Prison work and convict rehabilitation*

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Abstract

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 and nonlinearities, I find that additional work impacts convicts at different points of the term distribution differently: it reduces the re-incarceration rate in the middle of the distribution, where prison work counteracts a rapid depreciation of earning ability, while for convicts on shorter or longer terms a liquidity effect that softens deterrence prevails.

JEL Classification: K42, J47

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1 Introduction

Work programs for convicts are widespread, yet little is known about whether or how these programs actually contribute to rehabilitation. 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 novel, mutually consistent way – a quasi-experimental approach, to achieve a credible identification, with structural econometrics to disentangle mechanisms.

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*, all able inmates under sentence should work for pay in useful occupations 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. Prison overcrowding and scarce funds for work programs result in the rationing of work opportunities for inmates or in extremely low earnings. 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 generate a quasi-experiment that enables me to provide such an answer. Prison wardens resolve job scarcity by implementing 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

[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).

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: the order of entry into prison, which is determined only by the timing of apprehension and criminal proceedings. Within cohorts of similar inmates who were incarcerated for the same time, for a similar set of crimes, and who experienced similar prison conditions during the term, the order of entry is essentially random but induces systematic differences in work shares because it determines the *de jure* ranking. 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 analysis, which I refer to as "reduced-form", 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"). Because the effects of rehabilitation or work programs are presumably nonlinear in time, I estimate the causal effect of interest for different portions of the incarceration term distribution, using quartiles as delimiters. For ex-convicts above the 1$^{\text{st}}$ quartile (about six months), I find 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 by approximately 9 percentage points (p.p.) in the year after release – a persistent effect that increases to nearly 12 p.p. three years from the release date. A similar effect is found above the 2$^{\text{nd}}$ quartile (about a year). The short-term internal rate of return on marginal funds allocated to prison work programs implied by these estimates was *at least* 36.7% 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 p.p. three years after release; or

[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).

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 below the 1$^{\text{st}}$ quartile or above the 3$^{\text{rd}}$ quartile of the prison term distribution (2.14 years), I find instead that a 1-SD increase in average monthly hours spent working in a prison job *increases* the re-incarceration rate within three years of release by up to nearly 8 p.p.

At a second level of analysis, which I refer to as "structural", I investigate underlying mechanisms by building and estimating a dynamic model of prison work and crime that enables me (a) to disentangle liquidity, social, and training effects; (b) to analyze treatment effect heterogeneity; and (c) to perform counterfactual policy experiments. The model formalizes the warden's allocation problem, the technology linking prison work with rehabilitation, and the ex-convict's recursive decision problem after release. A liquidity effect stems from prison earnings, which provide valuable resources during the term and a liquidity buffer upon release. Whereas the latter makes crime a less compelling option (Munyo and Rossi, 2015), the former increase the value of being in prison relative to being free.[5] The social effect arises because work alters the pattern of social interactions in prison and, thereby, one's stock of criminal capital (Bayer et al., 2009). Finally, there is a training effect because employment, even in an unskilled prison job, builds "soft" skills such as goals and motivations (Heckman and Kautz, 2012), work discipline, and – what is crucial in the prison context – mental health. Liquidity, social, and training effects are separately identified by way of standard assumptions on the technology of criminal and labor market skills: *self-productivity* of such skills, as first modeled by Ben-Porath (1967) in the context of on-the-job training and subsequently generalized by Cunha and Heckman (2007) and Cunha et al. (2010). After deriving the model's solution, I apply the generalized method of moments (GMM) to identify parameters directly, via effectively *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. The identifying conditions at the two levels of analysis are isomorphic. My estimates indicate that deep parameters that are unrelated to the incarceration ex-

[5] Cox (2009) discusses the possibility that prison work programs actually increase crime, ceteris paribus, by reducing the disutility of being incarcerated. Another possibility – not incorporated in my model – is that prison earnings yield an income effect that favors idleness and therefore crime (Rossi et al., 1980).

perience – such as criminal learning and the depreciation of criminal capital outside prison – are equal along the term distribution. However, structural parameters associated with rehabilitation programs or the liquidity, social, and training effects of prison work programs, are heterogeneous in a way that is consistent with the idea that these programs' effects are nonlinear in time, e.g., take time to exert their effects at the outset of a prison term and have diminishing returns later on.

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 have the same sign as the LATE but a different magnitude. When restricting to plausible compliers though, the model-predicted ATE is closer to the LATE estimated by 2SLS. 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 the liquidity and training effects work in opposite directions, while the social effect is modest. The training effect prevails above the 1$^{\text{st}}$ quartile, where it drives a net negative effect of prison work on re-incarceration. The liquidity effect turns out to favor re-incarceration by increasing the value of being in prison relative to being free – thereby weakening deterrence – and prevails in the tails of the term distribution, either because prison earnings are more valuable for inmates who will leave the prison within few weeks (left tail) or because of a diminishing training effect (right tail). The important 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.[6]

[6] 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. My estimates also indicate that the training effect is characterized by diminishing returns. For convicts below the 1st or above the 3rd quartile of the term distribution, I find that the social effect is statistically insignificant. This finding suggests that criminogenic social interactions in prison take time to establish at the beginning an incarceration term and are too ingrained to be altered by a different allocation of a convict's time later on.[7] These results imply that the mandatory prison work programs adopted in Italy (and elsewhere) could be quite effective if the liquidity effect were dampened or the training effect boosted. In this respect, my analysis suggests that the optimal program (i) does *not* feature the relatively high wage rate currently observed in Italy;[8] and (ii) assigns new convicts to work as soon as possible so as to leverage dynamic complementarities in the technology of skill formation, 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 special contexts that 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) stud-

[7]For example, Bayer et al. (2009) identify the influence of peers in juvenile correctional facilities on recidivism by exploiting the variation in the length of time that convicts spend in the same facility.

[8]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.

ies 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, which affects rehabilitation in many ways and not only through prison work (a 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. 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 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 combining in a novel way reduced-form and structural methods in the GMM framework, which enables me to (i) demonstrate 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); and (ii) to both identify the causal effect of prison work and perform a mechanism decomposition. There is no conflict between the two methods that I use. 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.

Section 2 describes the Italian prison labor system and illustrates my research design. 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. Section 6 concludes.

2 Institutional setting and research design

2.1 The Italian prison labor system

Prison work in Italy is regulated by the Penitentiary Code (PC), which stipulates that work is compulsory for all convicts (i.e., for all inmates with a final guilty verdict). Convicts can refuse to work only for health reasons approved by the prison warden. Two types of jobs are available. 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.[9] Because they consist primarily of low-ability tasks, prison jobs 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.

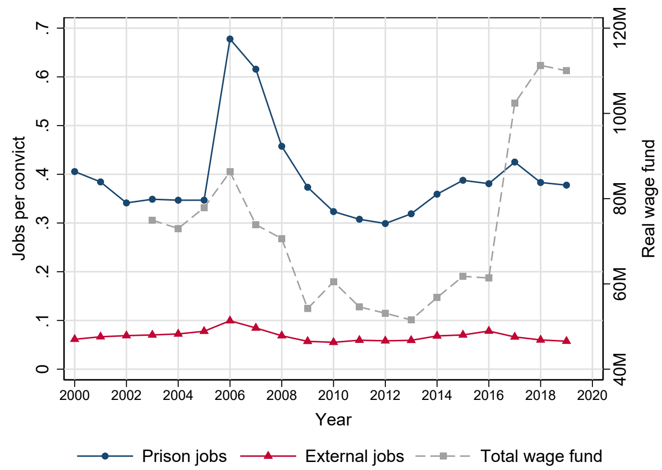
The wage rate in prison jobs is set by a committee appointed by the DPA, and it must be at least two thirds of the compensation determined by national collective agreements for the corresponding occupation. The nominal rate averaged €3.5 between 1994 and 2017, when new wage rates averaging about €7 came 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 (the time series is reported in Figure 1). Up to two thirds of a convict's earnings can be withheld by the DPA to pay for personal maintenance costs in

[9] 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. 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.

prison and outstanding debts related to compensating victims and other legal expenses, 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 he can use to purchase consumption goods at the prison's outlet or to transfer money to dependents. Upon release, the prisoner cashes in his outstanding balance.

Although the DPA is required by the PC to ensure all convicts a job as part of their rehabilitation, the two thirds wage floor renders the aggregate wage fund insufficient; hence work opportunities are strictly rationed. As illustrated in Figure 1, the number of prison jobs per convict normally ranged between 0.3 and 0.4 between 2000 and 2019 and the number of prison jobs per convict is directly affected by the total wage fund (at a given wage rate) 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.

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 (in millions of euros at 2019 prices) allocated by the Italian government to the DPA for the purpose of compensating inmates in prison jobs. The notable 2006/2007 "blip" in the number of jobs reflects a collective pardon that led to the early release of more than half of all convicts. The large increase in the wage fund observed from 2017 onward reflects instead an increase in the nominal wage rate from about €3.5 to about €7. *Source*: Author calculations from statistics published by the DPA.

The PC sets up a rationing mechanism for prison jobs – a simple work-sharing system – that pivots on the duration of the unemployment spell while in custody. 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 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, or already busy in other activities.

