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 evaluating the effects of punitive incarceration reform on crime, inequality, and labor markets. Individuals' past choices regarding crime and employment under previous policies have persistent consequences that limit their responsiveness to policy changes. A quantitative model of this theory, calibrated using administrative data, predicts nuanced dynamics of crime and incarceration that are distinct across property and violent crime and similar to the U.S. experience after 1980. Increased inequality and declining employment accompany these changes, with unequal impacts across generations.

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1 Introduction

Before the 1980s, the incarceration rate in the United States remained stable and comparable to other nations. Subsequently, the paths diverged.[1] A four-fold increase in the imprisonment rate from 1980 to 2000 made incarceration a common experience for less-educated men in the United States, despite recent modest declines.[2] It is widely accepted that from the 1980s onward, increased use of punitive incarceration for those arrested — not changes in crime or arrest rates — contributed to this divergence.[3] There is little agreement, however, on the broad impacts of this substantial change in the justice system.[4] Open questions range from assessing the effectiveness of these reforms in reducing crime to understanding the implications for economic outcomes and inequality.

We argue that understanding the dynamic consequences of policy reform – the changes slowly unfolding in the transitional decades following a policy change – is crucial for evaluating punitive incarceration policy.[5] Criminal behavior is persistent at the individual level, on average.[6] This leads to a weak deterrent effect of increased punitive incarceration in the short run, as the lingering consequences of past choices are difficult 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 accumulation of criminal capital. In the long run as new cohorts born under the stricter policy reach their peak crime years, the full deterrent effect is finally realized, and both crime and incarceration fall in tandem. This pattern remarkably resembles the U.S. experience after 1980, particularly for property crime: a monotonic decrease in crime, alongside a rise and fall in incarceration (Figure 1 shows these patterns for each property and violent crime). In this paper, we study how these dynamic paths can stem from a single increase in punitive policy.[7]

[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, an estimated 12.0% (37.2%) of white (black) males between the ages of 20 and 34 without a high school degree were incarcerated, (Pettit (2012)).

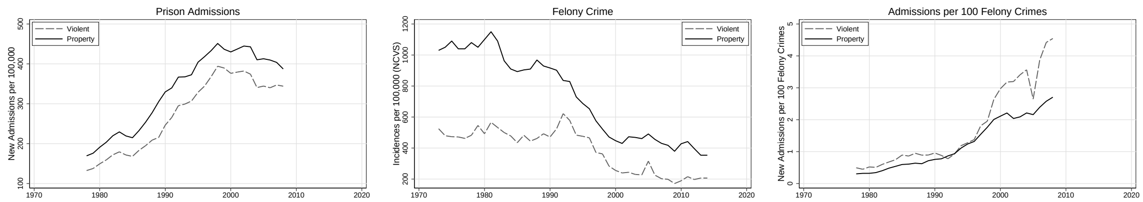
[3] Neal and Rick (2014) make this argument using the same administrative data as this paper. See also Blumstein and Beck (1999), Pfaff (2012), and Raphael and Stoll (2009) for theories of the underlying drivers, ranging from policy changes to career incentives of district attorneys.

[4] Bushway (2011) points out that in addition, little is 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 et al. (2004), compares property crime in the early 1980's with that in the late 1990's assuming full transition to a new steady state after policy change. A large literature estimates dynamic models of criminal behavior, but does 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).

[7] This is a particularly important point, given the inference on the relationship between aggregate crime and incarceration featured in policy discourse. For example, Eisen and Cullen (2016) point out that "Impris-



(a) New Prison Admissions (b) Crime (c) New Admissions per Crime

Figure 1: Trends in incarceration and crime. Authors' calculations from NCRP, BJS, and NVS data. See Section 4 for details.

To investigate the dynamic consequences of punitive incarceration policy reform, we develop an overlapping generations model with several channels contributing to criminal persistence. Building on Becker (1968) theory of rational crime, where agents trade off labor market opportunities and criminal activities, we enrich the model with additional elements necessary to replicate the joint persistence of criminal behavior and labor market outcomes observed in data. First, human capital accumulates during employment and depreciates during non-employment. Second, criminal capital grows with engagement in crime and decays with age. Third, a criminal record, observable to employers, can limit employment opportunities. These ingredients lead to divergent paths of individuals' employment and criminal propensities consistent with micro data: widespread crime among the young, low new crime entry among the old, high recidivism rates, and limited crime-employment or crime-wage differentials.

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 leverages an array of high-quality administrative data from various sources, including the Survey of Inmates of State Correctional Facilities; a three year panel of parole officer data on over 12,000 individuals (Recidivism of Felons on Probation, 1986-1989); and the large-scale panel of annual prison censuses (National Corrections Reporting Program Data). This approach is distinct from prior micro-econometric and structural estimations that have typically relied on survey data from current and former inmates self-reporting their employment and criminal activity, which suffer from non-response, misreporting, and small sample sizes. In contrast, we utilize substantially larger and more reliable administrative data.[8]

Our main quantitative exercise evaluates the contribution of increased punitive incar-

onment and crime are not consistently negatively correlated... This contradicts the commonly held notion that prisons always keep down crime." We provide a model explicitly showing the flaw in applying causal interpretation to aggregate series in this way that goes beyond convoluting orthogonal factors.

[8]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 features fewer than 200 people, and these individuals have many non-responses.

ceration to the U.S. prison boom and related outcomes. Our primary analysis considers property crime, which we later contrast with violent crime.[9] For property crime, we simulate an increase in the probability of incarceration conditional on committing a crime from 0.5% to 3.4%, as estimated from U.S. data. We incorporate observed changes in real wages and estimated changes in returns to crime. The incarceration rate increases 130% over the first 25 years, but half of this increase is gradually erased as declines over the next 30 years towards a new steady-state. Crime falls continuously amounting to a 70% decline over the first 30 years, as in US data, and the model predicts an additional 5 ppt decline towards the new steady state. The decline in crime is a result of both the immediate incapacitation of the most active criminals and more gradual deterrence effects on new generations' crime entry decisions. Furthermore, as is consistent with the data, crime becomes more concentrated among persistent career criminals.

The model provides testable predictions of how the criminal population changes over the transition that are supported in the data. First, crime becomes more concentrated among persistent career criminals. Second, it provides unique cohort predictions suggesting a "lost cohort" of individuals born in the mid-to-late 1960s. These individuals were in their 20s, the prime crime age, in the 1980s when punitive policy became much more strict. The model predicts they would have higher rates of prison admission and arrests *throughout their lives*, compared with those of the generations before them *and generations following*. We provide suggestive evidence supporting this prediction in the data. These findings highlight additional reasons why considering dynamics is important in policy design. First, the cohort effects imply that the costs and benefits of blunt reforms are borne unequally across generations. Second, the increased concentration of crime is linked to permanent effects on inequality. The employment gap for those with records steadily widens to a 2.5 percentage point deficit as fewer employers offer jobs to individuals with criminal records.

To complement the main exercise, we add several illustrative experiments and decompositions. A regression analysis on model data shows that aging is the largest factor deterring crime. Employment status has no significant impact, but income has a significant effect on crime propensity. Having a past prison experience is an important predictor of future crime. Considering these factors in the transition, we find that harsher punitive policies lowered crime by counteracting trends of increasing criminal rewards and declining real wages. Finally, we study how the impact of punitive policy depends on the initial steady state. The marginal reduction in crime diminishes sharply when starting from more punitive initial

[9] How do property and violent crime translate into understanding larger trends? More than 50% of prisoners have a conviction for violent crime. Only 16% of state prisoners are on drug charges, and 5-6% are nonviolent drug offenders. Sevigny and Caulkins (2004)

policies. This is because in more punitive regimes, a larger share of crime reduction comes from incapacitation rather than deterrence, which affects dynamics since incapacitation is instantaneous, while deterrence can be delayed. Thus, the short-run elasticity of crime to policy approaches the long-run elasticity when starting from a more punitive initial stance. Repeating our analysis for violent crime provides an interesting comparison. The model estimation produces a calibration where violent crime resembles “crimes of passion”– it is more random and less persistent. Consequently, crime entry is less elastic to policy, and so dynamics become less important for the transition after a policy change.

These findings are not only important for accurately evaluating justice policies in real-time, but hold promise for improving their design. When crime is more persistent, as with property crime, crime reduction immediately after a policy change comes almost entirely from incapacitation effects, while deterrence effects on crime entry build over time. These conclusions should encourage the study of dynamic punitive policies specifying paths for multiple levers: the probability and duration of incarceration, as well as differential penalties for new and repeat offenders.

The literature on crime features few structural equilibrium approaches. Engelhardt et al. (2008) consider how the ability of employers to write efficient contracts tempers the labor market response to crime and vice versa. Huang et al. (2004) and Burdett et al. (2003) study interactions with the labor market in search frameworks. The most related papers are İmrohoroğlu et al. (2004), Fella and Gallipoli (2014) and Engelhardt (2010). İmrohoroğlu et al. (2004) quantify the contributions of changes in apprehension probability, labor markets, and population aging to the decline in property crime.[10] Fella and Gallipoli (2014) also consider property crime, but evaluate the impact of educational policy as well as punitive policy on crime. Engelhardt (2010) develops a model with rich heterogeneity to match the cross-sectional distribution of who commits property crime. Our work differs because we consider transitional dynamics.[11] Nonetheless, there are many similarities between our model and the ones in these papers: pecuniary considerations that differ according to life-cycle human capital growth and on employment status, and criminal capital or fixed heterogeneity to account for patterns of crime that pecuniary features alone cannot match within their respective frameworks. As will be come clear, we place extra care in parsing those components of heterogeneity, as this is important for transition dynamics.

[10]Similarly, Caucutt et al. (2021) study the effect of the War on Crime on the marriage gap between black and white men.

[11]Fu and Wolpin (2018) and Lochner (2004) are other prominent examples of structural models of crime that focus on long-run effects of policies on crime. Fu and Wolpin (2018) study the effects of policing on crime. Lochner (2004) studies the effects of education policies on crime.

2 Evidence of Criminal Persistence

In this section, we motivate our focus on linking criminal persistence to dynamic responses to changes in punitive policy by firstly providing intuition of how these things are connected and secondly providing empirical evidence of criminal persistence.

Criminal persistence relates to the dynamic response of crime and incarceration to changes in punitive policy through two potential channels. First, criminal behavior is persistent, but age eventually deters crime. Second, an incarceration experience can affects the likelihood of future crime and incarceration. The first channel of persistence implies that individuals with no criminal history have a higher elasticity to policy changes than those with a criminal record. When policy becomes more punitive, individuals who are already engaging in crime lower crime less than the reduction in crime for young individuals of new cohorts who are choosing whether to enter into crime for the first time. This causes the short run elasticity of crime, shaped mostly by those who have already entered crime, to be lower than the long run elasticity of crime, shaped most by the crime entry decisions of new cohorts. The second channel of a potential criminogenic effect of prison can actually lead to an increase in crime following an increase in punitive policy. If crime is very unresponsive to an increase in imprisonment per crime then more criminals will be imprisoned and, if prison is criminogenic, this will spawn even higher crime rates than before. This scenario depends on the extent of criminal persistence and the first channel predicts this case is more likely in the short run.

Recidivism by Time Since Release			3-year Recidivism by Age		
	Violent	Property		Violent	Property
6 months	7.9	11.9	18-24	41.2	64.0
1 year	13.5	19.9	25-34	26.2	32.6
2 year	19.3	27.1	35-64	13.9	27.0
3 year	22.2	30.7			
4 year	23.7	32.5			
5 year	24.7	33.8			

Table 1: 3-year Re-imprisonment Rate on a New Felony Charge. Authors' calculation from the Recidivism of Prisoners Released in 1983 Survey.

The United States has a notably high recidivism rate, a measure of criminal persistence. Table 1 displays the rate at which prisoners were released from state prisons in 1983 became re-imprisoned on new felony charges. Observe that, even in 1983, the 3-year re-imprisonment rate was 30.7% for those released on a prior property conviction and 22.2% for those released on a prior violent conviction. Estimates of any new arrest are higher and become even higher over time. It is estimated from the Recidivism of Prisoners Released in 2005 survey that 68% are re-arrested in 3 years; a 70% rate for those released for a prior property conviction and 62% for those released on a prior violent conviction.

Table 1 also shows that aging reduces recidivism. The three year recidivism rate was 64% for the felons ages 18-24 released from a conviction on property crime but just 27% for those over 35. The similar statistics are 41.2% for the younger and 13.9% for the older prisoners released after serving time for a violent crime. With respect to arrests later on in the 2005 survey, the age curve remains but is flatter: 76.5% of prisoners released under 24 are rearrested in 3 years and 61.0% of those over 40 are rearrested.

