ONLINE APPENDIX: Dynamics of Deterrence: A Macroeconomic Perspective on Punitive Justice Policy

1 Datasets and Variable Construction

The empirical counterpart to incarceration in the model is incarceration in a state or federal prison. Convictions resulting in state or federal imprisonment are typically serious felonies with a sentence of a year or more. We treat the crime data similarly and focus on serious crimes that would likely be charged as felonies. When measuring admissions we exclude, where possible, admission due to a parole or probation violation; a transfer; a return escapee; or those incarcerated in prisons without a conviction (often immigration violations which have an increasing trend of their own).

1.1 National Corrections Reporting Program (NCRP).

Prison admissions, stocks, and sentence lengths are computed using a panel from the National Corrections Reporting Program (NCRP, accessed through ICPSR United States Department of Justice. Office of Justice Programs. Bureau of Justice Statistics (2013)). The NCRP is a restricted access offender-level administrative dataset set maintained by the Bureau of Justice Statistics. Detailed tabulations on prison admission, release, parolee, and prison stock data are reported to the Department of Justice by individual states. We clean the NCRP data by the following criteria. First, we restrict the sample to states meeting internal consistency checks and data completeness requirements from the audit study of Neal and Rick (2014).[1] Next, we include only states that have a consistent time series from 1985-2016; and consistently report the category of offense and whether it was a new court commit.[2] This leaves us with a sample consisting of 17 states: California, Florida, Georgia, Illinois, Kentucky, Michigan, Minnesota, Missouri, New Hampshire, New Jersey, New York, North Dakota, Ohio, South Carolina, Utah, Virginia, and Wisconsin. Trends in this sample of states follow similar broad trends as estimated by the Bureau of Justice Statistics for the nation (see Figure 1) and account for 42-60% of total national admissions over the time period.

Gender and birth date of each offender are fully reported across states with few missing cases. We restrict the sample to adult men only. Some states, however, have internally inconsistent age demographics in stocks and admissions. As a result, we drop Florida, Ohio,

[1] We depart from Neal and Rick (2014) in that we do not impute missing data on demographics and offense.

[2] Researchers interested in more recent data will find improved reporting with 38 states providing some kind of data after 2000.

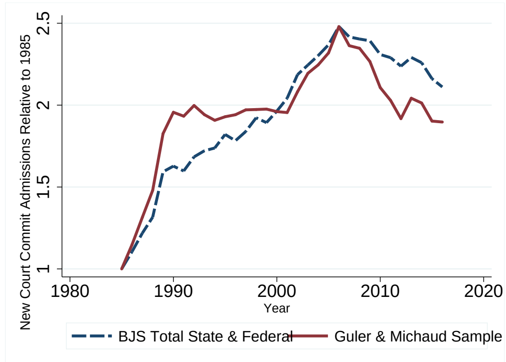


Figure 1: Total admissions count from new court commitments relative to total admissions counts from new court commitments in 1985 from each the National Prisoner Statistics (Bureau of Justice Statistics) and from our 17 state prison sample of NCRP micro data.

and Virginia when comparing outcomes by age or cohort. Education fields are frequently missing and therefore we do not restrict our incarceration sample by education.

The NCRP data are available starting in 1983. We drop 1983 and 1984 because of elevated occurrences of missing or incomplete data in these years. National estimates on male admissions and the male prison population for 1978 onward are published by the Bureau of Justice Statistics constructed from National Prison Statistics data.[3] These estimates do not, however, striate by offense type which is necessary for our analysis. We impute the time-series of admissions and stocks striated by type of crime for the years 1978 through 1984 under the assumption that the composition of offenses are unchanged between 1978 and 1985. In other words, we apply the shares of violent, property, and other crimes that we calculate from our 1985 sample to the national estimates from 1978-1984 to impute the years missing from the NCRP micro data. We remove years of data in the case that a State is missing data, has admissions under 50, or has a change in stock by over 50%. This amounts to 8 state-year observations. We impute the data for each of these years by linearly interpolating from the two adjoining years.

We append data from US Decennial Census and Current Population Survey (Census, accessed through IPUMS Ruggles (2004)) to calculate admission and prison population rates relative to a reference population. We define the reference population as males without a college degree age 18-35.

Offenses are classified into property, violent, and other according to given NCRP code categories.[4] Examples of violent crime include: murder, kidnapping, rape, robbery (armed

[3]These data are easily accessed using the Correction Statistical Analysis Tool (CSAT) at https://csat.bjs.ojp.gov .

[4]While prison admissions involving a drug charge have been the category with the largest expansion over the past 30 years, admissions with a drug charge represent less than 20% of admissions in 2010 and many

and unarmed), assault, and blackmail. Examples of property crimes include: burglary, arson, theft, and destruction of property. Crimes categorized as "other" include: drug trafficking, weapons offenses, obstruction, fraud, and tax and revenue violations. We categorize an individual as having one or more of each type of offense according to two metrics: (i) category of offense with the longest sentence only; and (ii) category of any offense with a sentence. The latter implies that a single admission can fall under multiple categories of crime if there are multiple offenses spanning more than one category. Note that the NCRP data only lists up to 3 offenses, prioritizing more serious offenses. This means that offenses such as trespassing or possession of drugs are likely to be omitted even if they add to total sentence length. Our main analysis in the text classifies a prisoner as having a property offense if they are charged with any property offense, and similarly for violent, but our discussion of crime specialization addresses most serious offense as well.

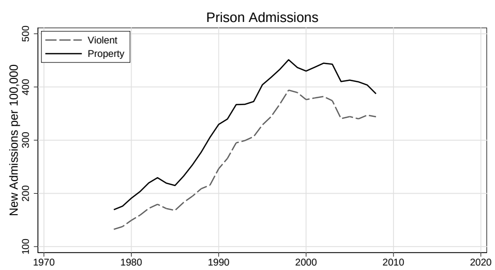


Figure 2: Admission rates for new convictions per 100,000 adults estimated from NCRP and Census data.

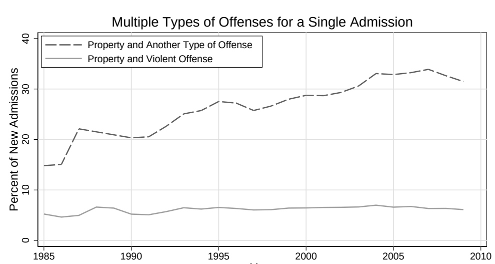


Figure 3: Percent of admissions for a property crime that include crimes in other categories (violent, drug, or other).

