Who Gets a Second Chance? Effectiveness and Equity in Supervision of Criminal Offenders

Evan K. Rose

Microsoft Research

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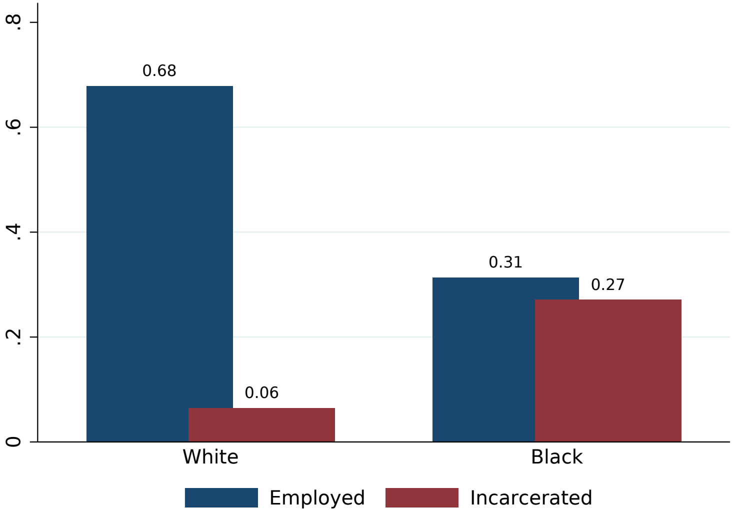
Race gaps in criminal justice are an important social issue



Note: Figure constructed from the 2013-2017 5-year public use American Community Survey Data (Ruggles et al., 2019). Includes White and African-American men aged 20-40 with less than 12 years of education. 11% of white men 18 and over and 14% of black men 18 and over are dropouts, according to the Census.
→ No college.

How does probation contribute to this picture?

Most common punishment; biggest part of system (4m people)

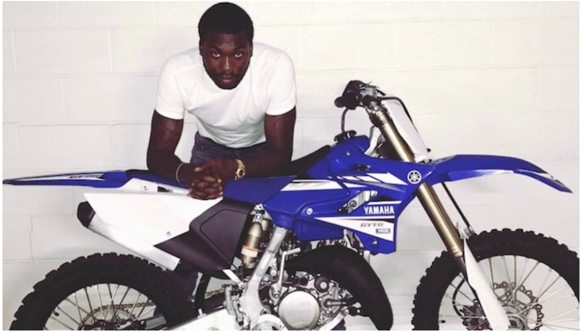
Probationers return home at sentencing, but are monitored and have to obey technical rules

- Pay fees and fines, meet regularly with a caseworker, abstain from drugs and alcohol, etc.

If you break technical rules, you can go to prison $\rightarrow$ probation itself drives incarceration

- Rule breakers account for $> 30\%$ of new prison spells in many states

Concerns about racial impacts: The case of Meek Mill



"What's happening to Meek Mill is just one example of how our criminal justice system entraps and harasses hundreds of thousands of black people every day...Instead of a second chance, probation ends up being a land mine, with a random misstep bringing consequences greater than the crime" - Jay-Z, The New York Times, Nov. 17, 2017

Timeline

Are we doing this right?

Two reasons to imprison rule breakers:

1. Rule breaking as "early warning system" $\rightarrow$ can shift risky probationers into prison
2. Rule following socially desirable $\rightarrow$ harsh punishments encourage compliance

This paper:

1. Test if technical rules accomplish goals 1 and 2 (*effectiveness*)
2. Measure racial differences in effectiveness (*equity*)

I study big reform in North Carolina in 2011 that reduced prison for rule violations sharply

Measure and interpret resultant increases in arrests

Preview of results

Limited deterrent effects of harsh punishments for rule breaking

- No racial differences in deterrence responses

Rule breaking does predict risk, but much less so for black offenders

- Disparities about differences in behavior, not probation officers' discretion

Implies reducing punishments for rule breaking increases crime, but reduces disparities

- Trade off hinges on valuation of crime and equity

Not all rules created equal: fees and fines particularly bad tags with big disparate impacts

- Still used heavily in many states

Related literature

- **Discrimination**: Becker (1957), Phelps (1972), Arrow (1973), Knowles, Persico, Todd (2001), Bertrand Mullainathan (2004), Durlauf (2005), Bertrand e.a. (2005), Anwar Fang (2006), Grogger Ridgeway (2006), Brock e.a. (2012), Abrams e.a. (2013), Janetta e.a. (2014), Rehavi Starr (2014), Fryer (2016), Arnold e.a. (2017), Raphael Rozo (2017), Arnold e.a. (2019)
- **CJ policy**: Grogger (1992, 1995), Weisburd e.a. (2008), Cook e.a. (2011), Durlauf e.a. (2012), Barnes ea. (2012), Boyle e.a. (2013), Mueller-Smith (2013), Raphael (2014), Bhuller e.a. (2016), Dobbie e.a. (2017), Harding e.a. (2017), Barnes e.a. (2017), Hyatt Barnes (2017), Rose Shem-Tov (2018), Sakoda (2019), Norris e.a. (2019); HOPE (2004-), HOPE DFE (2018)
- **Delegation / discretion**: Kuziemko (2013), Kleinberg e.a. (2017), Chouldechova (2017), Kleinberg e.a. (2018), Norris (2019); Aghion Tirole (1997), Dessein (2002), Prendergast (2007), Mookherjee (2006), Duflo e.a. (2018)
- **Competing risks**: Cox (1962, 1972), Tsiatsis (1975), Lancaster (1979), Heckman Singer (1984), Heckman Honoré (1989), Honoré (1993), Abbring van den Berg (2003)