2.2 The identification problem and its solution

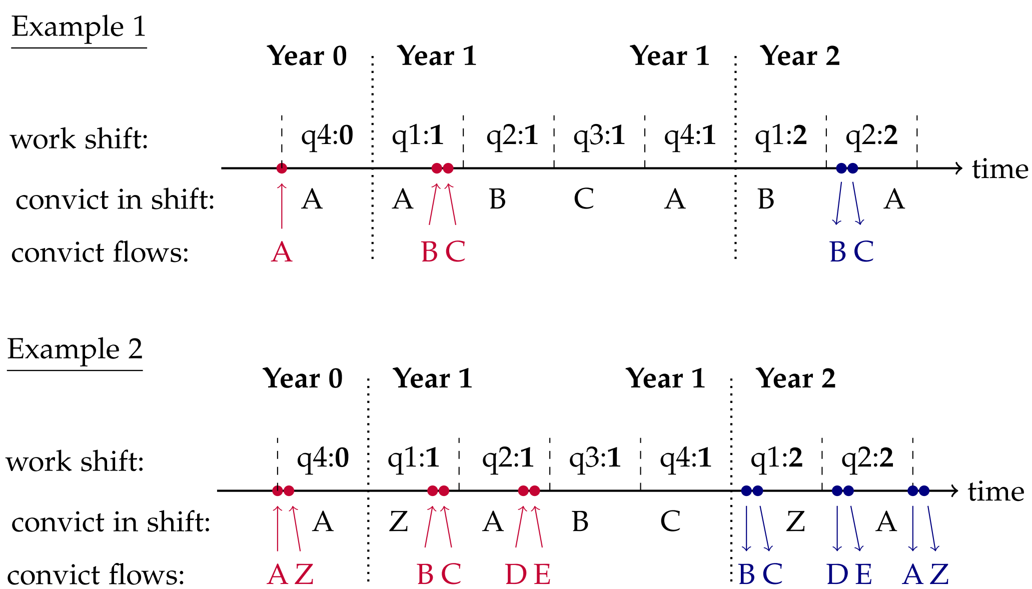
The assignment mechanism's discretionary component is the source of the identification problem because the time spent at work during an incarceration term reflects unobserved individual characteristics that are correlated with the unobserved (to the econometrician) propensity to re-engage in criminal activities after release. Solving this problem requires: (i) a source of exogenous variation in work shares; and (ii) groups of convicts who are a good counterfactual for each other. The order of entry into prison provides the former because it determines the assignment mechanism's *de jure* component while being determined *only* by the timing of apprehension and judicial decisions. As for groups, I adopt exact matching on sufficiently narrow entry-by-release periods ("cohorts") after conditioning on incarceration length, prison fixed effects, conviction offenses, and other observable characteristics. Within such data cells, differences in work time must reflect either warden discretion or the order of entry. My identification exploits the quasi-experiment generated by the latter: for any two convicts in a data cell and absent warden discretion, 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. When defining cohorts, a trade-off arises between comparability and precision. Ideally, one would like to match convicts admitted to prison in two consecutive days and also released in two consecutive days – i.e., define entry-by-release

[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*).

periods using narrow 48-hours windows – so as to maximize comparability. However, most of the resulting data cells would be empty or contain few observations. A larger window improves precision. I obtain sufficiently precise estimates when I employ entry-by-release years, and I show in the online appendix that similar results are obtained when employing entry-by-release quarters, at the cost of much larger standard errors.

The examples in Figure 2 illustrate the logic of my identification 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 cannot override this ranking and so job assignments have no discretionary component.

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 Z 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.

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 days 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 days – 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 a short time earlier ends up working more than the other.[11] Consider next the slightly more complex situation in Example 2, where there are two cohorts. Convicts A and Z 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 Z and thus ends up working three shifts while Z 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.

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 – a proxy for entry order that enables me to implement my instrumental variables strategy nonparametrically via week dummies – 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,

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

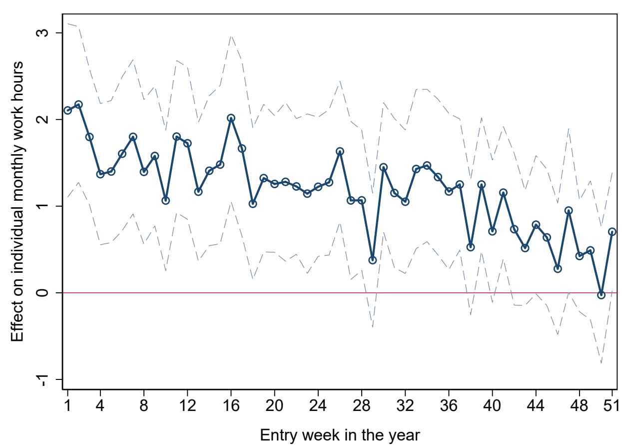
where $H_{i,I,O,\mathbf{p}}$ are work hours per month in prison for inmate i, who was admitted to prison in year I, was released in year O (i.e., belongs to the I,O cohort), and served his sentence in prison $\mathbf{p}$ (possibly a set of different facilities). On the right-hand side (RHS) of equation (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

[11] 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 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.

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 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 those admitted in the last week – again, for a given number of days spent in prison. Consistently with the examples in Figure 2, this effect is reduced as entry order increases, until the work advantage approaches zero toward the end of the admission year.

Figure 3: Within-cohort effect of entry order 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.

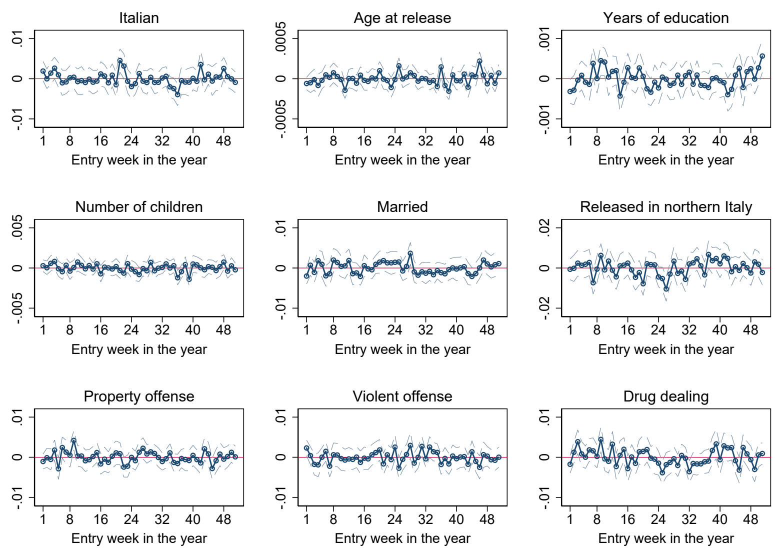
However, entry order turns out to be unrelated to covariates. This is what one expects given that within a cohort such order reflects only the timing of apprehension and criminal proceedings. In analogy with the balancing test that a researcher would perform to verify random assignment in a randomized experiment, Figure 4 reports the estimated

$\boldsymbol{\beta}_w$ from the following linear probability model,

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

where $\mathbf{X}_i$ is a $1 \times K$ vector of regressors and $\boldsymbol{\beta}_w$ is a $K \times 1$ vector of coefficients. For this exercise, I include in $\mathbf{X}_i$ a constant and 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 the order of entry into prison – 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.[12]

Figure 4: Within-cohort effect of covariates on entry order, given term length



Notes: The circles are the OLS estimates of coefficients $\boldsymbol{\beta}_w$ 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.

[12] 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. 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 by regressing work hours per month in prison on entry-by-release year dummies, days spent in prison and prison dummies. The regression's R^2 is 0.243 – 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.

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), an administrative information system for the management of prisoners. 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. 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, the crimes for which prisoners were convicted, 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.

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).[13] The resulting final sample consists of 100,350 convicts. 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. Panel 1 summarizes demographic and socioeconomic characteristics. Marital status and educational attainment are missing for more than (respectively) 10% and 40% of observations.[14] Panel 2 presents admission,

[13] 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.

[14] This reflects in part the greater difficulty in verifying such information for foreign-born than for Italian inmates: 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%.

Table 1: Descriptive statistics

Variable	Universe ($N = 125,670$) Mean	Universe SD	Final sample ($N = 100,350$) Mean	Final sample 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

Table 2: continued

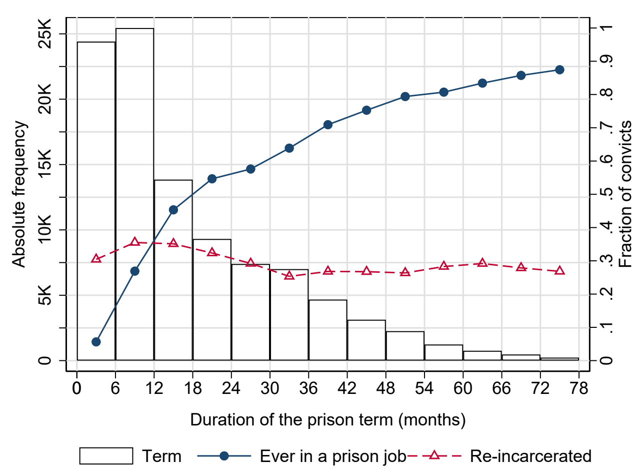
Variable	Universe (N = 125,670) Mean	SD	Final sample (N = 100,350) Mean	SD	Min	Max	p-val
3. Conviction offenses							
Number of offenses	1.71	1.16	1.72	1.10	1	12	0.10
Drug dealing	0.362	0.480	0.410	0.492	0	1	0.00
Larceny/burglary/MV	0.266	0.442	0.296	0.457	0	1	0.00
Assault	0.193	0.394	0.161	0.368	0	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.