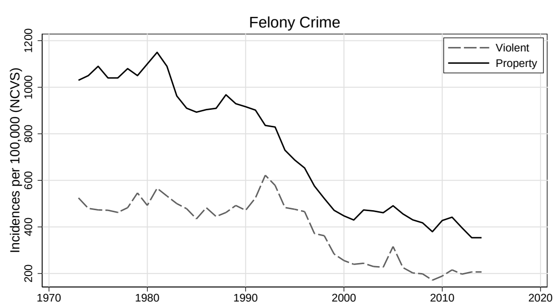
Prison duration is calculated to provide a stationary distribution in the initial calibration that replicates the stocks in the data given the admissions. The model imposes a constant hazard rate of prison exits, or a geometric distribution of prison lengths. The computed duration consistent with all of these features gives a median spell of 30 months in prison for

such admissions also include violent or property crime and these will be in our sample.[5]

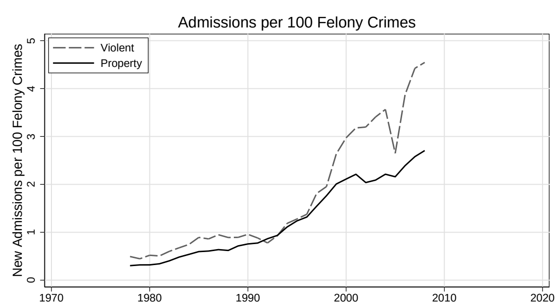
violent crimes and 10 months for property crimes. This duration is similar to Perkins (1992) who calculate a median spell of 27 months in state prisons for violent crimes and 12 months for property crimes in an analysis of BJS administrative survey data. We hold the median time served to be constant throughout our time-series analysis. This choice is consistent with the empirical findings of both Neal and Rick (2014) and Raphael and Stoll (2009).

1.2 National Crime Victimization Survey (NCVS)

Crime volumes are calculated using the National Crime Victimization Survey 1979-2020.[6] The NCVS is a nationally representative survey of respondents age 12 and older. The survey identifies respondents who have been a victim of crime within the past six months and asks further questions about the nature of that crime. We use incident-level weights to estimate national crime incidence by type of crime: property, violent, and other; taking only offenses that are likely to be charged as felonies. We take this as a measure of total crime of each type committed in the U.S. annually. We combine this with aggregated BJS data on prison admissions from the National Prison Statistics program and define the probability of prison admission conditional on crime by dividing the NCVS crime measure by the BJS prison admission measure.



(a) Crime



(b) Prison Admissions per Crime

Figure 4: Crime per 100,000 adults and prison admission rates per crime calculated from NCRP, Census, and NCVS data.

Caution must be used when comparing our estimates to others. For example, İmrohoroğlu, Merlo, and Rupert (2004), considered property crime alone and set their probability of apprehension to equal the clearance rate for these crimes and therefore find higher values than we do because they do not require the crime to be serious enough to result in imprisonment. It is also the case that papers that use UCR statistics will have lower levels of crime

[6]The NCVS includes all offenses reported to the survey whereas the Uniform Crime Report includes only crimes known by authorities. Further, we find a high incidence of missing offense codes in the UCR for our time period. For these reasons we use NCVS instead of UCR.

compared to the NCVS and therefore higher apprehension rates.

1.3 Survey of Inmates of State Correctional Facilities (Prison Survey)- 1974, 1979, 1986, 1997, 2004

The Survey of Inmates of State Correctional Facilities is a restricted-access, representative survey of inmates in adult correctional facilities. We use the 1979 survey consisting of approximately 12,000 inmates in 300 institutions for the initial calibration of the model. The calibration sample is restricted to male inmates entering the prison in the 1970's. All observations are weighted with frequency weights provided by the survey to construct a nationally representative sample. These weights account for non-response.

Targeted Statistics from the Prison Survey 1979				
		Violent	Property	All, Incl other
Prevalence of prison by age 35 (%)		2.4%	1.7%	
Employed Month of Crime (%)				
	Age 18-64	71.5	71.8	71.0
	Age 18-35	71.2	71.2	70.5
Unemployed Month of Crime (%)				
	Age 18-64	14.1	14.6	13.9
	Age 18-35	15.3	15.7	15.1
NiLF Month of Crime (%)				
	Age 18-64	14.1	13.2	14.7
	Age 18-35	13.4	12.8	14.1
Mean income if Empl				
	Age 18-64	27,029	26,413	27,264
	Age 18-35	25,786	24,980	25,934

Table 1: Source: BJS- Survey of Inmates of State Correctional Facilities 1979 series

These data include prisoner's responses to their labor market characteristics *at the time they committed the crime for which they are currently incarcerated for*. Table 1 provides mean the distribution of prisoners across labor market statuses striated by age and type of crime. Employed includes both part and full time. The general patterns are that there are little differences in the employment to population ratio across violent and property criminals but property criminals are more likely to be in labor force and have lower mean earnings conditional on being employed.

Table 1 also provides estimates of the extensive margin of crime: the percentage incarcerated for a crime by age 35. These estimates are constructed using the estimates of lifetime incidence of imprisonment in a Federal or State prison calculated in Bonczar (2003). The estimate of incidence of imprisonment by age 35 for each violent and property crimes is calculated by multiplying the lifetime incidence for males in Bonczar (2003) by the share of inmates whose most serious crime is violent or property, respectively. This calculation is consistent with our calibration strategy which assumes that first time admissions for individuals over 35 are zero. This choice is motivated by the estimates in Bonczar (2003) that the share first admissions after age 35 to be less than 5% of all admissions in 1979.

Current and Prior Admissions from the Prison Survey 1997			
Current Offense	First Timer	Prior Non-Violent	Prior Violent
Property	15.5	57.21	27.2
Violent	30.6	38.7	35.8
Drug	26.5	52.1	21.5

Table 2: Charges in multiple types of crime for different prison admissions. Note the question is asked slightly differently for violent crime, allowing a single individual to report both violent and non-violent priors, resulting in shares that add up to more than 100%.

Table 2 displays statistics related to the degree of criminal specialization over the life course. These statistics are calculated from the 1997 wave of the Prison Survey because this wave includes questions asking current prisoners about past offenses resulting in incarceration. There is some specialization. Prisoners serving time for a property offense are less likely to have a prior violent offense but specialization is far from complete. 27% of prisoners serving time for a property offense have served time in the past for a violent offense and 38.7% of prisoners serving time for a violent offense have served time in the past for a non-violent offense.

1.4 Recidivism of Prisoners Released Series, 1983 and 1994

The Bureau of Justice Statistics organized the compilation of data tracking three years of post-released outcomes for prisoners released in 1983 and 1994. These restricted data cover a representative sample of 16,000/272,111 released prisoners in 1983/1994 from California, Florida, Illinois, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, and Texas.[7] Prisoners in these states comprise approximately two-thirds of the prison population. The files have two layers of data. The first layer includes socio-demographic data and corrections records data at the time of inmate release. The second layer contains information on subsequent events over the three years after release including arrest,

[7] Arizona, Delaware, and Virginia were added in the 1994 survey, but we exclude them for consistent comparison across surveys.

imprisonment, and non-criminal data.

Our statistics for recidivism in the 2000's come from restricted micro-data we have obtained from the study: "Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida, 2004-2008". The study provides similar variables to the Recidivism of Prisoners Released Series for over 156,000 offenders released from the Florida Department of Corrections between 1996-2004. Outcomes for each released individual are available from state criminal records for 3 years following their release. We restrict our analysis to individuals admitted to prison after 2000 for comparability.

