	0.368	0	1	0.00
Robbery	0.161	0.368	0.181	0.385	0	1	0.00
Receiving stolen goods	0.106	0.308	0.116	0.321	0	1	0.00
Perjury	0.083	0.276	0.090	0.287	0	1	0.00
Menacing	0.066	0.248	0.072	0.258	0	1	0.00
Fraud/forgery/counterf.	0.069	0.254	0.076	0.265	0	1	0.00
Extortion	0.051	0.221	0.056	0.230	0	1	0.00
Criminal association	0.040	0.197	0.039	0.195	0	1	0.30
Sexual assault/abuse	0.039	0.194	0.020	0.141	0	1	0.00
Vandalism	0.034	0.180	0.029	0.168	0	1	0.00
Homicide	0.031	0.172	0.011	0.103	0	1	0.00
Domestic violence	0.020	0.139	0.014	0.116	0	1	0.00
Exploiting prostitution	0.014	0.116	0.012	0.111	0	1	0.03
Embezzlement	0.008	0.091	0.009	0.095	0	1	0.05
Other offenses	0.165	0.371	0.123	0.328	0	1	0.00
4. Prison work							
Worked during term	0.378	0.485	0.380	0.485	0	1	0.34
Monthly work hours	17.5	20.4	17.3	20.3	0.03	169.7	0.02
Hourly wage	3.82	0.58	3.80	0.56	2.41	48.18	0.04
Net hourly wage	3.23	0.72	3.22	0.72	1.63	43.48	0.03
Monthly earnings	66.7	78.8	65.5	78.0	0.1	692.3	0.02
Net monthly earnings	58.5	72.1	57.5	71.4	0.1	645.8	0.03
Monthly work hours	6.6	15.2	6.6	15.1	0	169.7	0.36
Total work hours	225.1	688.0	188.3	537.2	0	9875	0.00
Monthly earnings	25.2	58.3	24.9	57.6	0	692.3	0.16
Net monthly earnings	22.1	52.7	21.9	52.2	0	645.8	0.23
Total earnings	867.8	2701.7	717.3	2071.7	0	41862.9	0.00
Net total earnings	762.2	2418.8	632.6	1872.2	0	39874.3	0.00
Savings at release	106.1	401.9	100.5	372.4	0	15372.2	0.00

Notes: The table reports summary statistics for the universe (125,670 convicts released between 2009 and 2012, at the end of their sentence, from 209 correctional facilities in Italy) and for the final sample (100,350 male convicts from this universe who were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses). All monetary values are expressed in euros at 2019 prices as measured by the Consumer Price Index.

Panel 1 summarizes demographic and socioeconomic characteristics. Foreign-born inmates account for more than 40% of the releasees, about two thirds are 18–38 years old, and formal education averages about seven years, with nearly 30% having received no more than five years of schooling. Note that information on marital status and educational attainment is missing for more than (respectively) 10% and 40% of released convicts, which reflects in part the greater difficulty in verifying such information for foreign-born than for Italian inmates.[12]

Panel 2 presents admission, release, and re-incarceration statistics. The exact admission and release dates are observed for each prison term, as is the exact date of any re-incarceration for three years after release. The average term duration in the sample is 1.44 years and the median is one year, which indicates that the distribution of prison terms is right-skewed by the high incidence of short terms (see Figure 5). Following release, 18.3% of convicts in the sample return to prison within 365 days, 26.8% within two years, and about 31.7% within three years.

Panel 3 summarizes conviction offenses. Every inmate in the data is associated with a set of crimes for which he was found guilty. The average number of offenses is about 1.7. The table arranges these offenses in decreasing order of incidence in the universe.

Finally, Panel 4 reports prison work statistics. This information is available at the annual frequency. About 38% of released convicts worked at a prison job during their term, for an average of about 17.5 hours each month. The average real wage rate (at 2019 prices) is about €3.8 an hour (or €3.2 an hour after deductions). An individual's wage rate in a given year is estimated by the ratio of his annual earnings to his annual hours, which may result in some measurement error that reflects outliers observed in the data. In any case, about 96% of average individual nominal wages are between €3 and €4, where differences in this range stem mostly from the various available positions to which convicts are assigned to in different prisons. On average across all released convicts (i.e., including those who were never assigned to a prison job during the term), monthly work hours were 6.6. In my sample, the average net earnings during the entire term is about €630 (€1,660 for convicts who held a prison job during the term). The portion that is cashed in at release is captured by variable "Savings at release".

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[12]In the universe, marital status information is missing for 8.6% of Italian convicts and 16.4% of foreign-born convicts. For educational attainment, the corresponding figures are 32.5% and 59%.

As explained in Section 2.2, my identification relies on variation in work shares within cohorts of inmates who spent their term in the same facilities. In order to quantify the relevance of such variation, I decompose the variance of prison work in the sample by regressing average work hours per month in prison ($H_{i,I,O,\mathbf{p}}$ in equation 1) on entry-by-release year dummies ($\delta_I + \delta_O + \delta_{I,O}$), days spent in prison (D_i) and prison dummies ($\delta_{\mathbf{p}}$). The regression's R^2 is 0.247 – a measure of the between-prison variation in work shares across cohorts. Therefore, most of the variation in monthly work hours is due to within-prison and within-cohort variation.

Figure 5 illustrates the distribution of prison terms in the sample, the fraction of convicts in each bin who were ever assigned to work in a prison job during the term, and the fraction of former convicts who were re-incarcerated within three years of release. The distribution of terms is markedly right-skewed, with half of the convicts spending less than a year in prison and about 25% serving a term of shorter than six months. The re-incarceration rate is higher for convicts on shorter prison terms, with 33.3% of those who were incarcerated for up to two years returning to prison within three years of release – in comparison with 27.2% among former convicts who spent between two and eight years in prison.

Figure 5: Distribution of prison terms, fraction in prison jobs, and re-incarceration rates
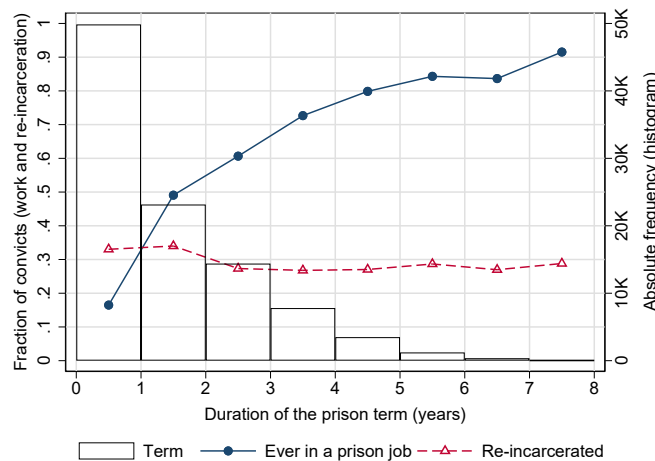
Notes: This figure illustrates the distribution of prison terms (absolute frequencies, right scale), the fraction of convicts who were ever assigned to a prison job during the term (dots, left scale), and the fraction re-incarcerated within three years of the release date (triangles, left scale). Each bin contains inmates who spent between t and $t+1$ years in prison, for $t \in (0,8]$. Sample: 100,350 male convicts who were released between 2009 and 2012, at the end of their sentence, from 209 correctional facilities in Italy, and who were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses.

The figure also shows that only about 16% of convicts whose term is shorter than one year work in a prison job. Given the level of rationing and the rotation mechanism described previously, most of these convicts never reach the top of long waiting lists. This rate increases to nearly 50% among those incarcerated for between 1 and 2 years, and it continues to increase over term duration until more than 90% of convicts on a 7–8-year term are assigned to a prison job at least once. That as many as seven years into their prison terms about 10% of convicts have never been assigned to a prison job strongly suggests that some individuals are systematically placed back at the bottom of the waiting list when their work turn arrives. These are either inmates who are affected by physical, mental, or behavioral conditions that make them unfit to work or convicts who are employed in external jobs. A limitation of my data is that these states are not observed. Therefore, some convicts have zero work hours in the estimation sample because they are *de facto* ineligible for prison jobs (although all of them are *de jure* eligible). In particular, the counterfactual will involve convicts with zero work hours in prison jobs but who actually worked at external jobs during the term. This contamination is unlikely to have first-order consequences when one considers the low incidence of external jobs shown in Figure 1. Another data limitation is that only work hours are observed, and *not* the specific tasks performed. However, we know from Section 2.1 that about 90% of all prison jobs consist of unskilled domestic work.

Figure 6 plots average work and earnings profiles by term duration over calendar year in prison. Because the figure pools different cohorts, I refer to these as *prison years*. The upper left panel presents employment profiles (i.e., the share of convicts assigned to work in a prison job during a given prison year) or the *extensive* margin of prison work. The upper right panel shows the hours profile of those employed (i.e., the average monthly hours worked in a prison job during a given prison year conditional on working that year) or the *intensive* margin of prison work. Two patterns are worth noting in these upper panels. First, there is generally an employment decline during the release year, which for each prison term represented in the figure is one of the last three prison years. Just as in the example of Figure 2, the indivisibility of work shifts makes it less likely that a prisoner works in his release year. After taking this into account, there are no meaningful cross-term differences in employment rates during a given prison year. The first prison year's low employment rate is a direct consequence of the rotation

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mechanism – in a convict's entry year, he has minimum priority in the work assignment process – and also of the average admission date being at the end of June.

Second, convicts in longer prison terms tend to work more along the intensive margin from the third prison year onward. Moreover, there is some return to experience in prison jobs in terms of work hours during the first and second prison years, which suggests that new convicts are initially assigned to smaller jobs involving fewer hours. These facts are explained by warden discretion. The lower left panel of Figure 6 shows that the average nominal wage is uniform over prison years and across terms – as implied by the institutional features described in Section 2 – at about €3.5 (or €3.8 when expressed in real euros at 2019 prices, as reported in Table 1). It follow that the humped shape of the earnings profile observed in the figure's lower right panel (which is averaged over all convicts and so combines intensive and extensive margins) reflects mainly the shape of the hours profile and, to a less extent, that of the employment profile.

Figure 6: Work and earnings profiles by term duration and by calendar year in prison
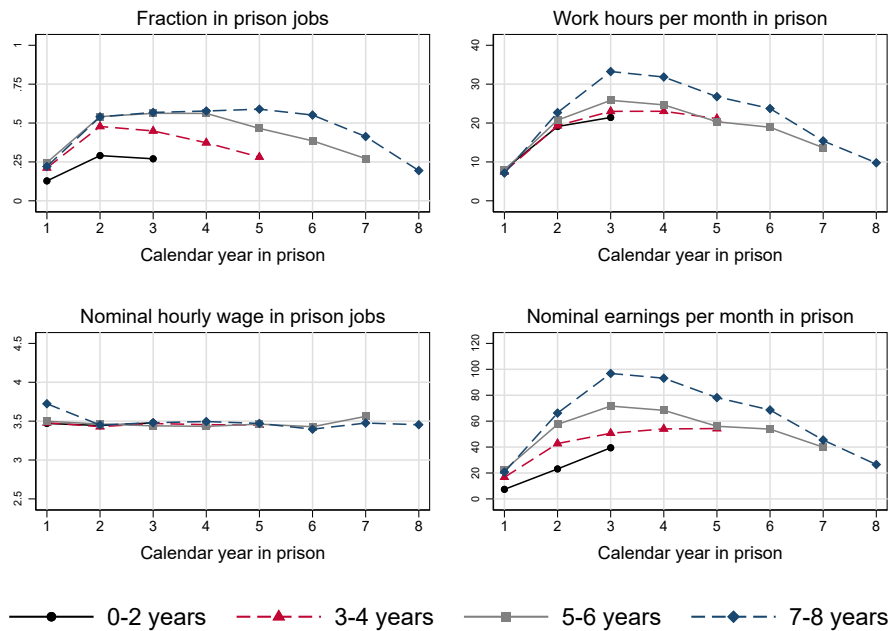
Notes: The graphs in this figure display work and earnings profiles as a function of the calendar year in prison ("1" on the horizontal denotes the entry year, "2" is the second calendar year of the term, and so on.) for four different prison term groups ("0-2 years" means between 1 and 730 days in prison, "3-4 years" means between 731 and 1460 days, etc.). Work hours are conditional on being employed in a given calendar year. Wages and earnings are expressed in euros at 2019 prices. Sample: 100,350 male convicts who were released between 2009 and 2012 (at the end of their sentence) from 209 correctional facilities in Italy and who were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses.

