DRAFT: Breaking The Intergenerational Crime Cycle: The Impact of Record-Hiding Policies

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Abstract

There has recently been a significant rise in policies designed to reduce the impact of a criminal record, mainly through expunging records or hiding criminal histories from would-be employers. Such record-hiding policies (RHPs) have a narrow aim of improving employment and recidivism outcomes for formerly-incarcerated individuals, and a broad aim of breaking the inter-generational cycle of criminality. This paper presents a framework for evaluating the inter-generational effects of RHPs, through the lens of an over-lapping generations model. The model is calibrated using a combination of new empirical evidence on the effect of RHPs and existing empirical evidence on the inter-generational effects of criminality. The model provides good fit to the data, and suggests that RHPs can significantly improve inter-generational equality and reduce the crime cycle.

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1 Introduction

In America, forty percent of adult males have an arrest record, and one fourth have a criminal conviction (Sabol, 2014). Minority groups, and in particular Black males, are disproportionately affected, and can suffer significant challenges finding employment, housing, and access to credit as a result of having a criminal record. In turn, this blocked access to services can lead to further crime, generating a vicious cycle of criminality. As such, the effect of a criminal record is of key interest to policy-makers, academics, and the public. Labor economists and policy makers are interested in how crime affects labor market participation, education rates, home ownership, social connectedness, marriage, and other economic and social outcomes.

The past five years has seen a rise in research on the effect of criminality on employment and on the flow-through effects on outcomes of their children and dependents. Similarly, the effects of imprisonment (as opposed to home-detention, community service, and / or fines) on the offender and others have been studied in detail. More recently, there has been increased interest in the effect of a criminal record on outcomes. Criminal records have been shown to be strongly deterrent to hiring managers – a positive answer to the question 'Do you have a criminal record?' on a job application reduces call-back rates, interviews, and hiring probability. In turn, this reduced employment can cause lower income and lead to higher rates of recidivism than among those with similar criminal history but without records.

In light of this, many jurisdictions have sought to enact policies to ameliorate the effects of a criminal record. These policies typically remove or expunge a criminal record after a certain period of time, or hide a criminal record from would-be employers during the hiring process. For example, many states and cities in the USA have enacted 'ban-the-box' (BTB) laws which require firms to remove check-boxes asking about criminal records from job applications. Similarly, certain jurisdictions have passed laws removing particular types of offenses from a criminal record, such as marijuana convictions in US states which have legalized marijuana. Broadly, I refer to these types of policies as *record-hiding policies* or *RHPs*.

Much of the literature on the effects of a criminal record is individual focused, focusing on how a record affects the earnings and hiring-probability of individuals after discharge from incarceration. However, it has been increasingly recognized that criminal records can have inter-generational consequences. In particular, decreased earnings and working for formerly-incarcerated individuals can lead to reduced childhood investment and lower parental input, increasing the propensity for future generations to commit crime. Research shows that having a close family member serve a prison sentence increases the likelihood that an individual will be incarcerated by around 50 percent (Glaze & Maruschak, 2010). Given the disproportionate incarceration rates of minority individuals, this can perpetuate in inter-generational crime cycles along racial lines.

This paper assesses the direct and inter-generational effects of RHPs. In particular, it presents a structural framework for assessing the ways that these policies can have affects through generations. The core of the paper is a structural over-lapping generations model of crime and labor-market participation.

This paper sits at the nexus of two important literatures in economics and social policy. The first is the literature on how criminality and criminal records affect individuals outcomes, and how policies can be used to reduce these outcomes. The second literature focuses on hows criminality has intergenerational effects. To my knowledge, this is the first paper that takes the dual approach of considering both. The difficulty in joining these two literatures largely stems from difficulty accessing restricted data on inter-generational effects of crime. This is exacerbated by the fact that many RHPs have been implemented within the last decade or so, and so there hasn't been enough time elapsed to fully analyze the results. In this paper I combine new empirical results on the effectiveness of RFPs for reducing criminality with existing evidence on the inter-generational effects of crime in a structural model to analyze these important questions.

The rest of the paper is arranged as follows. Section 2 discusses the setting of RHPs, presenting some notable examples of such policies and providing a theoretical framework for how these policies may affect outcomes. Section 3 uses jail discharge data from New York State (NY) to build up a set of stylized facts that a model of crime choice should satisfy. It also outlines some existing empirical evidence on the inter-generational consequences of crime. Using this empirical foundation, section 4 presents an overlapping-generations model to study the inter-generational effects of such policies. Section 5 provides a policy analysis of RHPs, calibrated using a series of 'Ban-the-Box' laws passed in NY between January 2014 and November 2015, and discusses the within-generation and inter-generational consequences of these policies. Section 6 discusses future work and concludes.

2 Background and setting

In order to understand the reasons for introducing RHPs, this section presents some notable examples of such policies, and a brief theoretical review of their intended and likely outcomes.

The most notable set of RHPs is the 'Ban-the-Box' (BTB) campaign, which was established in 2004 by *All of Us or None*, a national civil rights movement of formerly-incarcerated people. The campaign was designed to stop discrimination against ex-offenders after a series of Peace and Justice Community Summits identified job and housing discrimination as barriers to successful re-establishment into the community after jail or prison (see also Pager (2003) for an analysis of the negative effects of a criminal record on employability). One in four American adults has a criminal conviction history (Sabol, 2014), so this discrimination is a wide-spread issue.

The main idea behind RHPs, and BTB in particular, is that individuals applying for jobs should be assessed on their skills, qualifications, and suitability, and not on criminal history. This is particularly true for offenders whose criminal records are for non-violent, non-financial, and victimless crimes that should not affect employment behavior, but who nonetheless experience employment discrimination.

The main aim of the BTB campaign is to encourage jurisdictions (cities and states) to pass legislation requiring employers to remove questions about conviction history from job applications.[1] An affirmative response to a question such as *'Have you been convicted of a crime?'* lowers callback and offer rates, and so decreases the probability of finding a job (Craigie, 2017). BTB advocates argue that removing these questions will result in better employment opportunities, and so better post-incarceration lives, for offenders.

The BTB campaign has been successful in removing these questions. The campaign website states that to date:

> *over 45 cities and counties, including New York City, Boston, Philadelphia, Atlanta, Chicago, Detroit, Seattle, and San Francisco have removed the question regarding conviction history from their employment applications. Seven states, Hawai'i, California,*

[1]Recently, the campaign has expanded this goal to removing questions about conviction history from a number of applications, including housing and loans. The campaign also notes that questions about conviction history can result in discrimination against formerly-incarcerated people in applications for public benefits, college admissions, and opportunities for volunteering.

> *Colorado, New Mexico, Minnesota, Massachusetts, and Connecticut, have changed their hiring practices in public employment to reduce discrimination based on arrest or conviction records. Some cities and counties and the state of Massachusetts have also required their vendors and private employers to adopt these fair hiring policies. In some areas, private employers are also voluntarily adopting ban the box hiring policies.*[2]

Beyond BTB, a number of other RHPs have been enacted in different jurisdictions across the world. Some of these policies expunge a person's criminal record after a certain period of non-criminality, such as New Zealand's pioneering Criminal Records (Clean Slate) Act 2004, which clears a criminal record (except for certain violent crimes) after a seven-year period without conviction. The Clean Slate Act was significant, removing the criminal records of half a million New Zealanders (Goff, 2004). Similar 'Spent Convictions' legislation is in place in Australia, the United Kingdom, and other jurisdictions.