How does the Florida survey compare to the 1983 and 1994 surveys? Florida is consistently a top-3 state in number of state prison inmates accounting for 7-10% of the total national prison population but the survey covers only recidivism taking place within Florida. For this reason we would expect to under-estimate recidivism activities. However, a comparison of re-imprisonment rates over a three year time horizon with those reported for the 2005 Recidivism of Prisoners Released Survey are comparable: 36% from our sub-sample of the Florida data and 36.1% in the BJS report from the 2005 Recidivism of Prisoners Released Survey series. We cannot use the 2005 Recidivism of Prisoners Released directly because we were unable to secure access to the micro data but it seems our Florida sample is a reasonable substitute.

We are interested in a single dimension of recidivism most consistent with our model and measurements in other data sets: re-imprisonment for a new felony charge. Table presents trends in this statistic by the age partition used in our model.[8]

1.5 National Longitudinal Study of Youth 1979 (NLSY79)

We use data from the July 18, 2013 release of the NLSY79. The 1979 cohort of the NLSY consists of representative panel of 12,686 young men and women age 14-22 during their first interview in 1979. The timing of the study makes it appropriate to calibrate the initial steady state of the model to since we are targeting the late 1970's. Respondents were surveyed annually from 1979 to 1994 and biannually thereafter. The sample is restricted to Black or White males that do not have a college degree. The NLSY asks questions about crime and incarceration outcomes in both contemporaneous and retrospective questions. Within this sample, 19% report incarceration in jail or prison at some point in their lives.

[8] Caution must be used when comparing these data with the BJS summary papers on the surveys. Our analysis of the micro-data exactly replicates these reports when using the "Received" records from prisons/jails to identify re-incarceration. Using this measure we match their 40% 3-year recidivism rate for 1983 which breaks down to 51%/38%/29% for young, middle, and old respectively. However, this measure includes both jails which we are not considering in other datasets and includes re-confinement for violation of conditions of release, probation, or parole which we also do not model and do not include in the admission data from the NCRP data.

Age	1983		1994		2000-2003*	
	Violent	Property	Violent	Property	Violent	Property
6 months	7.9	11.9				
1 year	13.5	19.9				
2 year	19.3	27.1				
3 year	22.2	30.7				
4 year	23.7	32.5				
5 year	24.7	33.8				
	Total 3-year Recidivism					
18-24	41.2	64.0	37.8	41.0	40.7	48.8
25-34	26.2	32.6	31.9	40.3	33.4	49.6
35-64	13.9	27.0	25.1	35.6	21.8	44.3
Total (18-64)	22.2	30.7	34.0	39.3	32.6	47.7

Table 3: 3-year Re-imprisonment Rate on a New Felony Charge. *2000-2003: Florida only.

The NLSY data includes variables on both labor market outcomes and incarceration. Labor market variables, including labor force participation, employment and unemployment status, hourly wages, and job characteristics are available on a weekly frequency. In our model, all jobs are found through search and there is no intensive margin. Accordingly, we define employment in the NLSY sample as any non-self employed job worked a median of 35-100 hrs per week over the employment relationship. We match each job to its characteristics using the Employer History Roster. Hourly wage for each job in each week is also taken from the Employer History Roster.[9] We use CPI to calculate wages in 1987 dollars and exclude wages less than \$2.00 or greater than \$200.00 per hour as missing.

We construct a regression where the dependent variable is the natural-log of the hourly wage ($ln(w_{it})$). The regression includes $n_j = 2$ age group indicators to capture the typical life-cycle wage profile (A^j_{it}) which will be used to set transition probabilities and the grid shape for the employed. The regression also includes a quadratic transformation of the length of total non-employment over the past two years (N_{it}). This is motivated by the wage scarring literature showing persistent wage effects from periods of non-employment (Michaud (2018)). Finally, individual fixed (γ_i) effects are included to control for level differences across individuals as we are concerned with growth rates, not levels.

$$ln(w_{it}) = \alpha + \sum_j \beta^{Aj} A^j_{it} + \beta^N N_{it} + \beta^{N2}(N_{it})^2 + \gamma_i + \epsilon_{it}$$

We consider two variations on measures for the life-cycle: (1) age and (2) measured

[9] If a worker is employed in two jobs in the same week, we consider the longest held job.

experience (months of employment).[10] We also provide robustness as to the type of non-employment: (a) all non-employment spells aggregated; (b) non-employment and prison spells separated; (c) non-participation, unemployment, and prison spells separated. Table 4 shows the estimates and standard errors for each specification along with the persistence of the residual in the AR(1) corresponding to each specification.

	(1) Wagem_ b/se	(2) resid b/se	(3) Wagem_ b/se	(4) resid b/se	(5) Wagem_ b/se	(6) resid b/se
Age 25-34	0.1301		0.1290		0.1211	
	(0.00)		(0.00)		(0.00)	
Age 35-64	0.2140		0.2107		0.1982	
	(0.00)		(0.00)		(0.00)	
Non-Employed (mo)	-0.0044		-0.0047			
	(0.00)		(0.00)			
Non-Employed (mo)^2	-0.0000		-0.0000		0.0001	
	(0.00)		(0.00)		(0.00)	
Lagged Resid ln(wage)		0.9844		0.9844		0.9843
		(0.00)		(0.00)		(0.00)
Jail Last Yr			-0.0951		-0.0310	
			(0.01)		(0.01)	
Non-Participant (mo)					-0.0036	
					(0.00)	
Non-Participant^2					0.00005	
					(0.00001)	
Unemployed (mo)					-0.0075	
					(0.00)	
Unemployed (mo)^2					0.0002	
					(0.00)	
Constant	1.6647	0.0005	1.6721	0.0006	1.6795	0.0006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Individuals	1,262	1,262	1,262	1,262	1,262	1,262
Monthly Observations	182071	188364	182071	188364	182071	188364

Standard errors in parentheses

Non-employment, Non-participation, and Unemployment are total months in past two years.

Table 4: Wage Regressions table

Labor market flows are constructed at the weekly frequency with NLSY data. The states and flows are identified as follows. Employment is defined in the same way as described above for the Mincer regression. Non-employment is categorized into "unemployed"

[10]The data are censored with a maximum age of 50 on account of the single-cohort panel structure of the NLSY.

or "non-participant" according to a question asking the respondent's job search status. If the respondent has a job, but that job does not meet our requirement to be classified as "employed", we categorize the individual as "unemployed". We use the tenure variable to clean for spurious flows including transitory changes in hours that would move a respondent across states. If we see a switch from "employed" to any of our non-employment categories at time "t", we then check the tenure variable reported for the next 4 weeks. If we see the respondent becomes "employed" in the next four weeks and the tenure is greater than one month, then we count the individual as having had been continuously employed.