Whether prison is criminogenic is a contentious issue in the literature. It is clear that individuals who have been to prison have higher recidivism and worse employment outcomes. What is not clear is whether these differences are due to the treatment effect of imprisonment or due to selection on who is imprisoned. A large literature employs research designs ranging from random judge variation to cell-mate selection to isolate the causal treatment effect. A review by Nagin et al. (2009) concludes that criminogenic effects of imprisonment are present but small, but the range found in studies is wide. Since these estimates are so mixed, we will use our structural model to estimate how large these criminogenic effects must be to replicate rich cross-sectional data on recidivism, the share of individuals ever imprisoned, and the prevalence of crime. Importantly, our motivation is agnostic to whether these effects are positive, negative, or null. They are interesting but not critical to our study as the dynamics generated by criminal persistence are interesting in their own right.

3 Quantitative Model

We present a quantitative model built on Burdett et al. (2003) and Engelhardt et al. (2008) to study how punitive incarceration policy affects crime rates, incarceration rates, and equilibrium labor market outcomes.

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 experience one of three labor market statuses: (i) employment, (ii) unemployment, or (iii) incarceration.

3.1 An Individual's Problem:

An individual is characterized by five state variables: age, employment status, human capital, past incarceration records, and criminal capital. The first four sources (age, employment, human capital, and records) provide observable links between the model and salient cross-sectional variation in criminality in the data. In the data, crime is more concentrated in people who are younger, are unemployed, have lower earnings, and have criminal records, and so the economic mechanisms in the model should capture these dimensions. The final source, criminal capital, is an unobserved residual used to generate observed criminal persistence within individuals that cannot be provided by the first four ingredients. Together, these ingredients allow the model to match both the extensive (cross-section) and intensive (individual persistence) margins of crime both, of which contribute critically to the dynamics of deterrence.

Age takes a finite number of values: $m \in M = \{1, ..., \bar{m}\}$. Individuals become age $m+1$ at the poisson rate ϑ^m.[12] When individuals at the maximum age, $\bar{m}$, receive an aging shock, they exit the economy, receive zero continuation utility, and are replaced with age 1 individuals who start life with the lowest skill level and are initially unemployed.

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: wh, where w is the piece rate and h is their current human capital. Employed individuals receive a job separation shock at poisson rate δ, at which point they become unemployed. Unemployed individuals receive flow consumption bwh.

Each individual is endowed with the same initial human capital level. Human capital changes at the poisson rate ψ and evolves according to labor status dependent function $f_j(h)$ given current human capital level h. That is, $h' = f_j(h)$, where $j \in \{e, u, p\}$.

Individuals need to put effort to search for crimes. This effort determines the arrival rate of crime opportunities. We assume that crime arrival rate is proportional to the search effort. Individuals derive disutility from crime search. This disutility depends on the effort, s, and criminal capital and has a quadratic functional form: $\xi_i \frac{s^2}{2}$. Each crime opportunity that arrives presents an instantaneous reward κ, separable in utility from consumption. Individuals who commit crimes are caught with probability π.

Criminal capital takes two values: low (lc) and high (hc). The only difference between low and high criminal capital individuals is that high criminal capital individuals incur lower disutility when searching for crime $\xi_{hc} \leq \xi_{lc}$. All individuals are born with low criminal

[12]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. It is not a source of meaningful economic risk.

capital. Low criminal capital types transitions to high with probability ν when a crime is committed. High criminal capital depreciates to low with age-specific probability ζ^m.

Incarcerated individuals receive zero flow utility. They are released from prison to unemployment at rate τ. Individuals who have been to prison are distinguished to employers by a criminal record. We allow separate job markets: one for individuals who have never been incarcerated, called *non-flagged* individuals, and another for 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. This feature is included to capture the market segmentation that arose both from occupational restrictions for ex-felons and from employer use of criminal records in screening during our study period.[13] In keeping with realism, employers cannot observe certain individual characteristics, like criminal capital. They can, however, use the criminal record flag to statistically deduce criminal propensity.

We denote V_p, V_u, and V_e as the value of an incarcerated, unemployed, and employed individual, respectively. The recursive formulation of an incarcerated individual's problem is

$$\begin{aligned} rV_p(h,i,m) = \quad & \psi \underbrace{\int (V_p(h',i,m) - V_p(h,i,m))\, f_p(h')dh'}_{\text{human capital shock}} + \zeta^m \underbrace{(V_p(h,lc,m) - V_p(h,i,m))}_{\text{rehabilitation shock}} \\ & + \tau \underbrace{(V_u(h,i,1,m) - V_p(h,i,m))}_{\text{prison exit shock}} + \vartheta^m \underbrace{(V_p(h,i,m+1) - V_p(h,i,m))}_{\text{age shock}} \end{aligned} \quad (1)$$

where $i \in \{lc, hc\}$ is the criminal capital level, h is the current human capital level, and m is the current age of the individual. The first term on the right-hand side reflects the change in the value upon receiving human capital shock, the second term captures the change in value upon receiving rehabilitation shock, the third term captures the change in value upon receiving the prison exit shock, and the final term reflects the change in value upon receiving the age shock. We assume $V(.) = 0$ when $m = \bar{m} + 1$. Implicit in this formulation is that as a normalization, the incarcerated individual receives 0 flow utility while incarcerated.

The problem of an unemployed individual is

[13] Harmonized electronic records across jurisdictions began to be available in the mid-1990s, 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.

$$rV_u(h,i,k,m) = \underbrace{bwh}_{\text{flow benefit}} + \max_s \left\{ \underbrace{-\xi_i^m \frac{s^{1+\eta}}{1+\eta}}_{\text{search cost}} + s \underbrace{\max\left\{V_{up}(h,i,k,m) - V_u(h,i,k,m), 0\right\}}_{\text{crime opportunity arrives}} \right\} +$$
$$\lambda_w^{k,m} \underbrace{\left(V_e(h,i,k,m) - V_u(h,i,k,m)\right)}_{\text{job opportunity arrives}} + \vartheta^m \underbrace{\left(V_u(h,i,k,m+1) - V_u(h,i,k,m)\right)}_{\text{age shock}} +$$
$$\zeta^m \underbrace{\left(V_u(h,lc,k,m) - V_u(h,i,k,m)\right)}_{\text{rehabilitation shock}} + \psi \underbrace{\int \left(V_u(h',i,k,m) - V_u(h,i,k,m)\right) f_u(h')\,dh'}_{\text{human capital shock}} \quad (2)$$

where $i \in \{lc, hc\}$ is criminal capital and

$$V_{up}(h,i,k,m) = \underbrace{\kappa}_{\text{crime benefit}} + \pi \underbrace{\left(V_p(h,1,m)\nu + V_p(h,i,m)(1-\nu)\right)}_{\text{arrest}} + (1-\pi) \underbrace{\left(V_u(h,1,k,m)\nu + V_u(h,i,k,m)(1-\nu)\right)}_{\text{no arrest}}$$

denotes the value upon committing a crime. It includes the probability of incarceration π and probability of gaining high criminal capital ν, each associated with committing the crime. With probability $(1-\pi)$, the individual is not caught, but is still subject to change in criminal capital. The first two terms in equation 2 are the flow benefit of unemployment and disutility from crime search, respectively. The rest of the terms capture the change in value upon the receiving a crime opportunity, an employment opportunity, an aging shock, a rehabilitation shock, and a human capital shock, respectively.

The recursive formulation of an employed individual's problem is

$$rV_e(h,i,k,m) = \underbrace{wh}_{\text{flow benefit}} + \max_s \left\{ \underbrace{-\xi_i^m \frac{s^{1+\eta}}{1+\eta}}_{\text{search cost}} + s \underbrace{\max\left\{V_{ep}(h,i,k,m) - V_e(h,i,k,m), 0\right\}}_{\text{crime opportunity arrives}} \right\} +$$
$$\delta \underbrace{\left(V_u(h,i,k,m) - V_e(h,i,k,m)\right)}_{\text{job separation shock}} + \vartheta^m \underbrace{\left(V_e(h,i,k,m+1) - V_e(h,i,k,m)\right)}_{\text{age shock}} +$$
$$\zeta^m \underbrace{\left(V_e(h,lc,k,m) - V_e(h,i,k,m)\right)}_{\text{rehabilitation shock}} + \psi \underbrace{\int \left(V_e(h',i,k,m) - V_e(h,i,k,m)\right) f_e(h')\,dh'}_{\text{human capital shock}} \quad (3)$$

where

$$V_{ep}(h,i,k,m) = \underbrace{\kappa}_{\text{crime reward}} + \pi \underbrace{\left(V_p(h,1,m)\nu + V_p(h,i,m)(1-\nu)\right)}_{\text{arrest}} + (1-\pi) \underbrace{\left(V_e(h,1,k,m)\nu + V_e(h,i,k,m)(1-\nu)\right)}_{\text{no arrest}}$$

The first term is the flow wage income, which is proportional to the human capital. The second term is the disutility from crime search. The rest of the terms capture the change in value upon receiving crime opportunity, job separation shock, aging shock, rehabilitation shock, irrational crime opportunity, and human capital shock, respectively.

The crime decision rule of the individual, which we denote as I_u for the unemployed and I_e for the employed, is as follows:

$$I_j\left(h,i,k,m\right)=\begin{Bmatrix}1 & \text{if} & V_{jp}\left(h,i,k,m\right)\geq V_j\left(h,i,k,m\right)\\ 0 & o.w & \end{Bmatrix}$$

where $j\in\{u,e\}$. It states that the individual commits crime only if the expected value of committing a crime, which includes crime reward, possibility of getting arrested and sent to prison, and gaining criminal capital, is higher than the current value.

3.2 Matching

Employers create jobs conditional on individuals' observable traits: their criminal record flag k and their age m.[14] This segments the economy into $2M$ labor markets.[15] All labor markets are modeled as in Pissarides (1985). Employers with vacant jobs and unemployed workers meet randomly according to a 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. The matching function is strictly increasing in both terms and has constant returns to scale. The job arrival rate for workers can be expressed as:

$$\lambda_w^{k,m}=M(u_{km},v_{km})/u_{km}=M(1,v_{km}/u_{km})=M(1,\theta_{km}),\tag{4}$$

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

$$\lambda_f^{k,m}=M(u_{km},v_{km})/v_{km}=M(u_{km}/v_{km},1)=M(1/\theta_{km},1)=\lambda_w^{k,m}/\theta_{km}.\tag{5}$$

3.3 A Firm's Problem:

Firms choose to post vacancies in each labor market so long as the net expected value is positive. The flow cost of posting a vacancy is c. The expected revenues from posting a vacancy are equal to the expected revenues from a match discounted by the equilibrium match arrival rate. A match with a worker with human capital level h produces $y=h$. The

[14]Age has been shown to be an important screening mechanism when criminal records are not available (see, e.g., Doleac and Hansen (2020)).

[15]By assuming workers only search within markets for their age/flag type, we are silent about issues of hold-up problems or commitment if a worker is matched with a job in a market that is different than their age/flag type.

wage is assumed to be a constant fraction of the output of the match, and so the firm's flow profits equal $(1-w)h$.[16] The match dissolves if either (i) the worker receives a separation shock; or (ii) if the worker commits a crime and gets imprisoned. Firms use rational expectations in line with the equilibrium distribution of human capital and criminal capital of workers searching in each particular age-cross-criminal record flag market to compute both the expected revenues of a match.[17]

We denote the value of a filled job as J_f. The recursive formulation of a firm's problem is

$$\begin{aligned} rJ_f(h,i,k,m) = \; & \underbrace{(1-w)h}_{\text{flow profit}} + \delta \underbrace{(V_f(k,m) - J_f(h,i,k,m))}_{\text{job separation}} + \psi_e \underbrace{\int (J_f^e(h',i,k,m) - J_f(h,i,k,m)) f_e(h')dh'}_{\text{human capital shock}} + \\ & \vartheta^m \underbrace{(J_f(h,i,k,m+1) - J_f(h,i,k,m))}_{\text{rehabilitation shock}} + \zeta^m \underbrace{(J_f(h,lc,k,m) - J_f(h,i,k,m))}_{\text{age shock}} + \\ & g_s(h,i,k,m)(1-\pi) \underbrace{(J_f^{pe}(h,i,k,m) - J_f(h,i,k,m))}_{\text{crime opportunity arrives}} \end{aligned}$$

where J_f^{pe} is defined as

$$J_f^{pe}(h,i,k,m) = \begin{cases} J_f(h,hc,k,m)\nu + J_f(h,i,k,m)(1-\nu) & \text{if } V_{ep}(h,i,k,m) \geq V_e(h,i,k,m) \\ V_f(k,m) & \text{o.w.} \end{cases}$$

and g_s is the optimal crime search policy of the individual. The value of a vacant job is defined as

$$rV_f(k,m) = \underbrace{-c}_{\text{flow cost}} + \lambda_f^{k,m} \underbrace{\int (J_f(h,i,k,m) - V_f) d\Gamma_u(h,i|k,m)}_{\text{worker match}} \tag{6}$$

where Γ_u is the belief of the firms about the measure of the unemployed over human capital and criminal capital conditional on observable prison flag, k, and age, m.