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. Panel 3 summarizes conviction offenses – every inmate in the data is associated with a set of crimes for which he was found guilty. Panel 4 reports prison work and earnings statistics, which are available at the annual frequency.

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 tends to be higher for convicts on shorter prison terms. 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 more than 55% among those incarcerated for between 1.5 and 2 years, and it continues to increase over term duration until about 90% of convicts on term longer than 5.5 years are assigned to a prison job at least once.

Figure 5: Prison term distribution, fraction in prison jobs, and re-incarceration



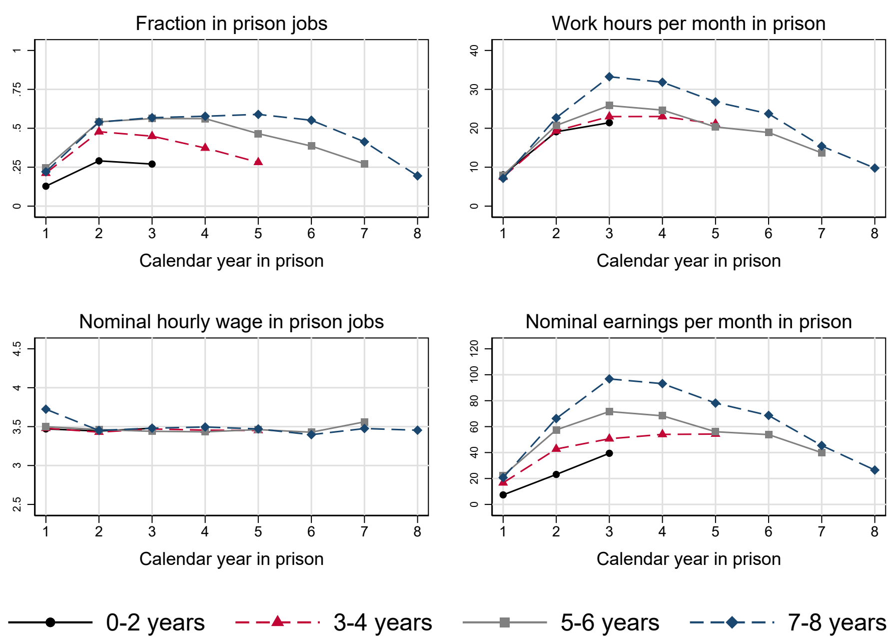
Notes: This figure illustrates the distribution of prison terms (absolute frequencies, left scale), the fraction of convicts who were ever assigned to a prison job during the term (dots, right scale), and the fraction re-incarcerated within three years of the release date (triangles, right scale). Each bin contains inmates who spent between m and $m+1$ months in prison, for $t \in (0, 78]$. 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.

That as many as five years into their prison terms more than 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 particular measurement error is unlikely to have first-order consequences when one considers: (i) the low incidence of external jobs; (ii) the fact that the LATE identified in my reduced-form analysis reflects the behavior of compliers only, a group which most likely excludes convicts who work in external jobs. In order to support this conjecture and to reassure the reader that the unobservability of assignments to external jobs is not an important issue, I provide in the online appendix results from a specification that considers only the intensive margin of prison work, i.e., excluding from the sample all convicts with zero work hours in prison jobs. Despite a loss of statistical precision, the empirical pattern is confirmed. Another data limitation is that only work hours are observed, and not the specific tasks performed. However, we know 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 (the *extensive* margin of prison work) and the upper right panel shows the hours profile of those employed (the *intensive* margin of prison work). Two patterns are worth noting. 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. The imperfect divisibility 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 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

4.1 Reduced-form econometric model

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,[15] which 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.[16] 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, conviction offenses dummies, and – in order to account for seasonal effects that contribute to recidivism – release month-of-year 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.[17]

[15] 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.

[16] 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 $(200/400) \times 30 = 15$.

[17] 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, a nonparametric proxy for entry order.[18] 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

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

where $\boldsymbol{\delta} = [\delta_I \ \delta_O \ \delta_{I,O} \ \delta_{\mathbf{p}}]$ 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.

[18]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, 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

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

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:

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

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 $\boldsymbol{\beta}_H$ and $\sigma_R \boldsymbol{\beta}_D$ are independent. In words, the within-cohort effect of order of entry into prison on monthly work hours that is generated by the prison job allocation mechanism's deterministic component (i.e., $\boldsymbol{\beta}_H$) must be *independent* of the effect of entry order on the re-incarceration rate via a longer prison term (i.e., $\sigma_R \boldsymbol{\beta}_D$). This assumption is plausible because $\boldsymbol{\beta}_H$ 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. The result also agrees with one of the robustness checks reported in the online appendix, where entry-by-release quarters (instead of years) are used to define cohorts, thereby reducing the scope for bias.

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 Results of reduced-form analysis

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 different portions of the term distribution illustrated in Figure 5: up to the 1st quartile, above the 1st quartile, above the 2nd quartile, and above the 3rd quartile.[19] The OLS estimates are zero. Not

[19] Monthly work hours are standardized within the estimation sample, so one standard deviation is a different quantity in the four groups, as indicated in the table's first row. 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 duration:	$\leq$ **1st quartile** (0.504 yrs)			$>$ **1st quartile** (0.504 yrs)			$>$ **2nd quartile** (1.010 yrs)			$>$ **3rd quartile** (2.140 yrs)		
Monthly hours:	Mean = 1.04; SD = 6.2			Mean = 8.42; SD = 16.6			Mean = 10.69; SD = 18.4			Mean = 13.89; SD = 20.8		
Mean of dep. var.:	0.180	0.259	0.306	0.184	0.271	0.320	0.166	0.253	0.303	0.139	0.219	0.267
OLS estimator												
	1y	2y	3y	1y	2y	3y	1y	2y	3y	1y	2y	3y
$\hat{\beta}_R$	0.006	0.007	0.007	0.003	0.003	0.005	0.001	0.001	0.003	–0.000	–0.000	0.003
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
2SLS estimator, over-identified model												
	1y	2y	3y	1y	2y	3y	1y	2y	3y	1y	2y	3y
$\hat{\beta}_R$	0.058	0.088	0.076	–0.094	–0.115	–0.119	–0.107	–0.148	–0.149	0.025	–0.000	0.020
	(0.021)	(0.025)	(0.030)	(0.023)	(0.026)	(0.027)	(0.030)	(0.035)	(0.040)	(0.036)	(0.044)	(0.045)
F-test stat.		3.67			6.23			4.21			3.38	
Anderson-Rubin's F		3.52			3.16			3.31			2.01	
Hansen's J-test, p-val.	0.09	0.13	0.55	0.27	0.29	0.58	0.18	0.64	0.81	0.14	0.14	0.63
MB2SLS estimator, over-identified model												
	1y	2y	3y	1y	2y	3y	1y	2y	3y	1y	2y	3y
$\hat{\beta}_R$	0.066	0.102	0.088	–0.108	–0.133	–0.137	–0.138	–0.189	–0.190	0.038	–0.000	0.028
	(0.021)	(0.024)	(0.025)	(0.022)	(0.025)	(0.026)	(0.028)	(0.033)	(0.034)	(0.030)	(0.036)	(0.038)
F-test stat.		6.90			7.82			4.73			3.03	
Hansen's J-test, p-val.	0.06	0.38	0.71	0.08	0.09	0.35	0.32	0.36	0.63	0.23	0.25	0.93
2SLS estimator, just-identified model												
	1y	2y	3y	1y	2y	3y	1y	2y	3y	1y	2y	3y
$\hat{\beta}_R$	0.075	0.106	0.089	–0.113	–0.135	–0.139	–0.143	–0.183	–0.185	0.013	0.002	0.014
	(0.022)	(0.029)	(0.034)	(0.024)	(0.027)	(0.028)	(0.035)	(0.039)	(0.046)	(0.042)	(0.051)	(0.054)
First-stage coeff. (s.e.)		–0.0157 (0.0018)			–0.0044 (0.0004)			–0.0039 (0.0004)			–0.0041 (0.0005)	
F-test stat.		78.98			152.90			79.19			58.64	
Anderson-Rubin's F		12.84			23.84			21.70			0.10	
Obs.	25,193	25,193	25,193	75,157	75,157	75,157	50,142	50,142	50,142	25,085	25,085	25,085

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, at different locations in the term distribution, as indicated in the table's first row. One SD is a different number of hours in each estimation sample, as also 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 were admitted to prison after 2004 with at least one economically motivated crime in their set of conviction offenses.

so the 2SLS estimates: above the 1st quartile, an additional SD of monthly work hours reduces by 9.4 percentage points the probability of being re-incarcerated within one year of release. This effect increases to 11.5 p.p. and 11.9 p.p. within two and three years of release, respectively, and these magnitudes are 1–3 p.p. larger among convicts above the 2nd quartile. Below the 1st quartile, the analogous effect is an increase in the reincarceration rate by 5.8 p.p. within one year from discharge and by 7.6 p.p. within three years. The point estimates are small and statistically insignificant above the 3rd quartile. Note that the magnitude of MB2SLS estimates is slightly larger. As mentioned previously, this result is consistent with a negative but small value of σ_R in equation (6).