Status at $t-1$	Employed			Non-Employed	Unemployed	Non-Participant
Status at t	NE	U	N	E	E	E
By Age						
18-24	1.91	1.01	0.89	3.20	4.12	2.43
25-34	1.04	0.51	0.53	2.56	3.87	1.83
35-50	0.53	0.23	0.31	1.09	1.89	0.75
Total (18-50)						
Never Incarcerated†	1.05	0.54	0.51	2.81	3.82	1.94
Incarcerated w/in last year‡	3.06	1.18	1.88	1.21	2.33	0.97
Total	1.19	0.59	0.60	2.44	3.54	1.67

† Never observed as incarcerated in entire sample: age 14-19 to age 50.

‡ We have 36,002 observations of employment status for 257 individuals incarcerated within a last year.

Table 5: Weekly Employment Transition Rates

2 Computational Appendix

2.1 Computational Algorithm for the Stationary Model

The state variables of the value and policy functions are human capital, crime capital (low and high), labor market status (incarcerated, unemployed and employed), prison flag and age (young, middle and old). We discretize the human capital into 21 grid points and approximate the age and labor market status dependent human capital process using Tauchen's method. The equilibrium objects are the market tightness for each age and prison flag, θ_{km}, individual value function, V_p, V_u, V_e, firm value functions, J_f, V_f and stationary distribution, Γ.

- Make a guess on the market tightness, , θ^0_{km}.
- Given the market tightness, compute the job arrival rates, λ_w^{km}, and worker arrival rates, λ_f^{km} using equations 4 and 5

- Iterate on the value functions V_p, V_u, V_e, and J_f, until convergence using equations 1-7. This step will also yield the decision rules and policy functions

- Using the individual decision rules and policy functions, iterate the distribution until convergence

- Given the stationary distribution and firm's value function, compute θ^1_{km} using equation 7

- If $\max_{k,m} |\theta^1_{km} - \theta^0_{km}| < \epsilon$ stop. Otherwise, update $\phi\theta^0_{km} = \theta^1_{km} + (1-\phi)\theta^0_{km}$ where $\phi = 0.8$, and return to step 2.

2.2 Computational Algorithm for the Transitional Model

We set the transition period $T = 15600$ corresponding to 300 years. Parameters that change along the transition are the incarceration probability, π, mean of the crime reward distribution, μ^k, and the individual productivity, z. These transitions are introduced as linear changes over 30 years, and each gradual change is introduced as surprise and permanent.

Given these assumptions, the transition of the model is solved as follows:

- Solve the initial steady-state of the model as in 2.1. Store the initial distribution as μ^0

- Solve the final steady-state of the model as in 2.1. Store the final steady-state value functions.

- Make a guess on the market tightness along the transition $\theta^{t,0}_{km}$ for all $t \in [1, T]$.

- Given the market tightness, compute the job arrival rates and worker arrival rates along the transition.

- Starting from the last period, compute the value functions iterating on the value functions as in 2.1 until the first period.[11]

- Given the value functions and decision rules, iterate on the distribution starting from μ^0.

- Given the distribution along the transition and the firm's value function, compute the updated market tightness, $\theta^{t,1}_{km}$

- If $\max_{k,m,t} |\theta^{t,1}_{km} - \theta^{t,0}_{km}| < \epsilon$ stop. Otherwise, update $\phi\theta^{t,0}_{km} = \theta^{t,1}_{km} + (1-\phi)\theta^{t,0}_{km}$, and return to step 4.

[11]Here we do not use the next period value functions since we assume all the changes along the transition are introduced unexpectedly and as permanent.

2.3 Estimation

The estimation procedure is a mixture of Simulated Method of Moments and Indirect Inference. There are 12 parameters to be estimated in the model. The details of these parameters are explained in the Calibration section of the main text. We denote $\Upsilon = \{\eta^1, c, \delta, \mu^{e,2}, \mu^{e,3}\mu^{u,1}, \zeta^3, \rho_h, \sigma_h, \nu, \eta_a^{1,hc}, \mu^k\}$ as the set of these parameters. We estimate these parameters by minimizing equally weighted square of percentage distance between model simulated moments and data moments. Denoting Ω_M as the model generated moments and Ω_D as the data moments, Υ solves:

$$max_{\Upsilon} \left(\frac{\Omega_M - \Omega_D}{\Omega_D}\right) W \left(\frac{\Omega_M - \Omega_D}{\Omega_D}\right)^T$$

where W is the identity matrix. The construction of the moments is explained in the Calibration section of the main text. Some of these moments are generated by running the same regression both in the real-life data and model simulated data.

2.4 Sensitivity of Moments to Selected Parameters

There is no analytical mapping of the parameters to the model moments. In Section 4.3, we discuss how the parameters are identified through the selected moments. In this section, we graphically show how certain parameters are linked to certain moments following that discussion.

Although each parameter affects all the moments calibrated, certain parameters have stronger effects on certain moments. Figure 5 plots the sensitivity of crime related moments to the crime related parameters that affect the moment strongest. In each plot, the dot shows the calibrated value of the parameter, and the line shows the change in the corresponding moment to the change in the selected parameter. The figure highlights the monotonic and strong relation between each of the parameter and the corresponding moment.

Figure 6 plots the same sensitivity analysis for the labor market related moments and parameters. Again, each of the moment is strongly and monotonically related to the corresponding parameter. Although this is not a formal proof of global identification of the parameters, the monotonic relations that exist between the model parameters and certain moments indicate local identification of the parameters.

2.5 Calibration of the Model with Violent Crime

We use the same externally set parameters as in the benchmark model as none of these parameters is specific to the type of crime. The only externally set parameter change is the