Crim literature

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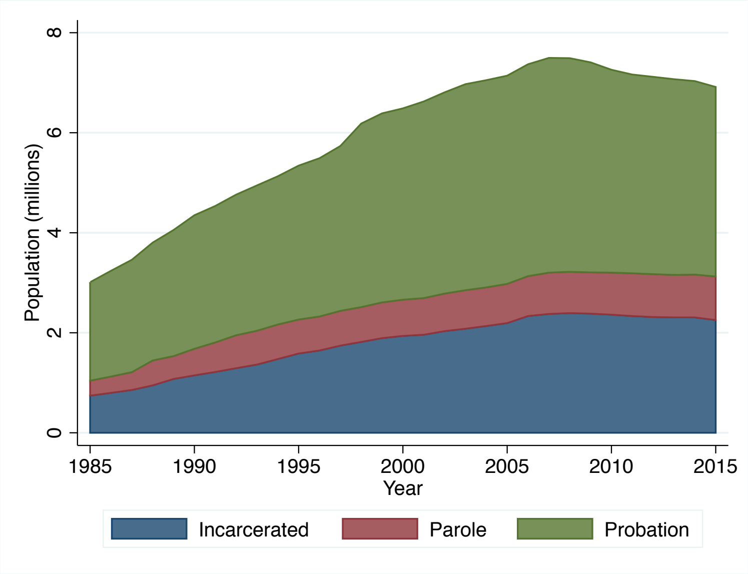
Probation roughly 2x incarceration



Source: BJS

What is probation?

Nationally, 51% felony defendants get probation as part of sentence (BJS, 2009), and higher rates for misdemeanors (NC: 65% and 73%)

Often first sanction people face in the system, especially if non-violent

- $>$ 78% of first-time felons get probation in NC
- $>$ 70% of 16-25 year-old offenders
- Twice as likely for property and drug offenses (BJS, 2009)

Rules include fairly standard set of conditions

- Pay fees / fines, meet regularly with caseworker (PPO), abstain from drugs and alcohol, do not travel without permission, find work, etc.

Rules details PPO Details

What happens if you get a violation?

If violation is serious enough, offender may be arrested immediately

Otherwise, report to local judge for a violation hearing, leading to:

- Sent to jail / prison (revocation)
- Modifying terms / conditions
- Verbal warning / reprimand

Judges agrees 83% of time overall and revokes in 85% cases where PPO recommends it; most of variation explained by Xs

Revokes are common: Probationers incarcerated without a new criminal conviction account for $\sim$ 40% of new prison spells over 2000s Graph

Data sources

Study probation system in North Carolina over 2006-18

- Roughly 530,000 individuals in 709,000 supervision spells
- Control group of similar size on *unsupervised* probation

Observe all probation violations and their dispositions in each spell

Combine with information from NC Administrative Office of the Courts and Department of Corrections on all arrests, charges, sentences, and incarceration in state prisons

Descriptive statistics for spells

	Supervised (treated)			Unsupervised (control)		
	Mean	Sd.	p50	Mean	Sd.	p50
Demographics:						
Age at start	32.059	10.85	29.83	32.707	10.77	30.29
Male	0.738	0.44	1.00	0.732	0.44	1.00
Black	0.435	0.50	0.00	0.355	0.48	0.00
White	0.490	0.50	0.00	0.522	0.50	1.00
Other race	0.074	0.26	0.00	0.124	0.33	0.00
Sentence:						
Sup. length (m)	19.449	9.58	18.17	14.841	8.77	12.00
Felon	0.429	0.49	0.00	0.032	0.18	0.00
Misd.	0.318	0.47	0.00	0.502	0.50	1.00
DWI / DWLR	0.208	0.41	0.00	0.457	0.50	0.00
Criminal history:						
Crim. hist. score	2.059	2.97	1.00	0.988	1.76	0.00
Prior sentences	1.917	3.28	0.00	1.251	2.69	0.00
Prior inc. spells	0.860	2.22	0.00	0.497	1.74	0.00
N	708623			895090		
Individuals	531099			661103		

Majority of probationers break a rule in their spell

	Violation	Share of violations	Share of spells
	Any violation	1.000	0.618
1	Not paying fees	0.343	0.496
2	Not reporting	0.129	0.286
3	Positive drug test	0.085	0.184
4	Fleeing supervision	0.064	0.163
5	New misdemeanor charge	0.063	0.138
6	Treatment / program failure	0.061	0.156
7	Moving / job change without notifying	0.034	0.084
8	Not completing community service	0.033	0.102
9	Breaking curfew	0.028	0.065
10	No employment	0.023	0.059
11	New felony charge	0.019	0.040
12	Admitting drug use	0.009	0.023
13	No education / training	0.007	0.018
14	Travelling without permission	0.006	0.014
15	Possessing drugs	0.006	0.013
16	Electronic monitoring failure	0.004	0.010
17	Refuse drug test	0.003	0.008
18	Disobeying curfew	0.003	0.008
19	Possessing weapons	0.002	0.006
20	Contacting drug users	0.002	0.005
	All others	0.162	0.558

Group violations into four categories

Violation type	Violation	Share of category
Drug related	Positive drug test	0.526
	Treatment / program failure	0.295
	Admitting drug use	0.071
	Possessing drugs	0.036
	Contacting drug users	0.022
New criminal offense	New misdemeanor charge	0.716
	New felony charge	0.263
	New DWI charge	0.013
	New drug charge	0.007
Administrative	Not paying fees	0.427
	Not reporting	0.202
	Other	0.099
	Moving / job change without notifying	0.058
	Breaking curfew	0.055
	Not completing community service	0.047
	No employment	0.043
	No education / training	0.012
	Traveling without permission	0.011
Absconding	-	1

Drug and admin violations targeted by reform

No revokes
after Dec. 1, 2011

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What else did the reform do?