There is also a series of more-detailed RHPs in place for particular types of criminal histories. These RHPs typically involve expungement of criminal records for illegal activities which are subsequently de-criminalized or legalized. For example, there are expungement campaigns in place to hide historical criminal records for marijuana possession across a number of US states which have legalized marijuana. Similarly, in 2011 the Turing Law in expunged criminal records of British men who had been convicted of homosexuality, a specific RHP which has since been emulated in other countries (George, 2019).

Intended consequences

The main intention of RHPs is to stop discrimination against formerly-incarcerated people, mainly in the hiring process, but extending to other aspect of society as well. Employment is a key step to successful re-integration into communities after a sentence, and strongly decreases the likelihood of recidivism (Tripodi, Kim, & Bender, 2010). As such, policies aimed at increasing employment for ex-offenders should reduce repeat offending and benefit the community. Moreover, because people-of-color are disproportionately arrested, convicted, and incarcerated (D'Alessio & Stolzenberg, 2003), employers' use of arrest or conviction history has a disparate impact on those communities.

There is a concern that RHPs increase the exposure of companies and their customers and employees

[2] https://bantheboxcampaign.org/about/

to potential crime, or increase the likelihood of legal action by unsuccessful applicants. In most cases however, the legislation allows for firms to still carry out criminal background checks on would-be employees. However, RHPs often require firms to delay these checks, allowing for a personal connection to be established between the hirer and the applicant, and giving the applicant time to demonstrate their skills and qualifications. Without RHPs, many individuals with a criminal record would be dismissed from contention immediately (Craigie, 2017). RHPs allows these individuals to demonstrate their job-readiness. Some policies even go so far as to prohibit a criminal background check unless a conditional job offer has been made, the idea being that a firm who likes an applicant enough to give a conditional offer may decide to employ them even if the background check uncovers a criminal history.

Actual consequences

The actual consequences of RHPs remain an open empirical question. The most widely-studied type of RHP is the set of BTB laws enacted in cities and states across the USA. Even looking at this specific type of policy, different authors reach different conclusions. This section presents a brief review of the empirical evidence on the effects of RHPs, focusing on the empirical results around BTB laws. A summary of the evidence is found in Table 1.

The most widely-cited evidence on the effect of BTB policy is by Doleac and Hansen (2016, 2017). They use country-wide data from the 2004-2014 Current Population Survey (CPS) focusing on Black and Hispanic men aged 25-34 with no college degree, as these are the groups most likely to be recently-incarcerated. They find that young low-skilled Black men are 3.4 percentage points less likely, and young low-skilled Hispanic men are 2.3 percentage points less likely to be employed after BTB. These effects are persistent, and are strongest for the lowest skilled groups (with no high-school GED).

This supports the audit study approach of Agan and Starr (2017), who perform a field experiment by sending 15,000 synthetic job applications for fictitious young men with randomized stereotypically-white and stereotypically-Black names before and after BTB. They focus on two large BTB jurisdictions (NY and NJ), and find that the implementation of BTB policy caused the Black-white callback gap to increase from six percent to 43 percent.

On the other hand, Craigie (2017) finds a positive effect of BTB legislation on employment. She uses country-wide data from the National Longitudinal Study of Youth (NLSY97) and a difference-in-difference (DD) as well as triple-difference (DDD) methodology to study the impact of BTB policies on *public* employment. She finds that BTB policies raise employment for those with convictions by four percentage points (a 30 percent increase of the outcome mean). This fits with other regional studies which show BTB increased public employment: Berracasa, Estevez, Nugent, Roesing, and Wei (2016) find that employment of those with criminal records increased by one-third after BTB in Washington, DC; Atkinson and Lockwood (2014) find that there was an eight-fold increase in the proportion of those with criminal records hired in Durham, NC between 2011 and 2014 (from 2.3 percent to 15.5 percent).

[Table 1 about here.]

The role of asymmetric information in hiring

A key aspect of the effect of RHPs is how they alter information in the hiring process. In practice, a RHP shifts hirers to a world of asymmetric information – previously they were in a full-information world in which the criminal history of applicants was known; afterwards they are in a limited-information world. The effect of RHPs depends on how this change in the information structure affects decisions.

There are two main possibilities of how the asymmetry could work – (1) asymmetric information on criminal history leads to hirers relying on other signals (qualifications, employment history, skills, etc.); and (2) asymmetric information on criminal history leads to hirers adopting policies of statistical discrimination.

(1) Use of other signals This response to asymmetric information is the desired outcome of RHPs. RHP advocates want hirers to look beyond criminal histories and consider suitability for the job. Doleac and Hansen (2016) refer to this as 'job-readiness', and note that, while a past criminal conviction may be related to job-readiness (for example by resulting in time out of the labor force), there are may other important determinants. Arguments for this form of asymmetry make use of the fact that even with RHPs in place, the uncertainty is resolved (as in most cases firms can still perform a criminal background check, just later in the hiring process). However, they argue that by this stage the candidate has had enough time to demonstrate their job-readiness, and so may be offered the job even if they have a criminal background. This argument is made by Love (2010), who claims that rejection is harder once a personal relationship (demonstrating job-readiness) has been formed.

(2) Statistical discrimination The statistical discrimination argument is the outcome that Agan and Starr (2017) and Doleac and Hansen (2016) document. Because RHPs stop employers from knowing the criminal history of applicants, hirers simply assume that Black applicants have criminal records and white applicants do not have criminal records. Beyond the RHPs context, this is the argument made by Holzer, Raphael, and Stoll (2006), who show that in the absence of criminal histories employers infer the likelihood of past criminal behavior using traits such as gender, race, and age. As such, it is likely to be young, Black males who are most negatively affected (Bonczar, Beck, et al., 1997). Supporting this, there is evidence that firms implementing universal background checks increase their employment of Black and Hispanic men, groups that might be discriminated against in an asymmetric information world.

3 Data

In order to build a model of crime and labor-markets, I first build some epmirical stylized facts on criminality. The data used for this are unit-record jail discharge data from eight populous counties in New York State: Erie County, Monroe County, Westchester County, and the five counties that make up New York City (Kings, Queens, New York, Bronx, and Richmond).[3] These counties account for over half of NY's population, and cover the major metro areas of New York City (including commuter suburbs), Rochester and Buffalo. The data are unit-records for every discharge from jails[4] in these counties.

The dataset tracks individuals with a (randomized) ID number, which allows for identification of recidivism – if a given ID appears more than once in the dataset, then that individual must have been

[3]These data are used to empirically test the effects of RHPs policies in Armstrong and Williams Jr. (in press).