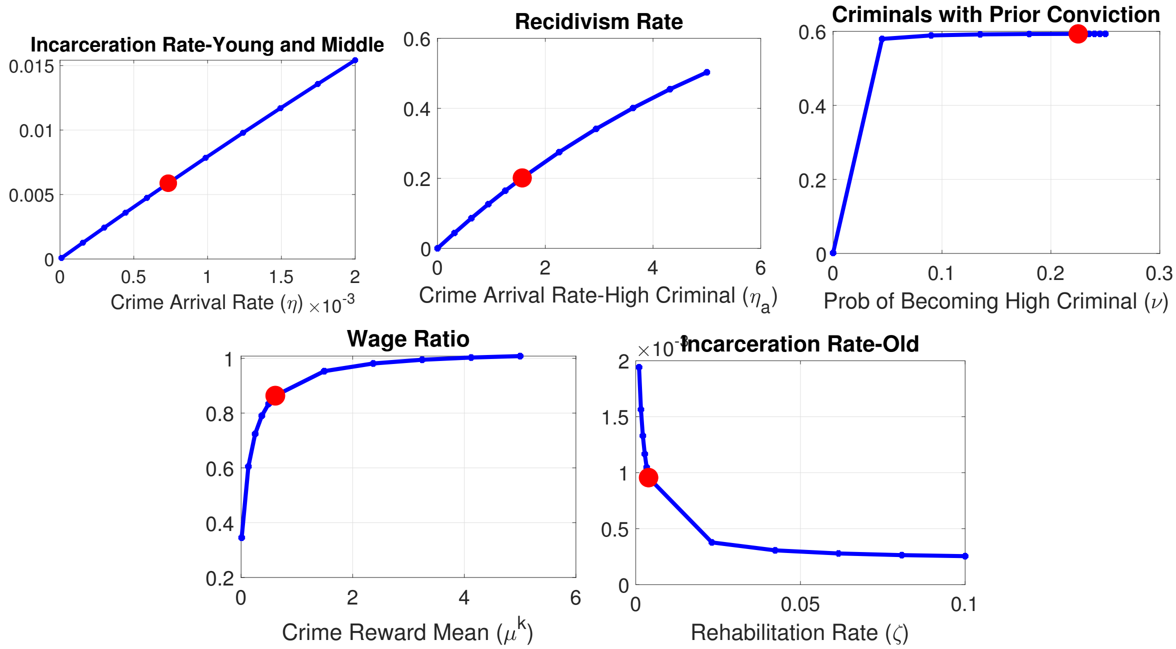


Figure 5: **Crime Related Moments:** The dot shows the calibrated value of the parameter.

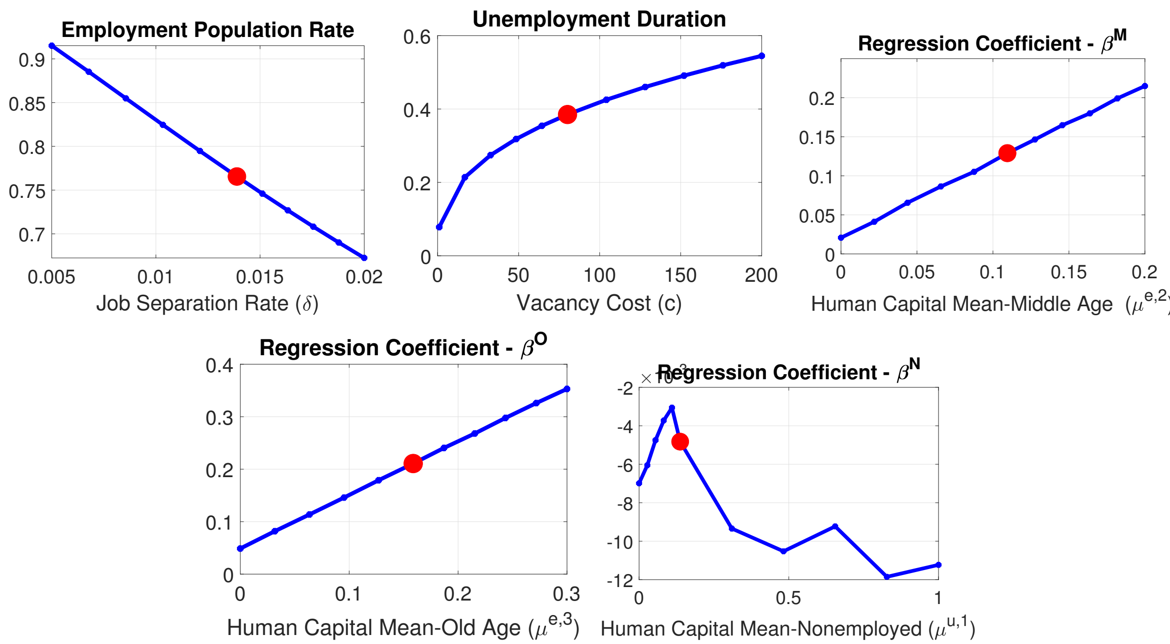


Figure 6: **Labor Market Related Moments:** The dot shows the calibrated value of the parameter.

arrest probability. Similar to the property crime, this value is estimated from NCRP's NPS restricted micro-data to the reported crimes estimated from the National Crime Victimization Survey (NCVS) for 1979-1980. For property crime, it is calculated as 0.3% whereas for violent crimes it is 0.5%. The rest of the internally calibrated parameters is listed in Table

6. Table 7 shows the performance of the model in matching the moments targeted.

Table 8 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. Table 9 shows the elasticity of crime to several observables computed from a linear regression of probability of crime as a function of model state variables. See the main text for further explanation.

Parameter	Explanation	Value
η^1	crime arrival rate	0.05%
c	vacancy cost	68.84
δ	separation shock	1.36%
$\mu^{e,2}$	human capital mean-middle employed	0.07
$\mu^{e,3}$	human capital mean-old employed	0.06
$\mu^{u,1}$	human capital mean-nonemployed	0.39
ζ^3	rehabilitation shock	0.35%
ρ_h	human capital persistency	0.94
σ_h	human capital shock std	0.25
ν	prob of being high criminal	0.15
$\eta_a^{1,hc}$	high criminal crime arrival rate	0.65
μ^k	mean crime reward	1.44

Table 6: Calibrated Parameters - Violent: The Table shows the internally calibrated parameters of model with only violent crime.

Moment	Data	Model
Incarceration - young and middle	0.44%	0.44%
Incarceration - old	0.09%	0.09%
Unemployment duration	20 weeks	20 weeks
Employment rate - young and middle	76.2%	76.9%
Recidivism rate (1 year)	13.5%	13.4%
Wage Ratio (criminals vs non)	87.7%	87.7%
criminal with prior	53.7%	54.7%
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 with only violent crime.

Table 7: Model Match

2.6 Steady-State Results with Violent Crime

Figures 7 and 8 plot the comparison of both steady-states for the crime probabilities along the human capital, criminal capital and employment status. Table 10 compares both steady-

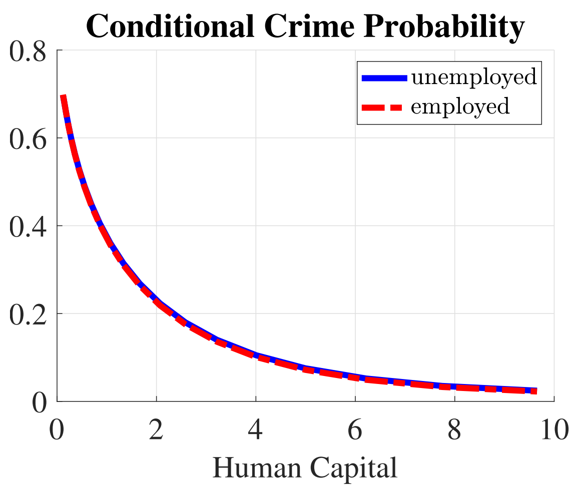
	Criminals	Overall
Employment rate	75.6%	76.9%
Human capital	0.97	1.18
Prison Flag	54.7%	1.5%
Young and middle population	74.1%	34.0%