The gradient of treatment effect along the term distribution that is revealed by these estimates indicates that the contribution of prison work to convict rehabilitation depends on the time an inmate is removed from society. As discussed in the Introduction and formalized in Section 5, within this time frame the net depreciation of labor market or criminal ability – as resulting from the interaction between prison life and rehabilitation programs – is nonlinear. For example, idleness varies with the duration of prison stay, mental health may be little affected during short terms or as a long-term inmate becomes hardened to prison life, rehabilitation programs take time to have an effect, and prison work – in particular – may have different returns at different levels of work time and experience. There is no reason to expect a constant treatment effect.

First-stage results are reported in the online appendix, in analogy to Figure 3. The progressive reduction in sample size 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 $\mathbb{E}[\mathbf{Z}_i v_{it}] = 0$ 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 (except above the 3rd quartile when Anderson and Rubin's F is used as recommended by Lee et al., 2020) and the 2SLS point estimates of β_R approach their MB2SLS counterparts in the over-identified case.[20] As for the Sargan test in

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

the over-identified model (performed in Hansen's variant because of clustered standard errors), note that the null hypothesis is never rejected.

A comparison of OLS and 2SLS estimates indicates that either (i) the causal effects of prison work for compliers are different from the analogous effects 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 the structural analysis, which allows me to estimate the ATE and to contrast it with the LATE. The second possibility suggests that, in the institutional context under investigation, among longer-term convicts a warden's discretion favors those whose characteristics are positively correlated with their (unobserved) propensity to return to prison (negative selection). However, among inmates on short sentences it is those with a lower propensity to return to prison who benefit from discrimination (positive selection). 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 *marginal* funds allocated to prison jobs in Italy. That rate is clearly negative, on average, for those below the 1st or above the 3rd quartiles of the term distribution. However, the bound turns out to be about 36.7% on average above the 1st quartile. The calculation details are reported in the online appendix. This is a lower bound because the calculation is based on the smaller (in absolute value) between the 2SLS and MB2SLS estimates and it considers only the reduction in the marginal cost of incarceration, not also 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. 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 (–31.7%) 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 marginal rate of return is likely negative for the general population of convicts above the 1st quartile.

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.

5 Structural analysis

5.1 Theoretical model

In order to uncover mechanisms that drive the estimated causal effects and to provide an interpretation of my reduced-form results, I build 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).

Setup: A risk-neutral individual 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, $t = 1, 2, 3$.[21]

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 $l_t + h_t = 1$. The warden dictates a convicts' allocation of time and so there are no choices to be made by an individual in state p. 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 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

[21] 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.

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 $\rho\pi m_t$. 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.

The technology of liquidity: During his term a convict earns resources totaling $y_0 = w\sum_{t=I}^{O} h_t$. 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, like transferring prison earnings to dependents or using those earnings to increase prison consumption beyond c_p or to generate a stock 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 (Munyo and Rossi, 2015); and (ii) an encouraging effect, by offering an individual 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, $\lambda_t < 0$.

The technology of earning ability: Although the prison jobs that I study are unskilled, they may contribute to a convict's earning ability in two ways. First, they may provide more general skills – such as the ability to focus on a task, goals and motivation, time management, and the habit of working – or reduce the scope for statistical discrimination against ex-convicts (Pager, 2003; Holzer et al., 2007; Doleac and Hansen, 2020) – 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 because work means replacing idle time in prison with active time in meaningful activities and the resulting mental stimulation (Nurse et al., 2003; Schnittker et al., 2012; Baćak et al., 2019).

I represent these concepts in the model by assuming that time spent at work during incarceration allows an inmate to 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 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:

$$\eta_{t+1} k_{t+1} = (1 - \delta_{st}) \eta_t k_t + \theta_{st} h_t \eta_t k_t. \tag{8}$$

In state f, this equation reduces to the human capital dynamics in Ben-Porath's (1967) model: effective human capital depreciates at rate $0 \leq \delta_{ft} < 1$, and $\theta_{ft} \geq 0$ captures a conventional on-the-job training mechanism for employed individuals. In state p, parameter $\theta_{pt} \geq 0$ captures the beneficial impact of unskilled prison work on earning ability via soft labor market skills and mental health. Recursive substitution of effective human capital in periods $t, t-1, \ldots, I-1$ into (8) 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:

$$\eta_1 k_1 = \eta_I k_I \prod_{t=I}^{O} (1 - \delta_{pt} + \theta_{pt} h_t). \tag{9}$$

Depreciation and training parameters may be different at different points of the term for two reasons. First, prison work is effectively a new career and it may take time for the training effect to set in; moreover, such effect may be subject to diminishing returns. Second, the prison experience exert effects that are likely nonlinear in time: earning ability may be little affected during a very short incarceration term but more severely harmed by more prolonged idleness in a difficult environment; however, rehabilitation programs also unfold over time and a convict may grow used to prison life to some extent. The technology in (9) features dynamic complementarities if $\theta_{pt} > 0$, i.e., $\frac{\partial^2 \eta_1 k_1}{\partial \eta_I k_I \partial h_t} > 0$ for any $I \leq t < O$. In this case prison work is an investment whose productivity, in terms of earning ability at release, increases with effective human capital at entry.

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

$$m_{t+1} = \begin{cases} (1 - d_{pt})m_t + \varsigma_t l_t m_t & \text{if } s = p, \\ (1 - d_{ft})m_t + \mu_t x_t m_t & \text{if } s = f. \end{cases} \tag{10}$$

Here $d_{pt} - \varsigma_t$ is the rate at which criminal capital depreciates in prison during term period t for a convict who does not work in that period. This depreciation captures the core component and time path of the rehabilitation process, and its sign can be either positive (if incarceration per se rehabilitates convicts) or negative (if an incarceration regime has a criminogenic effect). Parameter ς_t 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. Note that the same complementarity that characterizes investment in earning 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_{ft} and accumulates via criminal experience. As indicated by equation (10), an individual in state f who engages in crime in period t ($x_t = 1$) experiences an increase of μ_t% in his criminal capital (gross of depreciation) during that period. Replacing criminal capital recursively into (10) 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:

$$m_1 = m_I \prod_{t=I}^{O} (1 - d_{pt} + \varsigma_t(1 - h_t)). \tag{11}$$

This technology 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_t. If $\varsigma_t > 0$, 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. If instead $\varsigma_t < 0$, then having more criminal capital in period t increases the (*positive*) effect of prison work on future criminal capital.

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.[22] I denote by $V_t^f(\Omega_t)$ and V_t^p the values of being free and of being in prison, respectively, at time t, 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 i.i.d. and expressed in consumption equivalents. Then the problem is characterized by the Bellman equation,

$$V_t^f(\Omega_t) = \max_{x_t}\{\mathbb{E}_A c_t(x_t) + v_t(x_t) + \beta \mathbb{E}_{A,v} V_{t+1}^s(\Omega_{t+1})\}, \tag{12}$$

subject to the dynamics in (8) and (10), and where $\eta_t k_t$ and m_t in the first decision period $t = 1$ are given by equations (9) and (11), respectively, and

$$c_t(x_t) = \begin{cases} \lambda_t y_0 + \gamma \eta_t k_t & \text{if } x_t = 0, \\ \lambda_t y_0 + \gamma \eta_t k_t + \rho m_t & \text{if } x_t = 1 \text{ and not arrested}, \\ c_p & \text{if } x_t = 1 \text{ and arrested}; \end{cases} \tag{13}$$

$$V_{t+1}^s(\Omega_{t+1}) = \begin{cases} V_{t+1}^f(\Omega_{t+1}^0) & \text{if } x_t = 0, \\ V_{t+1}^f(\Omega_{t+1}^1) & \text{if } x_t = 1 \text{ and not arrested}, \\ V_{t+1}^p = \sum_{\tau=t+1}^{O'} \beta^\tau c_p & \text{if } x_t = 1 \text{ and arrested}. \end{cases} \tag{14}$$

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 (12) is taken with respect to the probability of

[22] Given that $t = 1, 2, 3$, this assumption is natural and allows me to simplify the analysis considerably.

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 $\Theta = \{\pi, \lambda_t, w, \gamma, \eta_I, k_I, \delta_{pt}, \delta_{ft}, \theta_{pt}, \theta_{ft}, \rho, m_I, d_{pt}, d_{ft}, \varsigma_t, \mu, c_p, \beta\}$ 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 (9)–(11), then this re-incarceration probability, for $t = 1, 2, 3$, is

$$\begin{aligned}
&\Pr(R_t = 1 \mid \mathbf{h}; \Theta) \\
&\quad = \pi F\big[-\pi\big(\lambda_t w \sum_{\tau=I}^{O} h_\tau + \gamma \eta_I k_I \prod_{\tau=I}^{O}(1 - \delta_{p\tau} + \theta_{p\tau} h_\tau)(1 - \delta_{f\tau} + \theta_{f\tau})^{t-1} - c_p\big) \\
&\qquad\quad + (1-\pi)\rho m_I \prod_{\tau=I}^{O}(1 - d_{p\tau} + \varsigma_\tau(1 - h_\tau)) \prod_{j=1}^{2}(1 - d_{fj} + \mu_j x_j)^{\mathbb{I}[t>j]} \\
&\qquad\quad + \pi\beta(C_p - V_{t+1}^f(\Omega_{t+1}^1; \Theta)) + \beta(V_{t+1}^f(\Omega_{t+1}^1; \Theta) - V_{t+1}^f(\Omega_{t+1}^0; \Theta))\big].
\end{aligned} \tag{15}$$

This expression seems cumbersome but is quite intuitive. Consider the part inside brackets. The first line represents 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 $\delta_{p\tau}$ in term period τ) and investment via prison work (at rate $\theta_{p\tau} h_\tau$) 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 $\theta_{ft} - \delta_{ft}$).

