Dynamics of Deterrence: A Macroeconomic Perspective on Punitive Justice Policy*

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Abstract

We argue that transitional dynamics play a critical role in the evaluation of punitive incarceration reform on crime, inequality and the macroeconomy. Individuals' past choices related to crime and employment under old policies have persistent consequences that limit their future responses to policy changes. Novel cohort evidence is provided in support of this mechanism. A quantitative model of this theory calibrated using restricted administrative data predicts nuanced, non-monotone dynamics of crime and incarceration similar to the U.S. experience following a single permanent increase in punitive incarceration in the 1980s. Increased inequality and declining employment accompany these changes and are borne unequally across generations.

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1 Introduction

Prior to the 1980's the incarceration rate in the United States stood at a stable level comparable to other nations. Subsequently these paths have diverged, (see Figure 9).[1] A four-fold expansion in the imprisonment rate from 1980 to 2000 has made incarceration a typical experience for less educated men in the United States despite recent modest declines.[2] It is widely accepted that increased use of punitive incarceration stemming from major policy reforms beginning in the 1980s has contributed to this divergence.[3] However, there remains a lack of consensus on how large this policy contribution has been.[4] Similar questions remain as to how successful these reforms have been in reducing crime and of the magnitude of collateral costs on economic outcomes and inequality.

In this paper we argue that understanding the dynamic consequences of policy reform— those changes slowly unfolding in the transitional decades following a policy change— is particularly important for assessing punitive incarceration policy.[5] It is well documented that criminal behavior is very persistent, on average, at the individual level.[6] Therefore, one would expect the deterrent effect of increased use of punitive incarceration would be weak in the short run since the lingering consequences of past choices are hard to reverse even when punishment becomes more severe. A temporary spike in incarceration can then occur amidst inelastic short run behavior. If an incarceration experience increases future deviance through worse labor market prospects or the building of criminal capital, this spike can translate to increased crime in the short-run when inmates are released. Ultimately, as new cohorts born under the stricter policy enter their peak crime years the full deterrent effect is attained and both crime and incarceration fall in tandem. In this paper, we show this pattern remarkably similar to the U.S. experience after 1980: a monotonic decrease in crime alongside a rise and fall in incarceration; can stem from a single increase in

[1]See Burnham and Burnham (1999) for cross-country data and Hindelang (2016) for historical U.S. data.

[2]On a given day in 2008 and estimated 12.0% (37.2%) of white (black) males age 20-34 without a high school degree were incarcerated, (Pettit (2012)).

[3]Neal and Rick (2014) make this argument using the same administrative data as this paper. See also Blumstein and Beck (1999), Pfaff (2011), and Raphael and Stoll (2009).

[4]Bushway (2011) points out little is also known about which specific policies have been most influential.

[5]Analysis of the dynamic effects of policy changes given the dynamic nature of individuals' choices to participate in crime, appears little explored in the literature (McCrary (2010) provides a review). The closest related paper, İmrohoroğlu, Merlo, and Rupert (2004), compares property crime in early 1980's to late 1990's assuming full transition to a new steady state after policy change. A large literature estimates dynamic models of criminal behavior, but do not include policy changes.

[6]As many of half of the individuals released from prison in the U.S. will be reincarcerated within three years (calculated from the Department of Justice: Recidivism of Prisoners Released in 1994 data series.)

punitive policy.[7]

The unique cohort predictions of this theory are validated with a novel empirical strategy to separately identify age, cohort, and time effects using a simple axillary model. We find evidence of a "lost cohort" of individuals born in the mid-to-late 1960's- individuals at the prime crime age of their 20's in the 1980's- that have higher rates of prison admission and arrests *throughout their lives* compared to generations before them *and generations following*. This is an important contribution because the criminal justice literature largely attributes the increased average age of criminals to a fundamental shift in the age profile.[8] We show this is actually only partially a shift in the age profile, as also predicted by the theory, and partially a cohort effect. It also highlights one importance of considering dynamics: the implication that the cost and benefits of blunt reforms are borne unequally across generations.

To research the dynamic consequences of punitive incarceration policy reform, we develop an over-lapping generations model with rich channels of criminal persistence. The starting point is a Beckerian model of rational crime in which agents face a pecuniary trade-off between labor market opportunities and crime. We enrich this model with additional elements necessary to replicate joint criminal persistence and labor market outcomes observed in data. The first is human capital, which grows during employment and decays during non-employment, particularly when incarcerated. The second is criminal capital, some of which is set through choices early in life and is further increased during a prison sentence or decreased when abstaining from criminal behavior. The third is a criminal record that is observable by employers and can limit employment opportunities. These ingredients lead to divergent paths of individuals' employment and criminal propensities consistent with micro-data: widespread crime amongst the young followed by high recidivism rates and low employment for those caught and incarcerated.

We calibrate the model to quantitatively discipline the channels of criminal persistence by requiring it to match both cross-sectional and aggregate data. Our empirical strategy allows use of an array of high-quality restricted administrative data from different sources. These include administrative surveys (*Survey of Inmates of State Correctional Facilities*); a three year panel of

[7]This is a particularly important point given the inference on the relationship between aggregate crime and incarceration featured in policy discourse. For example, from Eisen and Cullen (2016): "Imprisonment and crime are not consistently negatively correlated... This contradicts the commonly held notion that prisons always keep down crime." We provide an explicit model showing the flaw in applying causal interpretation to aggregate series in this way that goes beyond convoluting orthogonal factors.

[8]This is probably in response to the deteriorating view of age-profiles being remarkably stable across time and space as they had been prior to the end of the 20th century (Steffensmeier, Allan, Harer, and Streifel (1989) and Gottfredson and Hirschi (1990).

parole officer data on over 12,000 individuals (*Recidivism of Felons on Probation, 1986-1989*); and the wide-scale panel of annual prison censuses (*National Corrections Reporting Program Data*). This strategy is distinct from prior micro-econometric and structural estimations which have typically used survey data in which ex and future inmates answer questions on their employment and criminal activity. Obvious deficiencies of these data include non-response, incorrect responses, and small samples. By contrast, we use samples many times larger from more reliable administrative data. [9]

Our main quantitative exercise evaluates the contribution of increased use of punitive incarceration to the U.S. prison boom and other outcomes. We simulate in the calibrated model an increase in the probability of incarceration conditional on committing a crime from 2% to 5%, a similar magnitude to the increase in the US during the 1980's. The incarceration rate for the population increases from 1.8% to 7.1% percent over the first 10 years then declines over the next 30 years towards a new steady-state incarceration rate of 4.3%. Crime falls sharply by half in the first few years: from 0.7% to 0.17%, due to the increased incapacitation of the most active criminals. It then flattens out for about a decade before gradually falling further to 0.1% due to the higher deterrence effect on new-born generations. Furthermore and in accordance with the data, crime becomes more concentrated among fewer and more persistent career criminals. Labor markets show interesting non-monotone dynamics. Over the first 10 years of the policy, the employment-to-population ratio falls from 68.7% to 64.7%. As the deterrent effects kick in on younger generations, their labor force attachment increases and the employment-population ratio gradually rises to a new steady state of 66.9%. The policy change has the largest permanent effects on inequality due to criminal records. The average wage of those with a criminal record falls by 15% in the first 10 years and settles at a loss of 10% in the new steady state. Employment prospects for those with a criminal record, particularly young individuals, fare far worse. The labor market tightness– number of jobs per unemployed worker— falls by over two-thirds from 0.13 to 0.04.

To the main exercise we add several illustrative experiments and decompositions. First, we examine the role of each channel of persistence in driving our results. We find contemporaneous deterrence is most important, early life choices gain importance in the long run, and the labor market response of firms to those with criminal records is mostly unimportant. Next, we decompose our results into the classic channels of incapacitation and deterrence. Incapacitation is most

[9] The National Longitudinal Survey of Youth includes a panel of interviews of a two cohorts of individuals before, during, and after imprisonment. The sample reporting incarceration is less than 200 and these individuals have many non-responses.

important for the short-run decline in crime, while deterrence gains importance in the long-run. Still, incapacitation remains quantitatively relevant in the long-run as crime becomes more concentrated among few individuals as a result of the policy change. Finally, we place these predictions in context relative to observed outcomes by simulating alternative scenarios where orthogonal exogenous changes in criminal rewards and real wages accompany policy reform. Increased crime rewards improve the model's fit to incarceration, but provide counterfactual increases in crime. We conclude that a combination of these type of other factors alongside policy changes are necessary to understand the evolution of crime and labor markets in the United States since the 1980s.

2 A Simple Model of Criminal Persistence with Empirical Cohort Evidence

In this section, we develop a simple model with two goals: (1) to illustrate the dynamic response to policy changes when criminality is persistent; and (2) to derive an empirical model of age, cohort, and time predictions of the theory used to test the theory in the data. The model features three key ingredients. First, there is an age-profile for crime. Second, the youth crime decision is decreasing in the probability of imprisonment and has a persistent impact on crime throughout life. Third, a prison experience can increase future criminality. Let $C_{j,t}$ and $I_{j,t}$ be the crime and incarceration rates, respectively, of cohort j at time t. Let the relationship between these variables over time be provided by the following equations.

$$\begin{aligned}
\text{Incarceration Rate } & I_{j,t} = \pi_t C_{j,t} \\
\text{Initial Crime Choice } & X_{j,0} = g^X(\pi) \\
\text{Evolution of Crime Rate } & C_{j,t} = X_{j,t} A_a + T_t \\
& X_{j,t} = (\phi + \beta \pi_{t-1}) X_{j,t-1}
\end{aligned}$$

The policy variable is π_t: the probability of incarceration conditional on committing a crime. It is exogenous and can change over time. Assuming a large population, the incarceration rate for cohort j at time t is equal to that cohort's crime rate $C_{j,t}$ multiplied by the incarceration probability π_t. The remaining equations explicate an extreme version of the cohort effects found in the full structural model. In the full model, choices made under the policy prevalent during youth persistently affect outcomes even as the policy changes later in life. Here, we model that cohort effect as a permanent component $X_{j,0}$ interpreted as an initial crime choice. The initial crime choice is given by a function $g^X(\pi) \in [0,1]$. We assume this function is twice continuously differentiable in $(0,1)$ and that $g'^X(\pi) < 0$, ie: that punitive policy deters.

The final two lines show the evolution of a cohort's crime rate given the initial crime choice and the evolution of the policy. First, the effect of aging (A_a) is specified as a growth rate.[10] This multiplies the persistent component of the cohort's crime rate $X_{j,t}$ which depends on $X_{j,t-1}$. The coefficient term $(\phi + \beta\pi_{t-1})$ has the following interpretation. The term $\phi < 1$ captures the direct effect crime today has on crime tomorrow. The term $\beta\pi_{t-1}$ captures the effect that a prison experience yesterday has on crime today. We assume $\beta > 0$ in which case a prison experience increases future crime or at least slows its decay.[11] Both ϕ and β can be interpreted as some persistent criminal capital.[12] Time shows up in two ways. The first is a level effect T_t. The second is through changes in the policy variable π_t over time.

The first set of predictions of this model, summarized in Proposition 2.1 and Corollary 2.2, explicate that cohort effects can generate a dynamic transition following an increase in π.[13] While the cohort effects are always present, whether or not the transition is non-monotone requires the elasticity of the initial crime choice to be large relative to the change in $\beta\pi$. In other words, the impact of the prison on criminal persistence cannot be too large relative to the early life deterrence. A sufficient condition is if crime falls in the new steady state, but this is not necessary. Taken together, Proposition 2.1 and Corollary 2.2 illustrate the importance of dynamics for policy evaluation in two ways. First, it shows that the timing of evaluating outcomes matters. Crime decreases less in the short run than in the new steady state. Incarceration increases more in the short run than in the final steady state. Second, it shows that the costs and benefits of a policy changes are borne differentially across cohorts.

Proposition 2.1 (The cohort born immediately before an increase in π has higher age-specific

[10] This specification is key for econometric identification. It is conceptually motivated by the life course and turning point theories in sociology (Elder Jr (1985)) and also motivated by the empirical profiles of crime as shown in detail in the online appendix.

[11] The case of $\beta < 0$ where incarceration reforms can be studied, but as we show it seems empirically unlikely.

[12] This specification fits with the refinements of the life-course theory applied to criminal deviance arguing that past deviance and disadvantage weaken the general life-course decay in deviance (Sampson and Laub (1990) and Laub and Sampson (1993)).