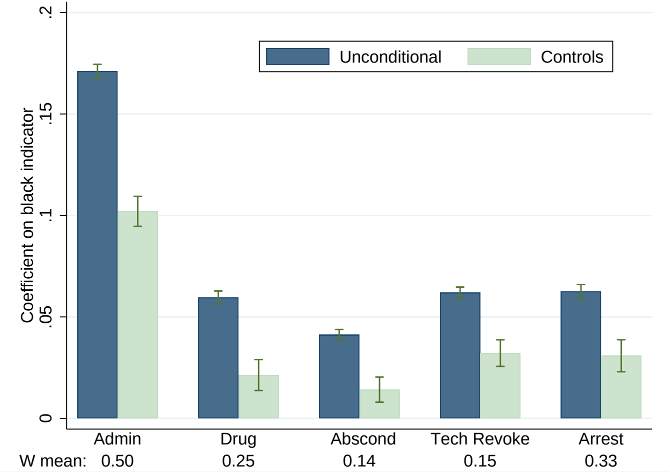
Change was part of a package of reforms in criminal justice

On probation, major changes were:

- Reduction in revocation authority
- Ability to impose short periods of confinement in response to violation (CRVs)
- More probation officer authority to ramp up sanctions

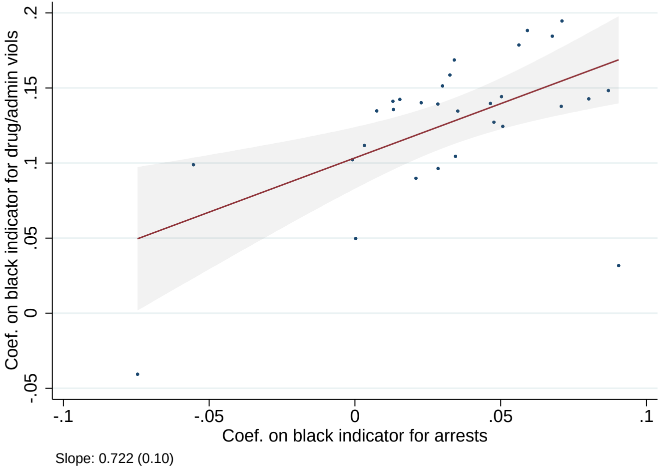
Change in officer authority applied to offenses committed after Dec. 1, 2011, so possible to focus on first two by zooming in spells starting close to Dec. 1

Black probationers get more violations and more arrests



Notes: Regressions include all treated probationers starting spells in 2006-2010. W mean refers to the white mean of the dependent variable, which is an indicator for the relevant outcome occurring at any point in the spell. Technical revocations are defined as any revoke without a preceding arrest. Adjusted estimate is from an OLS regression with controls for gender, 20 quantiles of age, district fixed effects, fixed effects for the offense class of their focal conviction, a linear control for the length of the supervision spell, fixed effects for prior convictions and revokes, a linear control for previous incarceration duration, and the most recent math and reading standardized test scores (normalized to have mean 0 and standard deviation 1 in the full test-taker population) observed between grades 3 and 8.

Black offenders break more rules in places where they reoffend more



Notes: Regressions include all spells starting in 2006-2010. Each dot plots the coefficient on black in regressions of indicators for any drug or administrative violation and any arrest in the spell on black, demographic, sentencing, and criminal history controls for each of the 30 probation districts in the state. Controls are as defined in Table **??**. To avoid mechanical relationships due to crime-driven revokes, I randomly split the sample in half and run regressions for each outcome in separate samples, as in a split-sample IV estimate.

Contents

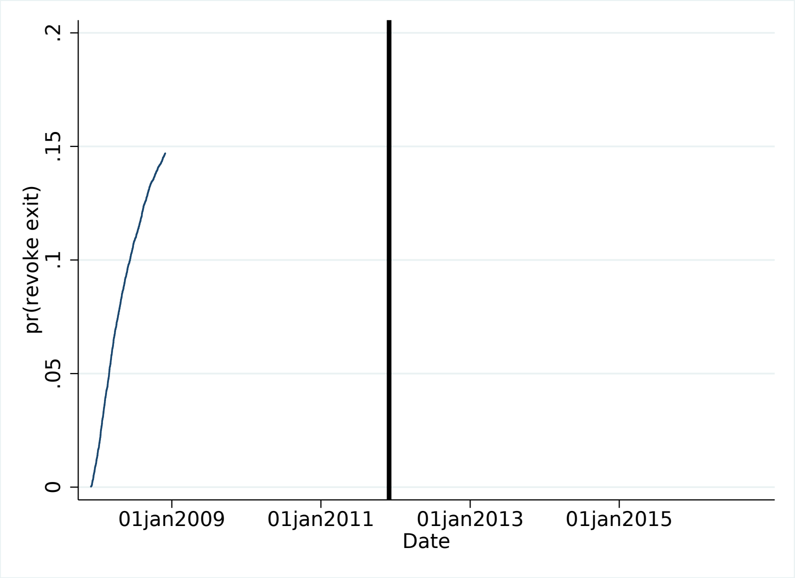
Start by laying out the raw data

Will begin by simply plotting observed failure rates for arrests and revokes

Failure has natural interpretation as share of individuals observed exiting probation due to arrests (or revokes) before t

Will start by showing you how this evolved around reform for crime and revokes

Reform sharply reduced revocation...