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 $d_{ft} - \mu_t x_t$). 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, $V^f_{t+1}(\Omega^1_{t+1})$, against the value of prison consumption. Yet given that $\mu_t \geq 0$, 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 $V^f_{t+1}(\Omega^1_{t+1}) - V^f_{t+1}(\Omega^0_{t+1})$.

Equation (15), 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, $\theta_{p\tau}$, and ς_τ). 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 (15) 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 $\{h_t\}^O_{t=I}$ 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 the three effects.

To estimate equation (15), 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 the subset of such parameters that cannot be calibrated. Econometric details are provided in Section 5.2.

The warden's problem: Closing the model requires that I specify how the warden chooses work profile $\{h_t\}_{t=I}^{O}$. 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 the order of entry into prison. In short, I consider a warden who is subject only to the budget constraint and who therefore optimizes the rehabilitation process by choosing work shares so as to minimize a weighted recidivism rate, net of output value. The solution determines redistribution shares relative to the work assignments implied by a "neutral" work-sharing policy (which are the source of the identification problem) and 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 the training and social effects are both positive (when statistically significant), indicating dynamic complementarity in the technologies of k and m. I discuss in the online appendix the conditions under which such complementarity extends to the probability of re-engaging in crime. 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.[23]

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.

[23]The type of selection induced by other institutional mechanisms may be different. In the United States, work under the FPI program is voluntary and so inmates self-select based on their individual abilities and attitudes. In this context, Saylor and Gaes (1997) find positive selection into prison work.

5.2 Structural econometric model

The structural analysis is based on equation (15) 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). When equation (15) is fit to the data, the re-incarceration probability in period t is written as

$$\Pr(R_{it} = 1 \mid \mathbf{h}_i; \Theta_i) = \pi F[\mathbf{h}_i; \Theta_i] + \tilde{v}_{it}, \tag{16}$$

where $\tilde{v}_{it}$ is the structural error – counterpart of the reduced-form error v_{it} in (3). Note that equations (16) and (3) coincide when $\pi F[\mathbf{h}_i; \Theta_i] = \beta_R H_{i,I,O,\mathbf{p}} + \mathbf{X}_{it}\gamma_R + \boldsymbol{\delta}\boldsymbol{\iota}$, where $\boldsymbol{\delta} = [\delta_I \; \delta_O \; \delta_{I,O} \; \delta_{\mathbf{p}}]$ and $\boldsymbol{\iota}$ is a vector of 1s. In that case $\Theta_i = \{\beta_R, \gamma_R, \boldsymbol{\delta}\}$ and the structural and reduced-form errors also coincide. 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 (16) is based on the structural equivalents of the population moment conditions in (5) that identify the reduced-form model; that is, on

$$\begin{aligned} \mathbb{E}[\mathbf{X}_{it}\tilde{v}_{it}(\Theta_i)] &= \mathbf{0}, \\ \mathbb{E}[\boldsymbol{\Delta}_i\tilde{v}_{it}(\Theta_i)] &= \mathbf{0}, \\ \mathbb{E}[\mathbf{Z}_i\tilde{v}_{it}(\Theta_i)] &= \mathbf{0}, \end{aligned} \tag{17}$$

for $t = 1, 2, 3$ and $i = 1, 2, \ldots, N$. The resulting GMM minimand is

$$Q(\Theta_i) = \begin{bmatrix} \mathbb{E}[\mathbf{X}_{it}\tilde{v}_{it}(\Theta_i)] \\ \mathbb{E}[\boldsymbol{\Delta}_i\tilde{v}_{it}(\Theta_i)] \\ \mathbb{E}[\mathbf{Z}_i\tilde{v}_{it}(\Theta_i)] \end{bmatrix}' \Omega \begin{bmatrix} \mathbb{E}[\mathbf{X}_{it}\tilde{v}_{it}(\Theta_i)] \\ \mathbb{E}[\boldsymbol{\Delta}_i\tilde{v}_{it}(\Theta_i)] \\ \mathbb{E}[\mathbf{Z}_i\tilde{v}_{it}(\Theta_i)] \end{bmatrix}, \tag{18}$$

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). 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. The moments in (17) 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. Like in the reduced-form analysis, this GMM estimator's variance is clustered at the release-prison level.

This procedure is more computationally convenient than is indirect inference or even maximum likelihood, and it has the further advantage of providing structural estimates that are meaningfully comparable with the reduced-form ones thanks to an isomorphism between the respective orthogonality conditions. To appreciate this advantage, 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 (17) – except that the linear approximation $\pi F[\mathbf{h}_i; \Theta_i] = \beta_R H_{i,I,O,\mathbf{p}} + \mathbf{X}_{it}\gamma_R + \boldsymbol{\delta\iota}$ implicitly assumed by the reduced-form model reduces the parameter vector to $\Theta_i = \{\beta_R, \gamma_R, \boldsymbol{\delta}\}$. 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 have a different appearance in the two cases.[24]

Yet estimation is computationally demanding given the products of functions of the parameters in equation (15). In order to reduce such complexity and facilitate convergence, I take three steps. 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). Second, instead of estimating parameters $\{\delta_{pt}, \theta_{pt}, d_{pt}, \varsigma_t\}$ for each prison year as required by equations (9) and (11), I again split the sample by term duration so as to capture the variation in these parameters along the term while reducing the number of estimands. Similarly, the criminal learning parameter μ_t is also assumed to be constant. Third, 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: $\Theta_i^e = \{\lambda_0, \lambda_1, \lambda_2, \eta_{iI}, \delta_p, \theta_p, d_p, d_f, \varsigma, \mu, c_p, u\}$ and $\Theta_i^c = \{\pi_i, w_i, \gamma_i, k_{iI}, \delta_{ft}, \theta_{ft}, \rho, m_{iI}, \beta\}$. The elements of Θ_i^c are calibrated as summarized in Table 4.[25]

[24] 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. For nonlinear model (16), global identification requires that the conditions in (17) be satisfied at only one point in the parameter space. Because equation (15) 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 (17), evaluated at the parameters' "true" values, to be of full rank.

[25] This calibration requires information on convicts' educational attainment. As shown in Table 1, this 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 nonmissing education.

Table 4: Calibration of pre-set parameters

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	Nonsleeping 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.

5.3 Results of structural analysis

The structural analysis focuses on the same groups of convicts considered in Section 4: up to the 1st quartile of the term distribution and above the 1st or 3rd quartiles.[26] There was no reason to expect a constant treatment effect in the reduced-form analysis. Similarly, there is no reason to expect *all* of the structural parameters to be the same for different groups of convicts; in particular, parameters that relate to different prison experiences may differ, thus generating the different results reported in Table 3. Explaining such differences is one goal of my structural analysis.

I first estimate semi-structural specifications (motivated by the model but still with no attempt to identify the structural parameters) that bridge the reduced-form and structural analyses. The model predicts that the treatment effect of prison work is 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). Thus, I estimate equation (3) by 2SLS after splitting the sample according to the median levels of net wage rate, term duration, and schooling. Detailed results are reported in the online appendix. There is no significant heterogeneity by net hourly wage, which reflects the fact that this variable exhibits very little variability. However, among convicts on terms above the 1st quartile, the beneficial effects of prison work are concentrated at or above the median of the term distribution (i.e., 1.45 years in prison) and at or above the median of the education distribution (8 years of schooling). This complementarity suggests that parameters ς and θ_p are positive in this group.

Fully structural estimation confirms this conjecture. The GMM estimates of model parameters are reported in Table 5 – separately for the three groups of convicts.[27] The first panel of this table 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

[26] Given similar reduced-form results above the 1st and 2nd quartiles (relative to the other two groups), hereafter I drop this distinction and I consider only the largest of these two samples.

[27] In the first step, convergence is achieved after 13 iterations below the 1st quartile and after 11 and 14 interations above the 1st and 3rd quartiles, respectively. In the second step, the process converges after (respectively) 3, 3, and 4 iterations, and the values of the criterion function $Q(\Theta_i)$ at the minimum are fairly close to zero: 0.015, 0.005, and 0.014, respectively. Hansen's (1982) over-identification test does not reject the validity of the over-identifying moment restrictions in either of the samples (p-values of 37-38%).