[13] The proofs here consider transition dynamics and look at relative quantities of crime, either across generations or across ages for a single cohort. The online appendix presents additional propositions and proofs concerning comparative statics on aggregate crime and incarceration levels with respect to the policy π. They show that crime and incarceration levels can either increase or decrease in response to an increase in π, depending on parameters.

crime and incarceration rates at all ages than all cohorts it precedes and follows.). *Let an initial π_0 be given. Denote with hat notation the variables related to the cohort born at $\bar{t}-1$ where $\bar{t}$ is when the policy is changed to $\pi > \pi_0$. Then:*

$$
\begin{aligned}
C_{\hat{j},t} > C_{t-\hat{j}+s,s} \quad &\forall \quad t > \bar{t}+1 \quad \text{and} \quad s \neq \bar{t}+1 \\
I_{\hat{j},t} > I_{t-\hat{j}+s,s} \quad &\forall \quad t > \bar{t} \quad \text{and} \quad s \neq \bar{t}
\end{aligned}
$$

Proof. See Online Appendix. □

Corollary 2.2 (The transition path of crime and incarceration after an increase in punitiveness are non-monotone if the elasticity of the initial choice is sufficiently large relative to the effect of prison on criminal persistence.). *Let an initial π_0 be given and consider the economy at a steady state for that π_0. Assume at time-zero the policy switches permanently and unexpectedly to $\pi_1 > \pi_0$. Then:*

- *a) The transition path for crime is non-monotone iff*

$$
\frac{g^x(\pi_0)}{g^x(\pi_1)} > \frac{\sum_{a=0}^{M-1}(\phi+\beta\pi_1)^a+1}{\sum_{a=0}^{M-1}(\phi+\beta\pi_0)^a+1}
$$

- *b) The transition path for crime is non-monotone iff*

$$
\frac{\pi_0 g^x(\pi_0)}{\pi_1 g^x(\pi_1)} > \frac{\sum_{a=0}^{M-1}(\phi+\beta\pi_1)^a+1}{\sum_{a=0}^{M-1}(\phi+\beta\pi_0)^a+1}
$$

Proof. See Online Appendix. □

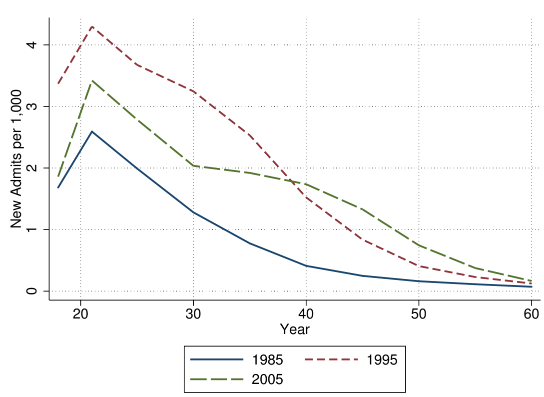
The second result from this model is summarized in Proposition 2.3. It states that if a prison experience increases criminal persistence, then the age profile of crime looks different in steady states with different incarceration probabilities π. In particular, as π increases crime is more persistent over the life-cycle resulting in higher incarceration rates for old individuals relative to young.

Proposition 2.3 (If a prison experience increases criminality, then a steady state with a higher incarceration policy exhibits higher crime and incarceration at older ages relative to young). *Let two policies $\hat{\pi} > \pi$ be given and $\hat{X}_a$ and X_a be the persistent component of crime at age a in the* *steady-state for each policy, respectively. Then:*

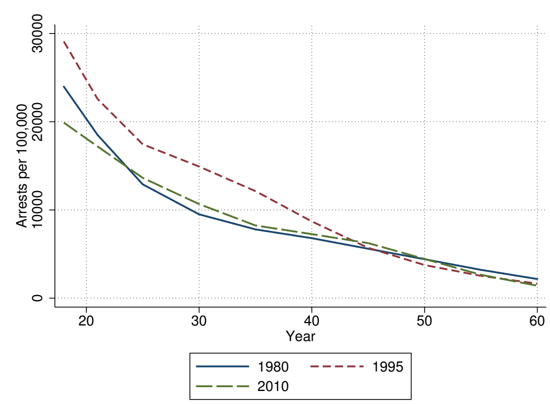
$$\frac{\hat{X}_a}{\hat{X}_{a-s}} > \frac{X_a}{X_{a-s}} \quad \forall \quad s \in (1, a)$$

Proof. See Online Appendix. □

The change in the life-cycle profile at the steady state when the policy increases occurs when a prison experience slows the life-cycle decay of crime. While crime decays monotonically over the life-cycle, incarceration is hump-shaped. Applying this model to incarceration it predicts the peak of life-cycle crime will move to older ages for β sufficiently large. This result is particularly important for how we think about time and age effects in the data. It is consistent with shifts towards deviance at older ages that are shown to be salient in the data as seen in Figure 1(b). It also suggests there is a permanent component of this shift can be interpreted as the effect of changes in policy. Both the permanent shift and the cohort effect from a simulation of the simple model can be seen in Figure 2 as an additional visual check on our propositions.[14]



(a) New Prison Admission Rate by Age



(b) Arrest Rate by Age

Figure 1: **Permanent and Cohort Shifts in Age Profiles (Data):** Prison admissions from National Corrections Reporting Program Data. Arrests from FBI crime reports accessed through the Bureau of Justice Statistics

Figure 3(d) illustrates the point that the inclusion of *both* the persistence of prior choices made under old policies ($X_{j,0} = g^X(\pi)$) and the assumption that incarceration increases (or slows the

[14]The model data are illustrative and for an arbitrary calibration: $\phi = 0.5$, $\beta = 0.9$, $g(\pi) = 1 - e^{-\pi}$, and 8 age groups. We consider a shift from $\pi = 0.1$ to $\pi = 0.4$.

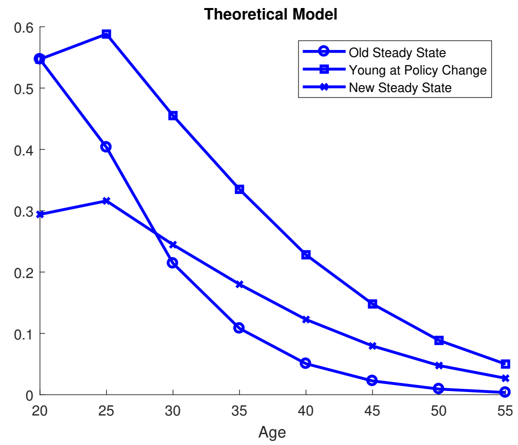
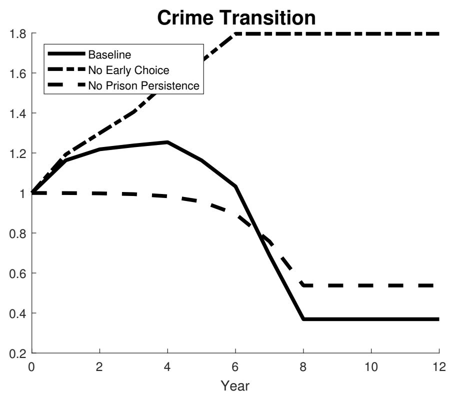


Figure 2: **Permanent and Cohort Shifts in Age Profiles (Simple Model)**

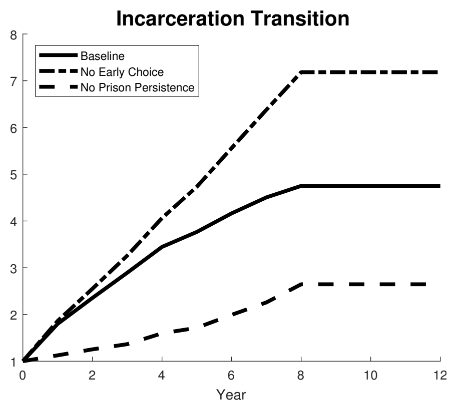
decay of) future deviance ($\beta > 0$) is critical for providing cohort effects that generate a non-monotonic transition. The baseline features both ingredients. The line "No Early Choice" sets initial crime X_0 as a constant independent of policy π. In this case, crime monotonically increases when policy π increases at time 0. The line "No Prison Persistence" sets the impact of a prison experience on future crime to zero ($\beta = 0$) In this case, crime monotonically decreases when policy π increases at time 0. Incarceration is similar, except both the non-monotonicity and the final steady state levels depend in the elasticity of the crime choice with respect to the policy π. A non-monotone transition and a smaller increase in incarceration (or even a decrease) in the final steady state are more likely when this elasticity is high. This is an important point for multiple reasons. It verifies that in order to replicate cohort features of the data, we need both an early life choice and for prison to affect future criminality. It also strikes at the policy crux of the paper: these are the two mechanisms that make policy evaluation using observed outcomes so different depending on the timing of the evaluation and they create differential costs across cohorts.

Regression Specification. The manner in which all four effects enter this simple model is crucial for identification. In a simple linear regression where these elements enter additively, they are co-linear and only two may be identified at once. By contrast, the theoretical model imposes an explicit structure in which these effects are not additive and co-linear.[15] This allows a novel estimation of the association between these three factors and trends in arrests and incarceration

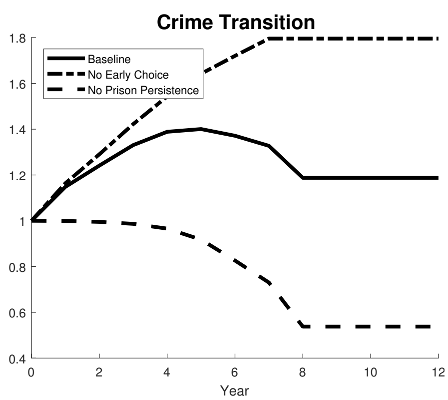
[15] An alternative approach would follow Lagakos, Moll, Porzio, Qian, and Schoellman (2016) in using theory to identify where the age effect is negligible.



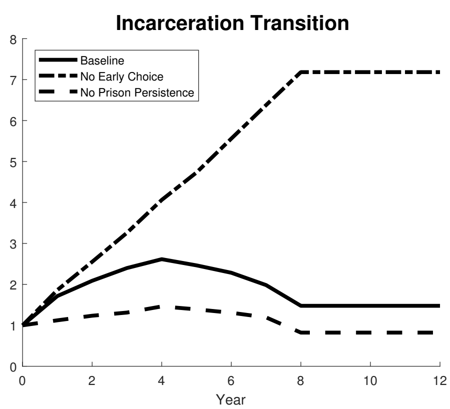
(a) Crime- High Elasticity



(b) Incarceration- High Elasticity



(c) Crime- Low Elasticity



(d) Incarceration- Low Elasticity

Figure 3: **Crime and Incarceration over a Transition in the Simple Model.** The first (second) row sets the elasticity of the initial crime choice to be high (low) with respect to the probability of prison conditional on committing a crime.

overtime.[16]

Conceptually, the age effect impacts growth rates while the time and cohort effects impact levels. However, we have shown that the age profile, or the persistence of crime over the life-cycle, can also be changing overtime in response to a change in punitive policy π.[17] This motivates a two-step procedure, explicated in detail in the online appendix, to separate these components into growth rate and level effects.[18] A summary of the procedure is to first estimate time-varying growth rate effects, generate residuals from the predicted values, and then estimate time and cohort effects on these residuals. The first stage dealing with growth rates, interprets age as the *time-invariant growth/decay* in crime/incarceration for individuals of all cohorts as they get older. The *time-variant change in growth/decay* in crime/incarceration for all individuals of all cohorts and ages from one year to the next is interpreted as the effect of policy changes. The second stage of our regression deals with levels. We estimate the time and cohort effects to best match the life-cycle profile of cohorts. The cohort component is a constant initial level for each cohort from which the life-cycle profile is created using the first stage regression. In other words, it shifts a single cohort's age-profile from the first stage up or down. The further time-level effects fill in gaps for years when individuals of all ages increase crime. The critical difference between the time effects in the first and second stage is that in the first stage, individuals are affected in proportion to their prior behavior where as in the second stage it is a common level increase for all individuals.

The resulting cohort and time coefficients of the second step are presented visually for Incarceration in Figure 2 and for arrests in Figure 2.[19][20] The peak time effect for prison admissions is the year 1990. This occurs in the first third of the peak of the total crime index. Cohort effects in arrests peak for the cohorts born in the early 1960's while cohort effects for prison admissions peak a couple of years later. These facts together are consistent with our theory of how a more punitive incarceration policy should differentially affect cohorts. The time effect in admissions rises sharply through the late 1980's. The cohort with the highest cohort effect would have been in their early 20's during this escalation, approaching the peak of the age profile of a typical criminal life-cycle

[16] This is an important contribution to the criminal justice literature which has mostly focused on the changing age-structure of prison admissions, something we demonstrate can be attributed partially to cohort effects.

[17] This strategy relates to Schulhofer-Wohl and Yang (2016). We overcome co-linearity by placing more structure on the nature of the age effects. We also directly address the issue raised in Schulhofer-Wohl and Yang (2016) advocating that the age effect may be changing over time and cohorts.

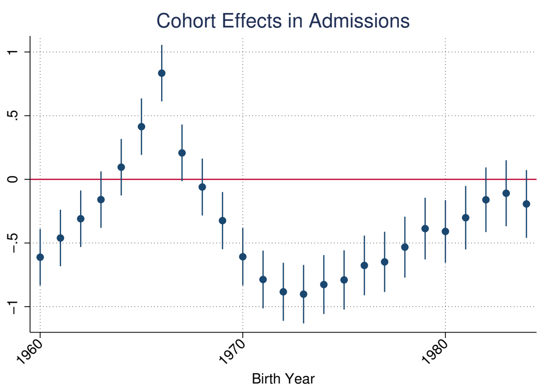
[18] In the appendix we show how the procedure and all of the following interpretations are derived directly from the simple model in this section.

[19] See the online appendix for details of the dataset and variable construction.

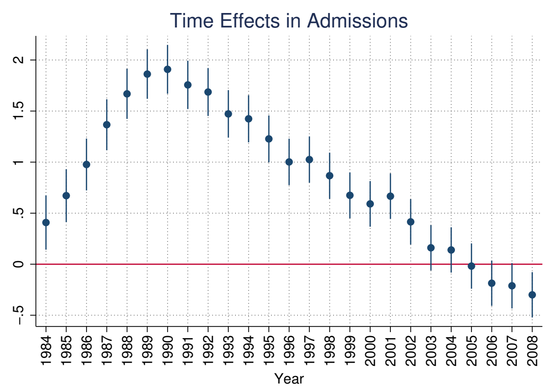
[20] The online appendix presents estimates of these effects for each of the three major crime categories: Drugs, Property, and Violent.

profile. Thus they cultivated their criminal careers prior to the time-related increase in punitive admissions and were at the peak of their careers where behavior is less elastic when the policy tightened.