4 Reduced-form causal analysis

At a first level of inferential analysis, I intend to identify the causal effect of prison work on convict rehabilitation – as measured by re-incarceration – without formally investigating the underlying pathways. I refer to this as a "reduced-form" analysis, although the theoretical framework laid down in Section 5 makes clear that the econometric model in this section can hardly be regarded as the reduced form of the structural model.

4.1 Reduced-form econometric model

My reduced-form analysis is based on the following linear probability model,

$$R_{i,I,O,\mathbf{p},t} = \beta_R H_{i,I,O,\mathbf{p}} + \mathbf{X}_{it}\gamma_R + \delta_I + \delta_O + \delta_{I,O} + \delta_{\mathbf{p}} + v_{it}. \tag{3}$$

Here $R_{i,I,O,\mathbf{p},t}$ is a dummy variable indicating whether convict i – who was admitted to prison in year I, was released in year O, and served his sentence in prisons $\mathbf{p}$ – was re-incarcerated within period t from the release date. The regressor of primary interest (the "treatment" level) is $H_{i,I,O,\mathbf{p}}$, which measures the number of monthly hours spent by i at work in a prison job during his term.[13] For this analysis, $H_{i,I,O,\mathbf{p}}$ is standardized within the estimation sample. As reported in Table 1, a standard deviation corresponds to about 15 hours per month, which is about 2.3 times the unconditional mean, and almost 90% of the average monthly work hours conditional on being ever assigned to a prison job during the term. Vector $\mathbf{X}_{it}$ contains – in addition to a constant – pre-determined characteristics that are available for all individuals in the sample, namely age dummies (the only time-varying covariate), nationality dummies, and conviction offenses dummies. Finally equation (3), like equation (1), contains fully interacted entry-by-release year fixed effects and prison fixed effects, as well as v_{it}, the residual unobservable determinants of re-incarceration in period t. Each prison dummy takes the value 1 for a convict who spent part of his term in that facility (and 0 otherwise). Matching inmates on these prison dummies ensures that, within each cohort, convicts experienced similar prison conditions, security levels, and rehabilitation programs.[14]

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[13]Formally, $H_{i,I,O,\mathbf{p}} = (D_i/30)^{-1} \sum_{\tau=I}^{O} h_{i\tau}$, where $h_{i\tau}$ denotes hours worked in year τ. So, if i worked a total of 200 hours during a term of 400 days, then his average monthly hours are $(200/400) \times 30 = 15$.

[14]More than 80% of the sample never moved across correctional facilities while incarcerated.

In this part of the empirical analysis I am interested in estimating β_R, the average causal effect of 1-SD's worth of additional prison work hours on the re-incarceration rate. Since the discretionary component of assignment to prison jobs results in a nonzero correlation between $H_{i,I,O,\mathbf{p}}$ and v_i, it follows that the OLS estimand does not identify β_R. I therefore estimate this parameter based on 2SLS, whose first stage is

$$H_{i,I,O,\mathbf{p}} = \mathbf{Z}_i \boldsymbol{\beta}_H + \mathbf{X}_i \boldsymbol{\gamma}_H + \tilde{\delta}_I + \tilde{\delta}_O + \tilde{\delta}_{I,O} + \tilde{\delta}_{\mathbf{p}} + \varepsilon_i, \tag{4}$$

where the excluded instruments in vector $\mathbf{Z}_i$ are entry-week dummies.[15] For comparison with the structural empirical analysis presented in Section 5, I write explicitly the orthogonality conditions under which – provided the instrument relevance condition, $\boldsymbol{\beta}_H \neq \mathbf{0}$ holds – the 2SLS estimand identifies β_R. Denoting by $\mathbf{0}$ a vector of 0s of the appropriate dimension, these conditions are

$$\mathbb{E}[\mathbf{X}_{it} v_{it}(\beta_R, \gamma_R, \delta)] = \mathbf{0},$$
$$\mathbb{E}[\boldsymbol{\Delta}_i v_{it}(\beta_R, \gamma_R, \delta)] = \mathbf{0}, \tag{5}$$
$$\mathbb{E}[\mathbf{Z}_i v_{it}(\beta_R, \gamma_R, \delta)] = \mathbf{0},$$

where $\delta = [\delta_I \ \delta_O \ \delta_{I,O} \ \delta_{\mathbf{p}}]$ contains the fixed effects and $\boldsymbol{\Delta}_i$ is the associated vector of dummies. If the treatment effect β_R in equation (3) is heterogeneous, then monotonicity of the treatment in the instruments must hold in order to interpret the 2SLS estimand as the LATE. In this context, the absence of "defiers" is implied by the institutional rules described in Section 2. Since the deterministic component of the work assignment mechanism is a ranking that reflects the duration of prison unemployment spells, it follows that (within a given cohort) if one convict works more than another because he was admitted one week earlier then this convict would have worked no less, and possibly even more, if he had been admitted two or three weeks earlier, for example. The downward-sloping pattern in Figure 3 is consistent with monotonicity. Under this additional assumption, my estimate of β_R is the LATE of prison work and applies only to "compliers": convicts who work more (resp. fewer) hours in prison jobs because they were admitted earlier (resp. later) than others within their cohort. These inmates are special because they are little affected by the warden's discretion assignment to work.

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[15]The first stage is the same for any t, so here $\mathbf{X}_{it}$ is fixed at $t = 1$ (i.e., at the first post-release period).

As explained in Section 2.2, the reduced-form identification strategy here requires keeping constant the number D_i of days spent in prison. A challenge to the implementation of this strategy in a 2SLS setting is that, although it was possible to condition on D_i in equation (1), such conditioning is not possible in equation (3), where the outcome is re-incarceration. The reason is that D_i is a "bad control" in the latter equation because convicts with certain unobserved characteristics (e.g., well-behaving convicts, possibly demonstrated by diligent work in prison jobs) may benefit from remission of sentence. Omitting D_i as a RHS variable from equation (3) – and so also from (4) – induces a direct, "mechanical" within-cohort correlation between the instrument and the re-incarceration outcome whose magnitude is proportional to the direct effect of prison time on the re-incarceration rate – a possible violation of the exclusion restriction formalized in equation (5) . To illustrate the problem, write (3) as

$$R_{i,I,O,\mathbf{p},t} = \alpha_R + \beta_R H_{i,I,O,\mathbf{p}} + \mathbf{X}_{it}\boldsymbol{\gamma}_R + \delta_I + \delta_O + \delta_{I,O} + \delta_{\mathbf{p}} + \sigma_R D_i + \psi_{it}, \tag{6}$$

where $\psi_{it} = v_{it} - \sigma_R D_i$, for σ_R the direct effect of actual sentence length on re-incarceration rates. In the within-cohort design, prison term duration is mechanically related to the instruments via this equation:

$$D_i = \alpha_D + \mathbf{Z}_i\boldsymbol{\beta}_D + \bar{\delta}_I + \bar{\delta}_O + \bar{\delta}_{I,O} + \xi_i. \tag{7}$$

So within the cohort of convicts admitted to prison in 2008 and released in 2010, for example, those admitted in the first week of January stay in prison for a few weeks longer (on average) than do those admitted later in 2008. Hence $\boldsymbol{\beta}_D \neq \mathbf{0}$ and so, even though $\mathbb{E}[\mathbf{Z}_i\psi_{it}] = \mathbf{0}$, in general we have $\mathbb{E}[\mathbf{Z}_i v_{it}] = \mathbb{C}(\mathbf{Z}_i, v_{it}) = \sigma_R\boldsymbol{\beta}_D\mathbb{V}(\mathbf{Z}_i) \neq \mathbf{0}$, where $\mathbb{C}$ and $\mathbb{V}$ are (respectively) covariance and variance matrices. In other words, D_i is a necessary conditioning variable in equation (3) for the exclusion restriction to hold, but it is also an endogenous variable so that $\mathbb{E}[D_i v_{it}] \neq 0$. Regardless of whether equation (3) includes or omits D_i, the result could be an inconsistency bias in the 2SLS estimand relative to the target causal parameter (i.e., the LATE).

I resolve this tension by omitting D_i, and thereby allowing for a possible violation of the exclusion restriction that leads to an inconsistency bias proportional to σ_R, but then correcting for that bias with the modified bias-corrected 2SLS (MB2SLS) estimator proposed by Kolesár et al. (2015). The Kolesár et al. estimator uses weaker assumptions

than conditions (5) and that are plausible in my application – namely, that β_H and $\sigma_R \beta_D$ are independent. In words, the effect of entry week on monthly work hours that is generated by the prison job allocation mechanism's deterministic component (i.e., β_H) must be *independent* of the effect of entry week on the re-incarceration rate via a longer prison term (i.e., $\sigma_R \beta_D$). This assumption is plausible because β_H reflects only the *de jure* priority determined by the order of prison admission within cohorts. As I will show, a comparison between conventional 2SLS and MB2SLS estimates of β_R indicates that any inconsistency bias in the 2SLS estimates is small and negative. This result agrees with the small and negative estimates of σ_R reported in the literature. Using credible research designs generated by the US judicial system, Abrams (2011), Kuziemko (2013), Roach and Schanzenbach (2015), and Zapryanova (2020) all find that an additional month in prison reduces the re-incarceration rate by about 1 percentage point.

A final note about standard errors is in order. Although the universe of correctional facilities is observed and so there is no clustering in the sampling process, the treatment assignment mechanism may be clustered within prisons because different wardens typically exercise their discretion in different ways. Therefore, standard errors should be clustered at the prison level (Abadie et al., 2017). The standard errors that I report are, in fact, clustered at the release-prison level (209 clusters).

4.2 Reduced-form results

Table 3 reports estimates of β_R in equation (3) that are obtained by applying the OLS, 2SLS, and MB2SLS estimators. The re-incarceration outcome is measured at one, two, and three years from the release date. To demonstrate that the causal effect of interest varies by length of incarceration, this table reports estimates for the full sample and for subsamples of convicts who were incarcerated for less than six months, at least six months, or at least twelve months.[16] The OLS estimates are systematically close to zero and positive, as are 2SLS estimates in the full sample. When the sample is restricted to prison terms of at least six or twelve months, 2SLS estimates turn negative and increase

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[16]Monthly work hours are standardized within the estimation sample, so one standard deviation is a different quantity in the four groups: 15.1 hours in the full sample, 5.9 among those incarcerated for less than six months, and 16.6 and 18.3 hours, respectively, among convicts on terms of at least six and twelve months, respectively. The online appendix reports full descriptive statistics, along the lines of Table 1, for these four groups.

Table 3: Effect of prison work on re-incarceration within one, two, and three years of release

Term:	All terms (SD = 15.1h)			< 6 months (SD = 5.9h)			≥ 6 months (SD = 16.6h)			≥ 12 months (SD = 18.3h)		
	1y	2y	3y	1y	2y	3y	1y	2y	3y	1y	2y	3y
OLS estimator												
$\hat{\beta}_R$	0.003 (0.002)	0.004 (0.002)	0.005 (0.002)	0.007 (0.003)	0.007 (0.004)	0.007 (0.004)	0.002 (0.002)	0.003 (0.002)	0.004 (0.002)	0.001 (0.002)	0.001 (0.002)	0.003 (0.002)
2SLS estimator, over-identified model												
$\hat{\beta}_R$	0.004 (0.018)	0.018 (0.021)	0.020 (0.021)	0.011 (0.035)	0.052 (0.039)	0.056 (0.041)	−0.077 (0.024)	−0.094 (0.027)	−0.096 (0.029)	−0.099 (0.030)	−0.134 (0.035)	−0.126 (0.039)
MB2SLS estimator, over-identified model												
$\hat{\beta}_R$	0.004 (0.017)	0.019 (0.020)	0.021 (0.021)	0.014 (0.034)	0.082 (0.039)	0.088 (0.042)	−0.090 (0.023)	−0.111 (0.029)	−0.113 (0.028)	−0.128 (0.038)	−0.173 (0.033)	−0.164 (0.021)
Excluded instruments, F-test stat.		12.4			2.5			7.0			4.5	
Sargan test, p-value	0.03	0.10	0.19	0.03	0.11	0.30	0.10	0.09	0.36	0.22	0.23	0.54
2SLS estimator, just-identified model												
$\hat{\beta}_R$	−0.002 (0.018)	0.011 (0.021)	0.012 (0.021)	0.096 (0.048)	0.180 (0.062)	0.176 (0.067)	−0.091 (0.025)	−0.109 (0.028)	−0.111 (0.029)	−0.136 (0.035)	−0.170 (0.039)	−0.162 (0.044)
First-stage		−0.0048 (0.0003)			−0.0043 (0.0007)			−0.0041 (0.0003)			−0.0036 (0.0004)	
F-test stat.		270.3			39.6			146.2			80.0	
Obs.	100,350	100,350	100,350	24,408	24,408	24,408	75,942	75,942	75,942	50,859	50,859	50,859

Notes: This table reports OLS, 2SLS, and MB2SLS estimates of parameter β_R in equation (3) – that is, the effect of one additional standard deviation in monthly hours worked at a prison job during the incarceration term on the probability of being re-incarcerated. One SD is a different number of hours in each estimation sample, as indicated in the table's first row. The dependent variable is a dummy set to 1 for ex-convicts who are re-incarcerated either within one year ("1y"), two years ("2y"), or three years ("3y") from the release date (and set to 0 otherwise). Standard errors are clustered at the release-prison level (209 clusters). Sample: 100,350 male convicts who were released between 2009 and 2012 (at the end of their sentence) from 209 correctional facilities in Italy, and who (a) were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses and (b) spent either any number of days in prison ("Term: All terms"), less than six months ("< 6 months"), at least six months ("≥ 6 months"), or at least twelve months ("≥ 12 months").

in magnitude as the term restriction becomes more binding. Yet among convicts on shorter prison terms the 2SLS point estimate is positive (albeit imprecisely estimated).