[4]While 'jail' and 'prison' are often used interchangeably in common parlance, there is a distinction – jails tend to hold detainees for pre-trial periods or short city-level or county-level sentences, while prisons tend to hold detainees for longer sentences and often more-severe crimes.

discharged from a jail more than once, and hence recidivated after the first offense.[5]

The datasets contains a rich set of covariates, including demographic variables (age, gender, race and ethnicity, mental health and substance abuse history) and detention-specific variables (length of sentence, charge, discharge reason). In this paper, I focus on aggregate statistics. In order to homogenize the sample, I trim the dataset to include only non-Hispanic[6] males between the age of 20 and 55 at discharge.[7] These prime-age workers are the most likely to benefit from BTB laws. Some summary statistics of the dataset are shown in Table 2.

[Table 2 about here.]

Stylized facts of criminality

These data (and existing empirical evidence on the inter-generational effect of incarceration) are used to produce some stylized facts of the jail population and recidivism decisions.

1. Most crime is committed by young people

It is well-documented that older people are less likely to commit crimes than young people. For instance, Ulmer and Steffensmeier (2014) use data from the Federal Bureau of Investigation's *Uniform Crime Report* to show that the peak crime age is younger than 25 for all types of crimes, and that even the median age of arrest is below 50 for most crime types. There are a number of possible explanations for this, including the fact that individuals experience age-graded norms to 'settle down', a loss of co-offenders and partners over time, diminishing physical capabilities making crime too risky, and reduced attractiveness of criminal behavior (money, excitement, status) particularly relative to legitimate sources of reward (Ulmer & Steffensmeier, 2014).

This tendency is documented in the NYS discharge data as well. Figure 1 shows the age-profile of

[5]This measure is slightly imperfect for several reasons. Firstly, I cannot see any detentions before or after the sample period, and it could be the case that some recidivism is either missed or coded incorrectly as a first-time offense. Secondly, the ID numbers are assigned at a jurisdiction level, and are not comparable across jurisdictions. Thus, an individual who offends in multiple counties will not be captured in our data as the same offender, and hence will not be counted as a recidivist.

[6]The decision to exclude Hispanic detainees was based on data issues, arising from a potential mis-coding in the data.

[7]There is some evidence that a moderate amount of first-offending occurs before 20 (see, for example, Brame, Bushway, Paternoster, and Turner (2014)), but in the un-trimmed dataset only a small number of detainees were below 20 at discharge.

detainees at discharge from the sample, in total as well as for first-time offenses and recidivist offenses. They are scaled to an offending rate by dividing by the male population in the eight counties in the data, and can be read as an annual per-capita detention probability. So, for instance, between the ages of 20 and 25, 9.1 percent of males each year are detained in total, with 2.9 percent being first-time offenders and 6.2 being recidivists.[8] There is a clear trend of reduced crime over the life-cycle, with offending rate between ages 50 and 55 less than half the rate between ages 20 and 25.

[Figure 1 about here.]

2. Most people do not offend, and most offenders do not recidivate very frequently

The FBI claims that around 40 percent of American males will end up with a criminal record at some stage in their lives. This of course means that 60 percent do not offend (and this is even higher for females). Even for those who do commit crimes, the median number of crimes is very low. Figure 2 shows a histogram of the number of detentions per individual in the New York State jail sample. The median number of offenses is 2, and three quarters offend fewer than five times. By definition, this sample omits individuals who never are never detained, and so the most significant portion of the population is missing.

[Figure 2 about here.]

3. Recidivism is front-loaded

Between 40 and 60 percent of American detainees are re-admitted to prison at a point in time after discharge (Pew Center, 2011; Wilson, Draine, Hadley, Metraux, & Evans, 2011). For jail detainees (as opposed to detainees in prison), the recidivism rate is higher due to the smaller-scale crimes. In my data, 64 percent of discharges result in recidivism.

For those who do recidivate, a stylized fact is that recidivism is front-loaded. Most recidivism happens within one year of discharge, and recidivism at horizons greater than five years is rare. This is documented in the my data. Figure 3 shows the cumulative recidivism rate at horizons out to three years.

[8] Of course, there are some crimes committed that does not result in a detention (for instance if the offender is not apprehended by police), and hence would be missed here.

Almost all recidivism happens within six months, and between two and three years the recidivism hazard is largely flat.

[Figure 3 about here.]

4. Parental incarceration is generally associated with bad outcomes for children

A key mechanism in this model is the transmission of parental incarceration through to the next generation. From a theoretical perspective, it is not immediately clear whether parental incarceration should *cause* worse outcomes or better outcomes for childron[9]. On one hand, parents are an obviously important source of support for children, and so removal of a parent can negatively impact outcomes. On the other hand, to the extent that parental behavior is emulated by children, removing a negative or disruptive influence can lead to better outcomes.

The empirical evidence predominantly suggests that the causal impact of parental incarceration is negative. For example, Dobbie, Grnqvist, Niknami, Palme, and Priks (2018) use a judicial-leniency instrument to show that parental incarceration causally increases teenage pregnancy and lowers both high school graduation rates and early-career employment. There is evidence that parental incarceration lowers household income and discipline (Kjellstrand & Eddy, 2011), increases child stress and behaivoral issues (Turney, 2014), and affects youth development through sleep and eating disorders (Jackson & Vaughn, 2017).

While this negative evidence is not universal, with with some studies finding positive causal effects in certain contexts (e.g. Arteaga (2018)), the balance of the evidence suggests that a model of inter-generational criminality should incorporate the stylized fact that incarceration leads to worse outcomes for the following generation.

[9] Of course, from a correlation perspective, parental incarceration is likely to be associated with a number of risk factors such as lower parental education, lower socio-economic status, and statistical racial discrimination, which generate an inter-generational correlation in incarceration: half of children with incarcerated fathers end up in prison themselves Glaze and Maruschak (2010).

4 An inter-generational model of labor markets with crime

Guided by these stylized facts, in this section I outline a model of labor-market participation and crime choice in which parental decisions can affect child outcomes.

Environment

The model uses an overlapping-generations (OLG) structure, in a discrete time setting. The model focuses on the decision problem of individuals and is partial-equilibrium, taking the hiring and wage-setting behavior of firms as given.

Each period t, a constant number of individuals is born. Individuals live for T periods, at which time they give birth to a child and then die. An individual is born with a bequest B from the previous generation of individuals. The bequest is used to generate skills according to the function $\theta_t = \theta_t(B)$.[10]

An individual participates in the labor market for a wage, and can also partake in criminal activity to make some illicit profit, but with the risk of punishment. An individual can save (but not borrow) an asset a, which pays a return r.

Labor market and crime

An individual of age j and skill level θ participates in the labor market to earn a wage $w(j, \theta)$, and can also commit crime. The crime decision framework is Beckerian, in which agents rationally choose to commit crime for economic reasons Becker (1968). In particular, an individual can choose a probability $p \in [\underline{p}, 1]$ to commit a crime[11]. If an individual commits a crime in period t, they receive a payment $L(j)$ in t.[12] Between t and $t+1$, they are caught with some exogenous probability q.