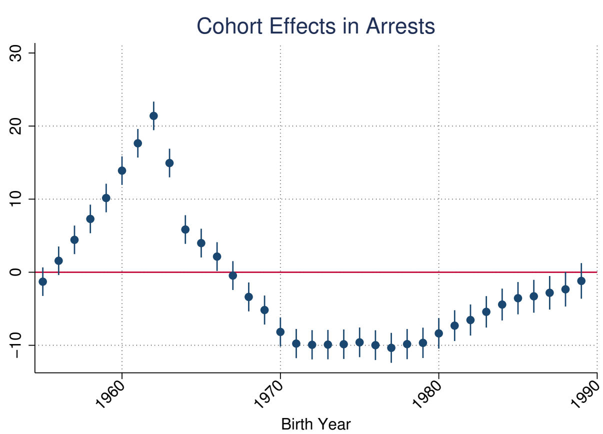
One word of caution is to take into consideration the relative magnitude of cohort and time effects in each series. Time effects are about double the magnitude of cohort effects in prison admissions. Cohorts are relatively more important for arrests.[21]



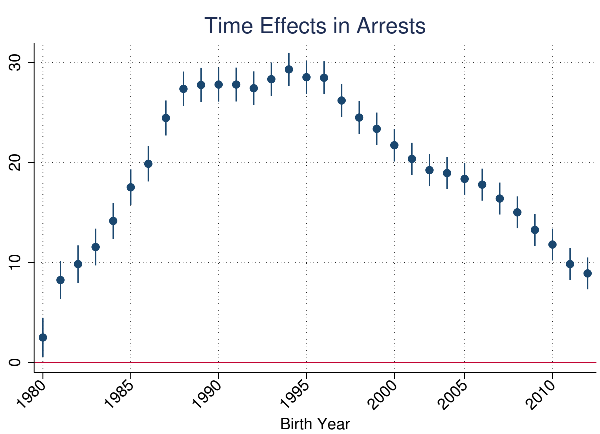
(a) Admission Time



(b) Admission Cohort



(c) Arrest Cohort



(d) Arrest Time

[21]The online appendix presents results for each type of crime: Violent, Property, and Drug.

3 Quantitative Model

We present a quantitative model built on Burdett, Lagos, and Wright (2003) and Engelhardt, Rocheteau, and Rupert (2008) to show how punitive incarceration policy affects crime rates, incarceration rates and labor market outcomes. Following Becker (1968), the main cost of crime is forgone labor market opportunities. Incarceration policy amplifies this cost through two channels. The first is at the individual level: an increase in the likelihood of incarceration increases the expectation of lost employment opportunities when an individual engages in crime. The second is at the aggregate level: incarceration policy and subsequent changes in the aggregate crime rate can decrease job arrival rates if firms' profits suffer and they respond by decreasing the job creation rate.

Time is continuous. The economy is populated by a continuum of finitely-lived ex-ante identical individuals and identical firms. Individuals have linear preferences over consumption and discount the future at rate $0 < r < 1$. At any point in time, individuals can be in any of three labor market statuses: (*i*) employment; (*ii*) unemployment; or (*iii*) incarcerated. Employed individuals are currently matched employed with one firm. Unemployed individuals are those agents not currently matched with a firm, but searching for a job. Lastly, incarcerated individuals are those agents currently in prison.

3.1 Individual's Problem:

Unemployed individuals receive flow consumption b. Employment opportunities arrive at the poisson rate λ_w. All jobs are identical. Upon receiving a job opportunity, the unemployed individual can either accept the offer or reject it. If they accept, they become employed and receive a flow wage proportional to their human capital (productivity) level: w.[22] Employed individuals receive job separation shock at poisson rate δ upon which they become unemployed.

All individuals outside of the prison receive crime opportunities at poisson rate η. Crime opportunities are characterized by an instantaneous reward of κ. These rewards are drawn from a common distribution $H(\kappa)$. The reward associated with a particular crime opportunity is observed to the individual before they make the choice of whether to commit the crime or not. If they choose to commit the crime, they receive the reward and, with probability π, they are caught and sent to

[22] In the simple model all agents have an identical, permanent level of human capital. A rich human capital process is introduced in the quantitative model.

prison.

Incarcerated individuals receive zero flow benefit while incarcerated. They receive a prison exit shock at rate τ upon which they are released and become unemployed.

We allow for several sources of heterogeneity across individuals: criminal capital, human capital, incarceration experience and age. The latter two sources (incarceration experience and age) provide an important link from the model to the data. They allow us to study the heterogeneous effects of the criminal policies for individuals along observable dimensions. The first two sources (criminal and human capital) are important for the quantitative performance of the model along dimensions that are not accounted for by observables. They will also contribute to the persistence of criminality generating cohort effects that we confirm.

Labor market opportunities result in additional ex-post heterogeneity across individuals. Luck in job arrival and separation shocks, as well as incarceration possibilities following a crime, generate different labor market status across individuals: incarcerated (p), unemployed (u) and employed (e).

To better match the data along several dimensions, we introduce heterogeneity in criminal capital. We assume two types of criminal capital: low (lc) and high (hc). Each type receives crime opportunities with probability η per unit of time. Upon receiving a crime opportunity, the individual decides whether to commit the crime or not. Committing a crime gives an instantaneous reward of κ to the individual. These rewards are drawn from a common distribution $H(\kappa)$. Individuals committing a crime are caught with probability π. We call these crimes as "rational crimes".

The difference between the types is that the high criminal capital individuals receive further crime opportunities at the rate η^{hc} that they must commit. These crimes bring no instantaneous benefit to the individual. We call these crimes as "irrational crimes". All individuals are born with low criminal capital, but we allow for a change in types. Upon committing a crime a low criminal capital type becomes high criminal capital type with probability ν regardless of whether the individual is incarcerated or not. High criminal capital types, in each period, become a low criminal capital type at the rate ξ. We include this feature to match recidivism rates in the data that cannot be accounted for.

The third ex-post heterogeneity happens due to stochastic changes in human capital. Each individual is endowed with an initial human capital level, identical across individuals. We assume that human capital stochastically increases on the job, and stochastically decreases while unemployed or incarcerated. We assume that human capital shock arrives at the poisson rate ψ_i, and upon arrival human capital evolves according to labor status dependent function $f_i(h)$ given current human capital level h. That is, $h' = f_i(h)$ where $i \in \{e, u, p\}$.

The fourth dimension of heterogeneity is due to incarceration experience. We assume that individuals who have been to prison can be distinguished by employers. As a result, there will be two types of jobs in the economy, one for individuals who have never been incarcerated, called *non-flagged* individuals, and one for the individuals who have been incarcerated at least once, called *flagged* individuals. We denote k as the flag type, and $k = 0$ refers to non-flagged whereas $k = 1$ refers to flagged individual. The main motivation for including this feature is to capture the fact that in real life criminal record is accessible by the employers.[23] Although, employers cannot observe certain characteristics of the individuals, like future crime propensities, they can extract some information through their incarceration experience summarized by this flag. So, in the model, this flag indicator will play the signalling role for the employers to infer the crime propensity of the individual.

The last dimension of heterogeneity is the age dimension. Age $m \in M = \{1, ..., \bar{m}\}$ individuals become age $m + 1$ at the poisson rate ϑ_m.[24] They live at most to the age of $\bar{m}$. When age $\bar{m}$ individuals receive aging shock, they exit the economy by receiving zero utility, and they are replaced with age 1 individuals who start life with the lowest skill level and as unemployed.

3.2 Matching

We assume that employers can observe the flag type k and the age of the individuals m. They create jobs conditional on these traits. This segments the economy into $2M$ labor markets because workers search only for jobs suitable to their observable traits. We assume that each type of the labor market is modeled as in Pissarides (1985). That is, employers with vacant jobs and unemployed workers meet randomly according to an aggregate matching function, $M(u_{km}, v_{km})$ where u_{km} and v_{km} are the number of unemployed workers and vacant jobs for individuals with flag type k and age m. We assume that the matching function is strictly increasing in both terms

[23] Harmonized electronic records across jurisdictions began to be available in the mid-1990's. However, analyzing the impacts of record access is non-trivial because access remained highly variable across states for over a decade. Also, explicit records are unlikely to be the only avenue through which criminal history could be ascertained. These issues are beyond the scope of this paper.

[24] Stochastic aging is a standard method of reducing the state space (in this case to 3 age groups instead of 2392 age-weeks) to make the computation feasible

and has constant returns to scale property. So, we can express the job arrival rate for workers as

$$\lambda_w^{k,m} = M\left(u_{km}, v_{km}\right)/u_{km} = M\left(1, v_{km}/u_{km}\right) = M\left(1, \theta_{km}\right), \tag{3.1}$$

where θ_{km} is the market tightness for type-km jobs. Similarly, vacant job filling rate for firms can be expressed as

$$\lambda_f^{k,m} = M\left(u_{km}, v_{km}\right)/v_{km} = M\left(u_{km}/v_{km}, 1\right) = M\left(1/\theta_{km}, 1\right) = \lambda_w^{k,m}/\theta_{km}. \tag{3.2}$$

3.3 Firm's Problem:

Now, we turn to a firm's problem: Firms post a vacancy by incurring a flow cost of k. Upon meeting with a worker, the match turns into an employment contract as long as the surplus of the match is positive. By hiring a worker, the match produces $y = p$, the worker receives a wage w, and the firm collects profits $p - w$. The match dissolves if either (i) the worker receives a separation shock; or (ii) if the worker commits a crime and gets caught. We assume that the wage is a constant fraction of the worker's productivity.[25]

3.4 Early-life Choice

Finally, we allow for an early-life choice that affects later criminal activity and is irreversible. We assume that at the beginning of life, individuals can pay a cost to increase their crime arrival rate η. Once it is chosen it will be fixed for the rest of life of the individual. The motivation behind such a choice is related to the near consensus reached across economics, sociology, and criminology that early life choices are instrumental in later life outcomes. These choices include things like effort in school, which peers to associate with, or even parents' choices. For our purposes, this feature will pick up the residual cohort effects documented in the data that cannot be accounted for by the criminal persistence provided by other features of the model. It accounts for the limited elasticity of criminal behavior for cohorts born prior to a policy change. Specifically, we assume that individuals choose their crime arrival rates by solving the following problem:

[25] Nash bargaining is an alternative wage protocol. However, several recent papers show Nash bargaining fails to quantitatively generate observed properties of business cycles, (See Shimer (2005), Hall and Milgrom (2008), Shimer (2013)). Thus, we do not take it as a gold standard for our analysis.

$$\max_{\eta} -A\frac{\eta^2}{2} + EV_u^{1,0}\left(h_0;\eta\right) \tag{3.3}$$

where A is a parameter to be calibrated. The first term in the above optimization problem, $A\frac{\eta^2}{2}$, captures, in a reduced form, the unmodeled costs of choosing a higher crime arrival rate η.[26] [27]

Mechanism. In the online appendix, we provide several analytical predictions of a simpler model to shed more light into the main mechanisms of the model. We show that a more punitive criminal policy -an increase in the probability of imprisonment for a crime- has two effects on the economy. The first is a direct effect on individuals' behaviors. As probability of incarceration increases, unemployed and employed commit less crime. However, the incarceration rate might increase or decrease depending on whether the increase in probability of getting caught or the decrease in crime rate dominates. If the increase in probability of getting caught dominates, the incarceration rate increases. The second depends on how firms respond in equilibrium. An increase in incarceration probability decreases the expected profits to a firm from hiring a worker. Firms respond by posting fewer vacancies which results in lower job arrival rates for individuals. This general equilibrium effect increases the crime probability for both unemployed and employed. The full quantitative model quantifies these effects in a more realistic framework.

4 Calibration and Estimation

We calibrate our model such that the initial steady state replicates empirical moments from the late 1970's and early 1980's according to availability. The assumption of a steady state at this time is motivated by the prior century of stable rates (see 9).[28] While most parameters are jointly estimated to minimize the distance between the model and data statistics, we briefly provide a heuristic explanation of the moments most informative to different parameters. A full description

[26]These costs include forgone education opportunities and higher income opportunities associated with that and any non-pecuniary costs of being associated in higher crime activities.

[27]To be clear: there is no ex-ante heterogeneity across individuals in the model: in the stationary environment individuals will choose exactly the same crime arrival rate. However, when we study the transitional dynamics, that will generate heterogeneity in crime arrival rates across cohorts since along the transition the return to crime will be changing.

[28]Indeed, rates were so remarkably stable across space and time that a theory of a "natural rate" of incarceration was prominent for many decades, (Blumstein and Cohen (1973).

of data sets, the calculation of target statistics, and the estimation procedure can be found in the Online Appendix.

4.1 Externally Calibrated Parameters

The time period is set to be one week. We assume that on average young individuals live for 7 years (between ages 18 and 24), middle-age individuals live for 10 years (between ages 25 and 34), and old individuals live for 30 years (between ages 35 and 64).[29] We set the prison exit probability to 0.007 implying 2.7 years of prison time on average, consistent with Raphael and Stoll (2009).[30] The probability of getting caught upon committing a crime, π, is set to 2% given our own calculations and which is also consistent with Pettit (2012).[31]

We choose $r = 0.1$ to provide an annual discount factor of 0.95. We assume that the criminal reward is drawn from a log-normal distribution with mean μ_κ and standard deviation σ_κ. We set $\mu_\kappa = 0$ and calibrate σ_κ to equal one half of the average annual labor income.[32] This gives us $\sigma_k = 2.265$.[33]

We follow Shimer (2005) for the matching function:

$$M\left(u, v\right) = \chi u^{\varphi} v^{1-\varphi}$$

where u is the unemployment rate and v is the vacancy rate. As in Shimer (2005), we set the flow utility of unemployment b to equal 40%; the matching function curvature φ to 0.72; and the matching function constant χ to 0.14. We assume that when workers and firms meet, they share the surplus equally, so we set the wage to be 50% of the productivity of the worker.

Table 1 shows the externally calibrated parameter values of the model.

[29] These average life-time for each age group implies the stochastic aging probabilities of $\vartheta_y = 0.00275$, $\vartheta_m = 0.00192$, and $\vartheta_o = 0.00064$ for the young, middle and old, respectively.