3.4 Definition of a Stationary Competitive Equilibrium:

A competitive stationary equilibrium is a set of value functions V_p, V_u, V_e, J_f and V_f; individuals' crime policy functions g_s, I_u and I_e; market tightness for each submarket θ_{km}; job arrival rate for workers in each submarket λ_w^{km}; worker arrival rate for firms in each submarket λ_f^{km}; beliefs of firms, Γ_u, and a stationary distribution of individuals Γ such that the following conditions hold:

[16] Nash bargaining is an alternative wage protocol but bargained wages create an odd outcome in models of rational crime: more criminally active individuals have better outside options and bargain higher wages. This tends to lead to equilibrium outcome that contradicts salient features of the data.

[17] Any match with negative expected revenues is not formed, and the value equals zero.

1. Policy functions g_s, I_u and I_e solve the individual's problem characterized in equations 1-3 taking job arrival rates λ_w^{km} as given. Value functions V_p, V_u and V_e are the associated value functions to these problems.

2. The firm's value functions J_f and V_f solve equations 6 and 6 taking worker arrival rates λ_f^{km} for each k and m, individual decision rules I_u and I_e, and beliefs of firms Γ_u as given.

3. Firms' beliefs are consistent with individual actions: Γ_u is the marginal distribution of Γ for the unemployed given prison flag, k, and age, m.

4. There is free entry: $V_f(k, m) = 0$ for each k and m.

5. The distribution is stationary and consistent with individuals' decision rules:

$$\Gamma = T(\Gamma)$$

   where T is an operator mapping the current distribution to the future distribution given individuals' decision rules and law of motion for exogenous variables.

Mechanisms: Policies and Outcomes in a Stationary Equilibrium. The impact of a more punitive criminal policy, an increase in the probability of imprisonment for a crime, can be understood through several effects. The first is the deterrent effect through individuals' choices. As the probability of incarceration increases, all individuals, regardless of their status (summarizing their history), choose to commit less crime. The second is the arithmetic effect of an increase in the probability of imprisonment. If the increase in probability of getting imprisoned dominates the deterrent effect, then the incarceration rate increases. A third effect depends on how firms respond in equilibrium. If 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 equilibrium effect counters the deterrent effect of policy by increasing inducing both unemployed and employed workers to choose more crime.

4 Calibration and Estimation

We calibrate our model so that the initial steady state replicates empirical moments from the late 1970s and early 1980s. This choice is motivated by the prior century of comparably stable rates.[18] Some parameters are directly calibrated but most are jointly estimated to minimize the distance between the model and data statistics. The population of interest in the data is men with a high school degree or less. This text focuses on the calibration of the model for property crimes only. We produce a calibration for violent crimes in the Online Appendix.

4.1 Sources of Criminal Justice Data.

We calibrate our model to replicate moments from several sources of criminal justice data. This approach leverages varied, large, and representative administrative datasets, contrasting with prior studies often relying on small, self-reported samples from the NLSY or data from a single state or local agency.

Consistent nationwide data on prison admissions and criminal records are a challenge. Historically, annual records on prison admissions at the institutional level and individual criminal histories were collected by subgovernmental units responsible for particular justice system components, and each followed their individual conventions. Some improvement followed the 1993 Brady Act, which mandated background checks for some firearms purchases, but overall, nationally aggregated data are collected by subnational authorities and should be viewed critically for irregularities.

The Bureau of Justice Statistics (BJS) estimates national prison admissions, stocks, and releases using data from the National Corrections Reporting Program (NCRP). The NCRP is a restricted-access dataset of offender-level data submitted to the BJS by state justice departments. As (Neal and Rick, 2014) note, the data require careful vetting. We clean the data by first dropping states in which the inflows, outflows, and stocks are not internally consistent, following (Neal and Rick, 2014). However, our interest in distinguishing property, violent, and other offenses necessitates additional consistency checks at the offense category level. This leaves us with data on 12 states, accounting for 42%-60% of all prison admissions over our period of interest, which exhibit trends similar to national BJS estimates (as shown in the Online Appendix). Finally, we perform additional checks for reliability, including investigating large growth or decline in admissions and more.[19] Finally, we perform additional reliability checks, interpolating outlier years instead of dropping entire states. These data consistently report offenders' age and gender, allowing us to restrict our sample to males and compute age group statistics where appropriate.[20]

[18]See the Online Appendix for a plot. 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).

[19]Outliers aren't the only problem. We found a case where a state simply sent the same data to the BJS several years in a row!

[20]Education is not reliably reported in these data and so we do not restrict our sample on the basis of

The Recidivism of Prisoners Released Series provides data on prisoner outcomes in the three years following release. These restricted offender-level administrative data include a representative sample of 16,000-38,624 prisoners released from states with large prison populations in the survey year, conducted every 11 years. We use the 1983 series to compute baseline recidivism statistics. Later surveys validate the model's predictions, but restricted 2005 micro-data are unavailable. Instead, we secured restricted micro-data from "Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida, 2004-2008, which contains over 156,000 offenders. We verify these data align with the published 2005 BJS statistics, with a 3-year recidivism rate of 36% in the Florida data and 36.1% in the BJS data.

The Survey of Inmates of State Correctional Facilities provides data on labor market and personal characteristics at the time of offense for convicted prisoners. We use the 1979 survey of 12,000 inmates in 300 state institutions to calibrate the model. Nearly all state prisoners serve convicted sentences for one or more felonies. State prisoners also consistently comprise over 80% of all convicted prisoners, with the remainder mostly in federal institutions.

We follow a few general principles in categorizing crimes and convictions. When measuring crimes, we restrict our data to offenses likely charged as felonies, as individuals are rarely imprisoned for misdemeanors. To classify the offense for prison admission, we employ two strategies. When computing aggregate statistics such as total property crime admissions, we include all associated offenses. For example, if an individual's main charge is violent but includes three property offenses, we count three property admissions. This approach more accurately assigns the probability of incarceration to a single crime occurrence in victimization data. When computing the number of persons admitted to prison or currently incarcerated, we classify imprisonment for a property offense if the individual is charged with any property offense, and similarly for violent. The share of admissions we classify as property crimes that also have a violent offense is small and stable at about 10% of all admissions throughout the sample.[21] Therefore, the dynamics of violent offenses are not driving the dynamics of admissions for property crimes.

This study focuses on property crime, with additional results for violent crime. Property and violent crimes are almost always victim-based, which facilitates estimation of a key policy parameter: the probability of incarceration per crime committed.[22]

education.

[21]See the on-line appendix for specific graphs and statistics on multiple offenses. Less than one-third of violent prisoners have another offense but it is also likely the case that some state justice systems only report the most serious offense.

[22]Details about crime counts and classification in the NCVS are in the Online Appendix.

4.2 Externally Calibrated Parameters

The time period is set to be one week. Individuals go through three stages of life ($M = 3$): youth, middle age, and old age. On average, young individuals live for 7 years (between ages 18 and 24), middle-aged individuals live for 10 years (between ages 25 and 34), and old individuals live for 30 years (between ages 35 and 64).[23] We set $r = 0.1\%$ to provide an annual discount factor of 0.95. We set the prison exit probability to 0.019, which implies 12 months of prison time on average, consistent with Both Raphael and Stoll (2009).[24]

The matching function for the workers and firms follows Shimer (2005)

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

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 set the wage to be 50% of the productivity of the worker.[25]

The incarceration probability upon committing a crime is set to $\pi = 0.5\%$. This value matches our calculation of new prison admits for property crime estimated from NCRP's NPS restricted micro-data divided by number of property crimes estimated from the National Crime Victimization Survey (NCVS) for 1979-1980.[26]

Table 2 shows the externally calibrated parameter values of the model.

4.3 Internally Calibrated Parameters

The remaining parameters in the model are jointly calibrated by minimizing the percentage deviation of the model-generated moments from their analogous data moments.[27] We explain our choices of moments to match below.

[23] These average lifetimes for each age group imply the stochastic aging probabilities of $\vartheta_y = 0.00275$, $\vartheta_m = 0.00192$, and $\vartheta_o = 0.00064$ for the young, middle-aged, and old, respectively.

[24] Raphael and Stoll (2009) and Neal and Rick (2014) show that the median prison time served has remained reasonably constant over time, whereas the average duration has increased because of the extreme tail (life sentences, etc.).

[25] This value is inconsequential. The more important assumption is that workers with a higher outside option do not bargain higher wages.

[26] See the Online Appendix for an extended discussion on how alternative measures of crime affect the time series of π. The appendix addresses why we do not use Uniform Crime Reports (UCR).

[27] Specifics on the objective function, weighting matrix, and computation algorithm of the estimation process can be found in the Online Appendix, along with graphical relationships between individual parameters and moments.

Table 2: Externally Calibrated 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	0.019
r	discount factor	0.001
b	unemployment benefit	40%
φ	matching function curvature	0.72
χ	matching function constant	0.14
w	wage share	0.5
π	arrest probability	0.005
ψ	human capital shock arrival rate	1/52

Labor Market Parameters: The employment rate is determined in equilibrium, in part by the decisions of workers and firms. Two parameters are also important: the exogenous job separation rate and the vacancy cost.[28] Targets for these parameters are the average employment rate and unemployment duration of men between the ages of 18 and 34, without a high school degree in 1980-83. We choose this demographic because they have the highest crime rates in the data. The estimated vacancy cost equals about one year of the average annual income in the economy. The calibration chooses a high vacancy cost to match the unemployment rate of 23.2% since we assume all non-employed workers are searching in unemployment.

Human Capital Parameters: The human capital shock is chosen to arrive at a Poisson rate $\psi = 1/52$, which implies one year as the average time individuals receive human capital shock. Upon receiving the shock, the log of the human capital follows an AR(1) process:

$$\log h' = f_{i,m}(h) = (1 - \rho_h)\mu_h^{i,m} + \rho_h \log h + \epsilon_h$$

where ρ_h is the persistence of the process, ϵ_h is a Gaussian white noise with variance σ_h^2, and μ_h^i is the unconditional mean of the log human capital conditional on employment status $i \in \{e, u, p\}$, which captures the potential scarring effects of unemployment and incarceration. Scarring effects of unemployment and incarceration are assumed to be age-independent, and the mean for the first age group is normalized: $\mu^{e,1} = 0$, which implies an average human capital of $h = 1$. The remaining parameters of the process are estimated using indirect

[28]The exogenous job separation rate cannot be set directly, because some matches dissolve endogenously when a worker is admitted to prison for a crime.

inference. The auxillary model is the following Mincer regression run on both our NLSY 1979 sample and on data simulated in our model:

$$ln(w_{it}) = \alpha + \beta^M I(A_{it} = 2) + \beta^O I(A_{it} = 3) + \beta^N N_{it} + \gamma_i + \epsilon_{it} \tag{7}$$

For an individual i at time t, w_{it} is the observed wage; I is the indicator function; A is an age bin; N is the months of non-employment, including unemployment and non-participation in the past year; γ_i is an individual fixed effect; and ϵ_{it} is a residual.[29] Given the shock arrival rate, ρ_h and ϵ_h are chosen to replicate estimates of the annual persistence and standard deviation of the residuals in the NLSY sample estimation. These statistics are 0.96 (persistence) and 0.2 (standard deviation), which are within the range of standard estimates used for men with a high school degree or less in the literature.[30] The three remaining parameters are estimated to minimize the distance between the coefficients on the age and last year non-employment indicators in the model and in the data, where prison counts as non-employment. These parameters are: $\mu^{e,2}$, $\mu^{e,3}$,and $\mu^{u,1}$.