This gradient of treatment effect suggests that the contribution of prison work to convict rehabilitation depends on the time an inmate is removed from the labor and criminal markets. For convicts who were incarcerated for at least six months, an additional standard deviation of monthly work hours (about 16.6 hours per month in prison) reduces by 7.7 percentage points the probability of being re-incarcerated within one year of release. This effect increases to 9.4 p.p. and 9.6 p.p. within two and three years of release, respectively, and these figures are 2–4 p.p. larger (in absolute value) among convicts on a twelve months term or longer. When statistically significant, the magnitude of MB2SLS estimates is slightly larger: by 3 p.p. percentage points for convicts imprisoned for fewer than six months; by 1–2 p.p. for those incarcerated for at least six months; and by 3–4 p.p. for those who were in prison at least twelve months. As mentioned previously, these results are consistent with a negative but small value of σ_R in equation (6). The positive MB2SLS coefficient estimated for inmates on short sentences is now statistically significant.

In analogy to Figure 3, first-stage results associated with the 2SLS estimates are reported in Figure 7; here the graph plots OLS estimates of the coefficients β_H in equation (4) and their standard errors. Observe that, in this figure and in Table 3, the progressive reduction in sample size – as shorter or longer prison terms are removed from the sample – makes it increasingly difficult to reject the null hypothesis that admission week dummies are jointly insignificant at the first stage of both the 2SLS and MB2SLS estimators (F-test on the excluded instruments) and the null hypothesis that the over-identifying restrictions in $\mathbb{E}[\mathbf{Z}_i v_{it}]$ are valid (Sargan test).

However, weak instruments are not a concern. As Table 3 also shows, if entry week in the year is employed parametrically as a single, continuous instrument taking values between 1 and 52 (just-identified model) rather than nonparametrically as admission-week dummies (over-identified model), then the F-test statistic on the excluded instrument becomes comfortably large and the point estimates of β_R produced by the 2SLS estimator approach their MB2SLS counterparts in the over-identified case and actually exceed them for short terms.[17] Thus, we are reassured that the increasing magnitude of the

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[17]This outcome is not surprising when one considers that, as explained by Kolesár et al. (2015), the

2SLS and MB2SLS point estimates, as longer or shorter prison terms are removed from the sample, is not due to a greater weak instruments bias. As for the Sargan test in the over-identified model, note that the null hypothesis is not rejected in the full sample, either – except when the dependent variable is re-incarceration within a year of release.

Figure 7: First-stage coefficients and standard errors
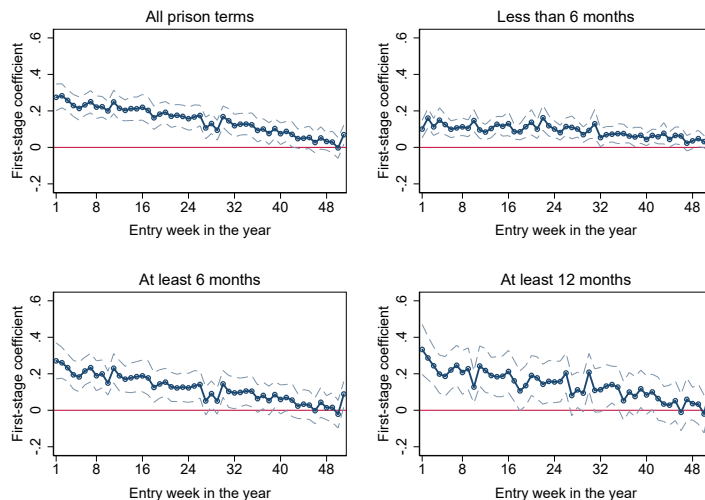
Notes: Open circles mark the OLS estimates of coefficients β_H for entry-week dummies $\mathbf{Z}_i$ in equation (4); here the dependent variable is the standardized number of monthly hours spent at work during a prison term. The dashed lines connect the respective extremes of the 95% confidence intervals, and standard errors are clustered at the release prison level (209 clusters). Sample: 100,350 male convicts who were released between 2009 and 2012 (at the end of their sentence) from 209 correctional facilities in Italy, who (a) were admitted to prison after 2004, with at least one economically motivated crime in their set of conviction offenses and (b) spent any number of days in prison ("All prison terms"), at least three months in prison, at least six months, or at least twelve months.

A comparison of OLS and 2SLS estimates indicates that either (i) the causal effect of prison work for compliers is different from the analogous effect for the rest of the sample, or (ii) the OLS estimand is affected by a positive inconsistency bias for inmates on longer prison sentences yet negative bias for those on shorter sentences. The first possibility is confirmed by my structural analysis, which allows to estimate the ATE and to contrast it with the LATE. The second possibility suggests that, in the institutional context under investigation, there is negative selection into prison work for convicts on longer sentences. In other words, among longer-term convicts a warden's discretion favors those

MB2SLS estimator combines multiple instruments into a single, constructed instrument that is used – as in my just-identified setting – to identify the causal parameters of interest. The estimated first-stage coefficient in the just-identified 2SLS model when all terms are pooled (see Table 3) indicates that, within a cohort, being admitted to prison a week later reduces the number of hours per month incarcerated by 0.48% of a standard deviation, on average. This amount corresponds to about 0.07 hours per month, which is considerably smaller than the average nonparametric effect of entry week that is suggested by Figure 3.

whose characteristics are positively correlated with their (unobserved) propensity to return to prison. However, among inmates on short sentences there is positive selection: it is those with a lower propensity to return to prison who benefit from discrimination. The theoretical model formalizes these conjectures.

These reduced-form estimates offer the basis for a simple calculation of a lower bound for the internal rate of return on funds allocated to prison jobs in Italy. That rate is clearly negative, on average, for those incarcerated for less than six months, but it is large and positive for convicts on longer sentences. According to the Italian Ministry of Justice, the annual cost of an inmate is about €45k (Ministero della Giustizia, 2013). In the short term, only the variable portion of this amount (€8k) is borne at the margin for each ex-convict who is re-incarcerated. That portion is the largest component of the marginal cost of incarceration because the bulk of expenses for police forces and the judicial system are fixed costs. Among those incarcerated for at least six months, the average prison term in the sample is 21.8 months. So if one assumes that that the new incarceration term would be of a similar duration, then the 2SLS estimate of a 9.6 p.p reduction in the re-incarceration rate within three years of release implies an expected reduction of $21.8 \times 0.096 \approx 2.1$ months of future prison terms for each released convict in this group – and therefore an annual economy of $2.1 \times €8k/12 = €1400$ per released inmate. This reduction comes at a cost of 16.6 hours of work per month in prison, or $16.6 \times 21.8 \approx 362$ hours at the expected average term duration for those who are re-incarcerated. At the nominal wage rate in Italian prison jobs that was in force until 2017 (about €3.5), these 362 hours cost the taxpayer €1,267; the implied rate of return is $1400/1267 - 1 \approx 10.5\%$. This is a lower bound because I have both taken the smaller (in absolute value) between the 2SLS and MB2SLS estimates and I have not considered the reduction in the marginal cost of police forces and courts. Furthermore, it is a short-term rate. In the long run, the rate of return would be higher owing to reductions also in the fixed costs of incarceration, policing, and judicial activity. Yet one must bear in mind that at the higher wage rate in Italian prison jobs since 2017 (about €7), this lower bound would be negative (–44.8%) and thus not very informative. It is most unlikely that the internal rate of return is positive at this higher wage. Also note that this calculation is based on the LATE and so applies to compliers only. I will later argue that the rate of return is likely negative for the general population of convicts on terms longer than six months.

5 Structural analysis

The next level of my inferential analysis seeks to uncover mechanisms that generate the causal effects estimated in the previous section. I first build in Section 5.1 a theoretical model of prison work and post-release outcomes that nests a dynamic model of crime (Flinn, 1986; Lochner, 2004; Mocan et al., 2005; Lee and McCrary, 2017) and in which liquidity, social, and training effects are captured by distinct parameters. I then show in Section 5.2 how these (and other) parameters are identified via the same orthogonality conditions that identify the reduced-form model. Finally, in Section 5.3 I estimate that model and simulate it numerically in order to produce a mechanism decomposition and to perform counterfactual experiments.

5.1 Theoretical model

5.1.1 Setup

Consider a risk-neutral individual who is either free or in prison, a state indexed by $s = \{f, p\}$. This individual has just transitioned from p to f, after serving a prison term that started at time I and ended at time O. Time, which is indexed by t, is discrete; a "period" equals a year. It is convenient to set $O = 0$ so that the first post-release period, which begins right after release, is $t = 1$. Because the data allow me to observe re-incarceration outcomes for only three years from the release date, I restrict the model at the outset to three post-release periods in which crime decisions can be taken, $t = 1, 2, 3$.[18]

In each period of a prison term, the inmate receives a fixed prison consumption c_p (broadly defined to include the disamenities of prison life) and has a unit time endowment that is split between lock-in time, l_t, and work time, h_t, in unskilled prison jobs at a fixed wage rate w; thus $l_t + h_t = 1$. There are no choices to be made by an individual in state p; in particular, labor supply is inelastic because the warden dictates an inmate's allocation of time. Conditional on having a job, an event that occurs with probability η_t, labor supply is inelastic also in state f. Yet the labor market offers jobs that require different skills than those needed in a correctional facility, so the market wage rate in state f

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[18]I will later calibrate the discount factor of convicts in Italian prisons to the value of 0.72 based on the estimates of Mastrobuoni and Rivers (2016). This value implies a small weight on the utility terms, upon release, that I miss: about 0.27 at $t = 4$, about 0.19 at $t = 5$, and so forth.

is determined by the rate of return γ on one's labor market skills k_t; hence expected labor market earnings in a given period are given by $\gamma \eta_t k_t$. I refer to the quantity $\eta_t k_t$ as *effective human capital*: the average skills that an individual in state f uses productively in the labor market and that thereby determine his earning ability.

Upon release and in all periods when $s = f$, the focal individual chooses whether or not to engage in crime again; this binary choice is denoted by $x_t = \{0, 1\}$, where $x_t = 1$ corresponds to committing a crime in period t. A crime opportunity arises with probability 1 in each period, and if the ex-convict takes that opportunity he is apprehended with probability π. The payoff of engaging in crime is the *crime wage*, which is determined by the rate of return ρ on one's criminal capital m_t (i.e., individual skills that determine criminal ability); therefore, expected earnings from criminal behavior are given by $\rho \pi m_t$.[19] The crime decision after release is the end point of a game that unfolds in three stages: (i) the prison warden chooses the inmate's work profile given a resource constraint; (ii) technologies transform this work assignment into stocks that affect crime choices; (iii) the convict is released and chooses whether or not to engage in crime again. After describing the technologies, I solve the game backwards.