[30] Raphael and Stoll (2009) also show that increases in admissions rates on new charges account for more than half of the rise in incarceration rates and when combined with parole failure would account for 90%. This leaves little room for considering changes in length of incarceration spells and so we do not include this.

[31] Please see the online appendix for details of our calculation of this number.

[32] In order to identify the crime reward distribution and arrival rate of crime opportunities separately, we need data on the realized benefits of criminal activities and crime rates. It is hard to observe the realized benefits of crimes especially for crimes other than property crimes like violent and drug related crimes. As a result, we fix the crime reward distribution and calibrate the crime arrival rate using data on incarceration rates. In the Appendix we provide robustness results with respect to the crime reward distribution parameters.

[33] The mean of a log-normal distribution is $exp(\mu_\kappa + \frac{\sigma_\kappa^2)}{2}$. So, σ_κ solves $exp(\frac{\sigma_\kappa^2)}{2} = 13$

Table 1: Externally Calibrated Parameters

	Preset Parameters	
Parameter	Explanation	Value
ϑ_y	aging prob - young	0.00275
ϑ_m	aging prob - middle	0.00192
ϑ_o	aging prob - old	0.00064
τ	prison exit prob	0.007
r	discount factor	0.001
π	arrest prob	0.02
b	unemployment benefit	40%
μ_κ	mean of criminal reward	13
σ_κ	std of criminal reward	2.265
φ	matching function curvature	0.72
χ	matching function constant	0.14
w	wage share	0.5

4.2 Internally Calibrated Parameters

The rest of the parameters in the model are calibrated jointly by minimizing the percentage deviation of the model generated moments from the data moments. The details of the estimation process can be found in Appendix. Below, we briefly outline how we choose the data moments to identify these parameters.

Labor Market Parameters: There are two parameters related to labor markets: exogenous job separation rate and vacancy cost. As in the literature, we calibrate these parameters to match average employment rate of black and white men between the ages of 18 and 34, without a high school degree in the 1980s and the average unemployment duration for the unemployed in the population.

Human Capital Parameters: We consider human capital to evolve on an exponential grid with an exponent ς.[34] As in Ljungqvist and Sargent (1998), we assume a constant probability that human capital increases by one level during each period of employment and a different constant probability that it decreases by one level while either unemployed or incarcerated. To estimate the

[34] We set the support of the human capital process as $\underline{h} = 1$ and $\overline{h} = 3$. Given this support, we space N grid points between $\underline{h}$ and $\overline{h}$ such that $h_i = \underline{h} + (\overline{h} - \underline{h}) \left(\frac{i-1}{N-1}\right)^{\varsigma}$ for every $i = 1, 2, ...N$. We set $N = 21$ in the estimation. We checked the robustness of the results with respect to the numbers of grid points and the support of the human capital process. Although the estimated parameters naturally change, qualitative and quantitative results do not change.

arrival rate of the human capital shock when employed, ψ_e, when non-employed (unemployed and incarcerated), $\psi_u = \psi_p$ and the exponent of human capital process, ς, we use indirect inference method. Using the data from NLSY, we run the following regression to estimate the effects of employment and non-employment on wages:

$$ln(w_{it}) = \alpha + \beta^A A_{it} + \beta^{A2}(A_{it})^2 + \beta^N N_{it} + \beta^{N2}(N_{it})^2 + \gamma_i + \epsilon_{it} \tag{4.1}$$

where w_it is the observed wages for employed individual i at time t, A is the age of the individual, N is the months of non-employment including unemployment, non-participation and incarceration in the last two years, and γ_i is the individual fixed effects. The details of this regression can be found in the Appendix. We included the square terms for age and non-employment spell to capture the non-linearities in the human capital process. They are captured through non-linear spacing of the human capital grids in the estimation as similar to Kitao, Ljungqvist, and Sargent (2017).

We run the same regression using the simulated data from the model.[35] Although the age is stochastic in the model, in the simulation, we can keep track of the age of individuals, and we use their actual age in the model regression. The model is weekly, but we store the information to construct the panel data at monthly frequency as in the NLSY, and use the maximum wage of the individual in the last month as wage observation.

Crime Parameters: Crime opportunities are exogenous and arrive at the same probability when employed or unemployed. The calibration targets informative about these parameters are incarceration rates.[36] We assume the crime arrival rate for young and middle-age individuals with zero criminal capital are the same. We set the crime arrival rate for the old individuals with zero criminal capital to 0. The underlying assumption of this empirical strategy is that all crime of the old is done by individuals who have committed crimes in their young or middle age years. This assumption is motivated by the very low admission rate of individuals over age 34 with clean criminal records (<1%, authors' calculations from NACJD data).

Criminal capital is binary: high or low. There are three parameters related to criminal capital process: the probability of gaining high criminal capital after committing a crime, ν; the probability of losing high criminal capital, ξ; and the additional crime arrival rate for high criminal capital

[35]We use equal number of individuals as in the data (1196 individuals), and simulate their labor market outcomes to construct a panel data for these 1196 individuals to run the same regression.

[36]The median exit rate is observable and calibrated directly, leaving inflow rates to be inferred in order to match the share of persons incarcerated in the initial steady state.

individuals, η^{hc}. Statistics on repeated incarceration are informative about the share of high criminal capital types and the additional crimes they commit. We add to our estimation targets the three-year re-imprisonment rate for the released prisoners.[37] This rate is 22.1% and 18.3% in early 1980s for the age categories we define as young and middle-age individuals, respectively. The three-year re-imprisonment rate for the oldest age group (35-64) within which only high criminal capital individuals commit crime is 9.6%.

We also include the fraction of the population who are incarcerated by the age of 35. In the data, 19% of the population have been into jail or prison at least one time by the age of 35. In the model, the probability of gaining criminal capital, ν is a crucial parameter to capture this fact. If $\nu = 0$, crime will be more widespread among the population, whereas as ν becomes larger, crime will be concentrated among a few individual.

In the model, we assume that old individuals (age 35 to 64) receive no crime opportunities accept the ones committed by the individuals with high criminal capital. So, in the model, the individuals who are incarcerated among the old population will only be the ones with high criminal capital. This feature of the model allows us to discipline the probability of losing the high criminal capital, ξ. In the data, 0.5% of the old population is incarcerated. We use ξ to match this moment in the model.

Lastly, the cost of the early-life crime arrival rate (A) in the optimization problem in equation 3.3 is another parameter targeting incarceration levels.

Table 2 shows the calibrated parameters. Table 3 shows the performance of the model in matching the moments targeted. The model does a satisfactory job in capturing the moments targeted in the calibration.[38]

5 Steady-State Analysis.

To better understand how a change in punitive policy affects crime, labor markets, and inequality, we first discuss the determinants of crime in the initial (pre-1980's) steady-state.

[37] These rates are calculated using the BJS Recidivism of Prisoners Released Series (United States Department of Justice. Office of Justice Programs. Bureau of Justice Statistics (2011-03-08)). We take care to include only those re-imprisoned who are convicted of a new felony charge. This excludes those re-incarcerated in jails or re-imprisoned for violations of conditions of their parole, probation, or other conditions of release in order to be consistent with the concept of incarceration and crime used in the model and in targets from other datasets. The details of these data and our calculations can be found in the online appendix.

[38] In the online appendix, we discuss how removing elements such as criminal capital or prison flag compromises the model's fit. We also provide robustness checks on the externally set parameters.

Table 2: Calibrated Parameters

Parameter	Explanation	Value
η	crime arrival rate	0.027
c	vacancy cost	121.3
δ	separation shock	0.0143
ν	prob of being high criminal	0.087
η^{hc}	crime arrival rate - high criminal	0.074
ξ	rate of switching from high to low criminal	0.034
ψ_p	human capital shock-incarcerated	0.013
ψ_u	human capital shock-unemployed	0.013
ψ_e	human capital shock-employed	0.011
ς	exponent for human capital grid	0.71
A	constant in cost function	188557.5

Notes: The Table shows the internally calibrated parameters of the model. See the main text for a discussion of the explanation of these parameters, and how they are identified in the model.

Table 3: Model Match

Moment	Data	Model
Incarceration - young and middle	3.9%	3.9%
Incarceration - old	0.5%	0.5%
Unemployment duration	20 weeks	20 weeks
Employment rate - young and middle	71%	71%
Recidivism rate (3 years)	20%	20%
Fraction incarcerated by age 35	19%	19%
Regression coefficient-β^A	0.0228	0.0228
Regression coefficient-$\beta^A 2$	-0.000425	-0.00016
Regression coefficient-β^N	-0.0045	-0.0045
Regression coefficient-$\beta^N 2$	-0.000025	-0.000019
Crime Arrival Rate in initial SS	0.027	0.027

Notes: The Table shows a comparison of empirical and simulated moments. See Appendix for a detailed discussion for data sources on the empirical moments.

The choice to commit crime weighs the costs and benefits of doing so. The benefits are common to all individuals in the economy: they draw an flow reward from a common distribution for the crime they are considering committing that period. The costs are starkly different across individuals. While all face the same prison risk, what they lose by going to prison depends on their current status. These opportunity costs are more pronounced for individuals with high human capital or currently employed. Figure 4 shows the probability of committing crime conditional on receiving an opportunity. This probability decreases as human capital increases, notably at a faster rate for the lower half of the human capital range. It is also lower for employed compared to unemployed.

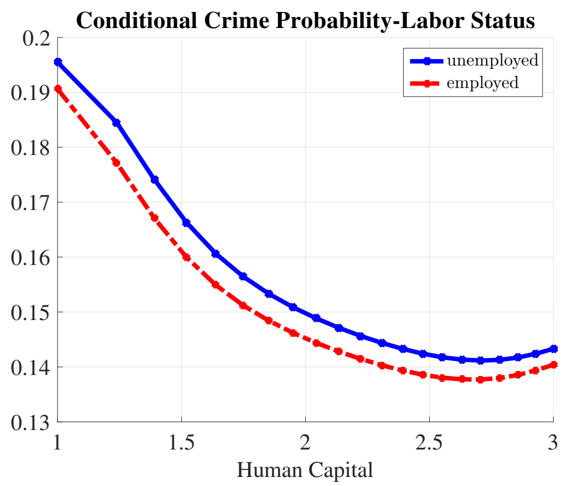


Figure 4: **Determinants of Crime - Labor Status:** The figure shows model generated crime probability conditional on receiving an opportunity as a function of human capital and labor market status for a middle-age agent with low criminal capital and prison flag.

The other factors contributing to criminal activities in the model are criminal capital, prison flag and age. Figure 5 shows that individuals with high criminal capital and previous incarceration experience are more likely to commit crimes. This is partially mechanical: high criminal capital types have more crime opportunities. This high likelihood of future crime also lowers the value of activities in the formal labor market because it lowers the duration during which the high criminal capital type expects to be out of prison. This amplifies criminal behavior by further lowering the opportunity cost of crime. The prison flag also increases crime by lowering the likelihood an unemployed individual with a criminal record may find a job. However, we find this channel is quantitatively small. Finally, age has a large deterrent effect on crime with individuals over 35 with a crime rate one-eighth of those younger than 35 (3).

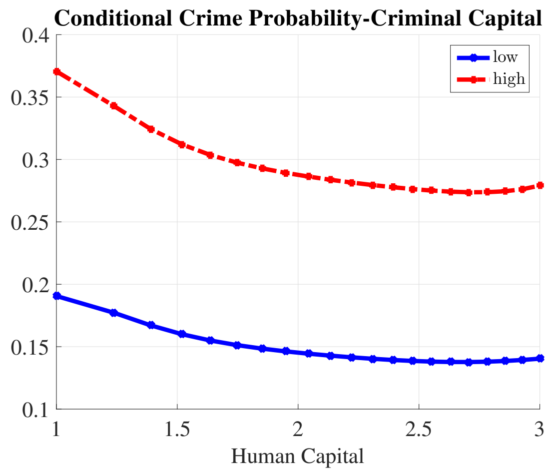


Figure 5: **Determinants of Crime - Criminal Capital:** The figure shows model generated crime probability conditional on receiving an opportunity as a function of human capital, criminal capital and incarceration experience for a middle-age employed individual. The qualitative properties of the figures remain the same for the unemployed and/or young individuals.

Table 4: Characteristics of Criminals

	Criminals	Overall
Unemployment rate	26.1%	22.9%
Employment rate	73.9%	77.1%
Human capital-average	1.59	1.98
Human capital among unemployed	1.54	1.90
Human capital among employed	1.61	2.00
Frac of high criminal capital	80.3%	7.4%
Prison Flag	35.7%	17.3%
Young and middle population	97.0%	36.2%

Notes: The Table shows a comparison of various statistics for criminal types (individuals with prison flag) and non-criminal types.

Table 4 shows criminals differ from the overall population along several dimensions. As expected, criminals are more likely to be unemployed, with lower human capital, younger, higher criminal capital and more likely to have criminal record in their history. In the initial steady-state only 74% of criminals are employed compared to 77% of the general population. However, this is not solely a result of being employed since employment is also associated with higher human capital, lower addiction and higher age. In the initial steady-state human capital of employed is on average around 5% higher than the unemployed (2.0 vs 1.9). The fraction of individuals with high criminal capital among employed is 6.1% whereas for the unemployed it is 7.0%. 15.8% of the employed and 15.7% of the unemployed have prison flags. The average age for the employed is 41.9, whereas for the unemployed it is 40.4. All these factors also decrease the crime probability of the employed. To better get at the contribution of each factor, we run a simple linear regression on the individuals' probabilities of committing crime within the week (Table 5).[39] The cells list the percentage-point change in crime probability associated with each independent variable. The average weekly crime probability in the economy is 0.8% chance per week, with a standard deviation of 2.0 percentage-points and a maximum of 8.2%. The first column shows there are two main deterrent factors: old age and high wages. Moving up one standard deviation in the wage distribution reduces crime by 0.025 percentage points per week. Factors that increase crime include unemployment, being middle age (relative to young), and high criminal capital. Clearly having high criminal capital is the greatest marginal contributor to crime and old age is the biggest marginal deterrent of crime. We present similar elasticities for different sub-groups. The most interesting result is that individuals with high criminal capital have higher elasticities of crime with respect to unemployment and wages.