Crime Parameters: Data moments on incarceration and recidivism rates serve as calibration targets to inform the parameters governing the cost of crime search. The share of the population with high criminal capital is crucial in determining the extent of recidivism (intensive margin) versus the extent of crime in the cross-section (extensive margin) in the economy. In other words, is crime done mostly by a few individuals who commit crimes frequently or by many individuals who commit crimes infrequently? This distinction helps distinguish two parameters related to the cost of crime search: the cost of crime search for low and high criminal capital individuals, ξ_{lc} and ξ_{hc}. Without additional crime opportunities, the criminality of the high criminal capital types would be close to that of the general population, whereas crime is more concentrated in a few individuals in the data. Statistics on recidivism to prison are informative about the share of high criminal capital types and the additional crimes they commit. We add to our estimation targets the one-year re-imprisonment rate *on new charges* for the released prisoners.[31] This rate is 19.9% in the

[29] Since there is no ex-ante heterogeneity among individuals, we omit the fixed effect in the regressions for the simulated data. The model is weekly, but we store the information to construct the panel data at monthly frequency, as in the NLSY. Further details of the NLSY implementation and results can be found in the Online Appendix.

[30] Storesletten et al. (2004) report higher variance for men with lower levels of education, with a range of 0.16-0.2 in a collection of similar studies.

[31] These rates are calculated using the BJS Recidivism of Prisoners Released Series (Bureau of Justice Statistics (2011)). 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 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.

1983 BJS Recidivism of Prisoners Released Study (Bureau of Justice Statistics (2011)) for young and middle-aged individuals.

The fraction of prison admits with prior incarceration experience is a complementary target. In the 1979 National Prison Survey, 64.2% of property criminals had been to prison before.[32] 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 individuals. Together, the probability of gaining high criminal capital and the higher arrival rate of crime for this type determines the size of the population with higher than average crime rates. This relationship is a key feature of the data.

The rehabilitation shock, ζ^m, is identified using the age profile of incarceration rates. The first-time incarceration rates of young and middle-aged individuals are similar to each other in the data. By contrast, the first-time incarceration rates for those over age 34 is near zero in the data (<0.1%, authors' calculations from NACJD data). So, we set $\zeta^1 = \zeta^2 = 0$ and calibrate ζ^3 to match the incarceration rate of the old individuals in the model representing the age group 35 and up.

Crime reward parameter, κ, is calibrated to match the average loss for a victim of a property crime in the data, which is reported as 5.87% of average annual income in Fella and Gallipoli (2014).

Table 3: Calibrated Parameters

Parameter	Explanation	Value
ξ^{lc}	cost of crime search-low criminal	996540
ξ^{hc}	cost of crime search-high criminal	0.05
ν	prob of being high criminal	0.1
κ	mean crime reward	2.15
ζ^3	rehabilitation shock	0.95%
c	vacancy cost	60.96
δ	separation shock	0.93%
$\mu^{e,2}$	human capital mean-middle employed	0.09
$\mu^{e,3}$	human capital mean-old employed	0.13
$\mu^{u,1}$	human capital mean-nonemployed	-0.32
ρ_h	human capital persistency	0.94
σ_h	human capital shock std	0.25

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 shows the calibrated parameters. Table 4 shows the performance of the model

[32] Authors' calculation from the National Prison Survey 1979.

Table 4: Model Match

Targeted Moments	Data	Model
Incarceration - young and middle	0.59%	0.59%
Incarceration - old	0.09%	0.09%
Recidivism rate (1 year)	19.9%	19.5%
Crime reward to income ratio	5.87%	5.88%
Criminal with prior	64.2%	64.9%
Unemployment duration	20 weeks	20 weeks
Employment rate - young and middle	76.2%	74.0%
Regression coefficient-β^M	0.13	0.13
Regression coefficient-β^O	0.21	0.21
Regression coefficient-β^N	-0.005	-0.005
income persistency	0.96	0.96
income std	0.20	0.20

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

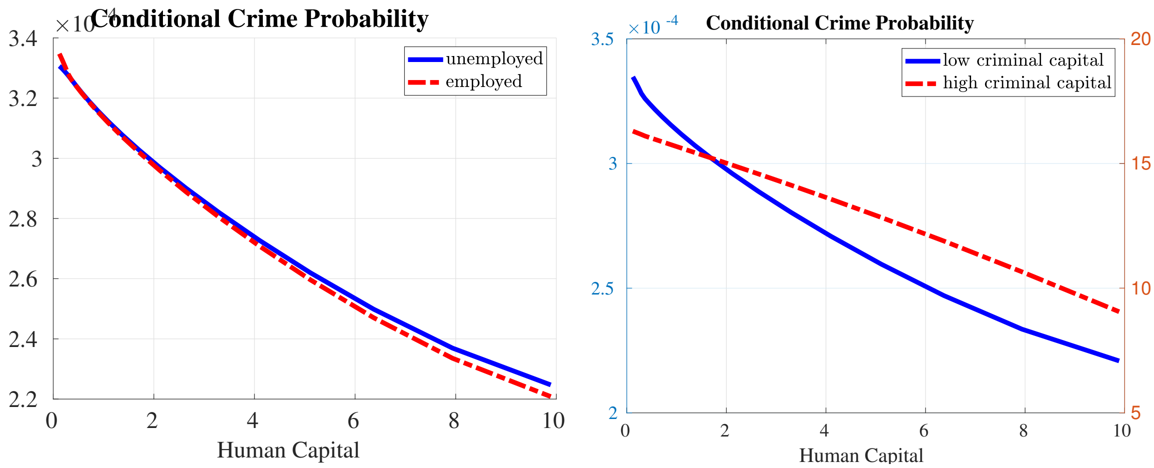
in matching the moments targeted. The model does a satisfactory job in capturing the moments targeted in the calibration.

5 Steady-State Analysis.

To understand the dynamics of deterrence following a change in punitive policy, we must first understand what determines crime in the initial (pre-1980s) steady-state.

The choice to commit crime involves weighing the costs and benefits of doing so. The benefits are common to all individuals in the economy: an instantaneous reward. 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 state. In addition to forgone earnings in prison, they are also subject to human capital depreciation from non-employment and unemployment after leaving prison, both of which lower their future expected earnings. These opportunity costs are higher for individuals with high human capital or currently employed. Figure 2(a) shows the probability of committing crime conditional on receiving an opportunity. This probability decreases as human capital increases, and notably does so at a faster rate for the lower half of the human capital range. It is also slightly lower for employed people than for unemployed people.

Criminal capital, the prison flag, and age also contribute to criminality in the model. Figure 2(b) shows that individuals with high criminal capital are significantly more likely to commit crimes due to the much lower cost of crime search. The prison flag also increases



(a) Labor Status

(b) Criminal Capital

Figure 2: **Determinants of Crime:** The figure shows model generated crime probability conditional on receiving an opportunity as a function of human capital, labor market status and criminal capital for a middle-age agent.

crime by lowering the likelihood an unemployed individual with a criminal record may find a job. However, we find that this channel is quantitatively small.

Table 5: Characteristics of Criminals

	Criminals	Overall
Employment rate	58.5%	74.0%
Human capital	1.19	1.30
Frac of high criminal capital	97.2%	1.0%
Prison Flag	65.0%	3.1%
Young and middle population	75.9%	34.0%

Table 5 shows how individuals who commit crimes in a given period in the stationary equilibrium differ from the overall population, comparing those with a prison flag to those without. Criminals are less likely to be employed, with lower human capital, younger, and more likely to have criminal record in their history. In the initial steady-state only 58.5% of criminals are employed, compared with 74% of the general population. The fact that most crime is committed by employed individuals may be surprising, but the same is true in the data.[33] Part of the reason why is a difference in pay. The human capital (and wages) of criminals is on average 10% lower than that of the overall population (1.19 vs. 1.3). As is well known in criminology, age is an important factor. More than three-quarters of the criminals are young and middle-aged individuals, whereas young and middle-aged individuals make

[33] The odds ratio of crime for employed individuals relative to unemployed individuals is 0.49 in the model. This is non-targeted and is actually a bit higher in the data at 0.86.

up only one-third of the overall population.

Crime is highly concentrated, and the majority of the crimes are committed by a few individuals. The share of criminals with prior criminal history is almost 65%, although the share of this group in the overall population is only 3.1%. Only 0.76% of individuals commit 95% of all crimes in the initial steady-state. Given these stark statistics, the entry margin into crime and the persistence of crime for individuals who do enter will be key in the policy analysis of the dynamics of deterrence in the following sections.

A simple linear regression of individuals' probabilities of committing crime within the week is another statistic summarizing factors correlated with criminality (Table 6).[34] We run this regression for both the all population and for only low criminal capital individuals separately to highlight the differences of crime determinants across the low criminal and high criminal individuals. The cells list the percentage-point change in crime probability associated with each independent variable. The second and the third columns present the estimates and the t-statistic of the estimates of the regression on the total population. The last two columns present the results of the regression for only low criminal capital individuals. The regression shows that for low criminal capital individuals age and wages are the main deterrent factors for crime. However, for the total population, prison flag, which is highly concentrated among the high criminal individuals, is the main determinant of crime.

Table 6: Crime Elasticities

	All Population		Low Criminal	
	Estimate	tStat	Estimate	tStat
Age 25-34	-0.06	-0.43	-0.18	-28.33
Age 35-50	-0.86	-6.93	-0.72	-135.12
Prison Flag	2.04	8.25	0.00	0.05
Employed	-0.05	-0.43	0.02	3.77
ln(wage)	-0.07	1.20	-0.08	-31.42
Constant	-7.77	-56.37	-7.92	-1342.7

Notes: The Table shows the estimates of regressing the probability of committing a crime on covariates in the initial steady-state. The population measure for each type is used as weights in the regression. The second and the third column present the results of the regression for all the population. The last two columns present the results of the regression for only low criminal capital individuals.

[34]Specifically, the dependent variable is $\log(p_c)$, where p_c is the probability of committing a crime. The independent variables are dummies for middle and old age, prison flag, employment, and log of wages.

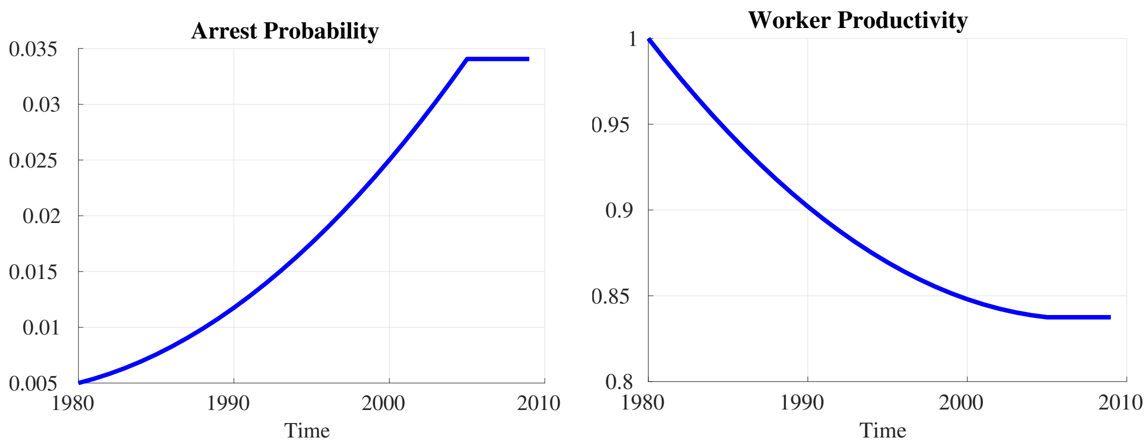
6 The Dynamics of Punitive Incarceration Reform

In this section, we study the effects of an increase in incarceration probability after committing a crime on aggregates like crime rates, incarceration rates, labor market variables, and inequality after the 1980s. Our intention is to mimic changes in punitive justice policy thought to be a key driver of the prison boom.[35] These policies, however, did not occur in isolation. Other factors shaping criminality evolved during this time as well. The first is related to the labor market. For low-skilled workers the real wage stagnated and job separation rate increased through the late 1990s. The second is potential changes in crime rewards. While crime rewards cannot be directly observed, there is evidence that the spread of cocaine and associated gangs raised criminal involvement from the late 1980s through the mid 1990s (Blumstein (1995)). Our second motive is that these theories correct the deficiencies of and complement the strengths of a theory of unilateral change in incarceration policy. They magnify the impact on the 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 these changes together, as they will interact through the various channels in our model.

We feed the changes in the incarceration probability and the productivity of the workers from the data as they are directly observed and calibrate the increase in the crime reward and the increase in the job separation rate over 25 years to match the time trends in each: the incarceration rate and the employment rate over 1980-2010. We assume linear changes over time for both the crime reward and the job separation rate.[36] Figure 3(a) and 3(b) plot the time series of arrest probability and worker productivity we exogenously feed using external data along the transition in the model. Given these changes, the calibration of the change in crime reward and job separation rate to match the evolution of incarceration and employment rate yields 119% increase in the crime reward and 29.4% increase in the job separation rate.