5.1.2 Technologies

The technology of liquidity: Prison earnings are paid into a zero-interest account and so during his term a convict earns resources totaling

$$y_0 = w \sum_{t=I}^{O} h_t. \tag{8}$$

In order to reduce the model's complexity and the number of parameters that must be estimated, it is convenient to assume that the utility of y_0 materializes upon release. Thus at $t \geq 0$ the ex-convict has *effective liquidity* $\lambda_t y_0$ due to his prison work; by this I mean that earning y_0 during custody is equivalent to having $\lambda_1 y_0$ in the first post-release period, $\lambda_2 y_0$ in the second such period, and so on. Parameter λ_t captures the effects of choices not modeled here, such as transferring prison earnings to dependents or using those earnings to increase prison consumption beyond c_p or to generate a stock

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[19]Strictly speaking, criminal capital is a component of human capital. However, I follow the convention – observed in the aforementioned dynamic economic models of crime – of distinguishing between these two stocks, and I label labor market ability "human capital" and criminal ability "criminal capital".

of savings for post-release consumption. It follows that my structural model is partially specified and that λ_t is a sufficient statistic: given the other parameters to be introduced shortly, knowledge of λ_t is sufficient to evaluate the effect of prison earnings on the re-incarceration outcome in period t through the liquidity channel – even if the deeper structural parameters embedded in λ_t are not made explicit (Chetty, 2009; Low and Meghir, 2017). Prison earnings have two effects on crime incentives: (i) a deterrent effect, by providing a liquidity buffer;[20] and (ii) an encouraging effect, by offering convicts the chance to earn money while in prison. Therefore, the sign of λ_t is not restricted. If (i) dominates (ii) in period t then $\lambda_t > 0$; otherwise, $\lambda_t < 0$.[21]

The technology of earning ability: Time spent working in prison is a form of on-the-job training. Although the prison jobs that I study are unskilled and so do not provide relevant skills, strictly defined, they may well contribute to a convict's earning ability in two ways. First, these jobs contribute by maintaining (or building) more general skills such as the ability to focus on a task, time management, and the habit of working. Goals and motivation are also part of such soft skills, which have a positive rate of return (Heckman and Kautz, 2012). Prison work may also reduce the scope for statistical discrimination against ex-convicts (Pager, 2003; Holzer et al., 2007; Doleac and Hansen, 2020) because work experiences in prison, even in unskilled jobs, could signal other soft skills such as "good character" and work discipline (Bushway and Apel, 2012).

Second, prison work may contribute to a convict's earning ability via mental health – a key component of human capital – because work means replacing idle time in prison with active time in meaningful activities and the resulting mental stimulation. As an example of the potentially detrimental effect of idle time in prison for earning ability along a mental health channel, prisoners interviewed by Nurse et al. (2003) in England reported "that long periods of isolation with little mental stimulus contributed to poor mental health and led to intense feelings of anger, frustration, and anxiety. Prisoners said

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[20]For example, Munyo and Rossi (2015) report that a threefold increase in the gratuity given upon release to inmates in Uruguay reduced first-day recidivism from about 0.5 crimes per release to zero.

[21]Assuming that the utility of prison earnings materializes upon release is without loss of generality because what matters for crime decisions is the value of resources in state f (which are lost in case of an arrest) relative to state p. However, there are consequences for the model's ability to answer counterfactual questions. For example, I cannot evaluate in this model a policy that forces convicts to save all of their prison earnings until release or one that allows them to use such savings only to support dependents or to compensate victims.

they misused drugs to relieve the long hours of tedium" (p. 1). Schnittker et al. (2012) discuss selectivity issues and show, for a sample representative of the US population, that the association between incarceration and mental health is robust to conditioning on a rich set of variables that capture childhood background and pre-existing mental health issues. This finding leads the authors to argue that incarceration causes psychiatric disorders that impair a prisoner's ability to re-integrate himself into society through employment – that is, owing to the impact of such disorders on motivation and on behavior more generally. Baćak et al. (2019) address selectivity by exploiting a natural experiment that reduced the average incarceration age of first offenders in Denmark: roughly from 20.2 to 19.7, on average. The authors find that incarceration at a more psychologically sensitive age leads to psychiatric issues.

I represent these concepts in the model by assuming that time spent at work during incarceration allows an inmate to retain or improve his earning ability – which reflects both the ability to secure a job match and the broad skills used in that job – in the same way that free (nonprison) work does via on-the-job training. Formally: I assume that, for a given state $s = \{f, p\}$, effective human capital ηk evolves according to the following law of motion:

$$\eta_{t+1}k_{t+1} = (1 - \delta_s)\eta_t k_t + \theta_s h_t \eta_t k_t. \tag{9}$$

In state f, this equation reduces to a version of human capital dynamics in Ben-Porath's (1967) model. A linear technology is restrictive but minimizes the number of parameters needed. The first term on the RHS of equation (9) indicates that a free individual's stock of effective human capital depreciates at rate $0 \leq \delta_f < 1$. The second term is the investment component; in state f it is $h_t = 1$, so $\theta_f \geq 0$ captures a conventional on-the-job training mechanism for employed individuals. This mechanism features a complementarity with the current stock of effective human capital, which reflects the self-productivity of skills (Cunha and Heckman, 2007; Cunha et al., 2010). In prison (state p), however, earning ability depreciates at rate $0 \leq \delta_p < 1$, it is $h_t \leq 1$, and $\theta_p \geq 0$ captures the beneficial impact of unskilled prison work on earning ability via the maintenance of soft labor market skills and mental health.[22] Recursive substitution of

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[22]In light of the foregoing discussion, it is reasonable to expect that earning ability depreciates faster in prison than in a free state, or that $\delta_p > \delta_f$. This conjecture is testable and is confirmed by the results reported in what follows.

effective human capital in periods $t, t-1, \ldots, I-1$ into (9) in state p yields the effective human capital $\eta_1 k_1$ for a convict who has just been released from prison and whose earning potential was $\eta_I k_I$ at the beginning of the prison term:

$$\eta_1 k_1 = \eta_I k_I \prod_{t=I}^{O} (1 - \delta_p + \theta_p h_t). \tag{10}$$

Note that the technology of earning ability during the incarceration term features dynamic complementarities if $\theta_p > 0$. In this case, for any period $I \leq t < O$ during the term, we have that $\frac{\partial^2 \eta_1 k_1}{\partial \eta_I k_I \partial h_t} > 0$. Thus prison work is an investment (chosen by the warden) whose productivity, in terms of a convict's earning ability at release, increases with the level of his effective human capital at prison admission.

The technology of criminal capital: Similarly to the case of labor market skills, criminal capital m evolves – given a state $s = \{f, p\}$ – according to the following law of motion

$$m_{t+1} = \begin{cases} (1 - d_p)m_t + \varsigma l_t m_t & \text{if } s = p, \\ (1 - d_f)m_t + \mu x_t m_t & \text{if } s = f. \end{cases} \tag{11}$$

Here $d_p - \varsigma$ is the rate at which criminal capital depreciates in prison during any period for a convict who does not work in that period and who therefore spends his entire time endowment in idleness ($l_t = 1$). This depreciation captures the core component of the rehabilitation process, which we can view as a reduction in the stock of criminal capital experienced in prison, and its sign can be either positive or negative. If $d_p - \varsigma > 0$ then, even in the absence of a work component, incarceration rehabilitates convicts to some extent. However, an incarceration regime has a criminogenic effect when $d_p - \varsigma < 0$. Given that $l_t = 1 - h_t$, parameter ς determines the social effect of prison work – that is, the extent to which reducing nonwork time (and hence also idle time) in prison affects the depreciation of criminal capital. This parameter can likewise be either positive or negative: idleness in prison favors criminogenic social interactions, especially for young convicts (Bayer et al., 2009; Aizer and Doyle, 2015; Stevenson, 2017), but work activity may also increase such interactions by connecting an inmate with the broader prison network.[23] Note that the same complementarity that characterizes investment in earning

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[23]The term ς is a composite parameter that reflects the importance of criminogenic social interactions in prison and the ability of work time to alter them. Like λ_t, it should be regarded as a sufficient statistic.

potential via prison work also characterizes investment (or disinvestment) in criminal capital via activity in prison jobs. For a free individual, in contrast, criminal capital depreciates at rate d_f and accumulates via criminal experience. As indicated by equation (11), an individual in state f who engages in crime in period t ($x_t = 1$) experiences an increase of $\mu\%$ in his criminal capital (gross of depreciation) during that period. Just like for labor market skills, the effect of criminal experience is proportional to one's current criminal skills, and replacing criminal capital recursively into (11) in state p yields criminal capital at release, m_1, for a convict whose stock was m_I at the outset of the prison term:

$$m_1 = m_I \prod_{t=I}^{O}(1 - d_p + \varsigma(1 - h_t)). \tag{12}$$

The technology of criminal capital during an incarceration term also features dynamic interdependence. For any period $I \leq t < O$ during the term, we have that the sign of $\frac{\partial^2 m_1}{\partial m_I \partial h_t}$ is the opposite of the sign of ς. If $\varsigma > 0$, then the cross-partial derivative is negative and so a greater amount of criminal capital in period t increases the (*negative*) effect of prison work – in that period and in previous periods – on future criminal capital.[24] If instead $\varsigma < 0$, then having more criminal capital in period t increases the (*positive*) effect of prison work on future criminal capital.

5.1.3 The ex-convict's problem

After release and as long as he is in state f, the ex-convict faces a recurrent binary choice problem beginning at $t = 1$: engage in crime again ($x_t = 1$) or not ($x_t = 0$). This problem's state variables are given by the stocks of effective liquidity, effective human capital, and criminal capital, and are denoted $\Omega_t = \{\lambda_t y_0, \eta_t k_t, m_t\}$. If not engaging in crime, the ex-convict enjoys effective liquidity from past prison work and current expected labor market earnings. If engaging in crime, he also receives the crime wage in the event he is not arrested. If he is arrested – an event represented by random variable A, whose mean conditional on committing a crime is π – the ex-convict is re-incarcerated immediately for a prison term that ends at time O'. At this point, the problem is over.[25] I denote by $V_t^f(\Omega_t)$ and V_t^p the values of being free and of being in prison, respectively,

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[24]In this case I still define, somewhat improperly, a negative cross-partial derivative as a complementarity because less criminal capital reduces the likelihood of re-incarceration following release.
[25]Given that $t = 1, 2, 3$, this assumption is natural and allows me to simplify the analysis considerably.

at time t. Denote by c_t consumption in period t, by β the discount factor, and by $v_t(x_t)$ an unobserved (to the econometrician) mean-zero crime shock that is independent and identically distributed and that is expressed in consumption equivalents (such a shock may represent the profitability of a specific crime opportunity, for example). Then the problem is characterized by the Bellman equation,

$$V_t^f(\Omega_t) = \max_{x_t}\{\mathbb{E}_A c_t(x_t) + v_t(x_t) + \beta\mathbb{E}_{A,v}V_{t+1}^s(\Omega_{t+1})\}, \tag{13}$$

subject to the dynamics in (9) and (11), and where $\eta_t k_t$ and m_t in the first decision period $t = 1$ are given by equations (10) and (12), respectively, and

$$c_t(x_t) = \begin{cases} \lambda_t y_0 + \gamma\eta_t k_t & \text{if } x_t = 0, \\ \lambda_t y_0 + \gamma\eta_t k_t + \rho m_t & \text{if } x_t = 1 \text{ and not arrested,} \\ c_p & \text{if } x_t = 1 \text{ and arrested;} \end{cases} \tag{14}$$

$$V_{t+1}^s(\Omega_{t+1}) = \begin{cases} V_{t+1}^f(\Omega_{t+1}^0) & \text{if } x_t = 0, \\ V_{t+1}^f(\Omega_{t+1}^1) & \text{if } x_t = 1 \text{ and not arrested,} \\ V_{t+1}^p = \sum_{\tau=t+1}^{O'}\beta^\tau c_p & \text{if } x_t = 1 \text{ and arrested.} \end{cases} \tag{15}$$

Here Ω_{t+1}^x, with $x \in \{0,1\}$, is shorthand for $\Omega_{t+1}(x_t = x)$, a dependence that results from building criminal capital via criminal experience in state f. Note that although the first expectation on the RHS of equation (13) is taken with respect to the probability of arrest, the second expectation is taken with respect to the joint probability distribution of arrest and the future preference shock v_{t+1}. It is the latter that, given the future state Ω_{t+1} and the parameters, determines the likelihood of criminal behavior at $t+1$.