The most important dimension of these data is that the majority of the crimes are committed by the individuals with high criminal capital and previously incarcerated individuals. Although the fraction of individuals with high criminal capital among the population is 7.4%, among the criminals this number is 80.3%. Similarly, 35.7% of the criminals has a previous incarceration record on their history whereas the ratio of individuals with prison flag in the overall population is 17.3%. So, while the margins of employment and human capital are instrumental in the choice to begin crime, the prison experience drives persistence at least until the deterrent effect of age takes over.

[39] Specifically, the dependent variable uses the individual crime reward threshold to calculate the probability of receiving a crime reward above that threshold.

Table 5: Crime Elasticities

	All	Young	Unemployed	Flagged	High Crim. Criminal
Age 25-34	0.057	0.000	0.061	0.009	0.003
Age 35-50	-0.376	0.000	-0.390	-0.514	-0.866
Unemployed	0.012	0.014	0.000	0.012	0.048
High Crim. Capital	7.536	7.648	7.565	7.460	0.000
Prison Flag	-0.006	0.007	-0.004	0.000	-0.001
ln(wage)	-0.031	-0.050	-0.032	-0.016	-0.100
Constant	0.409	0.399	0.423	0.519	8.037

6 The Dynamics of Punitive Incarceration Reform

In this section, we study the effects of an increase in the probability of incarceration after committing a crime on aggregates like crime rates, incarceration rates, labor market variables and inequality. In the initial steady-state probability of getting caught was set to $\pi = 2\%$. We assume this probability permanently and unexpectedly increases from 2% to a higher value 8%.[40]

We begin by comparing steady states. To see how a change in π affects the incarceration rate, consider the probability of incarceration for an individual with current state s: $\pi\eta\left(1 - H\left(\kappa^*\left(s\right)\right)\right)$. The overall crime rate is $\pi\eta\int\left(1 - H\left(\kappa^*\left(s\right)\right)\right)d\mu\left(s\right)$, where μ is the distribution of individuals across states. Increasing the probability of getting caught conditional on crime, π, affects the overall crime rate through three channels. The first is a direct effect by increasing π. The second is an indirect effect through endogenous responses of the individuals due to changes in $\kappa^*\left(s\right)$ and η determined by the early criminal choice, given an individual's state s. The last effect is an indirect compositional effect through a change in the distribution of individuals across states μ impacted by the changes in the crime rates *and* labor market opportunities of the individuals due to endogenous job creation response of the firms.

In our model, the second and third channels can mitigate the impact of the first channel. It is unclear then whether an increase in π will increase or decrease incarceration rates. If the change in behavior to reduce crime is small, then the "arithmetic" effect of higher conditional probabilities

[40] Calculations motivating the choice of 8% are provided in the online appendix.

Table 6: Steady-State Comparison

Steady-State Variables	SS1 $\pi = 2\%$	SS2 $\pi = 8\%$
Incarceration - young	2.3%	2.5%
Incarceration - middle	5.1%	5.4%
Incarceration - old	0.5%	0.5%
Incarceration - total	1.7%	2.0%
Crime Rate	0.6%	0.2%
Unemployment rate	23.3%	23.3%
Recidivism rate-young and middle	20%	48.4%
Lastly employed when arrested	73.9%	70.3%
Frac w/ high criminal capital	7.4%	2.7%
With prison flag	17.3%	13.9%
High criminal capital among criminals	80.3%	72.5%
Prison flag among criminals	35.7%	51.8%
Wage of criminals as a fraction of wage of employed	80.5%	73.5%

Notes: The Table shows a comparison of two steady states, one with $\pi = 2\%$ and one with $\pi = 8\%$.

can dominate and increase the overall incarceration rate. This typically generates a "Laffer curve" type of non-monotonicity between π and the incarceration rate whereby when $\pi = 0$ (no criminals go to prison) or $\pi = 1$ (nobody commits crime) incarceration rates are zero. What is different from typical in our model is that it is unclear that crime rates should fall. It is true that at every state s, individuals should raise their threshold $\kappa^* (s)$ and commit less crime. However, in our model a prison experience worsens an individual's state and makes them more likely to do crime. In this way it is possible that an increase in π leading to an increase in incarceration could also increase crime.

Table 6 shows the comparison of steady-states across two different criminal justice policy regimes. We find as the criminal system becomes more punitive, crime rate decreases, but this decrease is dominated by the direct effect of an increase in π causing the incarceration rate to increase.

Next we consider the transitional dynamics from one steady-state to the next. This transition can take several decades, and along the transition there can be substantial costs associated with the policy change. As we document in the empirical analysis, early cohorts have been affected quite substantially from the punitive crime policies compared to the later cohorts. To better understand these costs, we solve the transitional dynamics after the implementation of the policy.

Figure 6(a) shows the evolution of total incarceration rate along the transition. It starts with

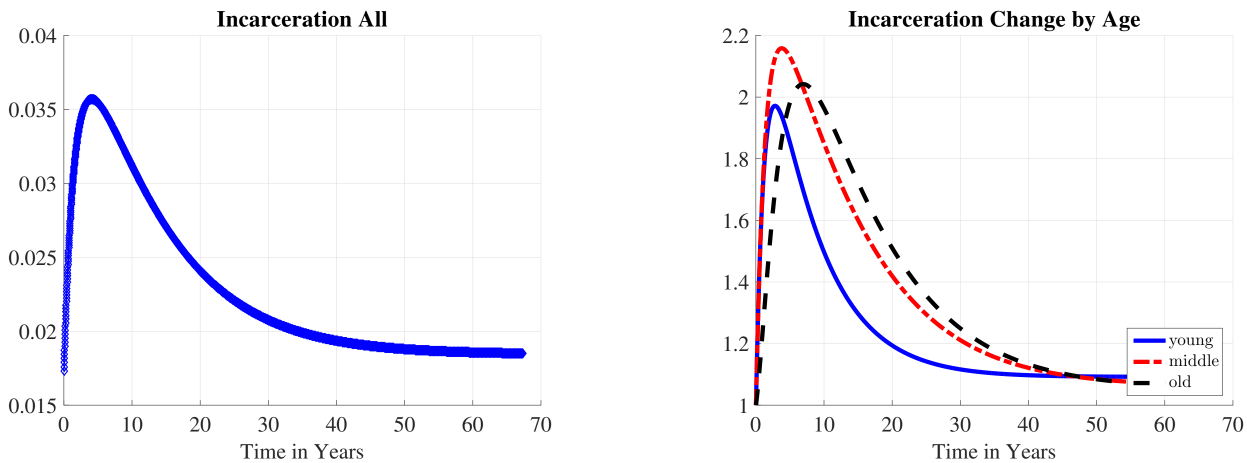
1.7%, doubles in 5 years, and then gradually declines to the new steady-state level of 1.8%. Note that the model does not generate a quadrupling of the incarceration rate as observed in the data. This is likely because of omitted factors. Therefore this should be viewed as an accounting exercise of the impact of changes in policy on its own.[41] However, it should be emphasized that there is a maximum increase in incarceration we can generate by increasing π alone because agents respond by lowering their crime rates. This holds even if we increase the role of criminal capital and irrational crime in the model. It is true that higher probability of gaining criminal capital or more frequent irrational crimes would raise the incarceration rate by increasing the future criminality of past criminals. However, agents view this as a cost of crime and react by reducing the number of first crimes committed. This endogenous reaction limits the scope of criminal capital process for increasing the incarceration rate.

In Figure 6(b), we show the change in incarceration rate for different age groups. Consistent with the empirical facts, the evolution of incarceration rate is different for different age groups. Young individuals' incarceration rate reaches the maximum in around 3 years, and converges to the steady-state level in around 30 years. However, for old individuals the incarceration rate reaches the maximum in around 10 years, and converges to the new steady-state in more than 50 years. These figures confirm that it takes several decades to fully observe the effects of the criminal policy change, and it can have heterogenous effects on different cohorts. Compared to the empirical evidence documented in Section 2, the model successfully captures the differential impact of the policy change on different cohorts, however the timing is a little off. The model predicts too sudden changes in the incarceration rates compared to what we observe in the data. This could be due to the implementation of the policy change in the model. We assume that the policy change is sudden and one-time event. However, in practice the de facto implementation of policy changes was more gradual than the de jure reforms.[42]

The impact of increased punitive incarceration policy on aggregate employment is modest: employment falls from 1.5 percentage points in the short-run and almost recovers in 30 years. The impact is much larger on younger agents and those with criminal records as shown in Figure 7(a) and 7(b). For young individuals the drop is around 2 percentage points and for middle-age

[41]In reality the policy was likely a reaction to changes in other crime factors. In later sections we explore whether changes in the benefit (crime reward) or opportunity cost (wages) can improve the model fit.

[42]A key constraint to such a drastic change in the use punitive incarceration was capacity constraints. From 1985 through 1990 fifty to seventy percent of prisons were over capacity. In fiscal year 1990, congress allocated an additional $1 billion for physical investment in expanding buildings and facilities. Since 1993 incidence of overcrowding has remained below 40% (James (2013)).



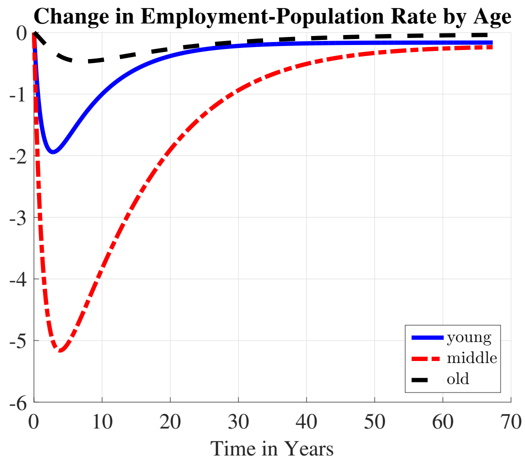
(a) Aggregate Incarceration

(b) Incarceration by Age

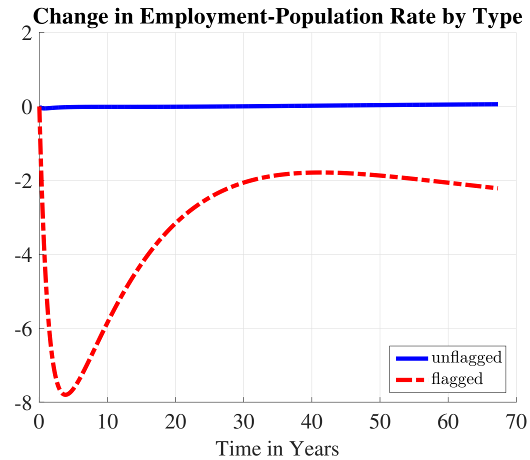
Figure 6: **Incarceration over Time:** The figure shows the incarceration rate along the transition. The left panel shows the evolution of the total incarceration rate whereas the right panel shows the evolution of incarceration rate for different age groups relative to their initial steady-state levels.

individuals, it is around 5 percentage points. The largest drop is for the middle-aged individuals, because this group experiences the largest increase in the incarceration rate (Figure 6(b)). This mechanism is reflected in the time series of employment for those with criminal records shown in Figure 7(b). Flagged types, who already start with substantially lower employment population ratio with respect to non-flagged ones (68% vs 77%), experience a drop of around 8 percentage points in the employment-population ratio at the peak of the transition. Interestingly, these cross-sectional differences across age are only present in the transition while the difference for those with a criminal record is amplified during the transition, but persists.

Wages also differentially impacted by the policy across cohorts and those with a prison experience. Figure 8(a) shows young individuals initially experience a drop of about 0.4% in wages, but later their wages recover, and reach to levels slightly higher than the initial steady-state. Middle-age individuals experience a similar pattern for wages, but the magnitudes are much larger. The initial drop is around 1% and later it reaches to levels 0.6% higher than the initial steady-state. Old individuals experience an initial increase in wages followed by a gradual drop and then a slow recovery. The initial increase is from the fact that the lowest human capital individuals are most likely to have high criminal capital and incarcerated- so the policy initially "cleanses" them from the population. Average human capital then decreases as the cohort who was younger at the policy change- the cohort with the highest incarceration experience, becomes old. This is because incar-



(a) Employment-Lifecycle



(b) Employment-Types

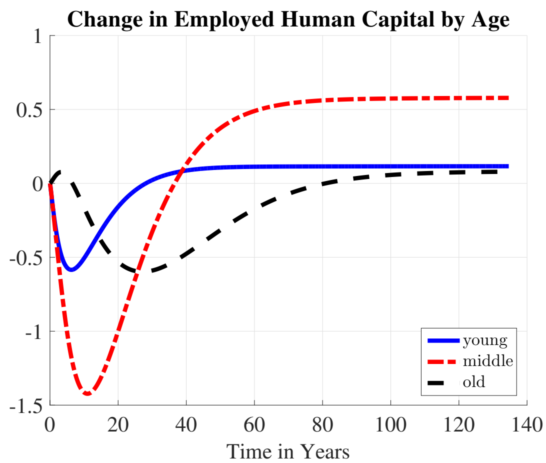
Figure 7: **Employment across Different Groups:** The figures show the evolution of employment-population ratio for different individual groups. The left figure is across age dimension and the right figure compares the employment-population ratio for non-flagged and flagged individuals. Both are changes in percentage points relative to the initial steady-state level.

ceration experiences lower human capital. However, as new cohorts are born, human capital for all age groups starts to increase once again. As a result, over time, wages recover and reach levels either similar to (for old individuals) or higher than (for young and middle-age individuals) the initial steady-state levels.