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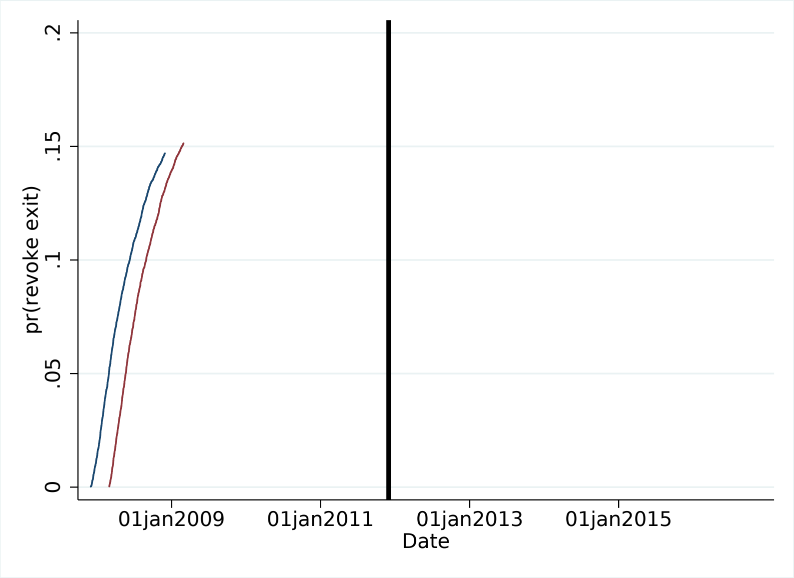

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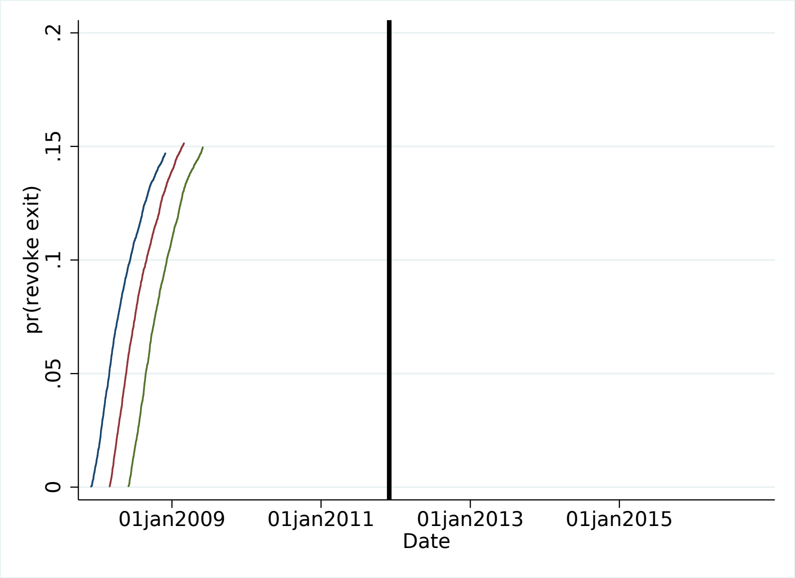

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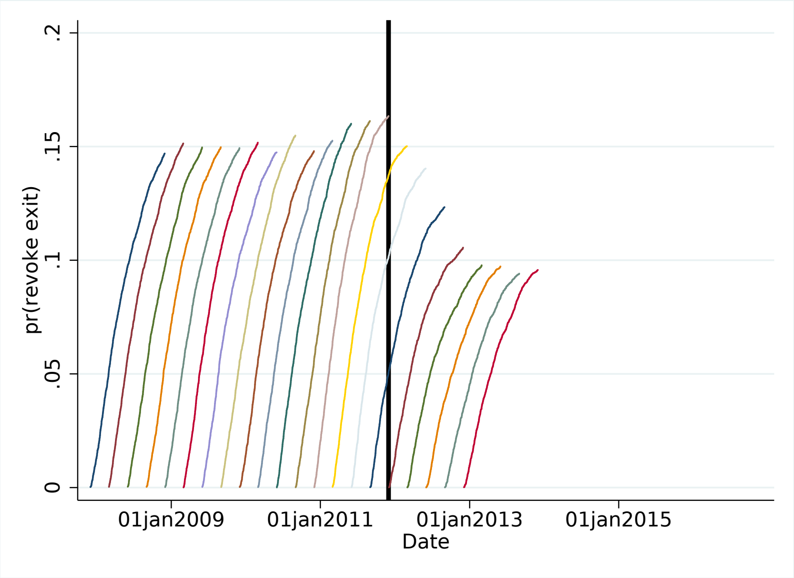