The probability of being re-incarcerated in period t is given by the probability of engaging in crime in that period, $\Pr[x_t = 1 \mid \Omega_t] = \Pr[V_t^f(\Omega_t; x_t = 1) \geq V_t^f(\Omega_t; x_t = 0)]$, multiplied by the probability π of apprehension. Denote by $\mathbf{h} = \{h_\tau\}_{\tau=I}^{O}$ the work profile during a prison term, by $\Theta = \{\pi, \lambda_t, w, \gamma, \eta_I, k_I, \delta_p, \delta_f, \theta_p, \theta_f, \rho, m_I, d_p, d_f, \varsigma, \mu, c_p, \beta\}$ the parameter vector, by F the cumulative distribution function of $v_t(0) - v_t(1)$, and by R_t a dummy variable set to 1 if the ex-convict is re-incarcerated during period t (and set to 0 otherwise). If we define $C_p \equiv \sum_{\tau=t+1}^{O'}\beta^{\tau-1}c_p$ and use equations (8)–(12), then this

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re-incarceration probability, for $t = 1, 2, 3$, is

$$\Pr(R_t = 1 \mid \mathbf{h}; \Theta)$$

$$= \pi F\Big[-\pi\Big(\lambda_t w \sum_{\tau=I}^{O} h_\tau + \gamma\eta_I k_I \prod_{\tau=I}^{O}(1 - \delta_p + \theta_p h_\tau)(1 - \delta_f + \theta_f)^{t-1} - c_p\Big)$$

$$+ (1 - \pi)\rho m_I \prod_{\tau=I}^{O}(1 - d_p + \varsigma(1 - h_\tau)) \prod_{j=1}^{2}(1 - d_f + \mu x_j)^{\mathbb{I}[t>j]}$$

$$+ \pi\beta(C_p - V_{t+1}^{f}(\Omega_{t+1}^{1}; \Theta)) + \beta(V_{t+1}^{f}(\Omega_{t+1}^{1}; \Theta) - V_{t+1}^{f}(\Omega_{t+1}^{0}; \Theta))\Big]. \quad (16)$$

This expression seems cumbersome but is quite intuitive. Consider the part inside brackets. The first line is a negative term representing the disincentive to crime that is generated by effective liquidity $\lambda_t y_0$ and expected earnings $\gamma\eta_t k_t$ relative to prison consumption c_p. Upon release ($t = 1$), effective human capital $\eta_1 k_1$ results from the combined effect of depreciation during the past state p (at rate δ_p) and investment via prison work (at rate $\theta_p h_\tau$) on earning ability $\gamma\eta_I k_I$ at entry; in subsequent periods, such capital is affected also by net investment in state f (at rate $\theta_f - \delta_f$).

The second line captures the positive influence of crime wage ρm_t on the likelihood of engaging in crime. Such influence is proportional to one's criminal capital. Like labor market skills, criminal skills at $t = 1$ are determined by the depreciation (or appreciation) of initial criminal capital experienced in prison through prison activities, including work; whereas at $t > 1$ criminal capital is also affected by depreciation net of possible criminal experience in state f (at rate $d_f - \mu x_t$). In this line, $\mathbb{I}[t > j]$ is an indicator function that takes value 0 at $t = 1$ and value 1 in subsequent periods $t > 1$.

Finally, the third line contains continuation values. The first term indicates that, if the ex-convict engages in crime again and is apprehended, then he trades off the value of being free with additional criminal experience in the next period, $V_{t+1}^{f}(\Omega_{t+1}^{1})$, against the value of prison consumption. Yet given that $\mu \geq 0$, the ex-convict also increases the value of being free with a relative increase in criminal capital obtained via criminal experience; the amount of that increase is equal to the difference $V_{t+1}^{f}(\Omega_{t+1}^{1}) - V_{t+1}^{f}(\Omega_{t+1}^{0})$.

Equation (16), which characterizes the optimum of an ex-convict, is the structural counterpart of reduced-form equation (3). The latter misses critical nonlinearities and interactions that are implied by the model and that assist not only in identification of the overall effect of prison work on re-incarceration but also in the separate identification

of liquidity, training, and social effects (i.e., the parameters λ_t, θ_p, and ς). To see how my structural modeling allows for such separate identification, note that the technologies of liquidity, earning ability, and criminal capital generate restrictions that break the collinearity between work time and total earnings from prison jobs during each period of the prison term. Equation (16) shows that, through the liquidity channel, the effect at post-release time $t > 0$ of prison work in a given period $t \leq 0$ of the incarceration term is independent of the allocation of an inmate's time in other periods of the term; through the training and social channels, however, the entire work profile $\{h_t\}_{t=I}^{O}$ during the term matters. Moreover, through the training channel that profile interacts with effective human capital at the beginning of the term whereas, through the social channel, the effect of prison work interacts with the level of criminal capital at the time of incarceration. It is these interactions that enable my separate identification of λ_t, θ_p, and ς.

To estimate equation (16), I first impose self-consistent expectations: at any decision date, expectations about one's future state $s = \{f, p\}$ are formed based on the model's implied conditional probabilities of engaging in crime at future dates. That is, I impose a rational expectations equilibrium. Adopting this notion of equilibrium, I then solve for the value functions analytically by proceeding backwards from the terminal period imposed by the data (i.e., $t = 3$). Under parametric assumptions on the distribution F of unobservables, such analytical solutions are closed-form functions of the parameters in vector Θ (and of F's parameters); hence maximum likelihood or minimum-distance estimation can be used to identify – via direct inference – the subset of such parameters that cannot be calibrated. Econometric details are provided in Section 5.2.

5.1.4   The warden's problem

Closing the model requires that I specify how the work profile $\{h_t\}_{t=I}^{O}$ of each ex-convict was determined. Details are reported in the online appendix because this part of the model plays no role in my structural estimation. Yet, it is useful because the solution to the warden's problem yields insights into interpreting both the OLS-2SLS gap that is observed in the reduced-form analysis – which partly reflects the bias in the worker selection process – and the LATE-ATE discrepancy that is revealed by the structural estimates – which is ultimately a matter of how the warden alters the ranking determined by entry dates. In order to understand the discretionary component of work assignments,

I consider a warden who is subject only to the budget constraint and who therefore optimizes the prison work–based rehabilitation process by choosing work shares so as to minimize a weighted average (across inmates) of the likelihood of re-engaging in crime upon release – net of output value, which is negative when work activity by problematic convicts ends up disrupting prison life. The solution determines redistribution shares relative to the work assignments implied by a "neutral" work-sharing policy. The identification problem originates precisely from such shares, i.e., the discretionary component of the work assignment. Such shares reflect unobserved characteristics of convicts and are responsible for the nonzero correlation between ε_i and v_{it} across equations (3) and (4), which is the source of the OLS inconsistency bias. The solution to the warden's problem is characterized by standard intratemporal and intertemporal conditions.

The intratemporal conditions indicate that the warden discriminates in favor of convicts whose welfare weight is higher and whose output is more valuable. If these values are positively (resp. negatively) correlated with variables that increase the likelihood of re-incarceration, then workers in prison jobs are negatively (resp. positively) selected. This is an untestable implication. However, the roles of earning ability and criminal capital in the selection process are testable. As shown in Section 5.3, my estimates of θ_p and ς are both positive, indicating dynamic complementarity in the technologies of k and m, i.e., $\frac{\partial^2 \eta_{i1} k_{i1}}{\partial h_{it} \partial \eta_{iI} k_{iI}} > 0$ and $\frac{\partial^2 m_{i1}}{\partial h_{it} \partial m_{i1}} > 0$. I discuss in the online appendix the conditions under which such complementarity also implies $\frac{\partial^2 r_{i1}(\mathbf{h}_i)}{\partial h_{it} \partial \eta_{iI} k_{iI}} < 0$ and $\frac{\partial^2 r_{i1}(\mathbf{h}_i)}{\partial h_{it} \partial m_{iI}} < 0$. In this case, within a cohort, the warden discriminates in favor of convicts who at entry are characterized by higher labor market ability and criminal capital. The online appendix also provides some evidence in favor of this implication, which accounts for part of the OLS-2SLS gap in the reduced-form causal analysis of the Italian prison labor system. The type of selection induced by other institutional mechanisms may be different. For example, work under the FPI program in the United States is voluntary and so inmates self-select based on their individual abilities and work attitudes. In this case, the evidence (Saylor and Gaes, 1997) is indicative of positive selection into prison work.

The intertemporal conditions, in turn, imply that if the shadow value of the prison wage fund is constant over time, then the optimal work profile is flat. In this case, an institutional constraint that assigns to new convicts the minimum priority score in the work assignment ranking leads to suboptimal rehabilitation outcomes.

5.2 Structural econometric model

The structural analysis is based on equation (16) after replacement of the value function solutions. The parameters of this equation can be estimated via GMM by using the same orthogonality conditions that identify the reduced-form equation (3). I illustrate such an estimation procedure by first noting that, when equation (16) is fit to the data, the individual re-incarceration probability in period t is written as

$$\Pr(R_{it} = 1 \mid \mathbf{h}_i; \Theta_i) = \pi F(\mathbf{h}_i; \Theta_i) + \tilde{v}_{it}, \tag{17}$$

where $\tilde{v}_{it}$ is the structural error – counterpart of the reduced-form error v_{it} in (3). Note that equations (17) and (3) coincide when $\pi F(\mathbf{h}_i; \Theta_i) = \beta_R H_{i,I,O,\mathbf{p}} + \mathbf{X}_{it}\gamma_R + \delta\iota$, where $\delta = [\delta_I \ \delta_O \ \delta_{I,O} \ \delta_{\mathbf{p}}]$ and ι is a vector of 1s. In that case $\Theta_i = \{\beta_R, \gamma_R, \delta\}$ and the structural and reduced-form errors also coincide: $\tilde{v}_{it} = v_{it}$. This remark illustrates the sense in which the reduced-form model described in Section 4 is but a rough linear approximation of the structural model. My estimation of (17) is based on the structural equivalents of the population moment conditions in (5) that identify the reduced-form model; that is, on

$$
\begin{aligned}
\mathbb{E}[\mathbf{X}_{it}\tilde{v}_{it}(\Theta_i)] &= \mathbf{0}, \\
\mathbb{E}[\mathbf{\Delta}_i\tilde{v}_{it}(\Theta_i)] &= \mathbf{0}, \\
\mathbb{E}[\mathbf{Z}_i\tilde{v}_{it}(\Theta_i)] &= \mathbf{0},
\end{aligned} \tag{18}
$$

for $t = 1, 2, 3$ and $i = 1, 2, \ldots, N$, where N is the number of convicts. In practice, however, only those individuals who are still free at t – and therefore have a choice to make – contribute to the estimation in that period. The resulting GMM minimand is

$$
Q(\Theta_i) =
\begin{bmatrix}
\mathbb{E}[\mathbf{X}_{it}\tilde{v}_{it}(\Theta_i)] \\
\mathbb{E}[\mathbf{\Delta}_i\tilde{v}_{it}(\Theta_i)] \\
\mathbb{E}[\mathbf{Z}_i\tilde{v}_{it}(\Theta_i)]
\end{bmatrix}'
\Omega
\begin{bmatrix}
\mathbb{E}[\mathbf{X}_{it}\tilde{v}_{it}(\Theta_i)] \\
\mathbb{E}[\mathbf{\Delta}_i\tilde{v}_{it}(\Theta_i)] \\
\mathbb{E}[\mathbf{Z}_i\tilde{v}_{it}(\Theta_i)]
\end{bmatrix}, \tag{19}
$$

where Ω is a positive semi-definite weighting matrix and where each row in the vector of population moment conditions contains three moments (one for each t). The GMM estimator replaces the population moment conditions with their sample analogues, which are functions of the parameters Θ_i, and estimates those parameters as

$\hat{\Theta}_i = \arg\min_{\Theta_i} Q(\Theta_i)$. I employ Hansen's (1982) optimal (i.e., minimizing the estimator's asymptotic variance) two-step GMM estimator while using the identity matrix as the first step's weighting matrix and relying on numerical optimization of $Q(\Theta_i)$ to locate a minimum. Note that the moments in (18) are not necessarily optimal; their selection is motivated only by the goal of deriving reduced-form and structural estimates that are characterized by an exact correspondence between the respective identification conditions. In line with the reduced-form estimation, this GMM estimator's variance is clustered at the release-prison level.

The procedure described here is more computationally convenient than is indirect inference (e.g., there is no need to simulate moments) or even maximum likelihood, and it has the further advantage of providing structural estimates that are meaningfully comparable with the reduced-form ones. To see this, observe that the 2SLS estimator of the parameters in equation (3) is the GMM estimator that uses the population moment conditions in (5), which are the same as the conditions in (18) – except that the linear approximation $\pi F(\mathbf{h}_i; \Theta_i) = \beta_R H_{i,I,O,\mathbf{p}} + \mathbf{X}_{it}\gamma_R + \delta\iota$ implicitly assumed by the reduced-form model reduces the parameter vector to $\Theta_i = \{\beta_R, \gamma_R, \delta\}$. It follows that identification in the structural model originates from the same sources that provide identification in the reduced-form model, although the identifying assumptions take a different form in the two cases. In the context of linear model (3), the orthogonality conditions (5) boil down to the requirement that matrix $\mathbb{E}[\mathbf{Z}_i[\mathbf{X}_{it}\ \boldsymbol{\Delta}_i]']$ has full rank (i.e., rank equal to the number of parameters that must be estimated). For nonlinear model (17), global identification requires that the conditions in (18) be satisfied at only one point in the parameter space.[26] Because equation (16) is highly nonlinear in the parameters, local identification is a more plausible assumption for my structural estimation. That approach requires the matrix containing the first derivatives of the conditions in (18), evaluated at the parameters' "true" values, to be of full rank.