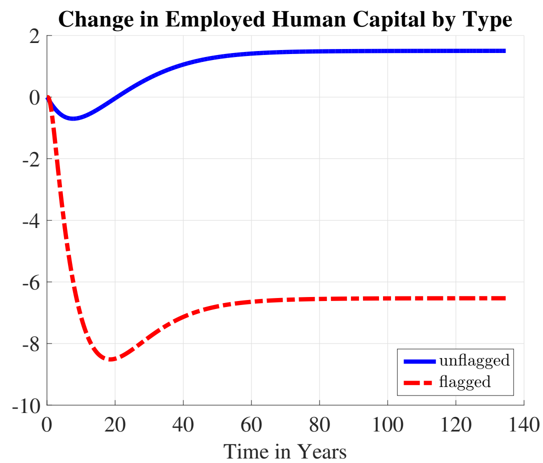
Figure 8(b) compares the dynamics of wages for flagged and non-flagged individuals. Upon impact, wages of flagged individuals increase due to the cleansing incapacitation effect. As this group accumulates incarceration experiences and as new generations only choose crime if their human capital is very low, the flag is associated with even lower human capital. At the peak of the transition, this drop can be as large as a little higher than 6%. For non-flagged types wages drop slightly in the earlier periods, but then recovers and reaches to levels almost 1% higher than the initial steady-state. These figures show that the policy widens the gap between the criminals and non-criminals substantially.

7 Decomposition of the Transitional Dynamics

Individual Response: Increasing punitive incarceration policy increases the cost of criminal activity. In the model individuals respond in two ways. First, new generations change the one-shot



(a) Human Capital Employed-Lifecycle

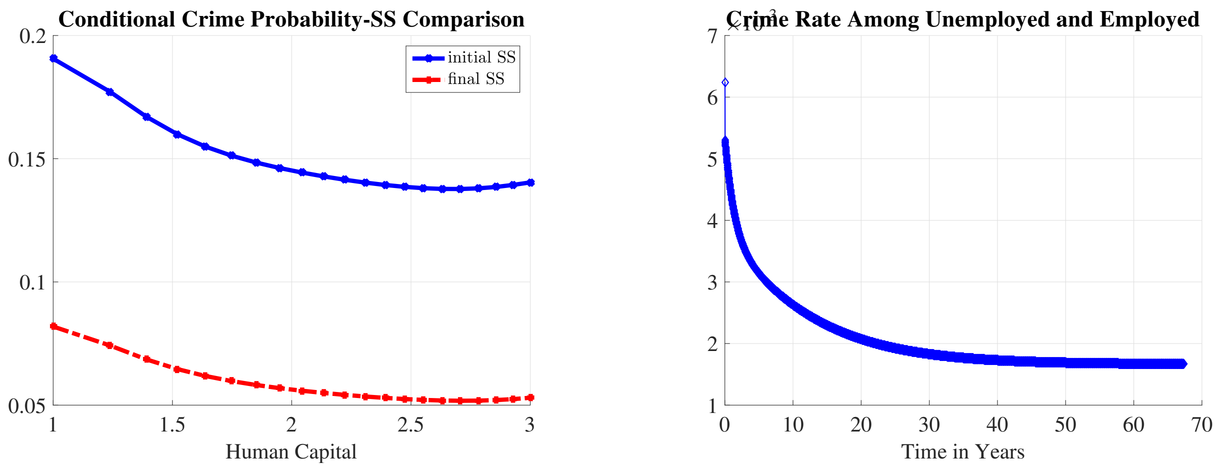


(b) Human Capital Employed-Types

Figure 8: **Human Capital across Different Groups:** The figures show the evolution of human capital for employed (a proxy for wages) for different individual groups. The figure on the left is across age dimension. The figure on the right compares the dynamics of the average human capital for non-flagged and flagged individuals. Both figures show percentage change from the initial steady-state level.

early life choice by choosing a lower crime arrival rate. In the initial steady-state, weekly crime arrival rate is 0.027 for young and middle age individuals. When the policy changes, this arrival rate drops to 0.021. This corresponds to a drop of around 20% in the crime arrival rates through the early life choice. Second, all individuals become more picky in the crime opportunities they actually take. They increase their threshold of reward required to commit a crime which decreases their overall criminal propensity. Figure 9(a) shows employed individuals reduce their crime probabilities by around 60% in response to the policy change.[43] This corresponds to a substantial decline in the crime rates in the economy. Figure 9(b) shows the evolution of aggregate crime rate along the transition. One-fifth of the drop happens on impact of the policy change. This represents the impacts of incapacitation and initial deterrence on the current population. The remaining that plays out gradually over-time is the combination of changes in the decision rules due to deterrence effect and the composition of the population: improved early-life choices of new generations and improvement in human capital among those who have avoided prison.

[43]The magnitude of drop in crime propensity is about the same for the unemployed.



(a) Crime Probability-SS comparison

(b) Aggregate Crime Rate

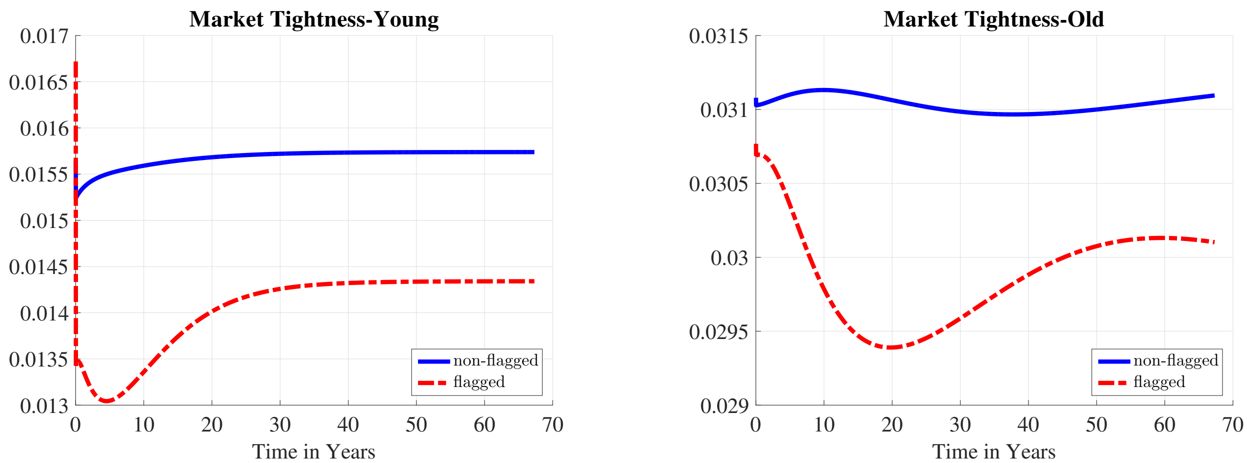
Figure 9: **Crime Rate over Time:** The figure on the left shows the crime probability for an employed individual as a function of human capital across two steady-states. The figure on the right shows the evolution of the aggregate crime rate over the transition. Aggregate crime rate is computed as the ratio of total crimes and the measure of non-incarcerated individuals.

Firm Response: In the model, the only choice of the firm is whether to create a vacancy or not.[44] Figure 10(a) shows the market tightness for the young individuals along the transition. Four observations are in order. (i) Market tightness decreases for both flagged and non-flagged individuals upon impact, which means lower job opportunities for the unemployed; (iii) The drop is more significant for the flagged; (iv) Market tightness recovers back for the non-flagged and reaches to a higher level at the final steady-state, whereas for flagged the recovery is less significant; (v) the effects are smaller for the old.

The equilibrium market tightness is such that firms earn zero-profit in expectation when they post a vacancy. This expected profit is affected by three factors: the probability of finding an unemployed worker, the human capital of the worker who is found, and the expected duration of the match. The latter is affected by the chance of endogenous separation due to incarceration.

In the initial steady-state both the incarceration probability and human capital among unemployed are similar across flagged and non-flagged individuals. In the final steady state, the incarceration probability is higher for the flagged than non-flagged. Moreover, average human capital is lower in the final steady-state for the flagged due to the depreciation in human capital from

[44]Notice that we assume that firms can create vacancies conditional on individual's prior incarceration experience and age. However, the criminal and human capital levels of individuals are not observed by the firm.



(a) Market Tightness-Young

(b) Market Tightness-Old

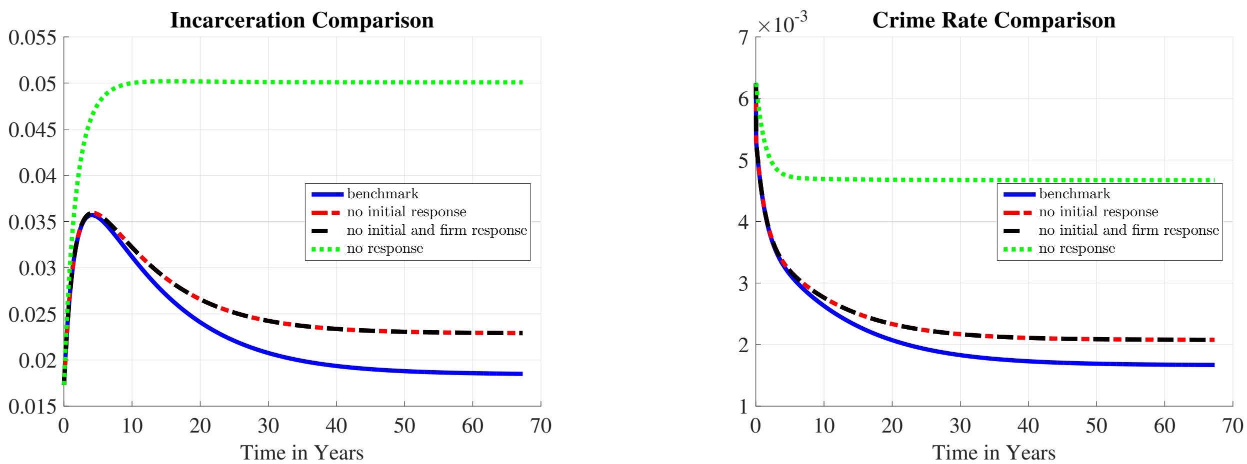
Figure 10: **Market Tightness over Time:** The figure on the left shows the dynamics of market tightness for the young individuals for both flagged and non-flagged individuals. The figure on the right shows the same statistics for the old individuals.

their increased likelihood of repeat incarceration experiences. As a result, in the final steady-state, market tightness for the flagged is much lower compared to the initial steady-state.

Decomposition: We run counterfactual experiments to quantify the role of each channel: the response of workers given their initial state and the response of firms. We focus on three decision rules: early-life choice of crime arrival rate, crime reward thresholds for individuals, and market tightness.

To conduct the decomposition, during the simulation of the transition, we first remove the early life choice response by holding fixed the early life choice at the initial steady state level. Next, we remove the firms' response by holding fixed the market tightness along the transition at its original steady-state level *in addition* to removing the early life choice response. Finally, we remove the response of workers by holding fixed the crime reward threshold policy rule of individuals along the transition at its initial steady-state level, also in addition to the prior two changes. In this final experiment the result is the removal of all channels of deterrence, leaving only the effects of incapacitation and impact of the prison experience on individuals who return to labor markets.

Figure 11(a) shows the incarceration rate for each counter-factual scenario. The change in the early-life crime arrival rate choice contributes significantly to the change in incarceration. The response of the firm does not change the evolution of incarceration since these responses are quantitatively very small. However, the major factor in the evolution of the incarceration rate is the individuals' response by increasing the crime reward thresholds to commit crime. If all the three factors were fixed to their initial steady-state level, the incarceration rate would be around 5% at the final steady-state as opposed to 1.8% as in the benchmark economy. Less than 10% of this change is due to the decrease in the early crime choice, and the rest is due to the increase in crime reward thresholds. This indicates that the early-life choice is important for transitional dynamics. We will also see that it implies crime becomes more concentrated among fewer individuals when punitiveness is increased. The same result applies to the dynamics of aggregate crime rate as shown in Figure 11(b).

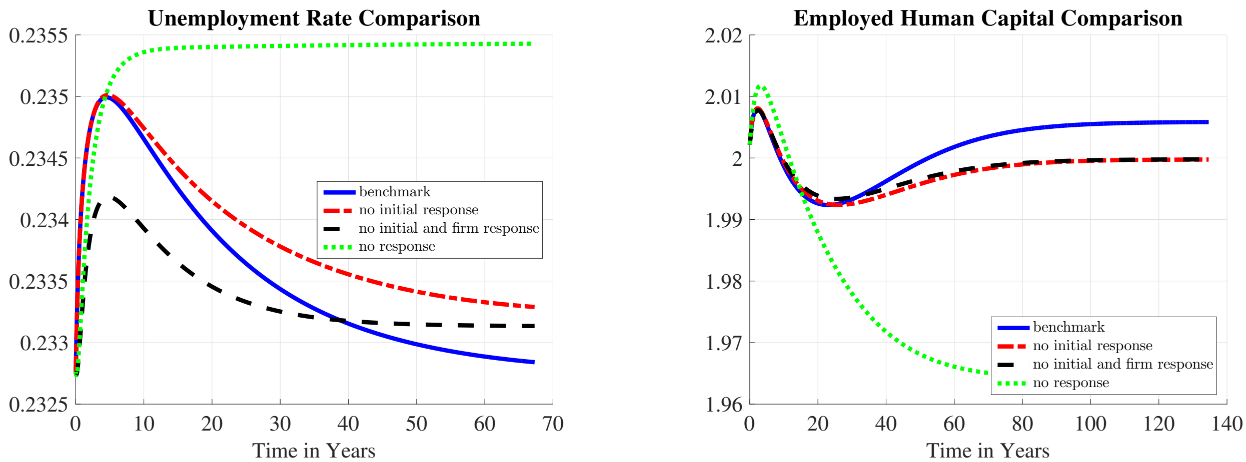


(a) Incarceration

(b) Crime Rate

Figure 11: **Incarceration and Crime Over Time:** The figures show the decomposition of the evolution of incarceration and crime rate along the transition. The solid line is the benchmark economy. The long dashed line is the economy when individuals keep their early life crime choices as in the first steady-state. The dashed line is the economy when firms keep the same job creation level and individuals keep their initial choices as in the first steady-state. Lastly, the dotted line is the economy when firm keep the same job creation level, individuals keep their initial and ex-post crime choices as in the first steady-state.