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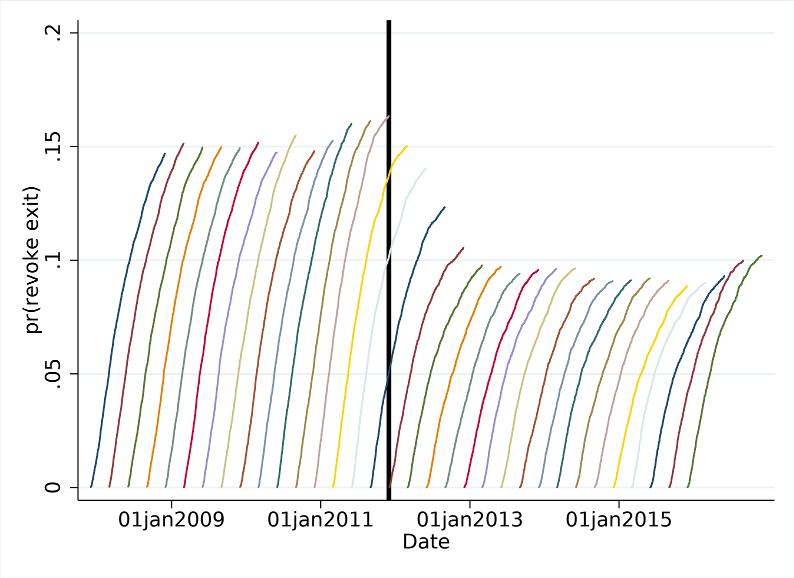
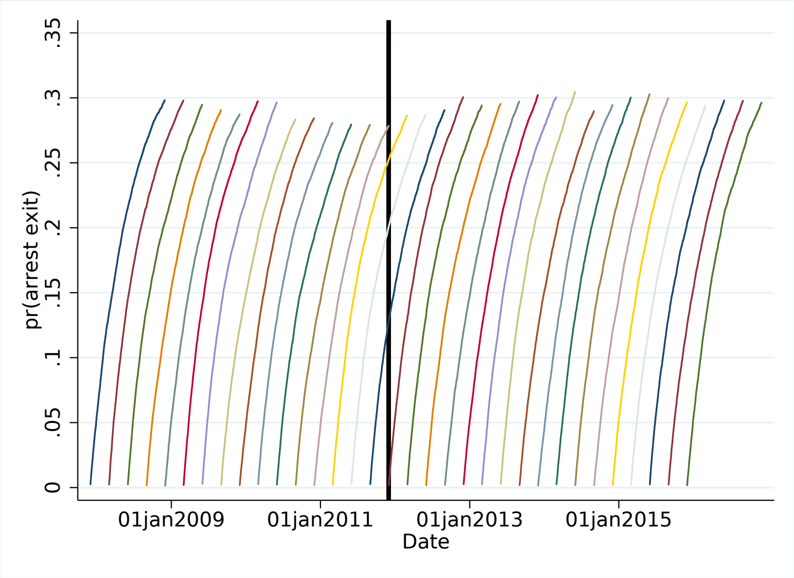
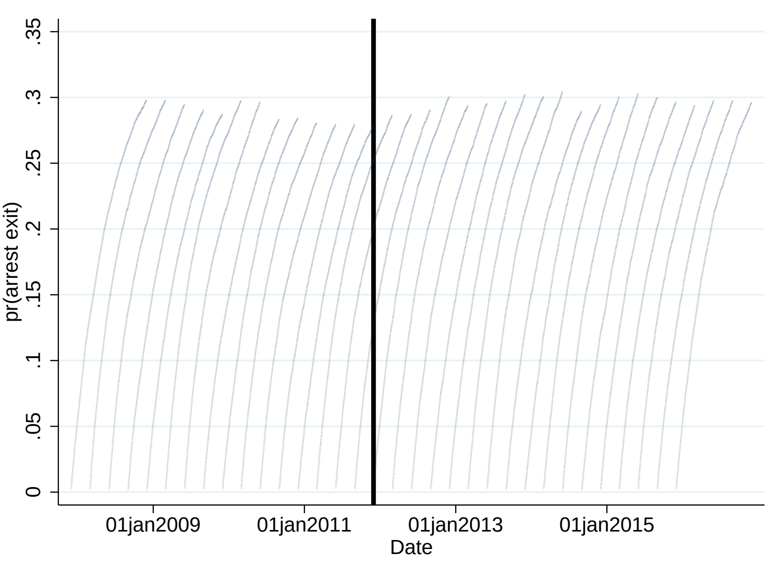


...with small corresponding increase in crime



No change in covariates



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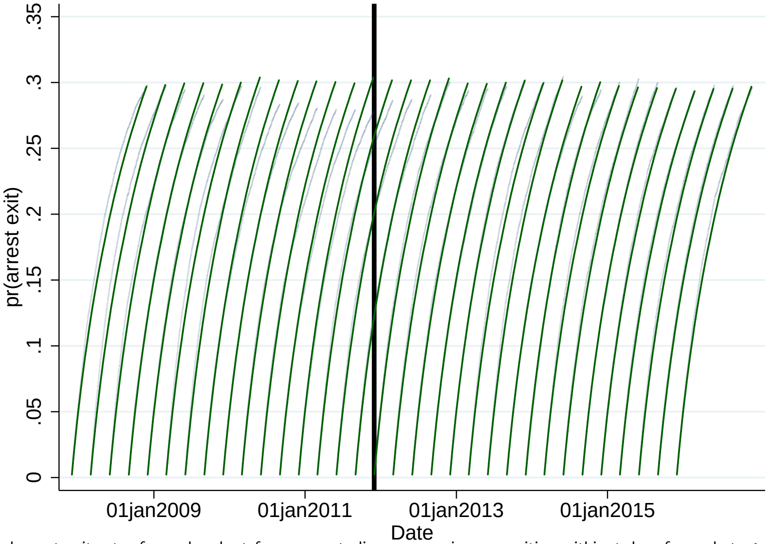
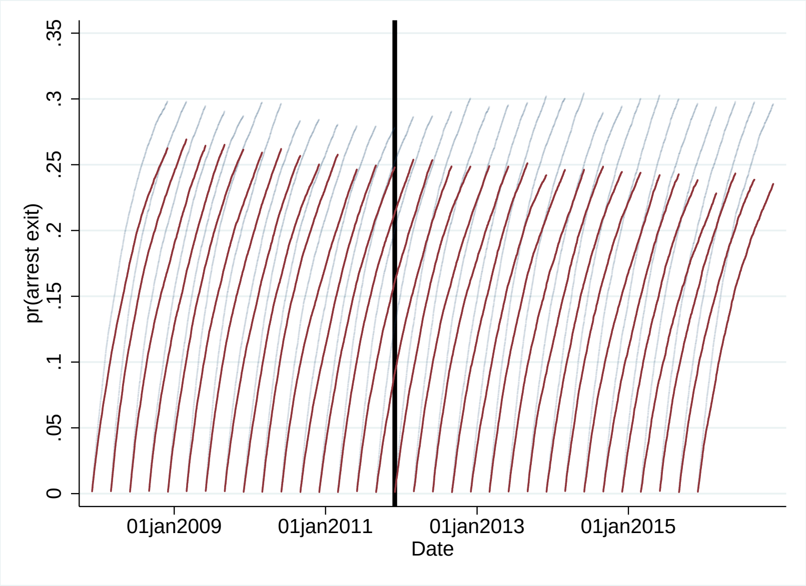
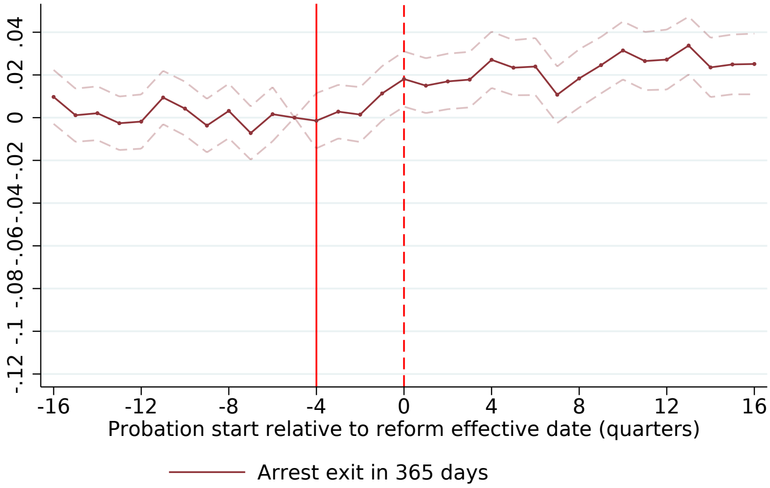