If the individual is caught, there are imprisoned for one period, and there are four negative consequences:

[10] The bequest B can be thought of as either a monetary bequest which is used to fund the child's education and skill formation, or as an inter-generational skill transfer. For simplicity in the implementation of the model I calibrate $\theta_t(B) = B$ – future work could incorporate a more sophisticated link between bequests and skills.

[11] For simplicity, I set $\underline{p} = 0$. An extension could consider the situation in which $0 < \underline{p}$, reflecting that some individuals who would not want to commit a crime do so 'accidentally'

[12] In this version of the model, I set $L(j) = L$ for individuals. In future versions of the model, it may be useful to make the 'size of the crime' a choice variable, and have the probability of being caught dependent on L.

1. They lose their assets so that $a_{t+1} = 0$ (reflecting the fiscal cost of crime such as paying fines or legal defence)
2. They are blocked from labor markets for some period of time and can earn only a minimal wage $\underline{w}$ during that period (reflecting the serving of a prison sentence and wages for prison work)
3. They suffer a skill depreciation so that $\theta_{t+1} = \rho\theta_t$ for some $\rho < 1$ (reflecting erosion of skills in prison)
4. They gain a criminal record

On discharge, I assume that the criminal record persists for two periods and allow for a *recent* record to affect labor-market outcomes more than an *old* record. I denote the criminal record status of an individual as $\mathcal{R} \in \{\text{none}, \text{old}, \text{recent}\}$.

I assume that the once past some retirement age j^{ret}, the individual is no longer able to commit crimes.

An individual of age j has a unit endowment of labor each period, which they trade inelastically for a wage. There exists an earnings schedule which has three components:

$$e_t^j(\theta) = g_t^j + \theta_j^t + z_t^j$$

where g^j follows a deterministic age profile, θ_j^t is the skill of the individual, and z^j is an IID shock. I also assume that after a certain age (j^{ret}) the individual retires and earns a constant wage for the rest of his life, which depends on their wage in the period immediately prior to retirement. I'll call this wage w^{ret}.

I exogenously assume a retention / efficiency wage – firms are willing to pay a fraction of next period's earnings schedule based on the probability of that individual remaining in the labor force next period (i.e. not committing a crime).[13] In particular, if an individual is perceived to have a probability p^f of

[13]This is exogenously assumed here, but it could be endogenized, or at least broadly justified, by having firms with large hiring costs. If it costs a lot to bring a worker on and train them, firms may be willing to pay more to an individual if they are likely to stick around for several periods.

committing a crime, the firm will pay them a wage $w_t(\theta) = e_t(\theta) + \lambda(1 - p^f)e_{t+1}(\theta)$. The probability p^f may depend on the criminal-record status of the individual.

The actual probability of committing a crime is endogenously determined in rational-expectations equilibrium. In particular, the vector $2T$ vector of probabilities of committing crime at age j if the agent has a recent criminal record or if the agent has no criminal record is determined in equilibrium. To capture the idea that a criminal record decays over time, I let $p(\mathcal{R} = old) = \eta p(\mathcal{R} = recent)$, for some run-off parameter $\eta < 1$.

The household's problem

Given a life-cycle schedule for wages, the individual must chose a path for consumption and crime-committing to maximize utility. In particular, let $u(c)$ be the one-period utility function.

I also assume a warm-glow utility from endowment - in the last period of the individual's life they get additional utility $\varphi v(B)$ from bestowing B to their children.

Then, the individual's optimization goal is thus

$$\max_{\{c_t, p_t\}_{t=1}^{T}, B} \sum_{t=1}^{T-1} \beta^t u(c_t(\theta_t)) + \beta^T [u(c_t(\theta_t)) + \varphi v(B)]$$

To think about the budget constraints, it is useful to define P_t as a random variable which indicates whether a crime is committed by the individual in time t or not, so that

$$P_t = \begin{cases} 1 & \text{w.p.} \quad p_t \\ 0 & \text{w.p.} \quad 1 - p_t \end{cases}$$

Then, the budget constraint in time t depends on whether an individual was convicted of a crime (i.e.

committed a crime and was caught) last period or not. If an individual was convicted last period, then they are in prison (earning a lower wage and with no ability to commit a crime) this period and lost their assets, so the budget constraint is

$$c_t + a_{t+1} = \underline{\mathrm{w}}$$

If an individual was is not incarcerated, they are back in the labor market and also may have assets and can commit crime if they chose to. Thus, the budget constraint is

$$c_t + a_{t+1} = w_t^j(\theta) + \lambda(1 - p^f(\mathcal{R}))w_{t+1}^j(\theta) + (1 + r)a_t + PL$$

In the final period, the individual must chose between consumption and bequest, so the budget constraint is

$$c_T + B = (1 + r)a_T + w_T$$

The recursive problem

The relevant state vector for the household is $(\theta, a, \mathcal{R})$ – the individual's skill, current assets, and current criminal record. The choice variables are c and p – consumption and the decision of whether to commit a crime or not. By substituting the budget constraint in for $t = 1, \ldots, T - 1$, I can replace the choice variable with next period's assets, a'. The problem is then

$$V(\theta, a, \mathcal{R}) = \max_p pV_{crime}(\theta, a, \mathcal{R}) + (1 - p)pV_{no-crime}(\theta, a, \mathcal{R})$$

The problem can be solved via backward induction. In particular, the assumption that individuals cannot commit a crime after j^{ret} means that no-one in period T has a criminal record, and so the value function is

$$V_T(\theta, a) = max_{c,B} u(c) + \phi v(B)$$

s.t.

$$c + B = w^{ret}(\theta) + (1 + r)a$$

For all ages after retirement (when there is no crime and no criminal record) and before T, we have a standard consumption-saving problem

$$V_j(\theta, a) = max_{c,a'} u(c) + \beta V_{j+1}(\theta, a')$$

s.t.

$$c + a' = w^{ret}(\theta) + (1 + r)a$$

The more interesting case is pre-retirement, when there is the possibility of crime. In this case, I make use of the fact that the optimal p will either be 1 or $\underline{p}$.[14] This means that the optimization problem of the individual can be split into a two-step decision:[15]

1. For each choice of committing a crime or not committing a crime, calculate the optimal choice of a'

2. Select either $p = 1$ or $p = \underline{p}$ depending on whether it is optimal to commit a crime or not

A key assumption here (which was made slightly loosely above) is that if a crime is committed, the payout is immediate (this period), but the costs (imprisonment and loss of assets) arise next period. This means that the decision balances guaranteed payout now, versus an expected loss in the future.

The value for an individual with no criminal record, assets a and skill θ is

[14] This is not proven here, but is clear to see – of the optimized value of committing crime is higher than not, then optimal p is 1. If the optimized value of not committing a crime is higher, then optimal p is the lowest possible value, i.e. $\underline{p}$. If the two are equal, I assume that the individual chooses to commit a crime with minimal probability.