[35] See Neal and Rick (2014), Blumstein and Beck (1999), Pfaff (2012), and Raphael and Stoll (2009), among others, for evidence that a change in admission conditional on crime was the main policy change. This probability changed little during crime waves, except for violent crime in the 1990s and in episodic instances of prison crowding in specific states. Median prison durations were relatively consistent.

[36] More specifically, we fit a third-order polynomial for each data series, fed the smoothed data series for incarceration probability and worker productivity, and targeted the smoothed data series for incarceration rate and employment rate. We introduce the changes as surprise and permanent changes in every period. We also experimented calibrating nonlinear time trends in crime reward and separation rate, but the results do not change significantly.



(a) Arrest Probability (b) Worker Productivity

Figure 3: **Arrest Probability and Worker Productivity:** The figures plot the time series of arrest probability and worker productivity we feed along the transition in the model.

6.1 Comparison of Initial and Final Steady States:

To see how a change in incarceration probability, π, affects the incarceration rate, define the probability of incarceration for an individual with current state θ: $p^c(\theta;\pi) = \pi s(\theta)$, where s is the policy function for crime search. The overall crime rate is $\sum_\theta p^c(\theta;\pi)\Gamma(\theta;\pi)$, where Γ is the measure of individuals across states θ. Increasing π affects the overall crime rate through three channels. The first is an arithmetic effect: the incarceration rate is the product of overall crime and π. The second is deterrence: higher π decreases each individual's crime search, s, regardless of their state θ. The final effect is how both π and all the endogenous responses in the model change the distribution of individuals across states, Γ. This includes the endogenous job creation response of the firms.

Whether an increase in π will increase or decrease incarceration rates is a quantitative issue. If the deterrence created by an increase in π is relatively small, then the arithmetic effect of a higher π can dominate and cause an increase in the incarceration rate. This typically generates a "Laffer curve" type of hump-shaped relationship between π and the incarceration rate. Incarceration rates are zero when $\pi = 0$ (no criminals go to prison) and when $\pi = 1$ (nobody commits crime). What is unusual in our model is that it is unclear that crime rates should fall. In simple settings, crime falls because all individuals lower their crime search and commit less crime. In our model, a prison experience worsens an individual's state and makes them more likely to commit crime. In this way it is possible that an increase in π leading to an increase in incarceration could also increase crime.

The estimated trends of both lower productivity and higher reward for crime along the transition work to increase crime and incarceration. Table 7 shows the comparison of the initial and final steady-states.

Table 7: Steady-State Comparison

Steady-State Variables	SS1	SS2
Incarceration	0.59%	0.90%
Crime Rate	0.84%	0.20%
Employment rate	73.98%	72.04%
Criminals with prison flag	64.95%	78.52%
Frac w/ high criminal capital	1.00%	0.50%
With prison flag	3.14%	3.02%
Share committing 95% of crimes	0.76%	0.18%

Notes: The table shows a comparison of two steady states

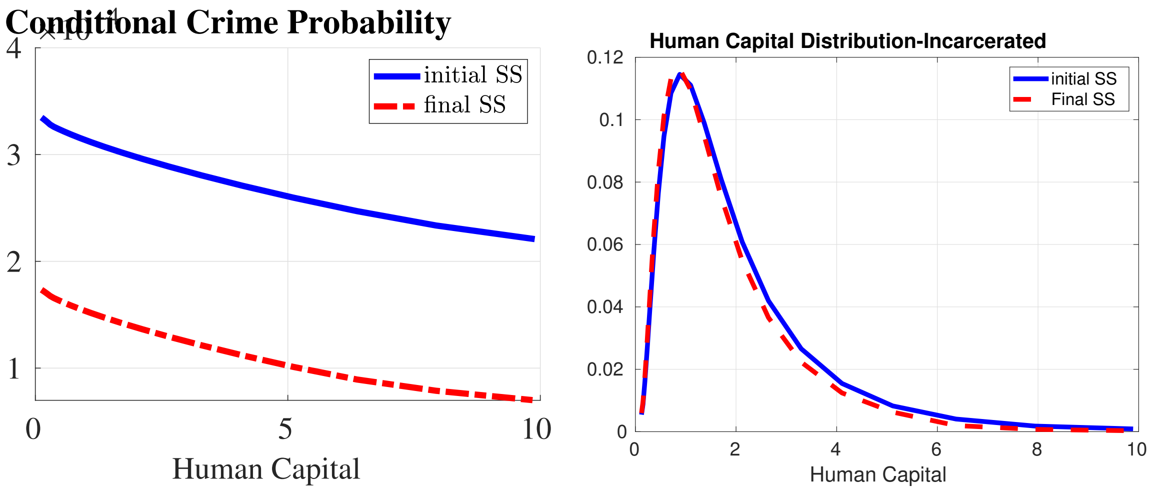
Crime decreases from a rate of 0.84% to 0.2% across the steady-states in the simulation. The increase in the incarceration probability offsets the fall in crime, and as a result, the incarceration rate increases from 0.59% to 0.9%. It is notable, however, that crime becomes more concentrated within a fewer individuals. The share of the population responsible for committing 95% of aggregate crimes decreases from 0.76% to 0.18%. The fraction of individuals with a prison flag decreases from 3.14% to 3.02%, and the fraction of crime committed by individuals with prior conviction increases from 64.95% to 78.52%. These repeat offenders have a substantially higher recidivism rate even though their crime intensity decreases, dominated by the large increase in incarceration probability.

The changes across steady states are due to changes in the policy functions of individuals and changes in the distribution of individuals. An example of how policy functions change is shown in Figure 4(a) where we plot the crime propensity of a middle-aged employed individual with low criminal capital and no prison flag. Observe that crime policy falls across all human capital levels. Figure 4(b) shows the change in the distribution of the agents across human capital. More punitive incarceration policy slightly shifts the human capital distribution to the left.

6.2 Transitional Dynamics:

The transition from the initial to final steady state can take several decades, and substantial policy costs occur along this transition. Figure 5 plots the transitional dynamics for incarceration rate, crime rate and employment rate. It is not surprising that we match the overall pattern for each variable since we target them using the changes in the job separation and crime reward.

Figure 5(a) shows the evolution of total incarceration rate along the transition, relative to the initial steady-state. It starts at 0.59%, more than doubles in 15 years, and then



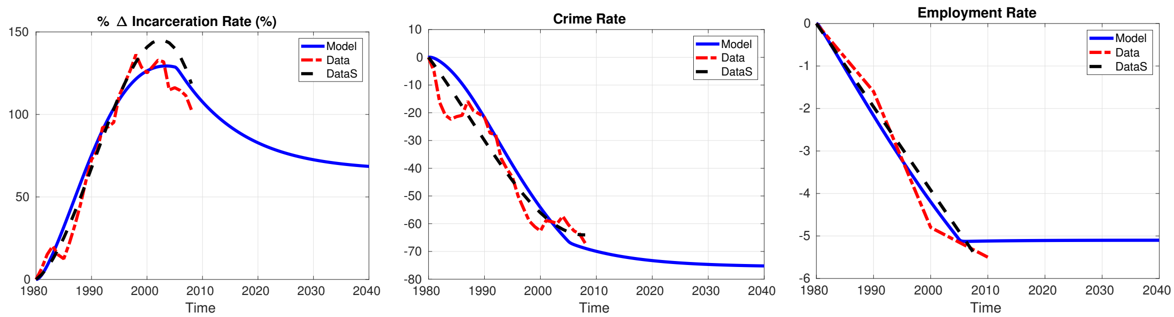
(a) Policy (b) Distribution

Figure 4: **Steady-State Comparison:** The left panel shows model-generated crime probabilities conditional as a function of human capital for a middle-aged employed individual with low criminal capital and no prison flag across the initial and the final steady states. The right panel plots the distribution of human capital among the incarcerated across the initial and the final steady-states.

gradually declines to the new steady-state level of 0.9%. This non-monotonic change in the incarceration rate happens despite the monotonic decline in the crime rate as captured in Figure 5(b). A naive analysis may conclude that if crime is falling as incarceration rates fall, then punitive incarceration is not driving the fall in crime. Our theory shows the fault in this logic. Past moves towards more punitive incarceration policy follow dynamics where the full deterrent effect is delayed, and thus crime and incarceration decrease at a tipping point where the added dynamic deterrence overtakes the arithmetic increase in π.

Shapley-Owen Decomposition of How Shocks Shape the Trend. Figure 6 plots a Shapley-Owen decomposition of the trend into the three series we feed in: incarceration policy π, labor market variables (productivity and the job separation rate), and crime rewards. The contribution of a shock is computed by first calculating the contribution of that shock to the change in the variable of interest, compared with the initial steady-state in the presence and absence of the other two shocks. We take all possible permutations of them and then compute the weighted sum of each contribution of the shock in all the permutations according to the Shapley-Owen combinatorial formula (Shapley et al. (1953) and Owen (2014)).

Figure 6(b) shows that the main driver of the evolution of the crime rate is the deterrence provided by an increase in the probability of incarceration for a crime and the increase in the crime reward. As policy becomes more punitive, individuals' crime rates decrease. In



(a) Incarceration (b) Crime (c) Employment

Figure 5: **Transitional Dynamics - Model vs. Data:** The figure shows the evolution of the incarceration rate, crime rate and employment rate along the transition. The left panel plots the total incarceration rate. The middle one plots the total crime rate, and the right panel plots the employment rate relative to their initial steady-state levels. The solid lines correspond to their model counterparts, whereas dashed lines correspond to the data.

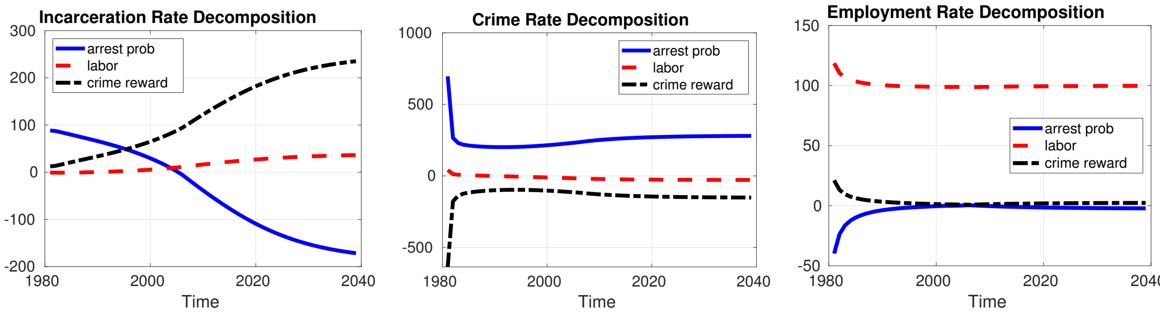
the absence of the other two shocks, we would expect the crime rate to drop another 70% in the long-run, but inferred crime rewards work against changes in punitive policy and increase the crime rate. Changes in incarceration policy increase the incarceration rate in earlier periods but decrease it later on. This has to do with whether the decrease in crime is arithmetically large enough to offset the increase in π. The increase in the crime reward would have increased the crime rate and incarceration rate substantially, partially offsetting the effects of incarceration policy in the long-run. Quantitatively, we find that in the absence of the other two shocks, the incarceration rate in the new steady state would be lower than in the initial steady-state. Finally, changes in productivity and job separation rate are the main contributor to the change in the employment rate.

6.3 Dynamics of Deterrence:

This section seeks to understand the dynamic impacts of punitive policy by studying outcomes following changes in the probability of imprisonment for a crime in the absence of the other factors we studied along the transition.

Incapacitation versus Deterrence. The criminology literature frames punitive policy as reducing crime through two channels: deterrence and incapacitation. Incapacitation lowers crime by putting likely criminals in prison, where they cannot commit crime. Deterrence is when more punitive policies lower crime by deterring individuals from committing crime in the first place.