Table 8: Characteristics of Criminals

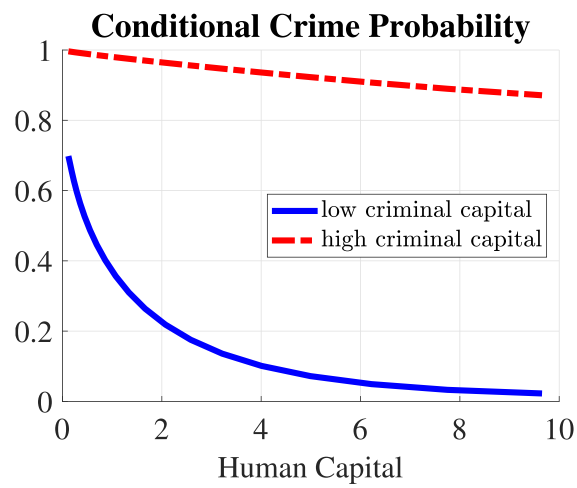
	Estimate	SE	tStat	pValue
Age 25-34	0.07	0.01	14.27	0.0
Age 35-50	0.23	0.01	56.19	0.0
Prison Flag	0.08	0.01	6.32	0.0
Employed	-0.003	0.003	-0.83	0.41
ln(wage)	-0.12	0.0	-65.48	0.0
Constant	0.25	0.01	55.1	0.0

Table 9: Crime Elasticities

states along several moments.



(a) Labor Status



(b) Criminal Capital

Figure 7: **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.

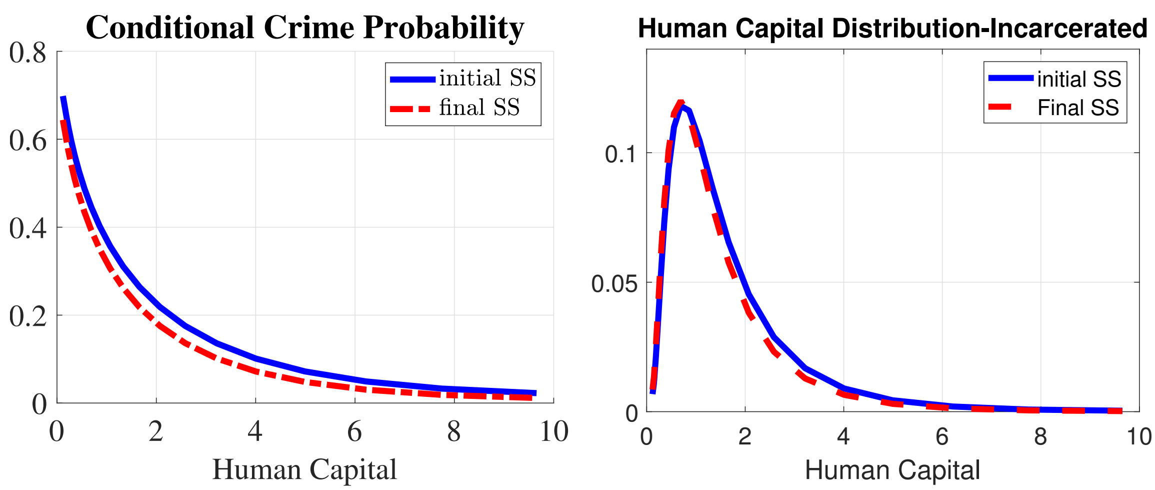
2.7 Transitional Dynamics with Violent Crime

Figures 9-16 reproduce the same set of plots we present in the main text for the property crime. See the main text for explanations of each figure.

Steady-State Variables	SS1 $\pi = 0.5\%$	SS2 $\pi = 2.9\%$
Incarceration	0.44%	1.45%
Crime Rate	0.3%	0.1%
Employment rate	76.9%	74.7%
Recidivism rate-1 year	13.4%	66.8%
Criminals with prison flag	54.6%	80.2%
Frac w/ high criminal capital	0.8%	0.7%
With prison flag	1.5%	2.2%
Share committing 95% of crimes	0.6%	0.05%
Wage ratio	87.7%	79.1%

Notes: The Table shows a comparison of two steady states, one with $\pi = 0.5\%$ and one with $\pi = 4.5\%$, productivity 20% lower and crime reward 150% higher.

Table 10: Steady-State Comparison



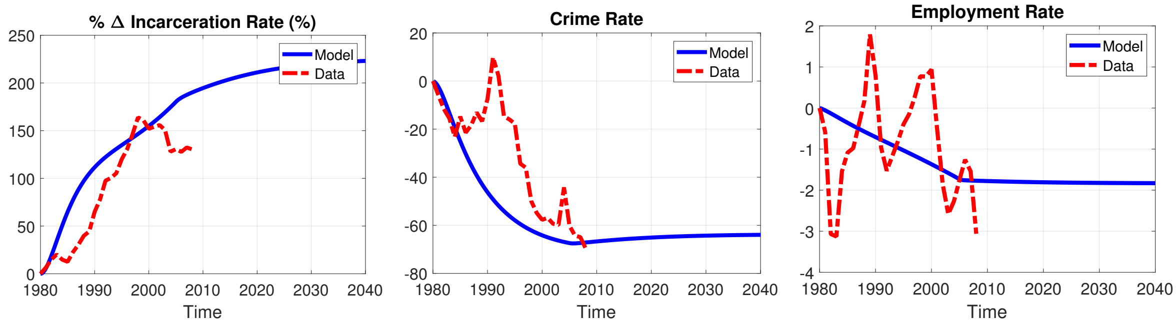
(a) Policy (b) Distribution

Figure 8: **Steady-State Comparison:** The left panel shows model generated crime probabilities conditional on receiving an opportunity as a function of human capital for a middle-age 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.

2.8 Calibration of the Alternative Models

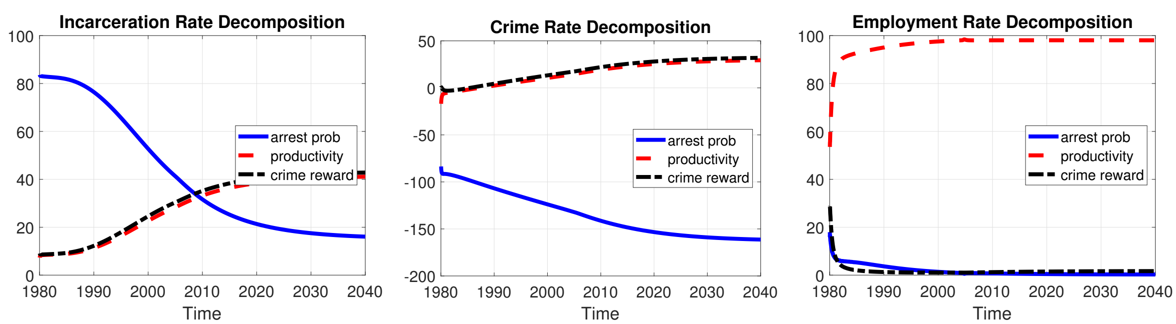
To highlight the significance of including criminal capital into our benchmark model, we recalibrate the model by removing criminal capital and using alternative assumptions to generate the persistence in criminal activity. In each alternative model, we target the same set of moments and use the same estimation procedure. Table 12 presents the calibrated parameter values for each alternative model. The column labelled as "M0" corresponds to the benchmark model. Below, we briefly describe the assumptions for alternative models:

- **M1: No Criminal Capital** This is the model without criminal capital and no other



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

Figure 9: **Transitional Dynamics - Model vs Data:** The figure shows the evolution of 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.