[15] If L is treated as a choice variable, then the optimal choice of L in the case of crime-committing can be calculated in the first step.

$$
\begin{aligned}
V_j(\theta, a, 0) = \max_{\text{crime, no}} \Big\{ & \max_{a'} u(w_j(\theta) + \lambda(1 - p^f) w_{j+1}(\theta) + (1 + r)a + L - a') + \\
& \beta \mathbb{E}[(1 - q)V_{j+1}(\theta, a', 0) + qV_{j+1}(\rho\theta, 0, 1)], \\
& \max_{a'} u(w_j(\theta) + \lambda(1 - p^f) w_{j+1}(\theta) + (1 + r)a - a') + \\
& \beta \mathbb{E}[V_{j+1}(\theta, a', 0)] \Big\}
\end{aligned}
$$

For an individual with no criminal record we have

$$
\begin{aligned}
V_j(\theta, a, 0) = \max_{\text{crime, no}} \Big\{ & \max_{a'} u(w_j(\theta) + \lambda(1 - p^f) w_{j+1}(\theta) + (1 + r)a + L - a') + \\
& \beta \mathbb{E}[(1 - q)V_{j+1}(\theta, a', 0) + qV_{j+1}(\rho\theta, 0, 1)], \\
& \max_{a'} u(w_j(\theta) + \lambda(1 - p^f) w_{j+1}(\theta) + (1 + r)a - a') + \\
& \beta \mathbb{E}[V_{j+1}(\theta, a', 0)] \Big\}
\end{aligned}
$$

Equilibrium

The within-generation equilibrium concept for this model is a rational-expectations equilibrium (REE). In particular, the REE is such that firms have some beliefs over the proclivity of workers to commit crimes (perhaps depending on age), and the resulting wages generate crime patterns that match firms' beliefs. There is also an inter-generational equilibrium concept which requires that the distribution of bequests B is constant over generations.

Equilibrium definition An equilibrium in this model is (a) a vector of crime probabilities $p_j(\mathcal{R})$ which depend on age j and record-status $\mathcal{R}$, and (b) a distribution of initial bequests $F(B)$ such that

1. firms pay a wage $w_j(p_j(\mathcal{R}), B)$ such that $p_j(\mathcal{R})$ of workers of age j, skill B, and record status $\mathcal{R}$ are imprisoned each period;

2. the distribution of optimal end-of-life bequest B is $F(B)$.

In this definition, one can think of the model as being a mapping from (firm-perceived) crime probability vectors $\vec{p}$ and bequest distributions $F(B)$ into (actual) crime probability vectors $\vec{p}$ and bequest distributions:

$$\mathcal{M} : \vec{p} \times F(B) \mapsto \vec{p} \times F(B)$$

The REE defined above is a fixed-point to this map.

Given the complexity of the mapping, it is not immediately clear that a fixed point (and hence an equilibrium) necessarily exists, and if so whether it is unique. Numerical analysis of the problem suggests that an equilibrium can generally be found, given reasonably parameter values.

Although a full proof of existence and uniqueness of the equilibrium does not exist, the following lemmas provide suggestive evidence that an equilibrium does exist. Both are proved in the appendix.

Lemma 1: For a sufficiently *high* firm guess $p_j(\mathcal{R})$, the mapping $\mathcal{M}(\vec{p}, F(B))$ is element-wise *decreasing* in $\vec{p}$. For a sufficiently *low* firm guess $p_j(\mathcal{R})$, the mapping $\mathcal{M}(\vec{p}, F(B))$ is element-wise *increasing* in $\vec{p}$.

Lemma 2: For a sufficiently *high* $F(B)$, the mapping $\mathcal{M}(\vec{p}, F(B))$ is element-wise *decreasing* in $F(B)$. For a sufficiently *low* $F(B)$ the mapping $\mathcal{M}(\vec{p}, F(B))$ is element-wise *increasing* in $F(B)$.

Calibration

The model is calibrated using a mixture of established values from the literature, and certain crime-specific parameters are calibrated to match key moments in the data established as stylized facts above. The utility function is logarithmic, and $\beta = 0.975$.

A summary of the remaining calibrated parameters and the assicoated sources and moments is given in table 3.

[Table 3 about here.]

Results

Using the calibrated model, I am able to simulate many generations of agents, and aggregate results to assess the ability of the model to replicate the stylized facts established above. Some of the key results are demonstrated below.

The first key result comes from analyzing the average arrest rate at each period (i.e. age) in the model. Just as in the data, the arrest rate decreases over the life-cycle, with the rate of arrest at retirement age around one-fifth of the rate at the start of prime-age (figure 4).

[Figure 4 about here.]

The second key result in terms of moment matching is that most individuals in the model do not commit crimes, and that serial recidivism is low (figure 5). Unlike the data, which are based on jail records, and so by definition do not capture any non-offenders, the model has a significant proportion of agents who are never arrested (either because they do not commit crimes or because they are not apprehended). The non-arrest rate in the model is around 65 percent, which broadly matches the empirical evidence that around 40 percent of American males end up with a criminal record. For those who do offend in the model, most are arrested at most one or two times, with less than three percent of agents being arrested six or more times.[16]

[Figure 5 about here.]

The third key moment to match is the recidivism hazard, which is very front-loaded in the data. In the model, a similar pattern is evident, with around 65 percent of agents recidivating, and over half of this recidivism happening within 3 periods (figure 6). Recidivism beyond 8 periods is very uncommon.

[Figure 6 about here.]

Finally, it is important to consider the effect of a criminal record, both within-generation and in terms of inter-generational dynamics. Figure 7 shows the average life-cycle asset accumulation for agents

[16]Relative to the data, there is an upper limit on the number of times that an agent in the model can be arrested. In particular, given that an arrested individual spends one period in prison (and cannot commit crime during this time), the theoretical maximum number of jail stints for an agent is $T/2$.

with and without a criminal record, as well as the average bequests for those with and without a record. The effect of a criminal record in the model is negative within and across generations – a criminal record reduces wealth of an individual, and (hence) also reduces the average size of bequest given to subsequent generations.

[Figure 7 about here.]

5 Policy analysis

A key question in this literature is what effect do RHPs have on outcomes for formerly-incarcerated individuals. There are two aspects to this – the within-generation effect, and the inter-generational effect. The within-generation effect has been widely covered (see, for example, Armstrong and Williams Jr. (in press) for the NY case), but the inter-generational effect is so far unexplored. In this section, I use the model developed in the previous section, along with new insights from NY's BTB experience to analyze the inter-generational effects of these policies.

Policy setting

In order to assess the effect of RHPs, I focus on a series of 'Ban-the-Box' laws enacted in NY in 2014 and 2015. NY lacks a comprehensive state-wide BTB law for private employers. However, certain jurisdictions within the state have implemented BTB laws. I focus on three such jurisdictions: Erie County, which implemented BTB effective January 1, 2014; Monroe County, which implemented BTB effective November 18, 2014, and New York City, which implemented BTB effective November 1, 2015. The dataset I use for this project also contains data on jail discharges in Westchester County, which had not implemented a BTB law by the end of my sample period, and hence may be used as a control group.