Two experiments in the structural model provide novel insights on how these effects



(a) Incarceration (b) Crime (c) Employment

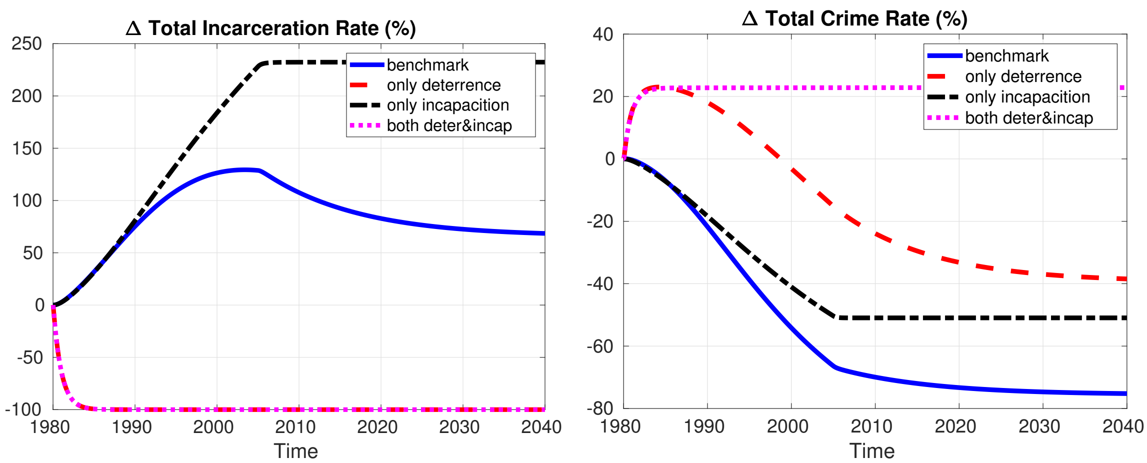
Figure 6: **Transitional Dynamics - Shapley-Owen Decomposition:** Solid lines show the contribution of the change in incarceration probability, dashed line shows the contribution of the change in the labor market variables (productivity and job separation rate), and finally the long-dashed line shows the contribution of the change in the crime reward. The left panel is for the incarceration rate, the middle panel is for the crime rate and the right panel is for the employment rate.

unfold dynamically after a policy change. The incapacitation effect is isolated in the first by setting the time spent in prison to 0.[37] The deterrence effect is isolated in the second by fixing the decision rules of the individuals and firms at the initial steady-state level along the transition.

We start by looking at the effects on incarceration, shown in 7(a) . When incapacitation is eliminated, incarceration rates obviously go to zero. What can be seen in the difference between the benchmark (blue) and the line with incapacitation but without deterrence (black) is the impact of deterrence. Without deterrence, the incarceration rate follows the increase in π, reaching 2.5 times higher than the peak with deterrence and staying at that level forever.

The effects on crime, shown in 7(b), are more nuanced. The pink line has no incapacitation or deterrence but includes the higher impact of prison by giving those who are caught all the expected cumulative impacts of prison (prison flag and lower human capital) and sends them straight to unemployment. The fact that this line increases crime from the initial steady state shows the criminogenic effect of prisons. Lower human capital and losing employment causes ex-felons to choose more crime. The next line, the red dashed line, adds in deterrence but not incapacitation. Crime rises initially before falling later on. This emphasizes that the policy deters mostly through crime entry and it takes many years for the full deterrent impact on crime entry to be realized. It also shows how important incapacitation is, especially in the short run. The black-line shows incapacitation only. It always works to decrease crime and hits immediately with changes in π (recall π is fed in linearly).

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



(a) Incarceration (b) Crime Rate

Figure 7: **Incapacitation vs Deterrence:** 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 red dashed line is the economy when incapacitation is eliminated. The black dashed line is the economy when deterrence is eliminated and all policy functions are fixed at the initial steady state. The pink dotted line eliminates both the incapacitation effect and the deterrence effect.

The broad lesson is that the incapacitation effect is what reduces crime immediately after a change to more punitive policy but deterrence is what provides the majority of the decline in the long run, around two-thirds of the decline in our calibration. This finding suggests that changes in punitive justice policy may be improved by following a thought-out dynamic path. In particular, larger crime reduction could be achieved more quickly by lengthening prison duration in the short run, when incapacitation effects are key, and reducing them in the long run, when full deterrence has kicked in.[38]

The Intensive and Extensive Margins of Crime: The decomposition of the transition highlighted that the crime entry decision is a key margin through which punitive incarceration policy provides deterrence. Another way to explore this theme is by investigating how the intensive and extensive margins of crime evolve. In other words, does crime become concentrated in fewer individuals, and do those fewer individuals commit more or less crime than earlier generations?

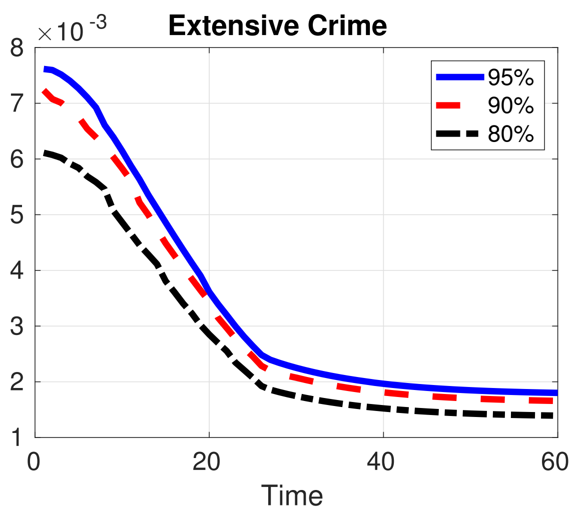
One measure of the extensive margin is how concentrated crime is across individuals. Figure 8(a) plots the evolution of the share of individuals responsible for a given fraction (80%, 90%, or 95%) of crimes along the transition. Crime unambiguously becomes more concentrated in fewer individuals. For example, the solid line shows that around 0.76% of

[38]Criminology studies have repeatedly found that lengthening prison sentences past a year or two provides virtually no additional deterrence. A recent example is Rose (2021).

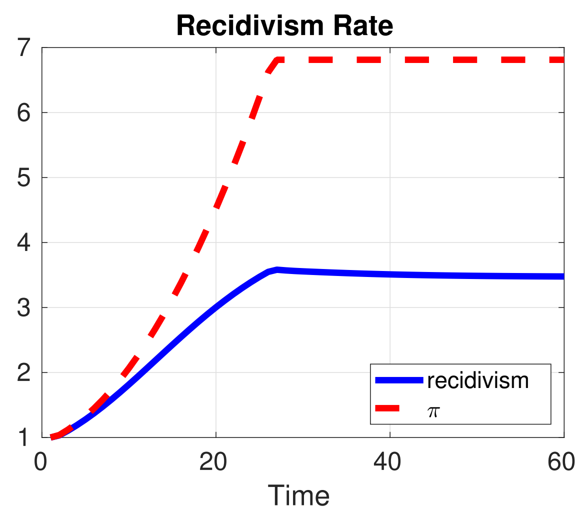
the population was responsible for 95% of crime at time zero and this falls to 0.2% of the population at the new steady state.

One measure of the intensive margin of crime is recidivism relative to incarceration probability π (8(b)). While it is true that recidivism increases over time (x4), it increases by less than would be arithmetically implied by the increase in π (x7). This means that the intensive margin is actually falling.

Combining these facts, we conclude that both the extensive *and* intensive margins are working together to provide the decrease in crime over time. Crime becomes more concentrated in fewer individuals *who actually do less crime each*. The increase in π always provides intensive deterrence through individuals reducing their crime search for any given state. The fact that the overall intensive margin (measured as recidivism) falls in the new steady state implies that the change in the distribution of individuals does not move the most criminally active to states that are bad enough to undo the deterrence provided by changes in policy functions. This is meaningful for practical policy because it implies that additional crime reduction of putting an additional person in prison (a pure marginal incapacitation effect) actually falls along the transition. This is a quantitative statement and could have plausibly gone the other way.



(a) Extensive Crime



(b) Recidivism

Figure 8: **Extensive Crime and Recidivism:** The left plots the measure of individuals committing certain shares of aggregate crime along the transition. The solid line is for 95% of crimes, the dashed line is for 90% of crimes, and the long-dashed line is for 80% of crimes. The right panel plots the one year recidivism rate, together with the arrest probability along the transition. Both the recidivism rate and arrest probability are normalized to their initial steady-state level.

Empirical measures are consistent with the model predictions that both the intensive and extensive margins of crime declined from 1980 to 2000. Table 8 shows the three year

Total 3-Year Re-imprisonment			
Age	1983	1994	2000-2003*
18-24	64.0	41.0	48.8
25-34	32.6	40.3	49.6
35-64	27.0	35.6	44.3
Total (18-64)	30.7	39.3	47.7
Expected % of Population Incarcerated by age 35			
	Year of Birth		
	1974-1979	1994	2000-2003*
	1.7	4.0	4.7

Table 8: Upper panel: 3-year Re-imprisonment Rate on a New Felony Charge, 1983 & 1994 Recidivism of Prisoners Released Series (United States Department of Justice. Office of Justice Programs. (2014)); *2000-2003: Florida only, (Bhati (2010)). Lower panel: estimated from Bonczar (2003) and authors' calculations in NCRP.

re-imprisonment rate has increased over time, but not as much as would be predicted by the seven-fold increase in observed prison admissions per crime. The same is true for the extensive margin: estimates of the percentage of people who would go to prison if they lived their lives entirely in a world of 2000-03 policy is higher than those living forever in 1974-79, but by less than would be implied by a seven-fold increase in π.[39] In these ways both crime entry (extensive margin) and repeat crime (intensive margin) offset the arithmetic impact of the increase in π on prison rates in the data.

6.4 Cohort Effects.

Cohort effects are another source of insight into how crime entry decisions and criminal persistence of those previously involved in crime each drive the dynamics of deterrence.

Figure 6.4 shows that the evolution of the incarceration rate is different for different age groups. The incarceration rate of young individuals rises the least and approaches the new steady state the quickest. The incarceration rate of the oldest individuals rises the most and approaches the new steady state the slowest. Middle-aged individuals are somewhere in between. This shows that the full deterrence impacts were realized quickly for the new cohorts but took until middle age and beyond for the cohort of initial young at the policy change, a result generated through the channels of criminal persistence present in the model.

These patterns are similar to the evolution of real age profiles of admissions in the data. Note that these are non-targeted statistics and so they also serve as a means of model validation. Figure 10(a) shows that admission rates stabilize for the younger cohorts before

[39] The data show a 2.8-fold increase.

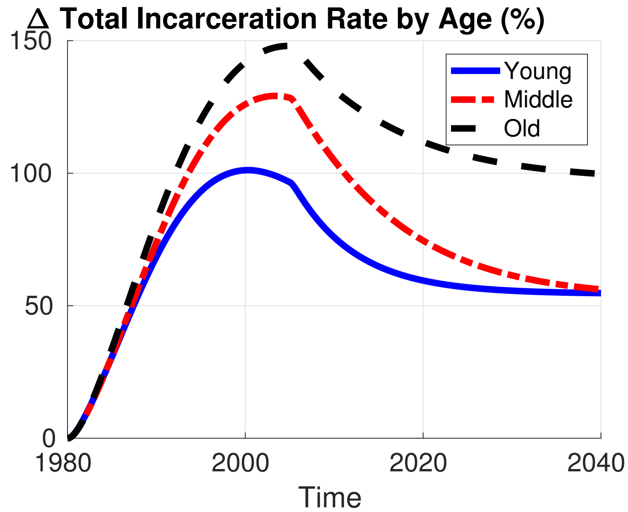
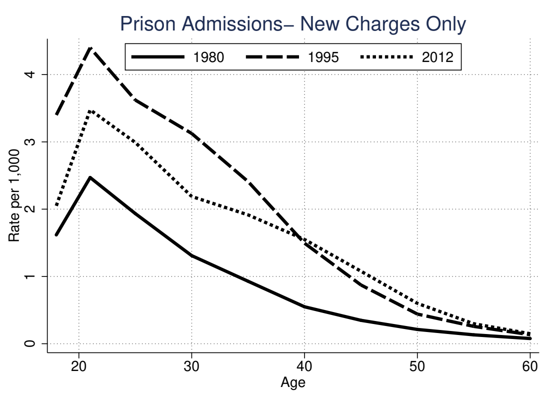
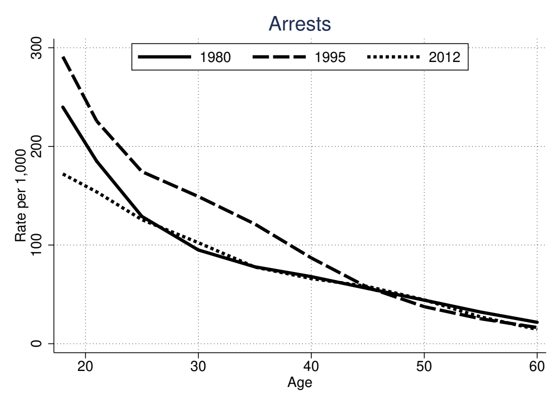


Figure 9: **Model Simulated Age Dynamics:** Incarceration rate across different age groups as deviations from the initial steady-state.

the older ones. Figure 10(b) shows the same qualitative feature in arrest data suggesting this is due at least in part to actual offending and not entirely due to how the justice system translates arrests to admissions.