Source: Plot shows predicted arrest exit rates for each cohort from separate linear regressions on exiting within t days for each $t <= 365$ estimated in control sample only and using all covariates.

Use unsupervised probationers to take a diff



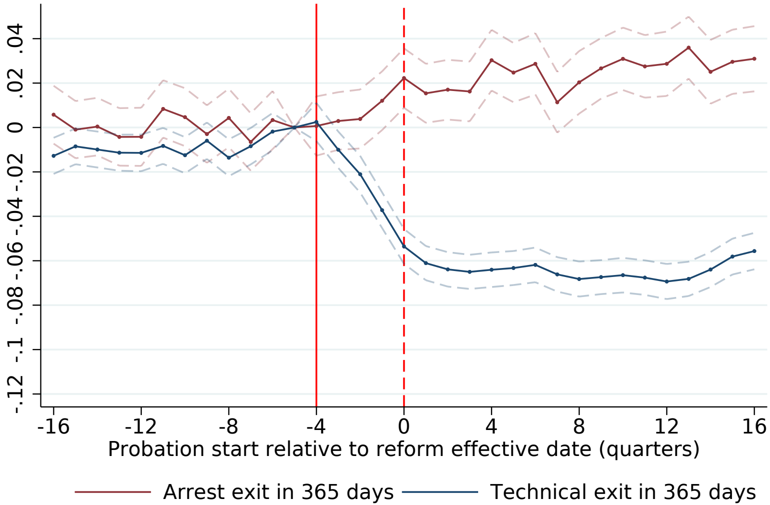
Roughly 2 p.p. increase in crime



Pre-reform means: 0.15 (revokes), 0.29 (offending)

Regression: $Y_i^j = \alpha + \sum_{s=-16}^{16} 1\{S_i = s\}(\beta_s + \beta_s^T T_i) + \gamma' X_i + e_i$. β_s^T are plotted.

Compared to 6-7 p.p. decrease in revokes



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What does this tell us about effectiveness?

Consider a simple binary treatment, binary outcome model:

- $R_i = 1 \ \rightarrow$ revoked for technical rule violation
- $Y_i = 1 \ \rightarrow$ rearrested for new crime

Potential outcomes $Y_i(0), Y_i(1)$ depend on revocation

- $Y_i(1) = 0$ due to incapacitation
- $Y_i(0)$ is crime if not revoked

Key object of interest: joint distribution of $R_i, Y_i(0)$, with normalizations

- Accuracy: $Pr(Y_i(0) = 1 \mid R_i = 1)$
- Type-I error: $Pr(R_i = 1 \mid Y_i(0) = 0)$
- Type-II error: $Pr(R_i = 0 \mid Y_i(0) = 1)$

Instrument allows us to estimate accuracy...

Given instrument Z_i that satisfies standard 2SLS conditions:

- First stage: $Pr(R_i = 1|Z_i = 1) < Pr(R_i = 1|Z_i = 0)$
- Monotonicity: $R_i(1) \leq R_i(0)\ \forall i$
- Independence / exclusion: $(Y_i(0), Y_i(1), R_i(0), R_i(1)) \perp\!\!\!\perp Z_i$

Abadie 2002 shows that:

$$\frac{E[Y_i(1-R_i)|Z_i=1] - E[Y_i(1-R_i)|Z_i=0]}{E[1-R_i|Z_i=1] - E[1-R_i|Z_i=0]} = E[Y_i(0)|R_i(0)=1, R_i(1)=0]$$

This is the effect of being spared revocation due to the reform on reoffending

In other words, it's the accuracy of revokes drug and administrative violations

CRVs DiD

...and error rates

Reduced form impact on $Y_i(1 - R_i)$ identifies $Pr(Y_i(0) = 1, R_i(0) = 1, R_i(1) = 0)$

Can identify Type-II error for population of "potential compliers" with $R_i(1) = 0$ because:

$$Pr(R_i(0) = 0 \mid Y_i(0) = 1, R_i(1) = 0) = 1 - \frac{\frac{Pr(Y_i(0)=1, R_i(0)=1, R_i(1)=0)}{Pr(R_i(1)=0)}}{Pr(Y_i(0) = 1 \mid R_i(1) = 0)}$$

Similar logic identifies Type-I errors

Note not error rates for full population; just those that *could* be caught by drug / admin rules

Error rates for all rules will be estimated using hazard model, but this is 90% of population

Is exclusion reasonable?