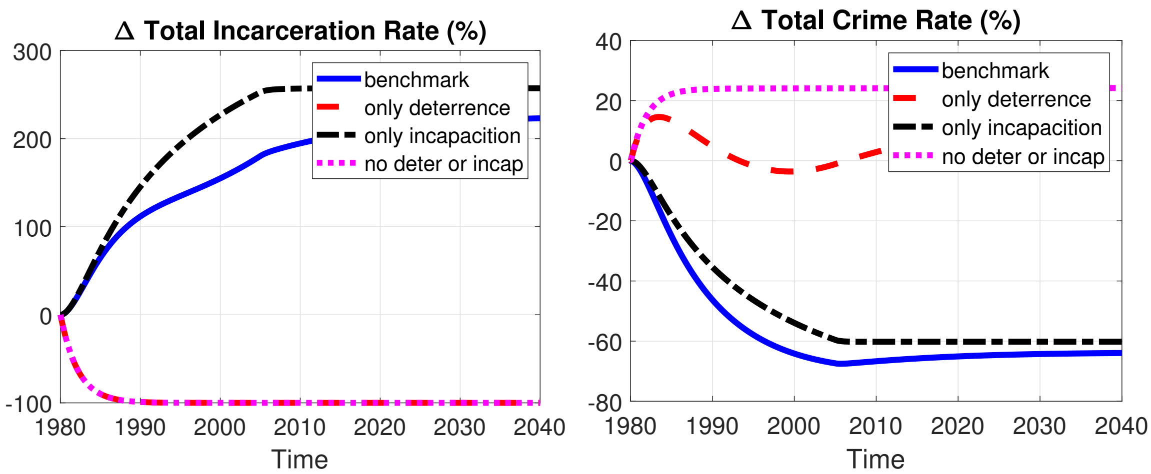


(a) Incarceration (b) Crime (c) Employment

Figure 10: **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 productivity, 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.

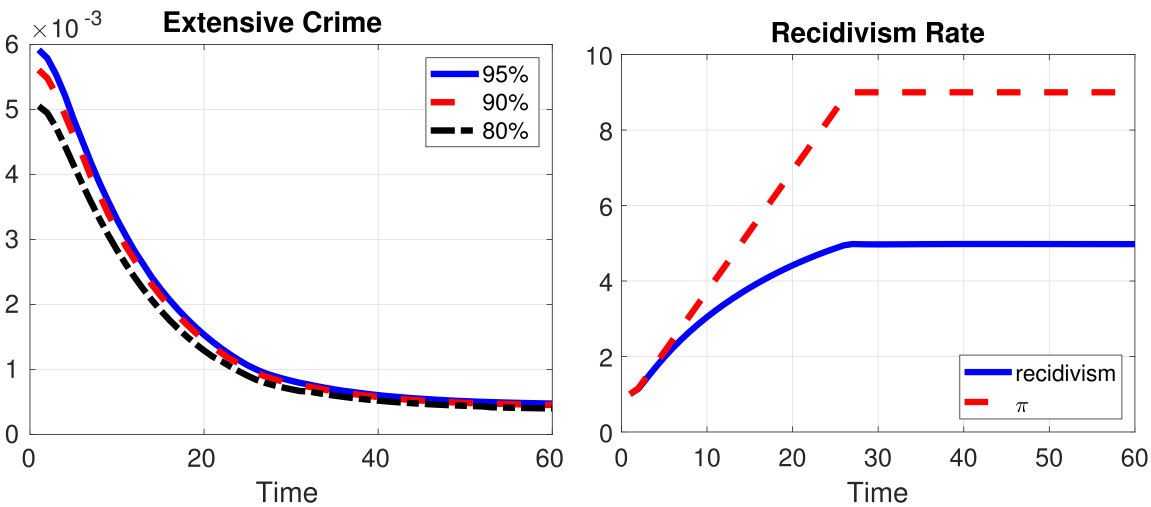
ingredients added to the model. The absence of criminal capital removes three parameters: probability of gaining high criminal capital upon committing a crime, ν, additional crime arrival rate for high criminal capital individuals, η_a^{hc}, and the probability of losing high criminal capital in old age, ζ^3. We also add another parameter, crime arrival rate for old individuals ($\eta^3 = \zeta^3$), to be able to match the incarceration rate for old individuals.

- **M2: Higher Human Capital Depreciation** In this model, we keep high criminal capital assumption, but remove the presence of irrational crimes for the high criminal capital. Instead, we assume that high criminal capital individuals' human capital



(a) Incarceration (b) Crime Rate

Figure 11: **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 long dashed line is the economy when incapacitation is eliminated. The dashed line is the economy when all decision rules of the individuals and firms kept at the initial steady-state levels.



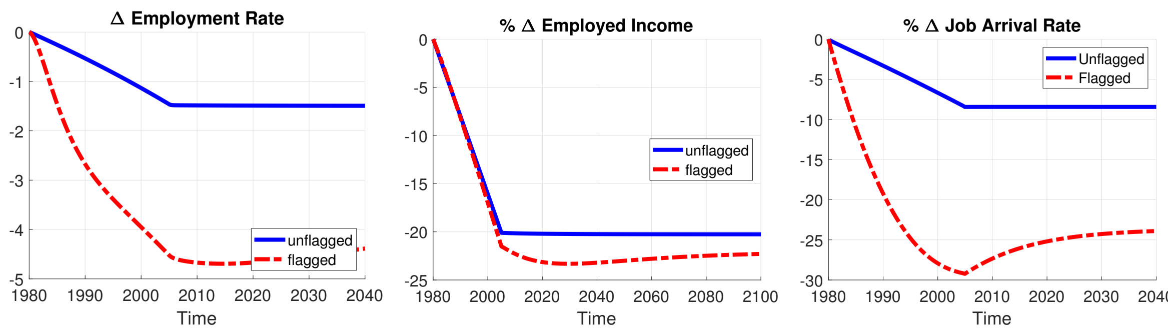
(a) Extensive Crime (b) Recidivism

Figure 12: **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 recidivism rate and arrest probability are normalized to their initial steady-state level.

depreciates at a faster rate, and reduce the mean of the human capital process for all individuals, including employed, unemployed and incarcerated, by η_a^{hc}. This model has the same set of parameters as the benchmark model. The only difference is the

	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 11: 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.