Table 5: GMM estimates of structural parameters

Parameter		$\leq$ **1st quartile** (0.504 years)	$>$ **1st quartile** (0.504 years)	$>$ **3rd quartile** (2.140 years)
Ancillary parameters				
Earning potential deprec. in prison	δ_p	0.134	0.768	0.049
		(0.017)	(0.007)	(0.005)
Criminal capital deprec. in prison	$d_p - \varsigma$	0.208	0.507	0.034
		(0.036)	(0.011)	(0.054)
Criminal learning outside prison	μ	0.126	0.103	0.364
		(0.004)	(0.002)	(0.130)
Criminal capital deprec. when free	d_f	0.948	0.980	1.155
		(0.011)	(0.006)	(0.089)
Prison consumption	c_p	–0.255	–0.260	–2.074
		(0.033)	(0.010)	(0.455)
Empl. rate at entry, natives	$\eta_{I,n}$	0.035	0.011	0.056
		(0.001)	(0.000)	(0.013)
Empl. rate at entry, foreign-born	$\eta_{I,f}$	0.048	0.025	0.080
		(0.002)	(0.001)	(0.019)
Support of unobservables	u	4.300	0.782	11.785
		(0.254)	(0.028)	(2.700)
Mechanism parameters				
Training effect	$\theta_p/2u$	6.102	2.337	0.060
		(0.780)	(0.104)	(0.016)
Social effect	$\varsigma/2u$	–0.401	1.429	–0.011
		(0.688)	(0.313)	(0.039)
Liquidity effect, first year	$\lambda_0/2u$	–0.666	–0.025	–0.007
		(0.133)	(0.001)	(0.001)
Liquidity effect, second year	$\lambda_1/2u$	–1.652	–0.017	–0.023
		(0.088)	(0.001)	(0.001)
Liquidity effect, third year	$\lambda_2/2u$	–1.256	–0.009	–0.028
		(0.250)	(0.001)	(0.002)
Moment conditions, Eq. 17		1,077	1,185	1,155
Overidentification test, p-value		0.39	0.34	0.37
Observations		12,910	41,239	14,502

Notes: This table reports the results of structural estimation of equation (15) 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 (17). 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 nonmissing education information.

potential is estimated to be 76.8% for those above the 1st quartile (term longer than than about six months) but 13.4% for those on shorter prison terms and only 4.9% above the 3rd quartile (term longer than 2.14 years). A positive rate accords with the negative effect of incarceration on earnings estimated by some authors (Waldfogel, 1994; Western, 2002; Mueller-Smith, 2015; Harding et al., 2018).[28] In the absence of work, criminal capital is similarly estimated to depreciate at an annual rate $\delta_p - \varsigma$ of 50.7% for prisoners above the 1st quartile, 20.8% below the 1st quartile, and at a far lower rate of 3.4% above the 3rd quartile. These gaps along the term distribution are consistent with the twofold idea that (i) the detrimental effects of incarceration increase with incarceration length and are countered by rehabilitation programs; and (ii) such programs need time to yield beneficial effects (e.g., to influence convicts' behavior or to improve their mental health) and are subject to diminishing returns.

My estimate of the effect of criminal experience on criminal ability, μ, is above 10% and somewhat higher for longer-term convicts. This magnitude is consistent with the values inferred by Lochner (2004) for the United States. The depreciation rate of criminal capital outside prison for those abstaining from crime, d_f, is also similar across the three 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: about €200, in absolute value, but about €2,000 above the 3rd quartile.[29] 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% and 8% and are higher for foreign-born convicts than for native Italians. These values 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 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

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

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

smaller for convicts on terms above the 1st quartile than in the other two groups, which indicates that the forces represented in the model are less predictive of the post-release behavior of short-term or long-term convicts.

The impact of additional prison work on post-release crime decisions is mediated by the mechanism parameters, whose estimates are reported in the second panel of Table 5 relative to the width of the support of unobservables.[30] The training effect is positive but diminishing with term duration, consistent with the idea of decreasing returns from investing in skills via on-the-job training. To interpret the magnitudes reported in the table, note 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 0.002 (SD = 0.0127) below the 1st quartile, 0.017 (SD = 0.0341) above the 1st quartile, and 0.029 (SD = 0.0428) above the 3rd quartile. So one full additional SD of work time in a given year decreases the depreciation of expected earnings by $\theta_p \times 0.0127 \approx 66.6$, $\theta_p \times 0.0341 \approx 12.4$, and $\theta_p \times 0.0428 \approx 6$ percentage points in that year in the three groups, respectively. The social effect is significantly different from zero only above the 1st quartile, and my estimate implies that for this group a 1-SD increase in work time during a given year accelerates criminal capital depreciation by $\varsigma \times 0.0341 \approx 7.6$ percentage points in that year. A plausible explanation for an insignificant social effect in the tails of the term distribution is that establishing criminogenic connections in prison also takes time and once entrenched such connections are hard to affect via a different allocation of a convict's time. Finally, the liquidity effect parameter, λ_t, is systematically negative. Thus earnings from prison jobs increase the value of being in prison relative to being free, and more so for convicts on short terms. For example, a value of -0.666 for λ_0 below the 1st quartile means that earning €2,000 during the prison term (this is approximately 1 SD in the sample; see Table 1) is equivalent – in terms of impact on recidivism – to reducing the gap between the values of being free and not engaging in crime or in prison by $0.666 \times 2000 =$ €1,332 in the first year from the release date, but only €50 above the 1st quartile and €14 above the 3rd. Keeping in mind that λ_t is a sufficient statistic and not a deep parameter, these different estimates indicate that one's allocation of prison earnings depends on term duration – e.g., only longer term convicts may be able to save enough to create a liquidity buffer.

[30] As shown in the online appendix, the response of recidivism to additional prison work is proportional to a given mechanism parameter divided by such width, i.e., $2u$.

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. 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 (15) 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. That fit is illustrated in the first row of Figure 7; as expected in light of the optimized GMM criterion function's low value (see fn. 27), it is very good.

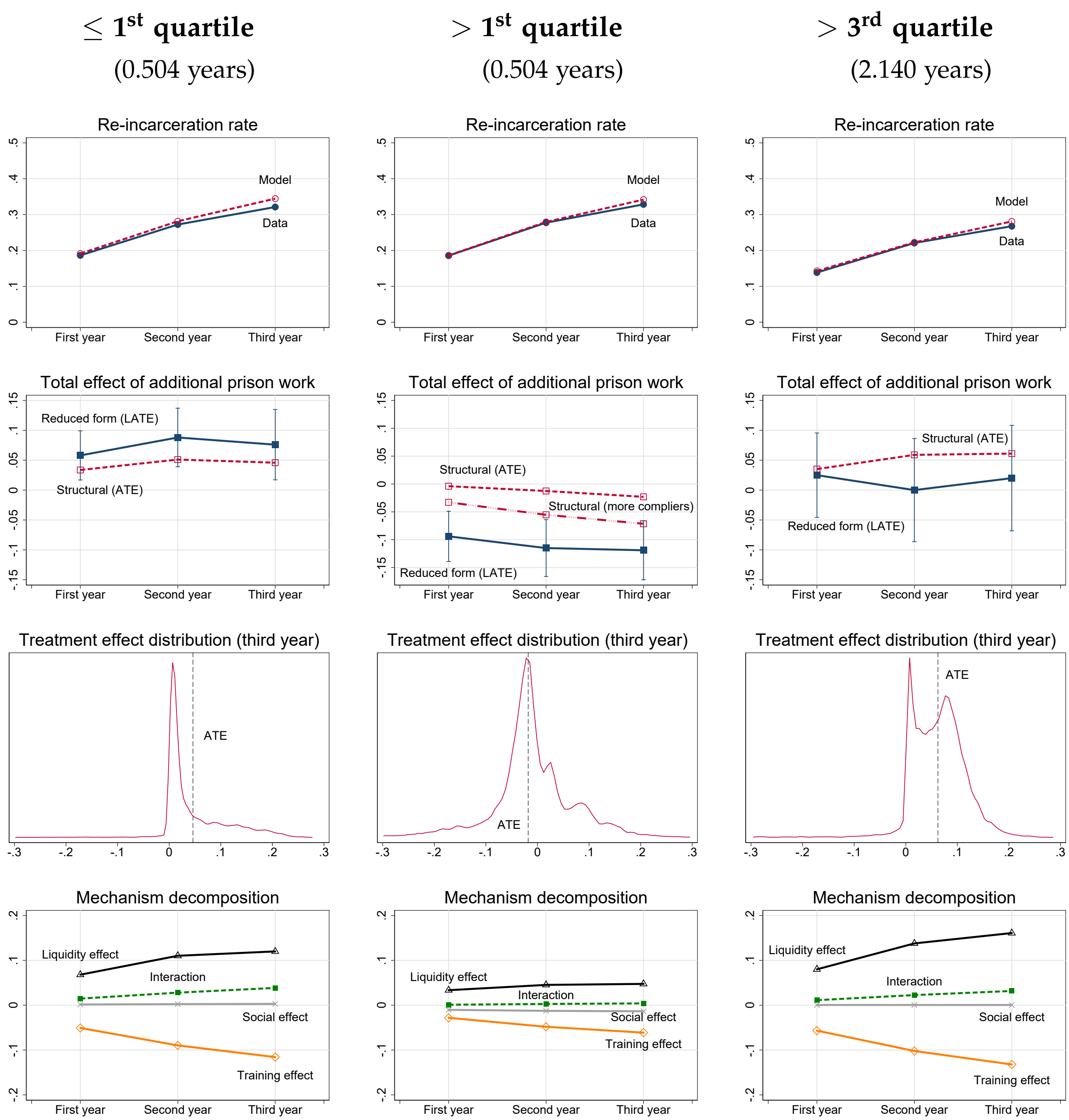
Second, the model is simulated numerically by increasing the work time per month in prison of all convicts by the same amount implicitly used to estimate the reduced-form causal effect – namely, 1 standard deviation. The individual treatment effect is then given by the difference between the resulting counterfactual re-incarceration probability and the baseline predicted probability. The 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 second row of Figure 7 (dashed line), along with the 2SLS estimates (continuous line). The third row of the figure illustrates the entire distribution of treatment effects after three years from discharge. There is important treatment effect heterogeneity. The ATE produced by the model has the same sign as the LATE, and these two parameters are generally closer to each other below the 1$^{\text{st}}$ quartile than elsewhere along the term distribution. I argue that this is because there are few noncompliers in this group. The instrument that identifies the LATE – order of entry into prison – defines compliers as those convicts whose assignment to work follows closely the deterministic rule. In other words, the compliers are rarely placed back at the bottom of the waiting list when their work turn comes up or are rarely given an advantage that overrides the ranking determined by entry dates. Due to their recent admission to prison, short-term 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. By this logic, restricting the group above the 1st quartile to convicts who spent in prison less than a year, we are isolating a subgroup with a higher proportion of compliers. Figure 7 shows that under this restriction the model-predicted ATE comes closer to the LATE. [31] Note that for convicts above the 1st quartile the ATE is a reduction in the re-incarceration rate of 2.3 p.p. in the third year from the release date (versus a LATE of about 12 p.p.), which implies that the lower bound for the internal rate of return on the wage fund calculated in Section 4.2 is large and negative for them (–73.6%).