Identification and empirical evidence

The effect of BTB laws in NY is identified using a generalized difference-in-differences framework. This set-up allows us to use not only Westchester County as our control group, but instead to use all other jurisdictions as the control group for each jurisdiction's implementation. For example, when Erie County implemented BTB, I am able to use Monroe County, Westchester County, and New York City as control groups. Then, when Monroe County implemented BTB, I am able to use Erie County, Westchester County, and New York City as control groups. Finally, when New York City implemented BTB, I am able to use Erie County, Monroe County, and Westchester County as control groups.

The formal model empirical specification to implement the model uses individual discharges as the unit of observation, and is as follows:

$$\mathcal{R}_{ict}^{H} = \beta_0 + \beta_1 BTB_{ct} + \beta_2 X_{it} + t + c + \varepsilon_{ict} \tag{1}$$

In this specification, $\mathcal{R}_{ict}^{H}$ is a binary variable taking a value of 1 if individual i released into jurisdiction c at time t recidivated within H periods.[17] The variable BTB_{ct} is binary, taking a value of 1 if the jurisdiction c had a BTB law in place at time t, and a zero otherwise. The coefficient β_1 is the coefficient of interest. X_{it} is a vector of individual-specific variables (which may vary over time, such as age at discharge), t and c are fixed effects for the month of discharge and the jurisdiction, and ε_{ict} is a mean-zero error term.

Figure 8 shows the results graphically, plotting the expected recidivism $\mathbb{E}[\mathcal{R}_{ict}^{H}]$ from Equation 1 for $BTB_{ct} = 1$ and $BTB_{ct} = 0$. I find economically- and highly statistically-significant evidence that (in aggregate) RHPs lower recidivism, by between 3 and 5 percent.

[Figure 8 about here.]

[17] Recidivism in this setting is measured by whether or not the individual has another jail discharge record within H periods. As noted above, this may understate *true* recidivism.

Modeling the effect of record-hiding policies

In order to incorporate an RHP into the model, I simply remove the dependence of wages on the record status $\mathcal{R}$. In particular, the model is simplified such that agents can take only two states: incarcerated or free. The model is then solved as discussed above, to find the new optimal crime decision, and hence the new equilibrium crime probabilities and distribution of bequests.

Results

The main aim of this policy experiment is to analyze the effects of these policies on outcomes. The removal of criminal histories means that wages for formerly incarcerated individuals increase, and hence the optimal crime decision threshold is raised – RHPs lower the crime rate.

Of particular interest is what effect this has on within-generation and inter-generational inequality. Firstly, I calculate the average asset distribution in the both versions of the model, and construct Lorenz curves (figure 9). The effect of these policies on within-generation inequality are small, but suggest that the policies can lower inequality. In particular, in the version of the model without a RHP, the Gini coefficient of asset holding is 0.3098, while in the version with RHP the Gini coefficient is 0.3073.

[Figure 9 about here.]

The inter-generational results are stronger. In particular, figure 10 plots the equilibrium bequest distribution with and without RHPs. The distribution with these policies first-order stochastically dominates the distribution without the policies – when criminal records are hidden from employers in the model, there is more inter-generational transfers and subsequent generations are made better off.

[Figure 10 about here.]

6 Conclusion

This paper provides new evidence on the effectiveness of record-hiding policies at breaking the inter-generational crime cycle. By combining an overlapping-generations model with empirical evidence from New York State's 'Ban-the-Box' laws, it demonstrates that RHPs can improve inter-generational outcomes and reduce within-generation inequality on aggregate.

However, the effectiveness of RHPs on discriminated groups in particular remains an open and important question. The modeled results in this paper provide some broader evidence, suggesting that these laws can have inter-generational benefits. However, these conclusions should be qualified, and there remains work to be done on fully understanding the outcomes.

Of primary importance is the role that statistical discrimination plays in determining how these policies affect hiring decisions, and hence outcomes for formerly-incarcerated individuals. As noted above, there is some evidence that in the absence of information on criminality, firms make statistical assumptions which generate large negative outcomes for minority groups. Even in the context of New York States BTB laws, there is evidence that different racial and ethnic groups experience different outcomes in terms of recidivism (Armstrong & Williams Jr., in press). The model presented in this paper treats individuals as homogeneous in type, with no means for statistical discrimination. This is true both in the case where firms can see criminal histories and when they cannot. A future approach to this problem may try to embed statistical discrimination and differential outcomes.

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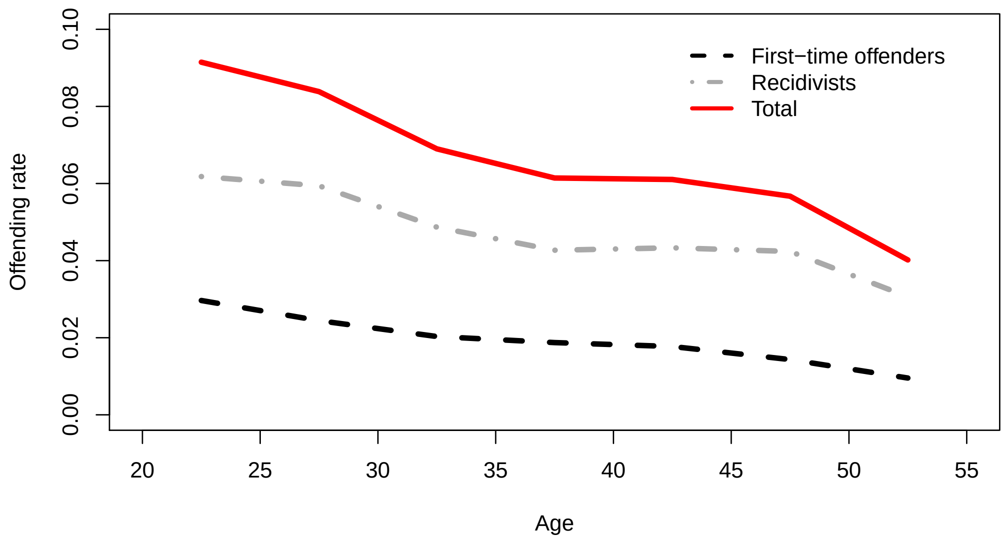
Appendix: Proofs of the two lemmas

List of Figures

Figure 1: Age profile of detainees



Source: Authors own calculations, New York State population data obtained from the New York State Department of Health website.