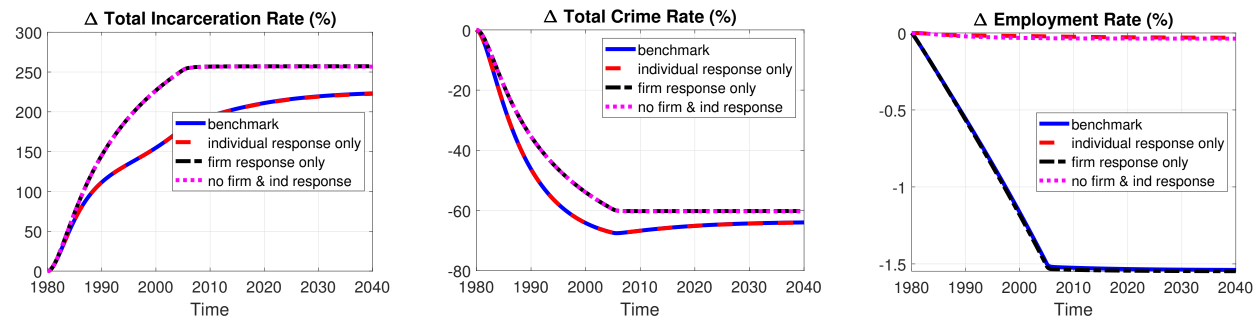
(a) Employment (b) Income (c) Job Arrival Rate

Figure 13: **Employment, Income and Job Arrival Rates across Different Groups:** The figures show the evolution of employment rate and income for individuals with (flag) and without (unflagged) prior incarceration record. The left panel is for employment, the middle panel is for income dynamics, and the right panel is for the job arrival rate of the middle-age individuals. All are changes in percentage points relative to the initial steady-state level.

interpretation of η_a^{hc}.

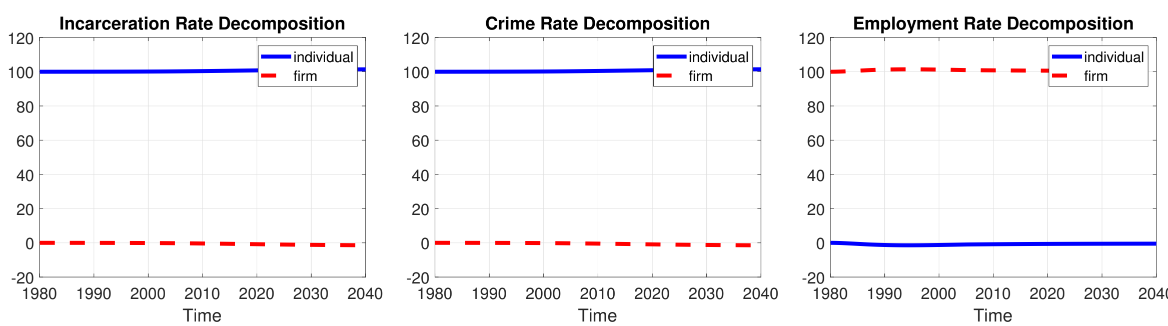
- **M3: More Crime Opportunities** This model is the same as the benchmark model. The only difference is that additional crimes high criminal capital individuals receive need not necessarily be committed. They are the same types of crimes low criminal capital individuals receive but at a higher rate. η_a^{hc} captures the additional crime arrival rate for the high criminal capital individuals.

- **M4: Better Crime Opportunities** This is very similar to M3. The only difference is that high criminal capital individuals do not receive crime opportunities at a higher rate, but from a distribution with a higher mean. η_a^{hc} captures the increase in the mean



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

Figure 14: **Transitional Dynamics: Policy Decomposition:** The figures show the decomposition of the incarceration, crime rate 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 firm keep the same job creation level, individuals keep their crime choices as in the first steady-state.



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

Figure 15: **Transitional Dynamics: Policy Decomposition:** The figures show the Shapley-Owen decomposition of individual and firm policy functions. The solid line is the contribution of individual criminal policy and the dashed line is the contribution of firm vacancy policy. 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.

of crime reward for the high criminal capital individuals.

- **M5: Ex-ante Heterogeneity in Criminal Capital** In this model, we assume there is ex-ante heterogeneity in the criminal capital, and ν represents the fraction of high criminal capital individuals. However, in this model, we assume committing a crime does not allow individuals to gain high criminal capital, i.e. there is no possibility for moving from low criminal capital to high criminal capital. However, we still keep the assumption of the possibility of losing high criminal capital when old to be able to match old incarceration rate.

- **M6: Higher Arrest Probability for the Incarcerated** In this model, we again

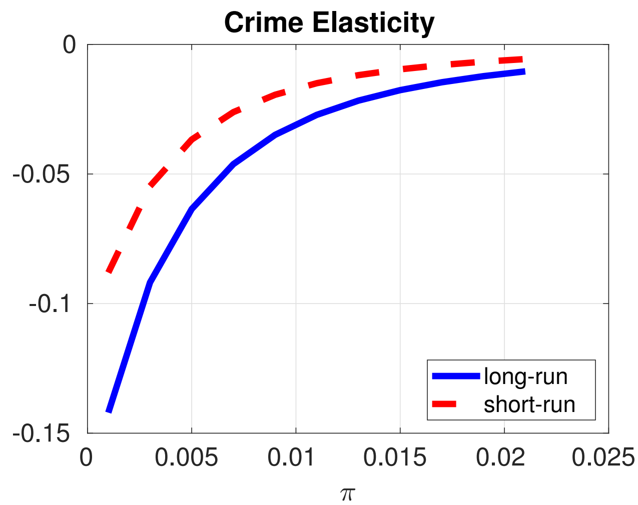


Figure 16: **Crime Elasticities:** The figure plots the aggregate crime elasticity both in the short-run and the long-run.

remove the arrival of irrational crimes for the high criminal capital individuals. Instead, we assume that ex-convict individuals face a higher probability of arrest upon committing a crime ($\pi^{hc} = \eta_a^{1,hc}$).

	M0	M1	M2	M3	M4	M5	M6
η^1	0.07%	3.95%	4.04%	0.08%	5.31%	0.2%	1.26%
c	80.17	68.82	65.71	62.14	38.36	82.23	73.30
δ	1.39%	1.37%	1.41%	2.0%	2.0%	1.33%	1.42%
$\mu^{e,2}$	0.11	0.07	0.08	0.12	0.05	0.10	0.11
$\mu^{e,3}$	0.16	0.07	0.19	0.20	0.0	0.15	0.13
$\mu^{u,1}$	0.14	0.36	0.38	0	0.61	0.15	0.24
ζ^3	0.39%	0.51%	0.51%	0.39%	0.1%	0.36%	0%
μ^k	0.61	2.48	5.0	5.0	0.50	0.1	1.31
$\eta_a^{1,hc}$	1.57	0	0.46	1.58	0	1.57	0.78
ν	0.23	0	0	0.01	0	0.05	0

Table 12: Calibrated Parameters - Alternative Models: The Table shows the internally calibrated parameters of the alternative models.

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