Loosely speaking, this route to estimating the structural parameters is akin to minimizing the distance between the re-incarceration rates produced by the model, equation (16), and the observed rates in the first three years from the release date. Yet estimation is computationally demanding given the products of functions of the parameters

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[26]Of course, these two requirements coincide in the linear model (3). See Hall (2005) for a comprehensive yet accessible introduction to identification in a GMM framework.

appearing in this equation. In order to reduce such complexity and facilitate convergence, I take two steps as described next. *First*, I assume that the cumulative distribution function *F* is the uniform distribution with support $[-u, u]$ for *u* an additional parameter to be estimated. This assumption is consistent with the use of a linear probability model in the reduced-form equation (3). Hence the computational simplification resulting from this assumption has the further advantage of improved comparability among estimates across the structural and reduced-form models.

Second, I partition the parameter space into $\Theta_i = [\Theta_i^e \, \Theta_i^c]$, where Θ_i^e contains the parameters to be estimated and Θ_i^c contains those parameters that instead can be calibrated because either the data provide information or external evidence is available:

$$\Theta_i^e = \{\lambda_0, \lambda_1, \lambda_2, \eta_{iI}, \delta_p, \theta_p, d_p, d_f, \varsigma, \mu, c_p, u\};$$
$$\Theta_i^c = \{\pi_i, w_i, \gamma_i, k_{iI}, \delta_f, \theta_f, \rho, m_{iI}, \beta\}.$$

The elements of Θ_i^c are calibrated as summarized in Table 4. This calibration requires data on convicts' educational attainment. As shown in Table 1, such information is missing for 44% of the final sample; hence the sample I use for structural estimation differs from the sample used in the reduced-form analysis. I make no attempt to impute missing information. Instead, I show in the online appendix that the reduced-form estimates reported in Table 3 for the full sample are strongly similar to estimates for the smaller structural sample of convicts with non-missing education data.

5.3 Structural results

I focus the structural investigation on two groups of convicts: those who spent less than six months in prison, and those who were incarcerated for a longer time. As indicated by the central columns of Tables 3, prison work has much different effects in these two groups. Explaining that difference is one goal of my analysis.

I first estimate semi-structural specifications that bridge the reduced-form and structural analyses. By "semi-structural" I mean reduced-form specifications that are motivated by the model but still with no attempt to identify the structural parameters, a common empirical approach that is useful but is limited in that its discussion of mechanisms is rather speculative. My model predicts that the treatment effect of prison work is

Table 4: Calibration

Parameter	Value	Source
Labor market:		
k_{iI}	0–17	Data (years of education)
γ_i	€0.83k–6.76k	SHIW (wage-schooling locus)
δ_f	0.091	Fan, Seshadri, and Taber (2019)
θ_f	1.76	Fan, Seshadri, and Taber (2019)
Crime market:		
π_i	0.040–0.918	Italian Criminal Justice Statistics
m_{iI}	1–6.03	Data (conviction offenses index)
ρ_i	€1.06k–25.12k	Data; Fu and Wolpin (2018)
Other:		
w_i	€1.63–26.2	Data (hourly wage in prison jobs)
β	0.72	Mastrobuoni and Rivers (2016)
Time endowment	16 hours/day	Non-sleeping time

Notes: This table summarizes, in addition to the convict's time endowment, calibration of the nine parameters in Θ_i^c as follows.

- k_{iI} (individual i's criminal capital at the beginning of the incarceration term) is proxied by the number of years of education, which is taken directly from the data.

- γ_i (return on human capital conditional on employment) is estimated using data from the Bank of Italy's Survey of Household Income and Wealth (SHIW). The estimand is the slope of a linear annual earnings–schooling locus of workers employed in Italy between 2005 and 2012 (i.e., the sample period) for Italian and foreign-born residents in four age groups (less than 30 years, 31–40 years, 41–50 years, more than 50 years). The estimated intercept γ_0 is also included to obtain the correct measure of earnings conditional on employment for each age-by-nationality group, so earnings are equal to $\gamma_0 + \gamma_1 k_{iI}$. The mean of γ_0 across age groups is estimated to be €8.33k for workers born in Italy and €9.59k for workers born elsewhere (the scale is thousands of euros); the estimated γ_0 is €0.75k for workers born in Italy and €0.31k for foreign-born workers. The range reported in the table is the range of $\gamma_0/k_{iI} + \gamma_1$.

- δ_f (effective human capital depreciation rate for a free individual) is set to 0.091, a value estimated by Fan et al. (2019) using data from the US Survey on Income and Program Participation.

- θ_f (effective human capital self-productivity for a free individual) is set to 1.76, a value also estimated by Fan et al. (2019).

- π_i (apprehension probability) is estimated using data from Italian Criminal Justice statistics. The latest available ratios (year 2005) between crimes with a known offender and total crimes from this source provide an estimate of apprehension rates by type of crime. Each released convict (a) is assumed to have the opportunity to re-engage in the same crimes for which he was previously convicted and (b) is assigned an individual-level apprehension probability equal to the maximum of the corresponding rates in his set of conviction offenses. This approach is consistent with the "hierarchy rule" adopted by the FBI in its Uniform Crime Reports (that rule stipulates that, if multiple offenses occur during a criminal act, then only the most serious one is reported by the police). The resulting distribution ranges between 0.04 and 0.92, with a mean of 0.62 and a standard deviation of 0.34.

- m_{iI} (individual i's criminal capital at the beginning of the incarceration term) is an index constructed by regressing the duration of one's prison term (in years) on dummies for conviction offenses. The predicted values from this regression are normalized by the minimum predicted value, and the resulting index ranges (continuously) between 1 and 6.03. Individuals with a higher index value were convicted on more serious charges, leading to a longer sentence, and so have the profile of a more hardened criminal.

- ρ_i (return on criminal capital conditional on committing a crime) is computed as follows. First, $\rho_i m_{iI}$ is the crime wage at entry, or how much the focal individual was making from criminal activities in the period before his incarceration. Fu and Wolpin (2018) use US data to estimate that a criminal act steals 10% of the victim's income, on average. I therefore estimate the average crime wage as the product of the number of crime acts (measured by $1/\pi_i$) and 10% of household disposable income in Italy during the release year (about €1.8k, using ISTAT's data). Next, this quantity is divided by the mean of m_{iI} in the sample to estimate ρ_i, so that the *average* criminal steals 10% of the victim's resources during each crime act. The resulting value ranges between €1.54k and €25.12k, implying a crime wage of $\rho_i m_{iI}$ whose mean is €5.48k and whose SD is €6.90.

- w_i (prison job wage rate) is taken from the data and is net of deductions for inmate maintenance and other charges.

- β (discount factor) is set to 0.72 based on the results of Mastrobuoni and Rivers (2016), who estimate that the annual discount factor among ex-criminal offenders in Italy ranges between 0.70 and 0.74.

heterogeneous along three dimensions: the prison wage rate w (because of the liquidity effect), criminal capital m (the social effect), and human capital k (the training effect). In order to gauge the relevance of these interactions, I estimate equation (3) by 2SLS after splitting the sample according to the median levels of net wage rate, term duration, and schooling. The results, reported in the online appendix, can be summarized as follows. Among convicts on terms longer than six months, the beneficial effects of prison work on rehabilitation are concentrated at or above the median of the term distribution (i.e., 1.42 years in prison) and at or above the median of the education distribution (8 years of schooling). This suggests that the parameters ς and θ_p are positive in this group. There is no significant heterogeneity by net hourly wage; yet the absolute values of point estimates at $t > 1$ are larger below the median of €3.25, which means that prison work reduces re-incarceration more among convicts who ended up working for a somewhat lower wage. This result, in turn, suggests that parameters λ_t are instead negative. Among convicts on shorter terms, the detrimental effects of prison work uncovered by the reduced-form analysis are instead concentrated at higher levels of the wage rate, which likewise suggests negative values of λ_t. For these convicts on shorter terms, estimates by median term duration or median education are not statistically significant.

Fully structural estimation confirms this pattern. The GMM estimates of model parameters are reported in Table 5 – separately for the two groups of convicts – along with the starting values for Θ_i^e that I used to initialize the computational procedure. These starting values are the same for the two groups. In the first step of my GMM procedure, convergence is achieved after 12 iterations in the sample on terms of at least six months and after 18 iterations in the smaller, complementary sample of convicts on shorter terms. In the second step, the process converges after (respectively) 3 and 4 iterations, and the values of the criterion function $Q(\Theta_i)$ at the minimum are fairly close to zero: 0.0048 and 0.0147, respectively. Hansen's (1982) over-identification test does not reject the validity of the over-identifying moment restrictions in either of the two samples (p-values of 37% and 47%, respectively).

I will briefly illustrate the parameter estimates before using them to simulate the model numerically and to perform counterfactual experiments. The first panel of Table 5 contains estimates that are ancillary to my mechanism decomposition exercise; however, they provide valuable information about parameters that figure prominently

in quantitative models of crime but have seldom been estimated. For convicts who do not work at all during the term, the annual depreciation rate δ_p of earning potential is estimated to be 81% for those who are imprisoned for more than six months but only 10.5% for those on shorter prison terms. The high rate for the first group is consistent with the previously mentioned detrimental effects of incarceration on mental health and post-release discrimination; it accords also with the large effect of incarceration on earnings estimated by some authors (Waldfogel, 1994; Western, 2002; Harding et al., 2018).[27] In the absence of work, criminal capital is similarly estimated to depreciate at an annual rate $\delta_p - \varsigma$ of 53.1% for prisoners on terms longer than six months and at a far lower rate of 14.1% for the other convicts. As already discussed, this baseline depreciation rate measures the effectiveness of a rehabilitation process absent prison work. The gap in the estimates across these two groups can be explained in this way: rehabilitation programs need time to yield beneficial effects and so are less effective for convicts on short terms than for those incarcerated for longer terms.

My estimate of the effect of criminal experience on criminal ability, μ, is similar across the two groups: between about 10% and 13%. This magnitude of "on-the-crime training" outside prison is consistent with the values inferred by Lochner (2004) for the United States. The estimated depreciation rate of criminal capital outside prison for those abstaining from crime, d_f, is also similar across the two groups and exceeds 90%. That value is arguably an overestimate because the implied depreciation rate for those re-engaging in crime (i.e., $d_f - \mu$) would still be more than 80%. Yet these estimates suggest that avoiding crime after release leads to a rapid increase in the ratio of labor market skills to criminal skills. The annual value of prison consumption, c_p, turns out to be negative: between €200 and €300, in absolute value.[28] This outcome is plausible when one considers that prison consumption is net of the dis-amenities of prison life, especially the loss of personal freedom.

The estimated employment rates immediately before incarceration range between 1.2% and 5.2% and are higher for foreign-born convicts than for native Italians. These low estimates are consistent with recent evidence for the United States reported by Looney and Turner (2018). Those authors combine data from the Federal Bureau of Prisons and

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[27] Kling (2006) finds negligible effects of a longer prison term on labor market outcomes.

[28] All monetary values are expressed in thousand of euros, so the parameters c_p inherit that scale.

Parameter		Terms $\geq$ 6 months	Terms $<$ 6 months	Common starting value
Ancillary parameters				
Earning potential deprec. in prison	δ_p	0.810 (0.005)	0.105 (0.023)	0.7
Criminal capital deprec. in prison	$d_p - \varsigma$	0.531 (0.010)	0.141 (0.050)	0.2
Criminal learning outside prison	μ	0.097 (0.003)	0.134 (0.004)	0.2*
Criminal capital deprec. when free	d_f	0.966 (0.009)	0.964 (0.013)	0.2*
Prison consumption	c_p	–0.242 (0.008)	–0.286 (0.054)	–1
Empl. rate at entry, natives	$\eta_{I,n}$	0.012 (0.000)	0.038 (0.002)	0.05
Empl. rate at entry, foreign-born	$\eta_{I,f}$	0.029 (0.001)	0.052 (0.002)	0.1
Support of unobservables	u	0.712 (0.025)	4.849 (0.352)	5
Mechanism parameters				
Liquidity effect, first year	λ_0	–0.010 (0.001)	–16.516 (1.614)	0.5
Liquidity effect, second year	λ_1	–0.074 (0.003)	6.970 (1.460)	0.3
Liquidity effect, third year	λ_2	–0.025 (0.002)	3.442 (1.539)	0.1
Social effect	ς	2.040 (0.478)	–4.521 (4.757)	0.1
Training effect	θ_p	3.790 (0.084)	–5.253 (6.370)	3
Moment conditions, Eq. 18		1,152	1,152	
Overidentification test, p-value		0.37	0.47	
Observations		41,652	12,497	

Notes: This table reports the results of my structural estimation of equation (16) via Hansen's (1982) optimal two-step GMM estimator, using the identity matrix as the first step's weighting matrix. The moment conditions are given by equation (18). The estimator's variance is clustered at the release-prison level. Sample: 54,149 male convicts who were released between 2009 and 2012 (at the end of their sentence) from 209 correctional facilities in Italy and who (a) were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses and (b) had non-missing education information. *Convergence was not achieved from a starting value of 0.2 for these parameters in the sample of terms $<$ 6 months, so a starting value of 0 was used instead.

the IRS and find that, in the year prior to incarceration (between 2009 and 2013) in either a state or federal prison, only 6.6% of adult convicts had strictly positive earnings. Finally, note that the support of unobservables $[-u, u]$, whose scale is thousands of euros, is much smaller for convicts on terms of at least six months than for those on shorter terms. This result suggests that the forces represented in the model are less predictive of the post-release behavior of shorter-term convicts, which is consistent with the different estimates of the mechanism parameters.