Figure 2: Number of detentions per individual

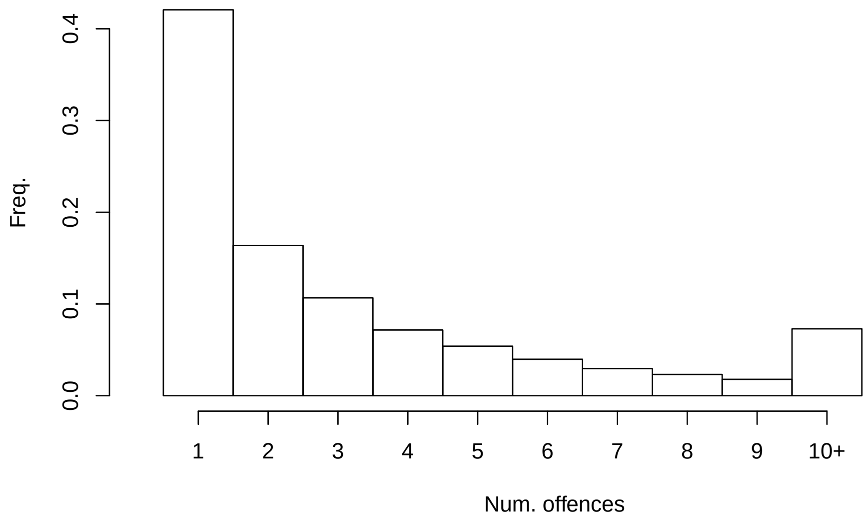
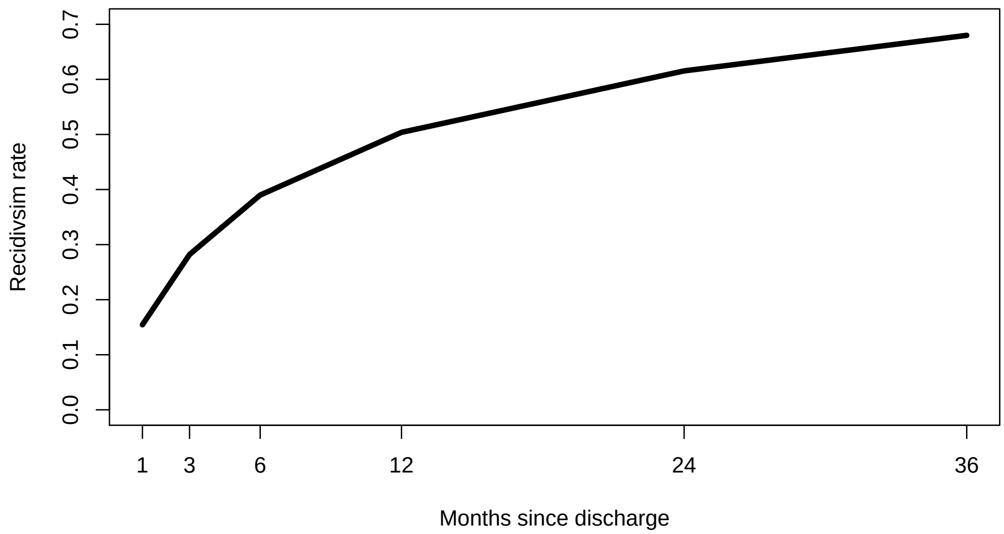


Figure 3: Cumulative recidivism rate



Note: The recidivism rate has been in general trending downwards over time. To take this into account, particularly when analyzing the effect of BTB policies which came into effect towards the end of the sample, I control for time in the production of this recidivism hazard, using a quadratic time trend.

Figure 4: Modeled arrest rate by age

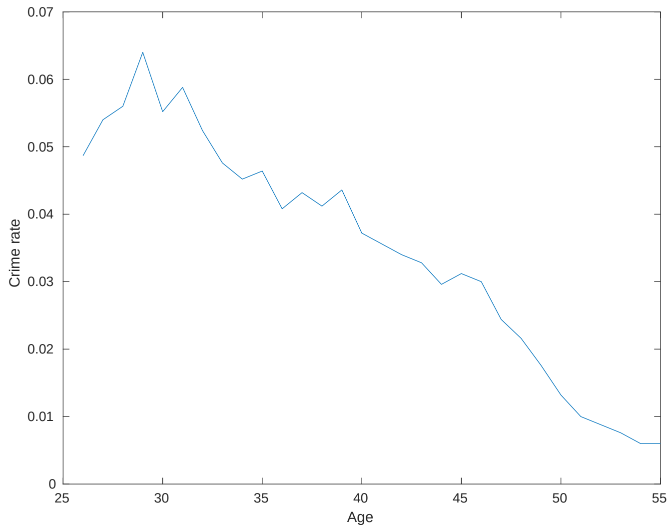


Figure 5: Modeled frequency of arrest

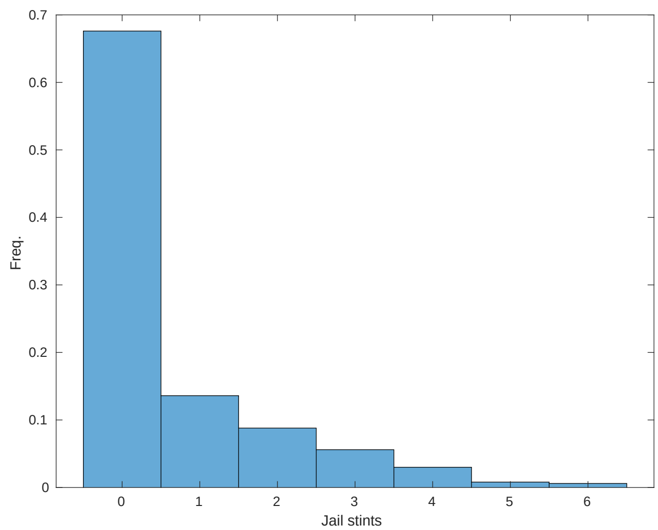


Figure 6: Modeled cumulative recidivism hazard

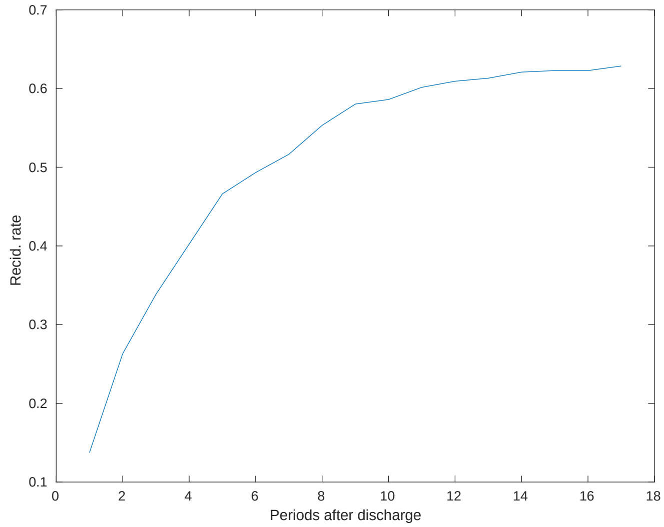
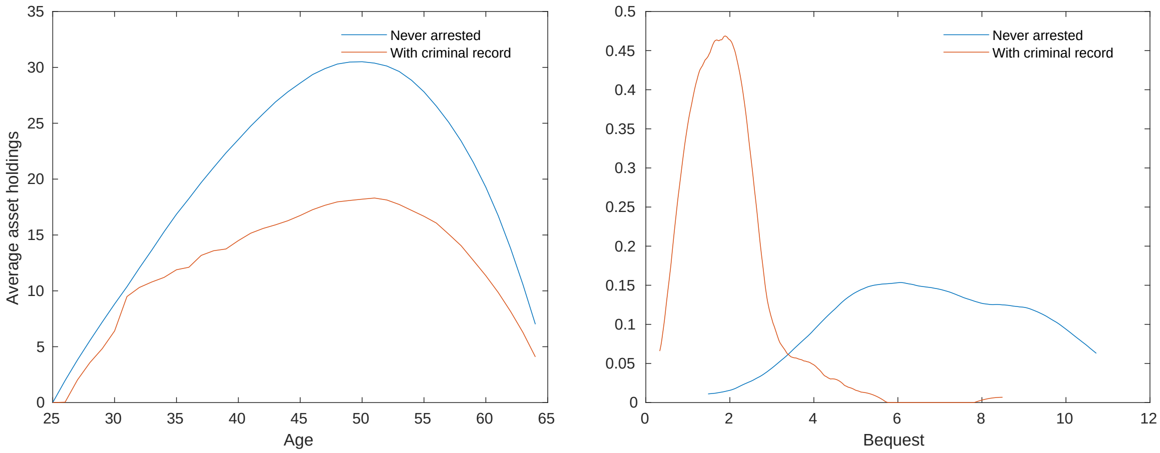