Third, the total effect (i.e., the ATE) is decomposed into liquidity, social, and training effects by simulating again a 1-SD increase in prison work time – but activating just one mechanism at a time while keeping the other two inactive. This decomposition is shown in the last row of Figure 7, where the different effects add up to the ATE.[32] We can see in the figure that the social effect is modest relative to important liquidity and training effects that work in opposite directions. The latter prevails above the 1st quartile, where it drives a net negative effect of prison work on re-incarceration. In the tails of the term distribution the liquidity effect prevails instead. The mechanism parameters reported in Table 5 indicate that this happens because of larger liquidity effect parameters (left tail) or because of a diminishing training effect (right tail). An important liquidity effect 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 weaker and prison work would be more effective at preventing recidivism if the prison wage rate were lower. 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. For example, if wages convey a sense of fairness that is part of the rehabilitation mechanism, then my conclusion that prison earnings dampen rehabilitation would be incorrect. As usual when harnessing structural estimation to disentangle economic mechanisms, conclusions reflect model assumptions and so should be taken with a grain of salt.

[31] The discrepancy between the LATE estimated via 2SLS and the ATE produced by the numerical simulation may also be due to the linear approximation imposed by the reduced-form model.

[32] Due to the dynamic nature of post-release crime decisions, the three effects are not independent. In particular, a positive training effect implies a lower probability of being re-incarcerated, which increases the likelihood of enjoying the (negative, given $\lambda_t < 0$) utility from prison earnings after release. As also represented in the figure, this induces an "interaction effect" that boosts the liquidity effect.

Figure 7: Model simulation and mechanism decomposition



Notes: The first row 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 second row 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 third row illustrates the distribution of model-simulated treatment effects three years from the discharge date, smoothed via kernel density estimation and using a triangular kernel and a bandwidth of 0.01. The dashed vertical line marks the mean of the distribution, which corresponds to the ATE. The fourth row illustrate the decomposition of the ATE into a liquidity, training, and social effect. The decomposition is obtained by alternately activating one mechanism while keeping the other two inactive. The different effects add up to the ATE. 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 nonmissing education information.

An intriguing result is obtained when the model parameters are estimated by GMM using only the OLS orthogonality conditions; that is, I use only the first two lines of equation (17), which correspond to the "included" instruments $(\mathbf{X}_i, \mathbf{\Delta}_i)$. I show in the online appendix that such alternative identifying assumptions result in essentially the same structural estimates and ATE 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 (15), 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).

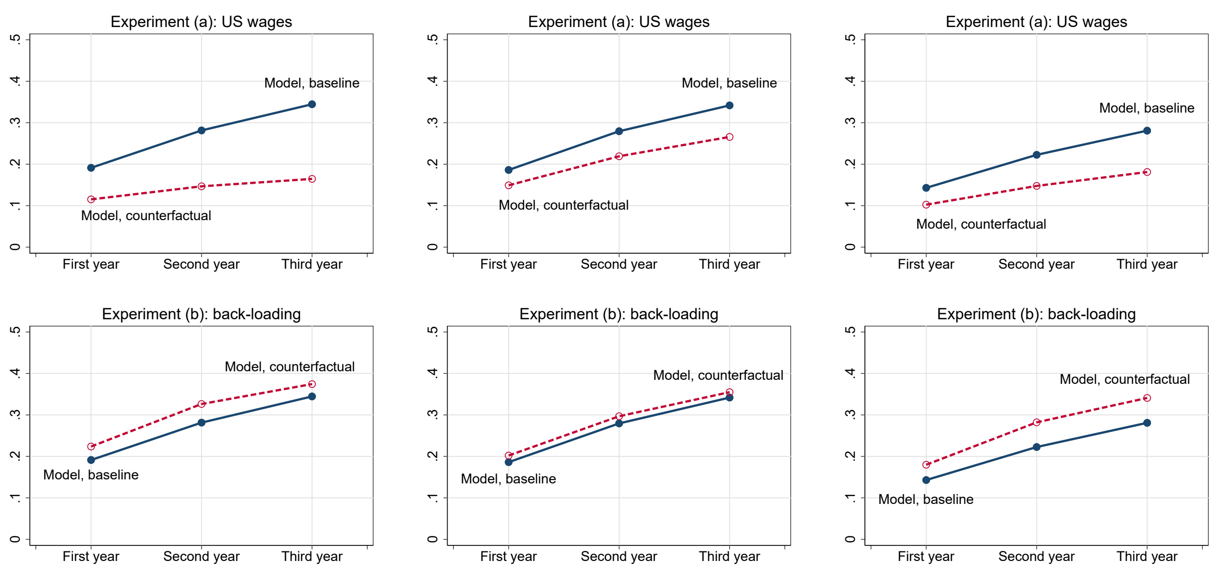
5.3.2 Counterfactual policy experiments

The mechanism decomposition exercise illustrated in Figure 7 suggests that the effectiveness of prison work in the convict rehabilitation process could be improved by either dampening the liquidity effect or boosting the training effect. To conclude my structural analysis, I use the model to perform two counterfactual policy experiments that follow from this suggestion and which are of particular interest in light of the characteristics of the Italian prison labor system: (a) providing an additional 1-SD of work hours in prison jobs at a reduced wage rate; (b) back-loading 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 for an additional 1-SD of work hours. As mentioned in Section 1, this is the maximum wage rate paid to state prisoners in the United States to perform compulsory institution work assignments – the most direct counterpart of the prison jobs that I study. The results are illustrated in the first row of Figure 8, which shows the baseline re-incarceration rate predicted by the model and the counterfactual re-incarceration rate induced by the policy. The difference between the two is the ATE . Unsurprisingly, this effect is now negative (i.e., the 1-SD additional work hours lead to a lower re-incarceration rate) because the liquidity effect would be greatly reduced by such a policy while the social and training effect would be little affected. 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.

Figure 8: Two policy experiments

$\leq$ 1st quartile (0.504 years) | **$>$ 1st quartile** (0.504 years) | **$>$ 3rd quartile** (2.140 years)



Notes: The figure illustrates the results of two counterfactual policy experiments performed in the model: (a) providing an additional 1-SD of work hours in prison jobs at a reduced real wage rate, 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).

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 second row of Figure 8. In this case the liquidity effect is completely unaffected 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 at all points of the term distribution. This undesirable outcome is suggestive of the importance of assigning longer-term convicts to work as soon as possible during an incarceration term, and of maintaining a uniform work profile thereafter.

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 that 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.

References

Abadie, A., S. Athey, G. W. Imbens, and J. Wooldridge (2017). When should you adjust standard errors for clustering? Working Paper 24003, NBER.

Abrams, D. (2011). Building criminal capital vs. specific deterrence: The effect of incarceration length on recidivism. Working Paper, University of Pennsylvania.

Agan, A. Y. and M. D. Makowsky (2018). The minimum wage, EITC, and criminal recidivism. Working Paper 25116, NBER.

Aizer, A. and J. Doyle, Joseph J. (2015). Juvenile incarceration, human capital, and future crime: Evidence from randomly assigned judges. *The Quarterly Journal of Economics 130*(2), 759–803.

Alós, R., F. Esteban, P. Jódar, and F. Miguélez (2015). Effects of prison work programmes on the employability of ex-prisoners. *European Journal of Criminology 12*(1), 35–50.

Archibong, B. and N. Obikili (2020). Prison labor: The price of prisons and the lasting effects of incarceration. Working Paper, Barnard College.

Baćak, V., L. H. Andersen, and J. Schnittker (2019). The effect of timing of incarceration on mental health: Evidence from a natural experiment. *Social Forces 98*(1), 303–328.

Bayer, P., R. Hjalmarsson, and D. Pozen (2009). Building criminal capital behind bars: Peer effects in juvenile corrections. *The Quarterly Journal of Economics 124*(1), 105–147.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy 75*(4), 352–365.

Bhuller, M., G. B. Dahl, K. V. Løken, and M. Mogstad (2020). Incarceration, recidivism, and employment. *Journal of Political Economy 128*(4), 1269–1324.

Bushway, S. (2003). Reentry and prison work programs. Urban Institute Reentry Roundtable, New York University Law School.

Bushway, S. D. and R. Apel (2012). A signaling perspective on employment-based reentry programming. *Criminology & Public Policy 11*(1), 21–50.