Figure 12(a) shows the results for unemployment rate. Across the steady-states, the main contributor is again individuals' crime threshold policy response. However, the firms' response is also significant. Without the firms' response, the unemployment rate would be lower both along the transition and in the final steady-state. By reducing the market tightness, firms contribute to the increase in the unemployment rate. The reduction in crime propensities, however, substantially reduces the unemployment rate. If the individuals would have not changed their crime propensities, the unemployment rate would be around 0.3% higher in the final steady-state. The response of the individuals both decrease endogenous separation of the workers from firms through lower incarceration probability, and higher average human capital among the unemployed. These changes partially offset the decrease in vacancy creation by the firms and result in a small increase in the overall unemployment rate both along the transition and at the final steady-state.



(a) Unemployment (b) Human Capital

Figure 12: **Labor Markets over Time:** The figures show the decomposition of the evolution the unemployment rate and human capital of employed individuals. The unemployment rate is the ratio of the unemployed to the labor force. The solid line is the benchmark economy. The long dashed line is the economy when individuals keep their early life crime choices as in the first steady-state. The dashed line is the economy when firms keep the same job creation level and individuals keep their initial choices as in the first steady-state. Lastly, the dotted line is the economy when firm keep the same job creation level, individuals keep their initial and ex-post crime choices as in the first steady-state.

Figure 12(b) shows the dynamics of human capital (wages) under each counterfactual. As the policy is implemented, average human capital increases due to a cleansing incapacitation effect: lower human capital individuals are most likely to be incarcerated. This is amplified when individuals' response to lower crime is shut down. Shortly after the policy change, average wages start to decline as a result of higher incarceration rates. If individuals do not respond by lowering crime rates, then incarceration rates remain high and the fall in human capital is much larger as more people transition through prison and lose human capital.

7.1 Incapacitation versus Deterrence Effect

A central question addressed in the literature is how much of the impact of punitive incarceration on crime operates through incapacitation effects versus through deterrence effects. The incapacitation channel lowers crime by putting likely criminals in prison where they cannot commit crime. The deterrence effect considers that more punitive policies lower crime by deterring individuals from committing crime in the first place.

These effects are hard to measure in the data, but easy to isolate in our structural model. The incapacitation effect is isolated in a counterfactual transition experiment by setting the time spent in prison to 0.[45] The deterrence effect is isolated in a second counterfactual transition experiment by fixing the decision rules of the individuals and firms at the initial steady-state level along the transition.

Figures 13(a) and 13(b) show the comparison for incarceration rate and crime rate, respectively. Without deterrence the incarceration rate reaches to 5% at the peak and stays at that level forever. The gap between that line and the benchmark shows the impact of deterrence on incarceration, which as we have emphasized is larger in the long-run than the short-run. By construction, eliminating incapacitation results in no one incarcerated in the economy. Both incapacitation and deterrence work to lower the crime rate, but at different times and in different magnitudes. In the short-run, the incapacitation effect dominates. This is the "cleansing" of the population while deterrence is limited by the inelasticity of individuals' crime choice in the short run. However, in the long-run when the full deterrent effect is realized, it accounts for about 80% of the total decline in crime.

Figures 13(c) and 13(d) show the effects of deterrence and incapacitation on the employment and unemployment rates. In the long run, for both employment and unemployment rates, the effects of deterrence are larger. However, in the short-run incapacitation can be significant. However, this is by construction, again. We assume that once an individual is released from prison, he is unemployed. So, sudden release of individuals from prison results in a large increase in unemployment rate. The more interesting observation is the asymmetric effect of incapacitation and deterrence on employment. Without deterrence, employment sharply declines and stays at that level forever. The decline is around 3%. This is because as the incarceration policy becomes more punitive, more individuals experience prison. This results in lower employment-population rate. However, the effect of incapacitation is just the opposite. Without incapacitation, the change in incarceration policy results in a permanently higher employment rate. The employment rate increases by almost 1%. This is again related to the nature of the policy. Without incapacitation, more people are eligible for work, which mechanically results in a larger employment rate.

[45] All of the expected cumulative effects of prison on human capital, the prison flag, and criminal capital from the baseline model are maintained.

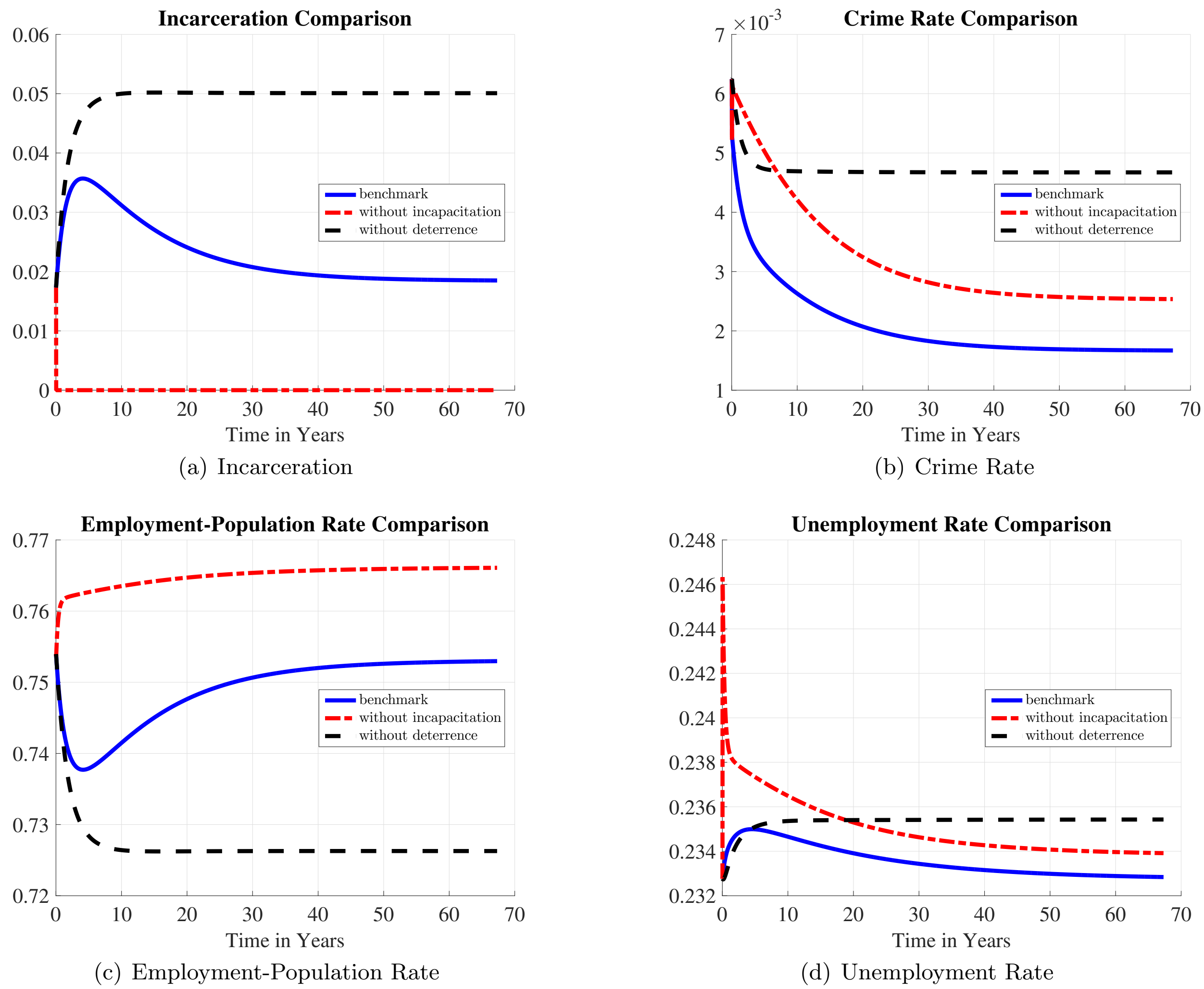


Figure 13: **Incarceration and Crime over Time:** The figures compare the evolution of incarceration and crime rate along the transition without incapacitation or deterrence effects. The solid line is the benchmark economy. The long dashed line is the economy when incapacitation is eliminated. The dashed line is the economy when all decision rules of the individuals and firms kept at the initial steady-state levels.

7.2 What Drives the Cohort Effects and Non-monotone Transition?

In section 2, we used a simple model to show both a persistent early life choice and the assumption that a prison experience increases future criminality are key to providing cohort effects which in turn drive a non-monotone transition after a single policy change (Figure 3(d)). In this section we explore how the early life choice and criminal capital developed in prison quantitatively contribute to these predictions of the model. To do so, ask what our results would look like if we omitted each of them individually, re-estimated the model to best fit U.S. data, and re-ran our transitional experiment.

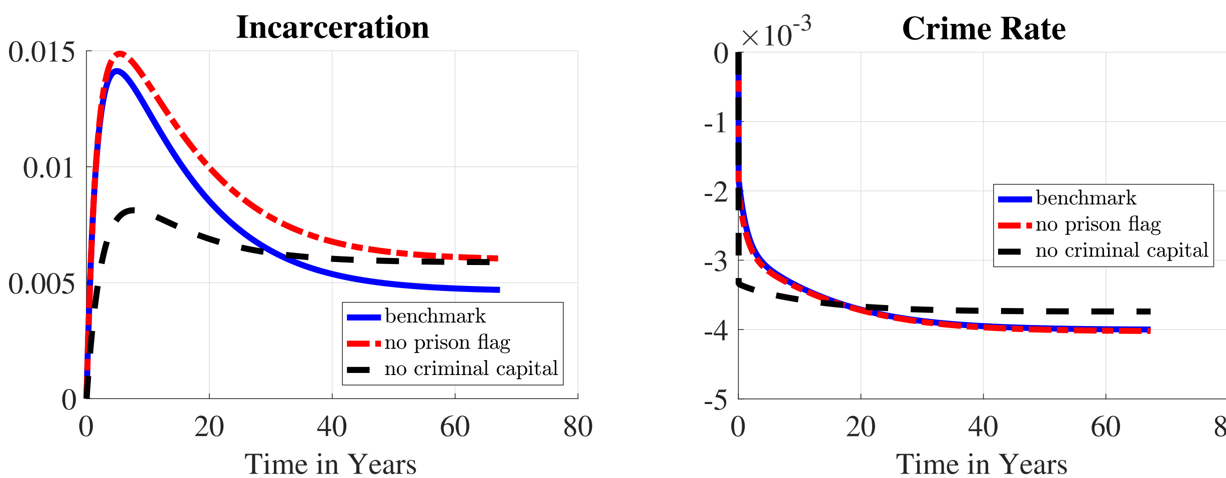
Criminal capital was added to the model to match a salient feature of criminal behavior: recidivism. The recidivism rate for released prisoners targeted in the calibration was 20% over 3 years after release in the early 1980s. When we re-estimate the model by dropping the criminal capital assumption, we can still generate a rise in incarceration but the recidivism rate drops to 6%. This is contrary to the data. Furthermore, recidivism does not rise along the transition and this is also contrary to the data. Using the Recidivism Among Released Prisoners (United States Department of Justice. Office of Justice Programs. Bureau of Justice Statistics (2011-03-08)), we calculate the average recidivism rate on *new* charges doubled from 17.8% in 1983 to 35% in a Florida sample from 2003 (Bhati (2010-07-29)).[46] The key difference between the models with and without criminal capital is who commits crimes. In the model with criminal capital, crimes are concentrated among a few individuals with a very high crime rate. Without it, crime is more spread across the population at lower rates for each individual.

Matching both the recidivism rate and the associated concentration of crime in the population, and the cohort effects, is important in shaping the transitional dynamics. To show this, we omit either criminal capital or the prison flag and re-estimate the entire model targeting a subset of our calibration moments.[47] Figures 14(a) - 14(b), plot the transitional dynamics of this counterfactual economy. Without these ingredients, the transition is more monotone. It has the additional im-

[46]The recidivism rate increased to 27% in the 1994 iteration of the Recidivism Among Released Prisoners Series with the same design as the 1983 iteration. There is a version of these data for 2005, but we did not have access to the micro data and weren't able to calculate the recidivism rate on *new* charges as would be consistent with our quantitative analysis. See the online Appendix for discussion of these datasets.

[47]More specifically, without prison flag, we re-estimate the model to target the same set of moments in the benchmark economy. The only difference is that without prison flag, we set the probability of being flagged after incarceration experience to 0. Without criminal capital we are left with six parameters to be calibrated: crime arrival rate, vacancy cost, job separation rate, human capital shock arrival rate for employed and unemployed, and the human capital grid parameter. As in the benchmark economy, we target incarceration rate for young and middle-age, employment-rate for young and middle-age, average unemployment duration in the whole population, and the regression coefficients in equation 4.1. The values of the parameters for each estimation is listed in the Appendix

plication that crime and incarceration in the new steady state are slightly higher. This is because both criminal capital and the prison flag magnify the cost of the policy change. In their absence, the deterrent effect is smaller. There is an additional, more subtle difference in the re-calibration without criminal capital. To match empirical moments it requires that crime is more widely committed in the population. In order to get more individuals to do crime, the elasticity of crime propensity with respect to the consequences of crime must become much smaller. Then, when the policy becomes tougher crime falls less than in the model without criminal capital.