Figure 7: Effect of criminal record on within- and inter-generation wealth



(a) Average asset accumulation

(b) Average end-of-life bequest distribution

Figure 8: Effect of BTB laws on recidivism hazard

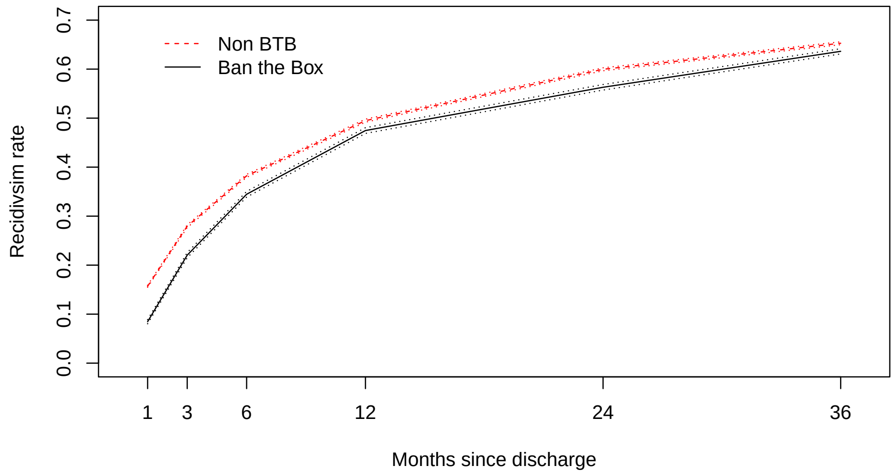


Figure 9: Effect of RHPs on within-generation inequality

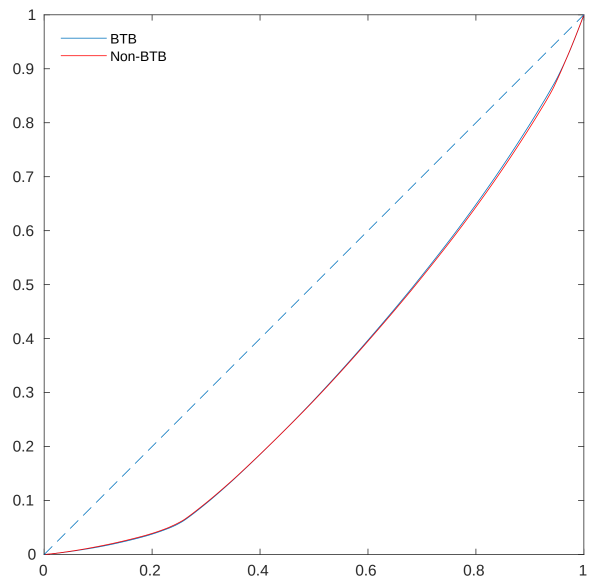
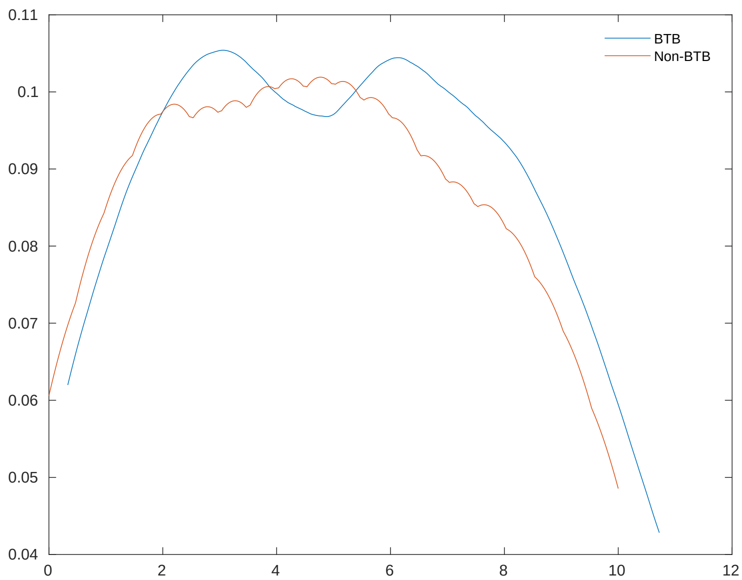


Figure 10: Effect of RHPs on intergenerational transfers



List of Tables

Table 1: Summary of RHP evidence

Authors	Jurisdiction	Employment type	Effect on emp.
Doleac and Hansen	Country-wide	Public and Private	$\downarrow$
Agan and Starr	NY / NJ	Public and Private	$\downarrow$
Craigie	Country-wide	Public only	$\uparrow$
Berracasa *et al.*	DC	Public only	$\uparrow$
Atkinson and Lockwood	NC	Public only	$\uparrow$

Table 2: Summary statistics for NY State jail discharge data

Variable		Full sample	BTB sample	Non-BTB sample
Mean age		34.6	33.8	34.7
Median age		33	32	34
White (%)		22.4	30.0	21.3
Black (%)		77.6	70.0	78.6
Mean Recidivism	1 year	42.5	40.4	42.8
	1-3 year	15.3	12.3	15.7
	3-5 year	4.5	0.1	5.0
Jurisdiction	Erie Co.	15.9	30.6	14.0
	Monroe Co.	11.4	17.2	10.6
	New York City	67.8	52.2	69.9
	Westchester Co.	4.9	-	5.6
Total obs.		751,409	89,338	662,071

Table 3: Calibrated parameters

Parameter	Description	Value	Source / Target moment
q	Arrest rate	0.176	Uniform Crime Reporting clearance rate
$\bar{p}$	Prison wage proportion	0.2	NY state prison wages
λ	Efficiency wage parameter	1.5	Total recidivism rate
ρ	Skill depreciation	0.85	Total crime rate
η	Record run-off parameter	0.8	Curve of recidivism hazard
φ	Relative bequest desirability	0.2	Stability of $F(B)$
j^{born}	Age at birth	25	Beginning of 'prime age'
j^{ret}	Age at retirement	55	End of 'prime age'
T	Age at death	65	