Chalfin, A. and J. McCrary (2017). Criminal deterrence: A review of the literature. *Journal of Economic Literature 55*(1), 5–48.

Chen, M. K. and J. M. Shapiro (2007). Do harsher prison conditions reduce recidivism? A discontinuity-based approach. *American Law and Economics Review 9*(1), 1–29.

Chetty, R. (2009). Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods. *Annual Review of Economics 1*(1), 451–488.

Cook, P. J., S. Kang, A. A. Braga, J. Ludwig, and M. E. O'Brien (2015). An experimental evaluation of a comprehensive employment-oriented prisoner re-entry program. *Journal of Quantitative Criminology 31*(3), 355–382.

Cox, R. (2009). *An Economic Analysis of Prison Labor*. Ph. D. thesis, Department of Economics, Georgia State University.

Cox, R. (2016). The effect of private sector work opportunities in prison on labor market outcomes of the formerly incarcerated. *Journal of Labor Research 37*(4), 412–440.

Cunha, F. and J. Heckman (2007). The technology of skill formation. *American Economic Review 97*(2), 31–47.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica 78*(3), pp. 883–931.

Doleac, J. (2019). Encouraging desistance from crime. Working Paper, Texas A&M University.

Doleac, J. L. and B. Hansen (2020). The unintended consequences of "ban the box": Statistical discrimination and employment outcomes when criminal histories are hidden. *Journal of Labor Economics 38*(2), 321–374.

Drago, F., R. Galbiati, and P. Vertova (2011). Prison conditions and recidivism. *American Law and Economics Review 13*(1), 103–130.

Durose, M., A. Cooper, and H. Snyder (2014). Recidivism of prisoners released in 30 states in 2005: Patterns from 2005 to 2010. U.S. Department of Justice, Bureau of Justice Statistics Special Report NCJ 244205.

Fan, X., A. Seshadri, and C. Taber (2019). Estimation of a life-cycle model with human capital, labor supply and retirement. Working Paper, University of Wisconsin-Madison.

Flinn, C. (1986). Dynamic models of criminal careers. In National Research Council (Ed.), *Criminal Careers and "Career Criminals", Volume II*, Chapter 6, pp. 356–379. The National Academies Press.

Fu, C. and K. I. Wolpin (2018). Structural estimation of a Becker-Ehrlich equilibrium model of crime: Allocating police across cities to reduce crime. *The Review of Economic Studies 85*(4), 2097–2138.

Gómez Baeza, F. and N. Grau (2017). The impact of prison labor programs on recidivism: The case of Chile. Working Paper SDT 440, Universidad de Chile.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 1029–1054.

Harding, D. J., J. D. Morenoff, A. P. Nguyen, and S. D. Bushway (2018). Imprisonment and labor market outcomes: Evidence from a natural experiment. *American Journal of Sociology 124*(1), 49–110.

Heckman, J. J. and T. Kautz (2012). Hard evidence on soft skills. *Labour Economics 19*(4), 451–464.

Holzer, H. J., S. Raphael, and M. A. Stoll (2007). The effect of an applicant's criminal history on employer hiring decisions and screening practices: Evidence from Los Angeles. In S. Bushway, M. Stoll, and D. Weiman (Eds.), *Barriers to Reentry? The Labor Market for Released Prisoners in Post-Industrial America*, Chapter 4, pp. 117–150. Russell Sage Foundation: New York.

Hopper, J. D. (2013). Benefits of inmate employment programs: Evidence from the prison industry enhancement certification program. *Journal of Business & Economics Research 11*(5), 213–222.

Kling, J. R. (2006). Incarceration length, employment, and earnings. *American Economic Review 96*(3), 863–876.

Kolesár, M., R. Chetty, J. Friedman, E. Glaeser, and G. W. Imbens (2015). Identification and inference with many invalid instruments. *Journal of Business & Economic Statistics 33*(4), 474–484.

Kuziemko, I. (2013). How should inmates be released from prison? An assessment of parole versus fixed-sentence regimes. *The Quarterly Journal of Economics 128*(1), 371–424.

LaLonde, R. J. (1986). Evaluating the econometric evaluations of training programs with experimental data. *The American Economic Review 76*(4), 604–620.

Lee, D. S. and J. McCrary (2017). The deterrence effect of prison: Dynamic theory and evidence. In *Regression Discontinuity Designs (Advances in Econometrics, Vol. 38)*, pp. 73–146. Emerald.

Lee, D. S., J. McCrary, M. J. Moreira, and J. Porter (2020). Valid t-ratio Inference for IV. Working paper.

Lewbel, A. (2019). The identification zoo: Meanings of identification in econometrics. *Journal of Economic Literature 57*(4), 835–903.

Lochner, L. (2004). Education, work, and crime: A human capital approach. *International Economic Review 45*(3), 811–843.

Looney, A. and N. Turner (2018). Work and opportunity before and after incarceration. Economic studies, The Brookings Institution.

Low, H. and C. Meghir (2017, May). The use of structural models in econometrics. *Journal of Economic Perspectives 31*(2), 33–58.

Maguire, K. E., T. J. Flanagan, and T. P. Thornberry (1988). Prison labor and recidivism. *Journal of Quantitative Criminology 4*(1), 3–18.

Mastrobuoni, G. and D. Rivers (2016). Criminal discount factors and deterrence. IZA Discussion Paper No. 9769.

Mastrobuoni, G. and D. Terlizzese (2018). Leave the door open? Prison conditions and recidivism. Carlo Alberto Notebooks No. 580.

Mocan, H. N., S. C. Billups, and J. Overland (2005). A dynamic model of differential human capital and criminal activity. *Economica 72*(288), 655–681.

Mueller-Smith, M. (2015). The criminal and labor market impact of incarceration. Working paper, University of Michigan.

Munyo, I. and M. A. Rossi (2015). First-day criminal recidivism. *Journal of Public Economics 124*(Supplement C), 81–90.

Nurse, J., P. Woodcock, and J. Ormsby (2003). Influence of environmental factors on mental health within prisons: focus group study. *British Medical Journal 327*(7413), 480.

Pager, D. (2003). The mark of a criminal record. *American Journal of Sociology 108*(5), 937–975.

Polinsky, A. M. (2017). Prison work programs in a model of deterrence. *American Law and Economics Review 19*(2), 391–422.

Prescott, E. C., R. Rogerson, and J. Wallenius (2009). Lifetime aggregate labor supply with endogenous workweek length. *Review of Economic Dynamics 12*(1), 23 – 36.

Raphael, S. (2011). Incarceration and prisoner reentry in the United States. *The Annals of the American Academy of Political and Social Science 635*(1), 192–215.

Redcross, C., M. Millenky, T. Rudd, and V. Levshin (2012). More than a job: Final results from the evaluation of the center for employment opportunities (ceo) transitional jobs program. *U.S. Department of Health and Human Services, OPRE Report 2011-18*.

Roach, M. and M. Schanzenbach (2015). The effect of prison sentence length on recidivism: Evidence from random judicial assignment. Working Paper, Northwestern University.

Rossi, P. H., R. A. Berk, and K. J. Lenihan (1980). *Money, work, and crime: experimental evidence*. Academic Press.

Rubio, M. (2019). From plantations to prisons: The legacy of slavery on black incarceration in the US. Working Paper, University of Gothenburg.

Sawyer, W. (2017). How much do incarcerated people earn in each state? *Prison Policy Initiative April 10, 2017*.

Saylor, W. and G. Gaes (1997). Training inmates through industrial work participation and vocational and apprenticeship instruction. *Corrections Management Quarterly 1*(2), 32–43.

Schnepel, K. T. (2018). Good jobs and recidivism. *The Economic Journal 128*(608), 447–469.

Schnittker, J., M. Massoglia, and C. Uggen (2012). Out and down: Incarceration and psychiatric disorders. *Journal of Health and Social Behavior 53*(4), 448–464.

Simon, F. H. (1999). *Prisoners' Work and Vocational Training*. Routledge.

Siwach, G. (2018). Unemployment shocks for individuals on the margin: Exploring recidivism effects. *Labour Economics 52*, 231 – 244.

Stevenson, M. (2017). Breaking bad: Mechanisms of social influence and the path to criminality in juvenile jails. *The Review of Economics and Statistics 99*(5), 824–838.

Tagliaferro, F. (2014). Analisi dei dati sulla popolazione detenuta. *Rassegna Penitenziaria e Criminologica 3*, 9–33.

United Nations (1977). Standard minimum rules for the treatment of prisoners.

U.S. Department of Justice (2008). Census of state and federal correctional facilities, 2005. Bureau of Justice Statistics, National Prisoner Statistics Program, NCJ 222182.

Waldfogel, J. (1994). The effect of criminal conviction on income and the trust" reposed in the workmen". *Journal of Human Resources*, 62–81.

Western, B. (2002). The impact of incarceration on wage mobility and inequality. *American Sociological Review 67*(4), 526–546.

Wilson, D. B., C. A. Gallagher, and D. L. MacKenzie (2000). A meta-analysis of corrections-based education, vocation, and work programs for adult offenders. *Journal of Research in Crime and Delinquency 37*(4), 347–368.

Yang, C. S. (2017). Local labor markets and criminal recidivism. *Journal of Public Economics 147*, 16 – 29.

Zapryanova, M. (2020). The effects of time in prison and time on parole on recidivism. *Journal of Law and Economics*. Forthcoming.