(a) New Prison Admission Rate by Age



(b) Arrest Rate by Age

Figure 10: **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

While these figures suggest that cohort effects are present in the data, they also demonstrate the difficulty of estimating these effects in a reduced form way. Not only are there obvious age and time effects in crime and imprisonment, the shape of the age curves can be changing over time as well with older individuals having a higher imprisonment rate relative to the young in the new, more punitive steady state. We can, however, cleanly disentangle these effects in our structural model through the following exercise. In the model, a cohort is essentially a distribution of agents across states at each age that is shaped by that cohort's unique history. To remove this history, we construct a counterfactual transition where each period the economy immediately jumps to its new steady state stationary distribution. Figure 6.4 compares the evolution of prison admission in the model with and without cohort effects.

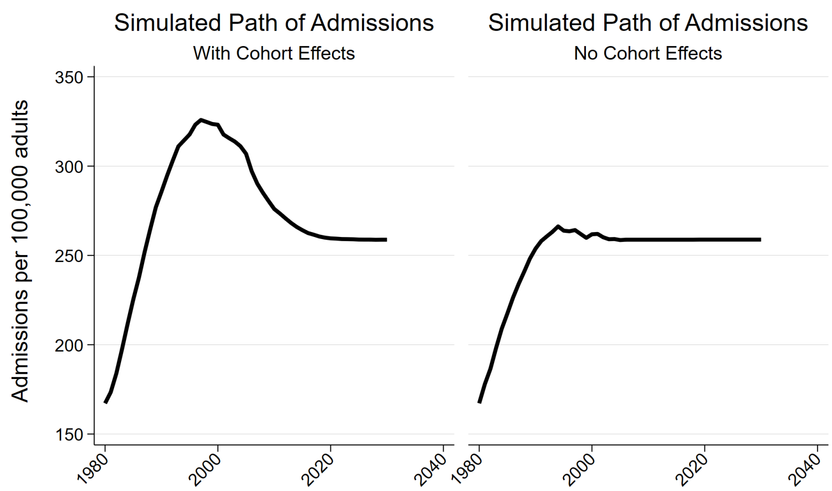


Figure 11: **Simulation with and without Cohort Effects:**

These results emphasize that the collateral costs of the change in policy are borne unequally across cohorts. Collateral costs of the prison system include costs released inmates face upon re-entry as well as the costs their families and communities face during and following their imprisonment. While our theory is not the only one that can generate cohort effects, other explanations for why the 1960s cohorts have uniquely high crime and incarceration rates – such as the lead hypothesis, trailing the baby boomers, or being the right age to enter the crack trade – point to temporary impacts affecting a single cohort. In contrast, the idea that these cohort effects are driven, at least in part, by a permanent shift in policy uniquely implies permanent changes to the age profile when criminal behavior is persistent. It predicts that even later-born cohorts with less overall crime in their lifetime should see increased crime and incarceration at older ages, relative to when they are young. In other words, our theory generates unique predictions for the intensive and extensive margins of crime both in the cross section and over the lifecycle.

6.5 Individual versus Firm Responses

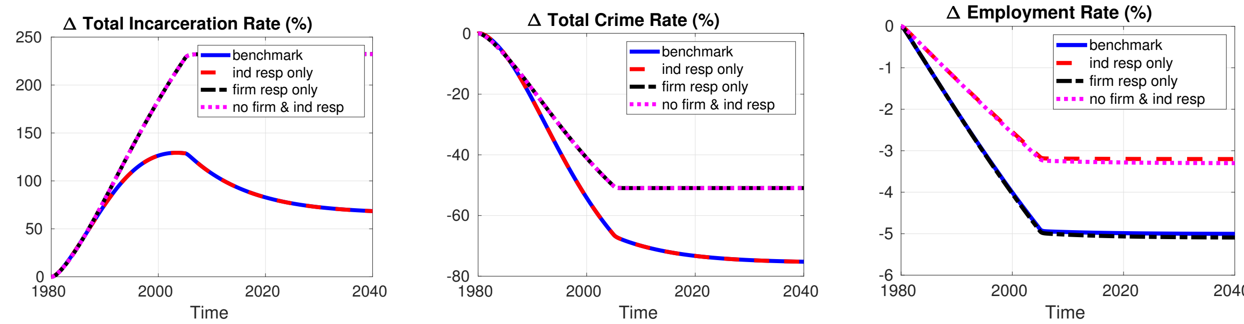
Changes in variables are an equilibrium product of both individuals' and firms' responses to punitive policy. The response of individuals is simple. Every individual decreases their crime search when the probability of incarceration for a crime rises. Quantitatively, changes in the policy function of individuals decrease overall criminal propensity by 75% in the new steady state. The remainder is a product of the changing distribution of agents across states and changes in the aggregate state, labor market tightness. Figure 4(a) shows employed individuals reduce their crime probabilities by around 75% in response to the policy change.[40]

The only choice of a firm is whether to create a vacancy. This choice responds directly to punitive policy. All else equal, an increase in the probability of prison for a crime reduces the expected duration of a match with a worker and lowers a firm's value of creating a vacancy. This choice also responds to policy indirectly through how it changes individual's crime choices and the distribution of individuals. We have shown that both of these factors improve on average. Everybody chooses less crime, and the distribution averages higher human capital and lower criminal capital. All of these factors improve a firm's value of creating a vacancy. We find that the direct impact of stricter policy dominates the indirect impacts of individuals' response and distribution resulting in lower market tightness for both job seekers with a prison record and those without.

Changes in market tightness can also feed back into criminal behavior and incarceration rates. We run three counterfactuals to quantitatively decompose how much of the firms' response is due to the policy directly and how much is due to changes in individuals' behavior, and to measure how much each piece affects crime, incarceration, and labor markets. Figures 12(a)-12(c) breaks down the benchmark transition into a counterfactual transition where only the policy function of individuals changes, a counterfactual transition where only the vacancy creation of firms changes, and a transition where neither change occurs (just a pure arithmetic impact of the policy).

In the last of these scenarios, incarceration follows the increase in π. Why then does crime fall when we omit the deterrence provided by changes in individual policy functions? This is due to the incapacitation effect of higher prison rates. Putting more of the most criminally active people in prison mechanically reduces crime. Comparing the pink dotted line to the benchmark shows that around half of the decrease in crime is from incapacitation and half from deterrence (adding in the response of individuals' crime policy). Higher π also mechanically reduces the employment rate both through incapacitation and through higher churn of workers through prison to unemployment; it takes them time to find a new job.

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



(a) Incarceration (b) Crime Rate (c) Employment

Figure 12: **Transitional Dynamics: Policy Decomposition:** The figures show the decomposition of incarceration, crime, and employment along the transition. The solid line is the benchmark economy. The dashed line is the economy when firms keep the same job creation level. The long dashed line is the economy when individuals keep their criminal policy as in the first steady-state. Lastly, the dotted line is the economy when firms keep the same job creation level, and individuals keep their crime choices as in the first steady-state.

The response of firms alone, shown in the black dashed line, has virtually no impact on crime and incarceration. This is not because firms don't respond; we have already shown vacancies and market tightness fall across the board. It is because crime is highly concentrated in individuals whose criminality responds little to changes in market tightness or employment status.

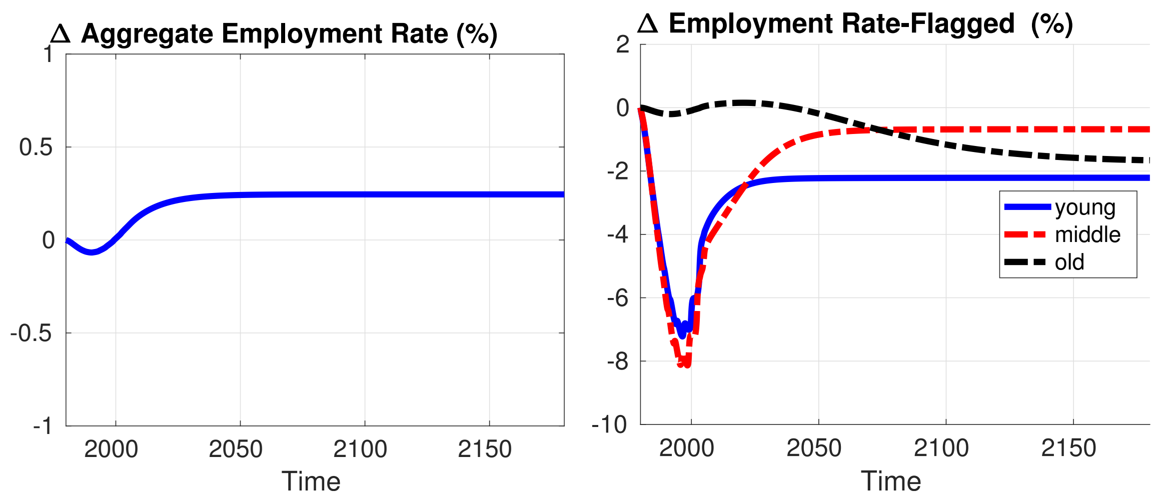
Figure 12(c) shows that the firm response dominates in providing outcomes in labor markets. Without the firm response, the employment rate is reduced only by the higher share of the population in prison, but this is just 0.6% of the total population.

6.6 Incarceration Policy, Labor Markets, and Inequality

Punitive justice policy has frequently been cited as a potential contributor to the stalling in the closure of Black-White employment and income gaps beginning in the 1970s. While our model does not have race, it makes two clear predictions: moving towards more punitive policy has a small impact on aggregate employment but increases inequality in employment and income.

To analyze only the effects of punitive justice policy, we shut down all other transitional shocks and feed in only the change in the arrest probability. Figure 13(a) shows policy changes in isolation had near zero impact on aggregate employment in the short run and can be expected to increase employment-to-population by around a quarter of a percentage point in the long run. This is because employment for people without prior incarceration, the majority of the population, does not to change significantly. None-the-less, the effect on individuals with a criminal record is substantial. Figure 13(b) shows the employment of the young and middle-aged with criminal records falls by 7 and 8 ppt, respectively in the short run. These declines partially recover in the long-run but the middle-aged gap remains 2 ppt larger than before the policy change.

To compute the causal impact of the policy on earnings in the model, we run a simulation where π, the market tightness, and the initial distribution of individuals are fixed at the final steady state equilibrium but nobody actually goes to prison. We compare the same individuals in this world to themselves in the baseline and find the ones going to prison in the baseline earn 16%, 6.5%, 3.2%, 2.4% and 2.3%, respectively, in the first 5 years after they are released from prison than compared with their earnings paths in the counterfactual world. This is a little less than the causal estimate of prison on earnings of 13% less over five years found in Garin et al. (2024).



(a) Aggregate Employment (b) Employment of Those with Criminal Records

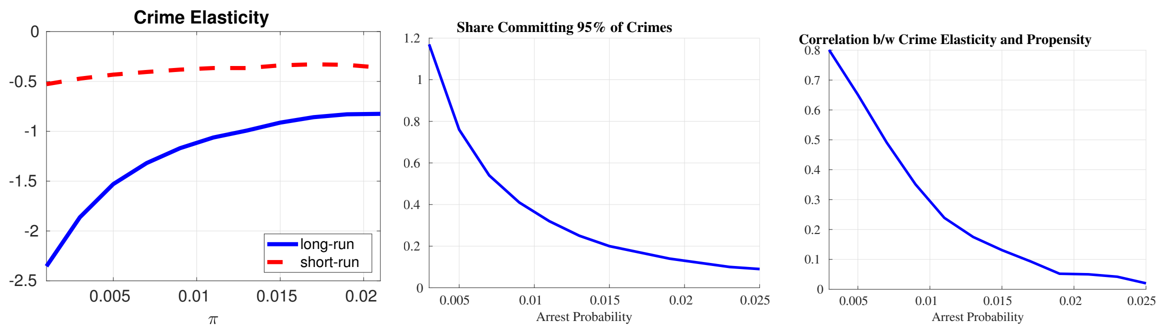
Figure 13: **Employment Impacts of Policy Change:** The figures show the evolution of employment rates generated by changes in π alone. The left panel is for aggregate employment and the right panel is for employment on those with a criminal record. All are changes in percentage points relative to the initial steady-state level.

6.7 The Importance of the Initial Steady State.

So far, we have taken a deep dive into the mechanisms that determine how crime and incarceration unfold over a transition following policy changes of magnitudes that comport with the 20th century U.S. prison boom. Yet, our structural approach allows more general lessons to be learned about how changes in punitive policy are likely to unfold. The most important lesson is that the elasticity of crime and incarceration in the short and long run–

that is, the response of crime and incarceration to a marginal change in the probability of incarceration– depends on the initial steady state from which the policy is tightened.