These estimates are reported in the second panel of Table 5. Among convicts on longer terms, the liquidity effect parameter, λ_t, is negative in all three of the post-release periods. Thus earnings from prison jobs increase the value of being in prison relative to being free. For example, a value of -0.074 for λ_2 means that earning €2,000 during the prison term (this is approximately 1 SD in the sample; see Table 1) is equivalent to reducing the gap between the values of being free – without engaging in crime – or in prison by $0.074 \times 2000 = $ €148 in the second year from the release date. This magnitude is comparable to that of the expected (with respect to the average apprehension probability of 0.62) negative value of annual prison consumption.

The social effect parameter, ς, is positive for this group of convicts; in other words, prison work accelerates the depreciation of criminal capital. Given that the time endowment is normalized to 1 and that the model variable $h_i = (O - I + 1)^{-1} \sum_{\tau=I}^{O} h_{it}$ therefore has mean 0.017 and standard deviation 0.034, a value of 2.04 for ς means that a 1-SD increase in work time during a given year increases criminal capital depreciation by $2.04 \times 0.034 \approx 6.9$ percentage points in that year.

The training effect parameter, θ_p, is estimated to be 3.79 for this same group; the implication is that working the *entire* time endowment during a term would, absent depreciation, increase one's expected labor market earnings in a given year by a factor of nearly 5. This large value should be interpreted in relation to the large depreciation rate of 81% per year that I have estimated and to the size a 1 SD. The estimate for θ_p implies that one additional standard deviation of work time in a given year decreases the depreciation of expected earnings by $3.79 \times 0.034 \approx 12.9$ percentage points in that year, which suggests that the training effect is more important than the social effect. The simulation to follow confirms these conjectures.

Yet in the group of convicts who were incarcerated for less than six months, the

social effect and training effect parameters are not statistically different from zero, and both point estimates are negative. Only the liquidity effect is precisely estimated; it is negative and large in the first year from the release date but positive later on.

5.3.1 Model simulation and mechanism decomposition

The next step in my structural analysis involves (a) using the model to reproduce the reduced-form causal estimates of prison work and then (b) decomposing those estimates into the contribution of the liquidity, training, and social effects. This exercise is crucial for assessing the mutual consistency of estimates obtained via different – and often conflicting – methodologies, and it allows me to both analyze the underlying heterogeneity of treatment effects and perform policy experiments. I start by considering convicts on terms longer than six months because the social and training parameters are more precisely estimated for them, and I proceed as follows. First, the values of the nine calibrated parameters in Θ_i^c and the twelve estimated parameters in Θ_i^e are substituted into the analytical solution to equation (16) for $t = 1, 2, 3$. This replacement generates numerical predictions for the individual re-incarceration rates within one, two, and three years from the release date – rates that can be compared with the actual rates to assess the distance between the model and the data.[29] That fit is illustrated in the upper left panel of Figure 8. The model reproduces the observed baseline re-arrest rates almost perfectly, which was expected in light of the optimized GMM criterion function's low value.

Second, the model is simulated numerically by increasing the work time per month in prison of all convicts by the same amount implicitly used to estimate the reduced-form causal effect – namely, 1 standard deviation. In order to be consistent with the reduced-form analysis, I do so by increasing uniformly the share of work time in every period (one of the counterfactual experiments carried out later explores a different temporal distribution) in proportion to the fraction of each period that an ex-convict spent in prison. The individual treatment effect is then given by the difference between the resulting counterfactual re-incarceration probability and the baseline probability. The

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[29]As per definitions in the linear probability model, if equation (16) predicts negative probabilities then these predictions are replaced with a value of 0 when comparing model-predicted and actual re-incarceration rates. Among 41,652 individuals on terms longer than six months, there are 822 such occurrences at $t = 1$, 938 at $t = 2$, and 978 at $t = 3$. Similarly, predicted probabilities greater than 1 are replaced with a value of 1. There are no such occurrences at $t = 1$ or $t = 2$ and only 130 instances at $t = 3$.

average of such differences is the ATE. Because this procedure yields the variation in the mean of the distribution of reincarceration rates induced by 1-SD increase in work time, the ATE produced by the structural model is directly comparable to parameter β_R in the reduced-form model (3). Such ATE is illustrated in the upper right panel of Figure 8 (dashed line), along with the 2SLS estimates (continuous line) and their 95% confidence intervals (caps). The model-predicted ATE is substantially smaller than the LATE: about 3 percentage points versus about 10 p.p. in the third year from the release date. This discrepancy suggests that the compliers in my 2SLS estimation, to which the LATE applies, respond differently to prison work than the general population of convicts, to which the model-predicted ATE instead applies. Recall that the instruments that identify the LATE in the reduced-form analysis define the compliers as those convicts who work more (or fewer) hours in prison jobs because they were admitted earlier (or later) than others within their cohort, i.e., their assignment to work follows the deterministic rule. In other words, the compliers are *never* placed back at the bottom of the waiting list when their work turn comes up or given an advantage that overrides the ranking determined by entry dates. Therefore, there is little doubt that the compliers have different characteristics: they are "more normal" than the rest. Based on this clue, I try to disentangle a group of "possible compliers" from the data to check whether the ATE approaches the LATE for them. A candidate group are convicts who spend in prison less than a year (but more than six months, which is the focal sample). Due to their recent admission to prison, such convicts may be little known to the warden, and this lack of information reduces the scope for negative or positive discrimination in assignment to work. Arguably, wardens exercise their discretion in light of knowledge about convicts characteristics that is acquired over time. The ATE for this group of possible compliers is also illustrated in the upper right panel of Figure 8 (dotted line). In this case the model-predicted ATE is always within the LATE confidence interval and also is very close to the 2SLS estimates at $t = 2$ and $t = 3$.[30] This similarity suggests that the reduced-form and structural estimates are mutually consistent. Note that the lower bound for the internal rate of return on the wage fund estimated in Section 4.2 is negative at an ATE of 3 p.p. (−65.6%).

Third, the total effect is decomposed into liquidity, social, and training effects by sim-

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[30]Another reason that explains the observed discrepancies between the 2SLS and structural estimates of the average treatment effect for the compliers is that reduced-form model imposes a linear approximation.

ulating the same 1-SD increase in prison work time already described – but activating just one mechanism at a time while keeping the other two inactive. More precisely: with reference to equation (16), I quantify the liquidity effect by increasing the h_τ's that are multiplied by w (which activates the liquidity mechanism) while keeping constant the h_τ's that interact with k_I and m_I (which shuts down the training and social mechanisms). Quantification of the social and training effects proceeds in a similar manner. The resulting decomposition is shown in the lower panels of Figure 8 for all convicts (left) and for the group of possible compliers previously discussed (right).

Figure 8: Model simulation and mechanism decomposition
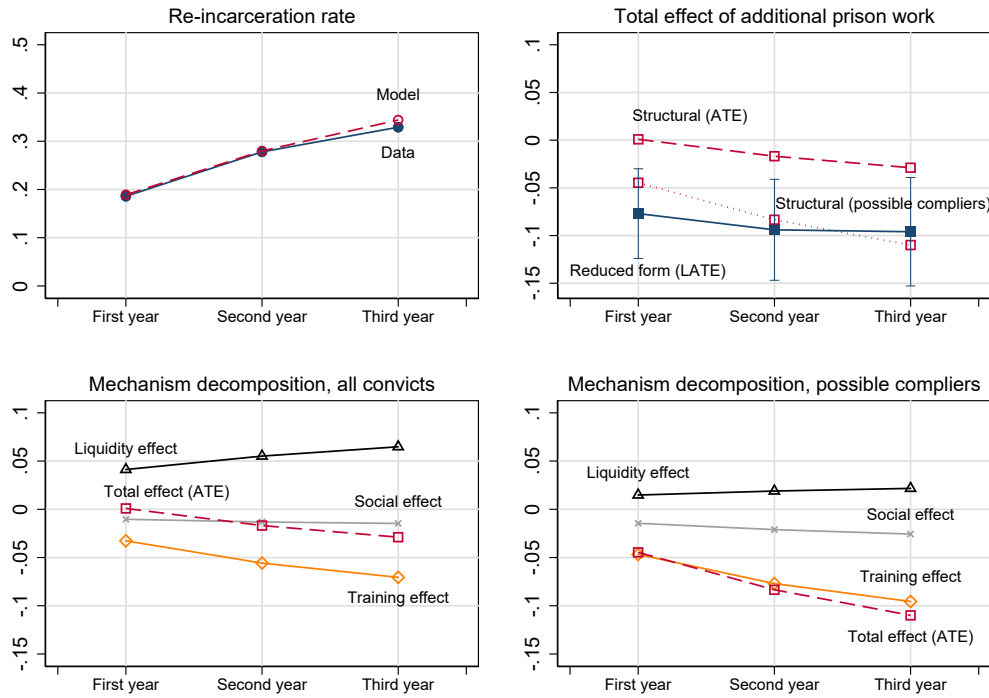
Notes: The upper left panel shows the fit of the structural model by comparing the re-incarceration rates predicted by that model with the empirical rates in the first, second, and third year from release date. The upper right panel compares the baseline 2SLS effects reported in Table 3, which identify the LATE (point estimates and 95% confidence interval), with the analogous effects (i.e., induced by a 1-SD increase in the hours per month worked at a prison job) that are simulated in the model, which identify the ATE. The lower panels illustrate the decomposition of these effects into a liquidity, training, and social effect. As explained in the text, the decomposition is obtained by alternately activating one mechanism while keeping the other two inactive. Sample: 41,652 male convicts who were released between 2009 and 2012 (at the end of their sentence) from 209 correctional facilities in Italy and who (a) were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses, (b) had non-missing education information, and (c) were incarcerated for at least six months.

We can see that the liquidity and training effects work in opposite directions. However, the latter is both stronger and reinforced by a modest social effect; hence it drives

the total, negative effect of prison work on re-incarceration.[31] Therefore, the total effect would be stronger if the prison wage rate were lower. The non-negligible liquidity effect shown in the lower left panel of Figure 8 indicates that ex-convicts may be liquidity constrained after release. In that case, the deterrent effect of incarceration in facilities where money can be earned is less effective. I return on this point below by simulating the effect of adopting prison wages similar to those prevailing in the United States. This conclusion depends, of course, on the validity of my implicit assumption that the training and social mechanisms are separable from the monetary compensation of convicts. The relatively small social effect that I infer is consistent with the idea that work time does not much alter criminogenic social interactions in prison. After all, an employed convict interacts with a similar set of inmates as in the counterfactual scenario of no work. Yet my estimates suggest that such interactions are reduced by prison work. The large training effect (especially among the possible compliers that I have considered) is not surprising when one considers the sizeable depreciation of labor market skills that comes with many idle hours in prison.

An intriguing result is obtained when the parameters in Θ_i^ϱ are estimated by GMM using only the OLS orthogonality conditions; that is, I use only the first two lines of equation (18), which correspond to the "included" instruments $(\mathbf{X}_i, \mathbf{\Delta}_i)$.[32] I show in the online appendix that such alternative identifying assumptions result in essentially the same structural estimates that are obtained by using the 2SLS orthogonality conditions. It is remarkable that – even absent the excluded instruments $\mathbf{Z}_i$ — GMM estimation of the structural model would have revealed the ATE of prison work that is missed by OLS estimates. Thus the included instruments contain enough identifying information in a nonlinear model such as equation (16), which exemplifies how the nonlinearities induced by economic models can assist in the identification of causal effects notwithstanding the absence of experimental or quasi-experimental variation. Absent excluded instruments, identification fails instead in a linear model such as equation (3).