Key assumption: outcomes does depend on Z_i only through treatment

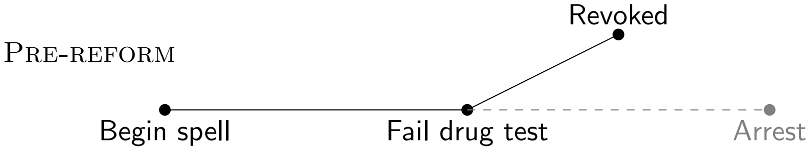
Implies no general increase on arrests due to laxer enforcement

Normally, exclusion is not testable

Here unique structure of reform provides simple test

- Works by undoing mechanical impact of change in R_i and seeing what's left

A simple test of behavioral responses



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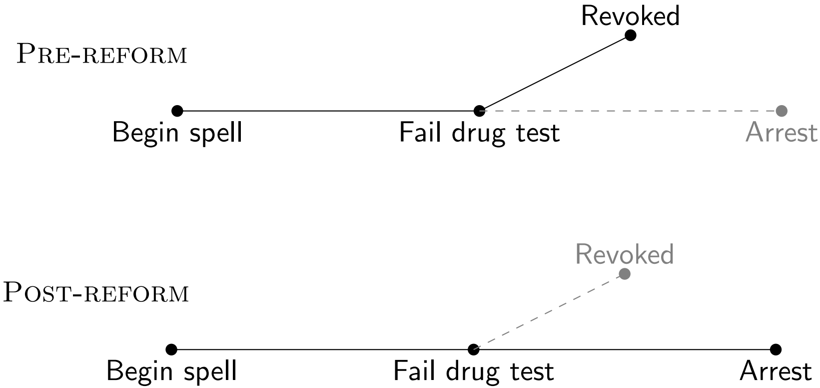

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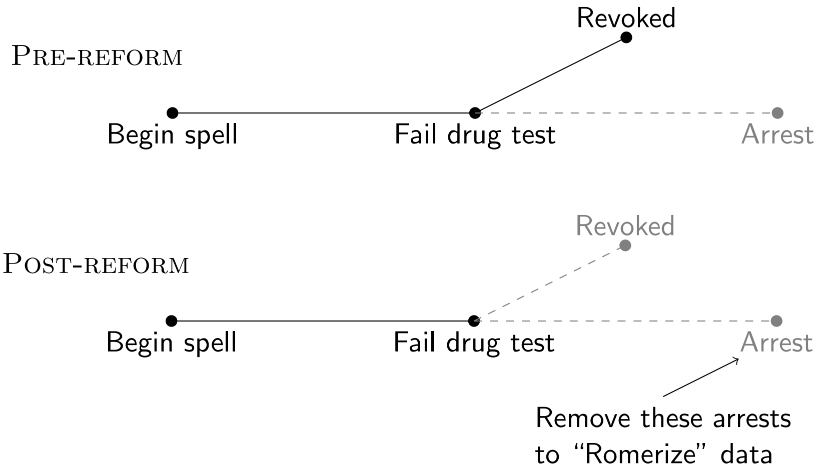
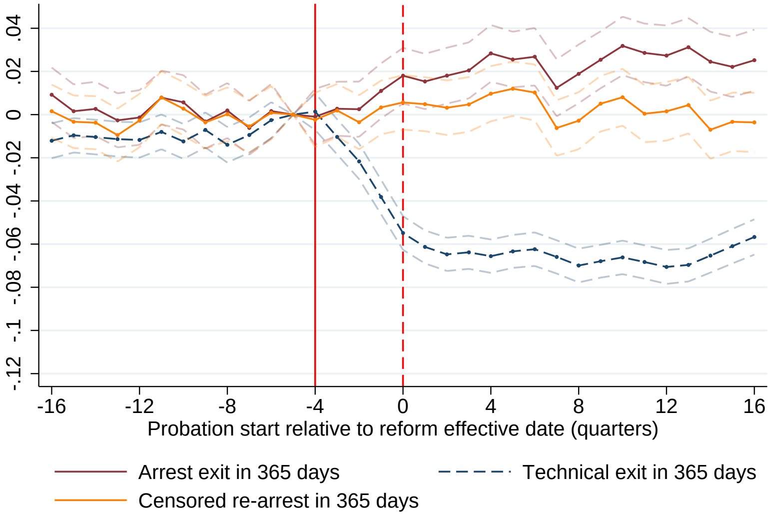