(a) Incarceration (b) Crime Rate

Figure 14: **Model Assumptions:** The figures compare the evolution of the economy in response to the policy change for different model assumptions. The solid line plots the benchmark economy, the long dashed line plots model without prison flag, and lastly the dashed line plots the model without criminal capital. In each case, parameters are re-calibrated to match certain moments of the data. See the text for a discussion of the re-calibration.

In summary, the criminal capital assumption is important for two reasons. First, the long-term impacts of the policy change can be quite different in the model with or without criminal capital. Second, criminal capital concentrates crime among a small population with high recidivism rates that increase when the policy becomes more punitive, just as in the data. Getting the channel of who commits crime correct in the model is important for policy for a variety of reasons. For example, in the world with criminal capital and few criminals committing the majority of crime, the incapacitation effect of prison is much larger than in the world without criminal capital. In the latter world luck is also more of a factor: many people engage in crime but a few are unlucky to be caught.

7.3 Interaction with Other Social and Economic Trends

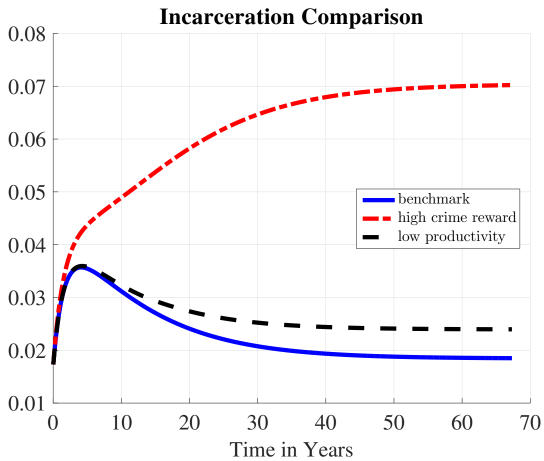
Our analysis thus far has considered unilaterally, a one-time change in incarceration policy. In reality, it is likely that the policy changes were in response to changes in underlying criminality and that evolved concurrently. To this end, we consider two factors: secular increases in the reward to crime and a decline in low-skilled real wages. Our motivation to consider these particular factors is two-fold. First, there is direct evidence that the spread of cocaine and associated gangs raised criminal involvement in the late 1980's through the mid 1990s. There is also a literature on "skill-biased" technical change providing theory and evidence that technological innovations left the low-skilled behind compared to rising real wages for skilled-labor. Our second motive is that these theories correct and complement the deficiencies of a theory of unilateral change in incarceration policy. They magnify the impact on incarceration rate and labor markets where incarceration policy alone quantitatively under-predicts trends from 1990 onward; and they counteract the decline in crime that is over-predicted by policy changes alone. It is necessary to consider all three changes together as they will interact through the various channels in our model.

Our specific experiments are as follows. We model the increase in crime reward to match the four-fold increase in incarceration rate.[48] We model the decrease in wages as a linear decrease in productivity over the first 15 years to 25% lower than the initial steady state. Productivity remains at this lower value permanently from then on. Each experiment is run one at a time in addition to the same starting steady state and change in the probability of getting caught that we considered in the benchmark.

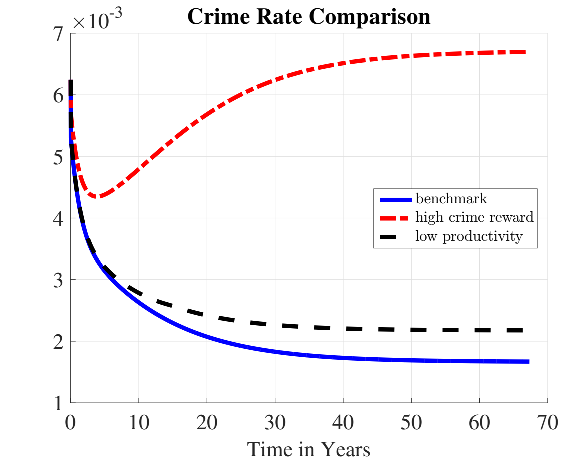
Figures 15(a) - 15(b), plot the responses of the incarceration rate and the crime rate. Unsurprisingly, both increase more in the version with higher criminal rewards than in the benchmark. With higher criminal rewards, incarceration rate monotonically increases. However, crime rate has a non-monotonic path. Initially, crime rate drops since individuals decrease their crime thresholds by responding to the higher punitive criminal system. However, higher criminal rewards result in higher crime choice by new-borns. As these individuals replace the existing ones, crime rate starts to increase, and eventually the latter effect dominates, and crime rate reaches to the levels higher than the initial steady-state.

Both incarceration and crime rates also rise in comparison to the benchmark when labor productivity falls. As wages fall, the opportunity cost of crime falls and crime increases relative to the

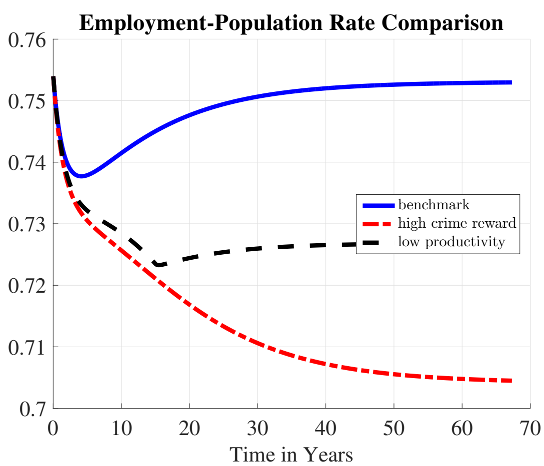
[48]We achieve this by adjusting the mean of the log-normal distribution of the crime rewards, μ_κ. To match the quadrupling of the incarceration rate, we need to increase μ_κ from 0 to 0.7, which implies that the mean of the distribution almost doubles.



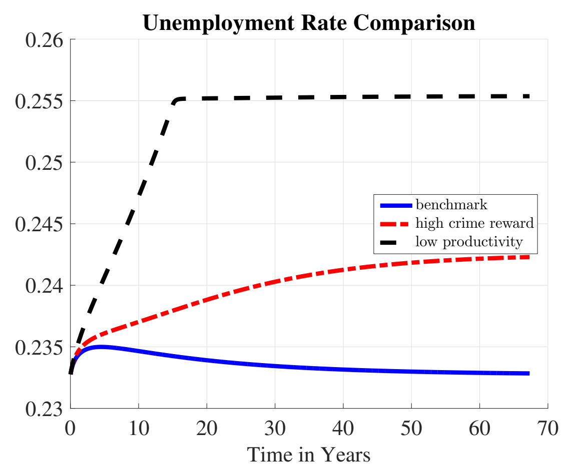
(a) Incarceration



(b) Crime Rate



(c) Employment



(d) Unemployment

Figure 15: **Model Assumptions:** The figures compare the evolution of the economy in response to the policy change and higher criminal rewards for different model assumptions. The solid line plots the benchmark economy, the long dashed line plots model without prison flag, and lastly the dashed line plots the model without criminal capital. In each case, parameters are re-calibrated to match certain moments of the data. See the text for a discussion of the re-calibration.

benchmark. The dynamics of the incarceration rate remain similar to the data: a rise through the early 2000's and then a decline, but remaining above the old steady state.

Figures 15(c) - 15(d), plot the responses of the labor market. Here we see that the fall in the employment to population ratio is larger with the higher criminal rewards. This is mostly a result of the higher incarceration rate accompanying higher criminal rewards. It provides both an incapacitation effect and a higher flow into unemployment as more individuals cycle through the prison. The fact that the unemployment rate rises more with lower labor productivity experiment provides insight into the firms' problem. Higher crime rates in the higher crime reward scenario translate into shorter match durations and reduce vacancies. Lower productivity directly reduces the value of matches and reduces vacancies. Consistent with the earlier results, the impact of incarceration on labor market variables is limited. As a result, labor productivity experiment has much larger effects on the unemployment rate.

We conclude from these experiments that a more comprehensive view of the impact of punitive policy on labor markets, crime, and incarceration should consider exogenous changes in labor markets and the criminal world. These changes complement the impact of criminal justice policy and allow the model to match magnitudes and dynamics of aggregate trends.

8 Conclusion

We began this paper by arguing the importance of considering dynamics driven by criminal persistence in the evaluation of punitive incarceration policy changes. We presented our argument rigorously by incorporating the theory in both a simple and a rich dynamic model. We bolstered the empirical relevance of our theory by providing both cohort and changing cross-sectional evidence consistent with the theory's predictions relying on criminal persistence.

To quantitatively evaluate policy changes, we developed a dynamic model grounded in the Beckerian theory of rational crime in which age, human capital, and employment all deter crime. We enhanced the model with additional channels: an early life choice and criminal capital developed with experience that each impact future crime opportunities as well as criminal records that segment labor markets. These channels enabled the model to replicate salient features of criminal behavior that pecuniary motives alone could not: high recidivism rates, even among the employed and old; and cohort dynamics after policy changes of the 1980s. Altogether we learned that unemployment and low-human capital are instrumental in the choice to enter crime, but criminal capital and to a minor extent, employment discrimination, drive criminal persistence after youth. Adding things up, most crime is done by a few individuals with long criminal records for whom pecuniary factors provide little deterrence.

The main application of the theory analyzed the impact of increased use of punitive incarceration akin to policy changes in the 1980's and arrived at two substantive conclusions. First, the change in incarceration policy on its own was only a minor contributor to trends in low skilled labor markets and aggregate incarceration from 1990 onward, but it was a major contributor to the drop in crime and also increased inequality within low-skilled populations. Second, the transition after a policy change follows nuanced dynamics that can take several turns over subsequent decades. Increases in incarceration initially "cleanse" the population of the worst criminals, who are also the worst workers. Later, the additional individuals who cycle through the prison the re-enter the population with even worse labor market prospects and higher criminality than before. Full deterrent effects are not realized until new cohorts are born under the new policy, choosing less crime and higher labor force attachment from early in life.

Our findings are far from the final word regarding the broad questions about important issues addressed in this paper. Still, we argue that the issue of dynamics should be addressed when approaching these questions in future work. It would be useful for interpretations of econometric inference to consider that short-run effects of policy changes can run in directions that are opposite from long-run effects, as we have shown. The consideration of dynamics also introduces new opportunities to consider in normative works looking to improve policies. A specific prescription to be further researched is whether the announcement of increasing punitive policy in the future followed by a gradual implementation could improve welfare. This would allow a greater chance for agents to respond and potentially avoid a large increase in incarceration and its collateral effects in the short term.

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9 Figures

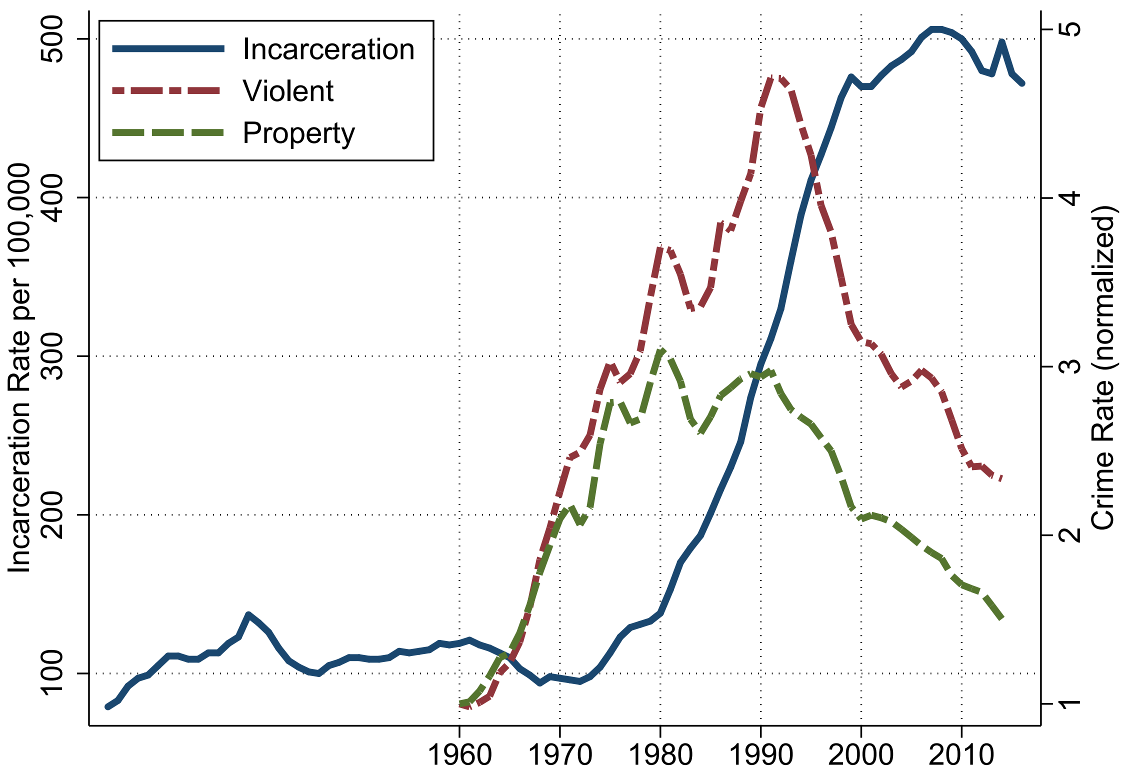

Figure 16: Crime rates from Uniform Crime Reporting Statistics (Federal Bureau of Investigation. (2017)). Incarceration rates 1925-82 from Cahalan and Parsons (Dec 1986) and 1983-2016 from Carson and Mulako-Wangota (2017) and include state and federal prisoners only.