This mechanism decomposition exercise is repeated in the online appendix for the sample of convicts on terms shorter than six months. For them, the large negative

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[31]The total effect does not exactly equal the sum of the liquidity, social, and training effects because there are intertemporal interactions when all three mechanisms are active.

[32]These alternative identifying assumptions reduce the number of moment conditions from 1,152 to 999 because (a) the 51 entry-week dummies in $\mathbf{Z}_i$ are removed and (b) there are three structural errors $\tilde{v}_{it}$, one for each $t = 1, 2, 3$.

liquidity effect in the first period is enough to produce a detrimental effect of prison work that is comparable to the reduced-form estimates: one additional standard deviation of work time leads to an increase in the re-incarceration rate of 4.3 percentage points in the first post-release year, 9.2 p.p. in the second, and 7.7 p.p. in the third. These magnitudes are in the same ballpark as the 2SLS and MB2SLS estimates reported in Table 3 for this group, which is composed of possible compliers only.

The discrepancy between the ATE and the LATE of prison work confirms the presence of important treatment effect heterogeneity that was already revealed by Table 3. The model, which provides us with the entire treatment effect distributions in each of the post-release periods, also enables a straightforward analysis of such heterogeneity. These distributions, smoothed via kernel density estimation, are illustrated in Figure 9 for convicts on terms longer than 6 months (and in the online appendix for the rest). The dashed vertical line in each panel marks the mean of the distribution, which corresponds to the ATE reported in the lower left panel of Figure 8. Note how the distribution of total treatment effects spreads out over time as the dynamic mechanisms embedded in the model unfold and amplify the initial heterogeneity.

Figure 9: Treatment effect distribution
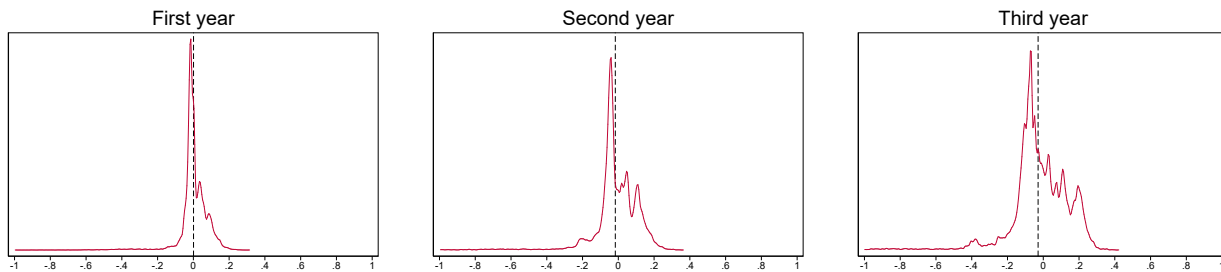
Notes: The figure reports kernel density estimates, using a triangular kernel and a bandwidth of 0.01, of the distribution of model-simulated treatment effects. Sample: 41,652 male convicts who were released between 2009 and 2012 (at the end of their sentence) from 209 correctional facilities in Italy and who (a) were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses, (b) had non-missing education information, and (c) were incarcerated for at least six months.

I report in the online appendix the results from multivariate OLS regressions of the individual total treatment effects on covariates (age, term duration, education, nationality, and conviction offenses). These covariates explain no more than 2.6% of the variation in the total treatment effect so the bulk of heterogeneity is from unobserved sources.

The linear projections indicate that the total treatment effect is more negative for convicts who are older, on shorter terms (conditional on being incarcerated for at least six months), more educated, and *not* native Italians as well as for those who have *not* been convicted for larceny, burglary, or MV theft. These results, when combined with the other finding in this paper, indicate that the relation between prison work and re-incarceration is U-shaped: positive for terms below six months, negative (and largest) for intermediate terms (between 6 and 18 months), and then reverting to smaller negative values for convicts on longer terms.
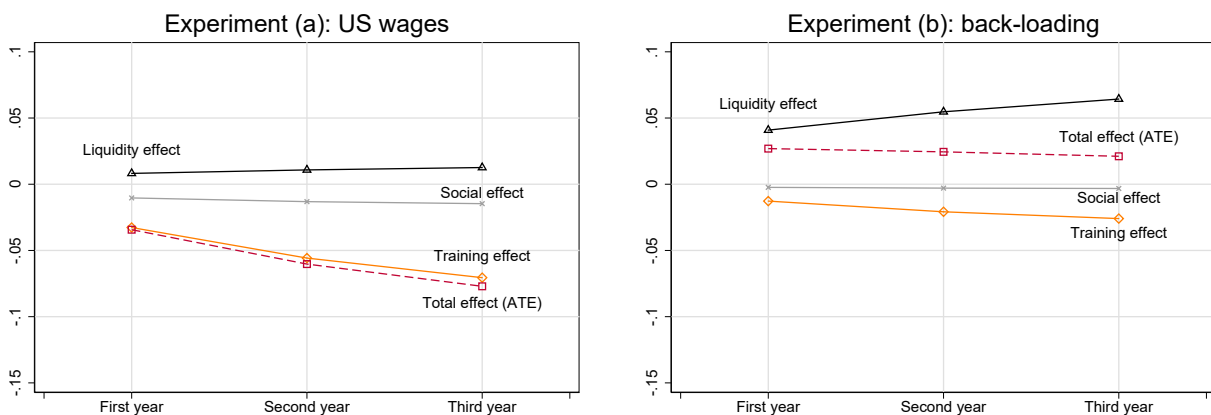
5.3.2 Counterfactual policy experiments

Finally, I use the model to perform two counterfactual policy experiments that are of particular interest in light of the characteristics of the Italian prison labor system: (a) reducing wages in prison jobs to the level currently in use in the United States; (b) backloading an additional 1-SD of work hours in prison jobs at the end of the incarceration term – rather than distributing such increase uniformly during the term.

In the first experiment, I set the hourly wage to €0.60, which is the maximum rate paid to state prisoners in the US to perform compulsory institution work assignments (see Section 1) – the most direct counterpart of the prison jobs that I study in this paper. The results are illustrated in the left panel of Figure 10, which refers to the ATE and which should be compared with the lower left panel of Figure 8. Unsurprisingly, the liquidity effect would be greatly reduced by such a policy, while the social and training effect would be little affected. The resulting ATE is entirely driven by the training mechanism and is stronger than the baseline effects in Figure 8: the predicted reduction in the re-incarceration rate following the adoption of this low wage policy is 3.4 percentage points within one year of release, 6 p.p. within two years, and 7.7 p.p. within three years. Moreover, such a policy would be self-financing because a lower wage rate relaxes the prison administration's budget constraint, thereby enabling prison wardens to create more prison jobs. The problem with the low wages paid in US prisons is that they may generate in a convict the sense of being exploited, which in turn may hinder rehabilitation. Although my model does not feature such "unfairness" effect, a possible solution to convey a stronger sense of fairness is to pay a notional salary that is then used to compensate victims or to cover the variable cost of incarceration.

In the second experiment, I simulate a 1-SD increase in work time for all convicts that is back-loaded toward the end of each prison term. This allocation mode is different from the uniform 1-SD increase implicitly implemented in the reduced-form model to estimate the LATE and from the one engineered in the structural model to figure out the ATE. However, recall from the discussion of Figure 6 that the work-sharing mechanism adopted in Italy does, in fact, result in back-loading: convicts work fewer hours during the first prison years. In order to demonstrate the importance of the intertemporal aspects of work allocations, in the experiment I concentrate the 1-SD increase during the last two years of the incarceration term or during the last year if the term is shorter than four years. The results are shown in the right panel of Figure 10. In this case the liquidity effect is completely unaffected (relative to the lower left panel of Figure 8) because it depends only on total earnings during the term. However, both the social and training effects are greatly reduced because postponing the hours increase until later in the incarceration terms implies that the self-productivity of skills in the technologies of criminal capital and human capital is not exploited optimally. The result is that the liquidity effect dominates and the ATE becomes positive. This undesirable outcome is suggestive of the importance of assigning convicts to work as soon as possible during an incarceration term, and of maintaining a uniform work profile thereafter.

Figure 10: Two policy experiments

Notes: The figure illustrates the results of two counterfactual policy experiments performed in the model and referring to the sample of convicts who were incarcerated for more than 6 months: (a) reducing real wages in prison jobs from €3.82 (the average level in Italy at the time the data refer to) to €0.60 (the maximum rate paid to state prisoners in the United States to perform compulsory institution work assignments); (b) back-loading an additional 1-SD of work hours in prison jobs at the end of the incarceration term (specifically: during the last two years of the incarceration term or during the last year if the term is shorter than four years).

6 Conclusions

My reduced-form and structural analyses point to the same conclusion: work in unskilled prison jobs can reduce the re-incarceration rate, but there is appreciable treatment effect heterogeneity. The LATE is different from the ATE (although they are both negative) and the latter masks substantial dispersion that is only partially accounted for by observables. That unobserved heterogeneity explains why the causal effects of prison work programs on convict rehabilitation have been elusive to date. In the context of the Italian prison labor system studied here, these effects are detrimental for convicts on prison terms shorter than 6 months but are conducive to a lower re-incarceration rate for convicts on longer terms (particularly between 6 and 18 months). The driving force is effective human capital, but not because prison work in these predominantly unskilled jobs builds new skills. As remarked by Bushway (2003) with regard to the lack of clear evidence on how prison work programs affect recidivism in the United States, econometric evaluations of training programs for the unemployed indicate that building such skills is difficult. Effective human capital is determinative, rather, because prison work contrasts with the large depreciation of expected labor market earnings that is experienced by convicts on longer incarceration terms. So from the perspective of prison administration, prison work time is an investment subject dynamic interdependencies; hence a convict (especially one with more skills to lose from inactivity) should be assigned to work, without delay, at the outset of an incarceration term – that is, rather than being placed on a waiting list. A counterfactual experiment in the structural model has shown the importance of avoiding a back-loading of work time.

The jobs studied in this paper are all created by the DPA and consist mostly of tasks for which (because of security reasons) there are no private-sector substitutes. In that case, the benefits of expanding prison work programs come without the externality on low-skilled, private-sector workers that characterizes industry programs employing convict labor in the United States and elsewhere. An additional advantage of such work provision mode is that the prison administration does not have a profit motive and so it can make use of prison work with a focus on rehabilitation – it has an incentive to minimize the re-incarceration rate. My conclusions do not apply to prison labor with a profit motive, which may induce a moral hazard problem (Archibong and Obikili, 2020).

Yet even for convicts who benefit from the prison jobs studied here, a lower monetary compensation seems desirable: the evidence I report consistently implicates a negative liquidity effect whereby prison earnings *reduce* the deterrent effect of incarceration. For convicts on shorter terms, this detrimental effect is the only mechanism that I have detected. Monetary compensation is often justified by the advisability of providing convicts with means to support their dependents; however, that support might be better provided through the general welfare system than through an economic distortion of the correctional system. The monetary component also undermines the cost-effectiveness of prison work as a rehabilitative tool. The lower bound (implied by my reduced-form estimates) on the internal rate of return from the prison job wage fund was positive at the nominal hourly wage of €3.5 in use until 2017, but it is negative at the current rate of €7 (or at the ATE implied by my structural estimates). Given the trade-off imposed by the DPA's budget constraint, the large and conflicting training and liquidity effects uncovered by my structural estimates suggest that a system that provides more prison jobs and lower earnings is preferable to one that offers higher earnings but rations work time. In a hypothetical scenario where job opportunities could be greatly expanded without proportionally increasing the wage fund, a convict's notional earnings (possibly computed at the full market wage rate) could be used to compensate victims or imputed to the costs of the criminal justice system – so to preserve a sense of fairness.

The credibility of my reduced-form estimates reflects their being grounded on quasi-experimental variations induced by the work-sharing mechanism adopted in Italy; however, the conclusions that are most relevant for public policy are based on estimates derived from a structural model. That model generates treatment effects that are consistent with the quasi-experimental ones and thereby inherits some of the latters' credibility, but the results are inescapably based on assumptions about convicts' preferences and the technology of rehabilitation. Furthermore, my model's time horizon is limited by the availability of re-incarceration outcomes for only three years from the release date. Hence my suggested interpretations should be closely examined by the criminology community – whose insight on these matters is richer than mine – and be corroborated by more research on the specific mechanisms examined here, before being elevated to policy prescriptions. This paper's contribution is to shed light on these important yet underexplored questions and to offer a first set of answers based on new evidence.

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