Figure 14(a) plots the short-run and long-run elasticities across a range of initial values of π.[41] The short-run elasticity is defined as the percentage change in the crime rate in the first year following a one percentage point unexpected and permanent increase in π. The long-run elasticity is defined as the percentage change in the crime rate between steady states in response to a one percentage point higher π.



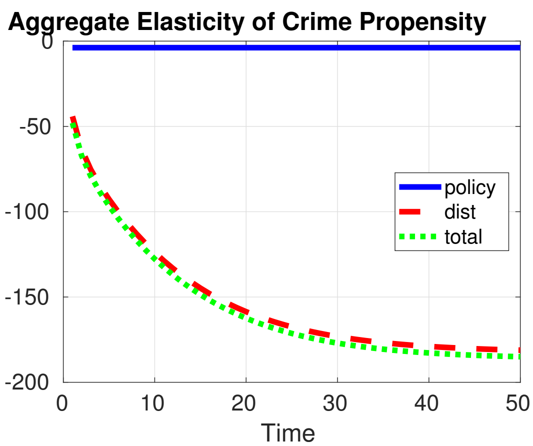
(a) Crime Elasticity (b) 95% Share (c) Correlation

Figure 14: The figures plot statistics across economies with different arrest probabilities in the initial steady-state. The figure on the left plots the aggregate crime elasticity in both the short-run and the long-run. The middle figure plots the share of individuals committing 95% of crime across economies. The figure on the right plots the correlation of individual level crime elasticity and the crime propensity

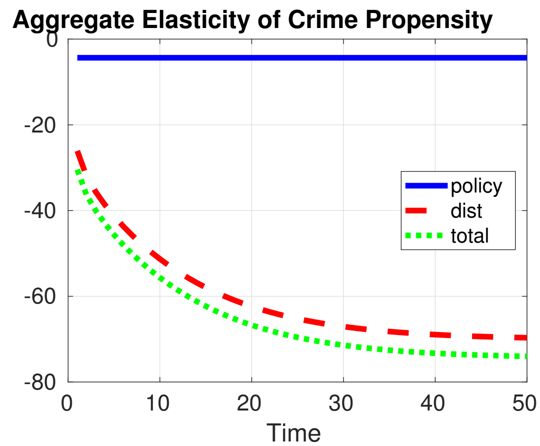
As the arrest probability increases, the share of individuals responsible for 95% of crimes decreases from 1.2% to less than 0.1%, as shown in Figure 14(b). Moreover, a higher arrest probability reduces the correlation between crime propensity and crime elasticity, as illustrated in Figure 14(c), which plots the correlation between individual-level crime elasticity and crime propensity. Together, these figures highlight that more punitive policies concentrate crime among a smaller group of individuals with lower crime elasticity, thereby reducing the aggregate crime elasticity.

Long-run elasticities are consistently larger than short-run elasticities, with the difference being most pronounced at lower initial levels of π. In fact, under more lenient regimes, the long-run elasticity can be nearly five times greater than the short-run elasticity. More punitive policies not only lead individuals to immediately reduce their criminal activity but also play a crucial role in deterring the young from committing their first crime. This reduction in criminal entry lowers the accumulation of criminal capital in new cohorts and leads to a distribution of types that engage in less crime. This dynamic distinguishes the slow-moving component of deterrence—captured by the long-run elasticity—from its immediate

[41] To better isolate the effects of incarceration policy, we only feed the change in the arrest probability along the transition. The main message of this section does not change if we also introduce the other shocks.



(a) Low



(b) High

Figure 15: The figures plot the decomposition of aggregate crime elasticity. The arrest probability in the initial steady-state is 0.3% in the figure on the left and 2.5% in the figure on the right.

counterpart, the short-run elasticity. To better understand how initial arrest probabilities shape this difference, we decompose crime elasticity into two components: (i) changes in the policy function, and (ii) changes in the distribution.

Note that aggregate crime in any period is given by $C_t = \sum_\theta s_t(\theta) \Gamma_t(\theta)$, where $s_t(\theta)$ is the crime search of type-θ individuals and $\Gamma_t(\theta)$ is the measure of type-θ individuals at time t. Then, crime elasticity between period 0 and period t can be written as:

$$\frac{\frac{C_t - C_0}{C_0}}{\pi_t - \pi_0} = \frac{1}{C_0(\pi_t - \pi_0)} \left[\underbrace{\sum_\theta (s_t(\theta) - s_0(\theta)) \Gamma_0(\theta)}_{\text{policy}} + \underbrace{\sum_\theta s_t(\theta) (\Gamma_t(\theta) - \Gamma_0(\theta))}_{\text{distribution}} \right] \tag{8}$$

Figures 15(a) and 15(b) present the decomposition of aggregate crime elasticity into its two components. Figure 15(a) shows the decomposition when the initial steady-state arrest probability is 0.3%, corresponding to the benchmark economy, while Figure 15(b) illustrates the same decomposition at an initial arrest probability of 2.5%. Both figures underscore the critical role of the distribution—a slow-moving component—in driving the gap between short-run and long-run elasticities. However, as the arrest probability rises and crime becomes increasingly concentrated among a smaller group of individuals with lower crime elasticities, changes in the distribution diminish, leading to a smaller difference between short-run and long-run elasticities.

This exercise shows that public policy evaluators should consider how a program or law separately affects crime entry and repeat offenders. Each effect carries independent information to evaluate the total long-run impact when only short-run information is available.

7 Alternatives to Criminal Capital

Criminal capital is a modelling tool that provides the persistence in criminal activity not accounted for by other features of the model, particularly labor market-related factors. It critically enables the model to match the intensive and extensive margins of crime in the population, and the hump-shaped cohort effects we identified along the transition to a more punitive incarceration policy. In this section, we show that several alternative modelling assumptions are incapable of matching these features of the data as well as criminal capital can. We give each alternative the best shot possible by re-calibrating all parameters each time to best match initial targets. We also re-calibrate the shocks along the transition each time in attempts to match the evolution of incarceration rate and employment rate as we have done in the benchmark model.[42]

We remove criminal capital from the benchmark in the first experiment. Each subsequent experiment adds other features.

No Criminal Capital. Without criminal capital the model does not generate the concentration of crime in a few individuals with high recidivism, as in the data. The best fit one-year recidivism rate of this model is 0.5%, compared with its data counterpart of 19.9%. In the model only 7.8% of the criminals are among the repeated offenders, whereas the data counterpart is 64.2%. Simply put, crime is too widespread when considering pecuniary factors alone. Cohort effects are monotone along the policy transition.

Higher Human Capital Depreciation for High Criminal Capital Types. The model with higher human capital depreciation for the high criminal capital types slightly improves the match but still produces crime that is far too widespread and a recidivism rate that is far too low. The one-year recidivism rate is 1.1%, and the share of repeated offenders among criminals becomes 10.6%. Cohort effects are again monotone along the policy transition.

Better Opportunities for the High Criminal Capital Types. A version with a higher crime reward for high criminal capital types also fails in matching the intensive and extensive margins of crime. The one-year recidivism rate is 0.1%, and the share of repeated

[42] We briefly explain these alternatives below and refer readers to the Online Appendix for a detailed explanation of each calibration.

offenders among criminals as 3.9%. Cohort effects are monotone along the policy transition.

Higher Arrest Probability for the Incarcerated. The model with higher arrest probability for the incarcerated also fails to match the recidivism rate and the share of repeated offenders among the criminals. The model generates one-year recidivism rate of 0.5% and share of repeated offenders among criminals as 13.3%. Cohort effects are also monotone along the policy transition as in the other versions of the model.

Ex-ante, Permanent Heterogeneity in Criminal Capital. This model is the next best after the benchmark in replicating the initial steady state targets but does not provide cohort effects in the transition.

This exercise revealed the key modelling features required to match the data targets. First, criminal capital that is orthogonal from human capital is key to decoupling the otherwise strong relationship between labor market factors and criminality. This is important because the relationship between these factors is weak in the data. Second, the punishment for crime, including labor market scarring through human capital depreciation, cannot be too costly. If the costs are too large, the model requires crimes to arrive infrequently but with a high reward that almost all agents would take. This effectively matches the crime rate in the data with a near exogenous shock, causing the model to miss the concentration of crime in fewer serial criminals.

8 A Comparison to Violent Crime

The dynamics of violent crime provide an example of the breadth of applications of this theoretical framework.[43] We re-calibrate the model using targets from our criminal justice data limiting our sample to those who's primary offense was a violent one. Table 9 and Table 10 summarize notable differences between the violent and property crime calibrations. It also shows the model is capable of replicating targeted moments of violent crime.

While the targeted moments may not appear to be very different, the model predicts violent crime is far more inelastic than property crime to changes in the incarceration probability π. The difference in elasticity between crime types is larger when starting in lax regimes (low levels of π). The crime entry decision is key to why violent crime has a lower elasticity to policy than property crime has. Violent crime has a recidivism rate that is two-thirds that of property crime, which leads to a higher share of crimes committed by first time offenders.

[43]Replications of all tables and figures located in this text for the case of violent crime are available in the Online Appendix.

Calibrated Parameter Values			
Parameter	Explanation	Value	
	n	Property	Violent
ξ^{lc}	crime search cost-low criminal	996540	332448
ξ^{hc}	crime search cost-high criminal	0.05	9.98
ζ^{3}	rehabilitation shock	0.95%	0.85%
ν	prob of being high criminal	0.10	0.95
μ^{k}	mean crime reward	2.15	2.47

Table 9: Calibration to Violent Crime, with Comparison to property crime.

Targeted Moments and Fit			
Moment	Data	Model	Property Crime
Incarceration - young and middle	0.44%	0.45%	0.59%
Incarceration - old	0.09%	0.09%	0.09%
Recidivism rate (1 year)	13.5%	13.8%	19.5%
Criminal with prior	53.7%	50.5%	64.9%
Incarcerated by age 35	1.5%	1.47%	2.47%

Table 10: Model fit, with comparison to property crime.

Punishment is also higher for violent crime: the probability of incarceration is higher, and prison spells last longer. This leads the calibration for violent crime to choose much lower cost of crime search and higher crime reward than property crime. With such a calibration, the majority of individuals take a crime opportunity when it arrives, versus more discretion, for the lower rewards for property crime. In this sense, violent crimes look like "crimes of passion" that are relatively inelastic to individual characteristics and, subsequently, policy.

9 Conclusion

We argued that dynamics are critical when evaluating changes in punitive incarceration policy, because of criminal persistence. The majority of felonies in the United States involve individuals with prior criminal records, whose crime choices are less elastic to policy changes than the choices of those without records. The deterrent impact of more punitive incarceration materializes gradually and is strongest for crime entry margins pertaining to young and new generations. We presented novel empirical evidence on cohort effects consistent with this idea.

The dynamic model developed sheds further light on the sources of criminal persistence. It replicates salient features of criminal behavior that pecuniary motives alone could not explain: high recidivism rates, even among the employed and elderly, and cohort dynamics following the 1980s policy changes. We learned that unemployment and low human capital are instrumental in the choice to engage in crime, but criminal capital and, to a lesser extent, employment discrimination drive persistence after youth. Cumulatively, most crime is committed by a few individuals with lengthy criminal records, for whom pecuniary factors provide little deterrence.

In analyzing the impact of increased punitive incarceration akin to 1980s policy changes, we arrived at two substantive conclusions for property crime. First, the change in incarceration policy alone was a minor contributor to trends in low-skilled labor markets and aggregate incarceration from 1990 onward but a major contributor to crime reduction and increased inequality within low-skilled populations. Second, the transition after a policy change follows nuanced, multi-decade dynamics. Immediate incapacitation of the most active criminals drives initial incarceration increases. Subsequently, individuals cycling through prison re-enter the population with worsened labor market prospects and higher criminality. Full deterrent effects manifest only as new cohorts are born under the new policy, who choose lower crime and higher labor force attachment from youth. Applying the model to violent crime yields contrasting results, as it is less persistent and less elastic to policy changes, responding less but more immediately, with near-zero cohort effects.

While far from the final word on these important issues, we argue that dynamics should be addressed in future work. Interpretations of econometric inference should consider that short-run policy effects can differ dramatically from long-run effects, as demonstrated. Our structural model complements econometric inference by interpreting short-run effects to predict dynamic paths. Considering dynamics also introduces opportunities to improve policies. When crime is more persistent, as with property crime, crime reduction immediately after a policy change comes almost entirely from incapacitation effects, while deterrence effects on crime entry build over time. These conclusions should encourage the study of dynamic punitive policies specifying paths for multiple levers: the probability and duration of incarceration, as well as differential penalties for new and repeat offenders.

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