No evidence of increase in “Romerized” arrests



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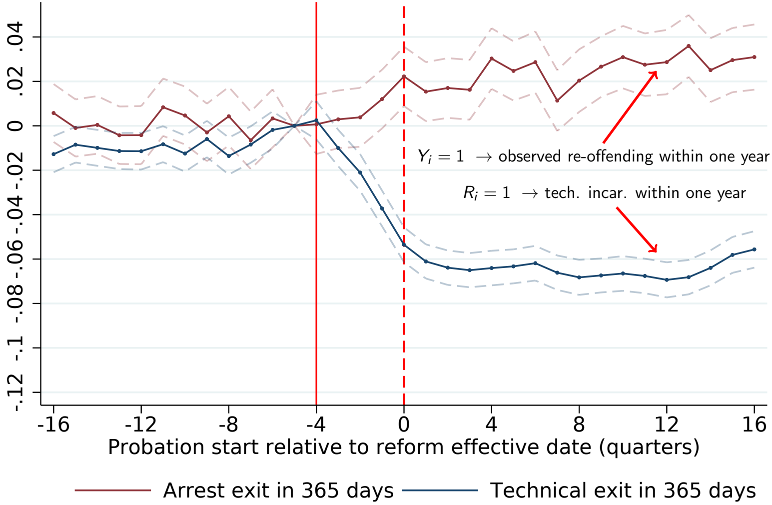
Hazard regressions show similar result

	Arrest		Any violation		Drug use		Fees and fines	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-reform	-0.00249	0.000236	-0.0205*	-0.0152	0.0202	0.0267	0.00183	0.00794
	(0.0116)	(0.0116)	(0.0101)	(0.0101)	(0.0177)	(0.0177)	(0.0118)	(0.0118)
N	152720	152720	152720	152720	152720	152720	152720	152720
Controls		Yes		Yes		Yes		Yes

Note: Cox proportional hazard regressions using all supervised probation spells starting within one year of the reform. "Post reform" is a time-varying indicator for dates after Dec. 1, 2011. Each pair of columns considers the listed behavior as failure and the other behaviors as a source of independent censoring.

Can treat first year of spell as one-period model



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One-year model diff-in-diff estimates

	Technical Revocation		Arrest	
	(1)	(2)	(3)	(4)
Post-reform	-0.00172***	-0.00205***	-0.00793***	-0.00705***
	(0.000273)	(0.000288)	(0.00167)	(0.00159)
Treated	0.143***	0.133***	0.0316***	-0.0155***
	(0.00103)	(0.00102)	(0.00166)	(0.00164)
Post-x-treat	-0.0532***	-0.0530***	0.0196***	0.0194***
	(0.00135)	(0.00135)	(0.00242)	(0.00233)
N	546006	546006	546006	546006
Pre-reform treated mean	.149	.149	.287	.287
Accuracy			.369 (0.045)	.369 (0.063)
False negative rate			.936 (0.01)	.936 (0.01)
False positive rate			.056 (0.004)	.056 (0.004)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Estimates based on probation spells starting 1-3 years before the reform and 0-2 years after.

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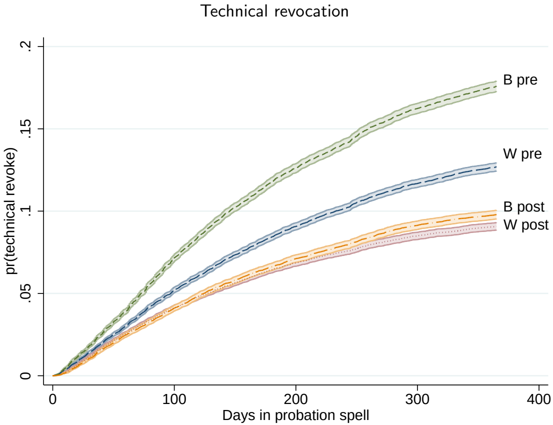
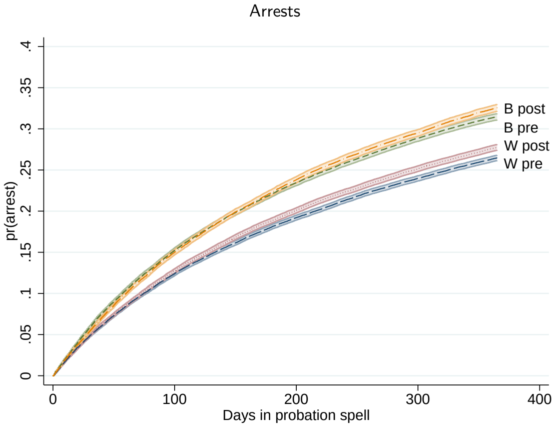
Source: Estimates based on probation spells starting 1-3 years before the reform and 0-2 years after.

Much larger decrease in revokes for black offenders





Non-black diff-in-diff estimates

	Technical Revocation		Arrest	
	(1)	(2)	(3)	(4)
Post-reform	-0.000522	-0.000875**	-0.00693***	-0.00666***
	(0.000317)	(0.000334)	(0.00199)	(0.00190)
Treated	0.122***	0.112***	0.0450***	-0.000334
	(0.00130)	(0.00126)	(0.00209)	(0.00207)
Post-x-treat	-0.0356***	-0.0360***	0.0198***	0.0179***
	(0.00173)	(0.00172)	(0.00304)	(0.00295)
N	328784	328784	328784	328784
Pre-reform treated mean	.127	.127	.265	.265
Accuracy			.556 (0.085)	.55 (0.081)
False negative rate			.93 (0.01)	.931 (0.01)
False positive rate			.025 (0.005)	.026 (0.005)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Black diff-in-diff estimates

	Technical Revocation		Arrest	
	(1)	(2)	(3)	(4)
Post-reform	-0.00387***	-0.00412***	-0.0118***	-0.0112***
	(0.000509)	(0.000534)	(0.00295)	(0.00281)
Treated	0.167***	0.160***	-0.00496	-0.0464***
	(0.00167)	(0.00167)	(0.00274)	(0.00268)
Post-x-treat	-0.0741***	-0.0736***	0.0228***	0.0233***
	(0.00215)	(0.00214)	(0.00399)	(0.00383)
N	217222	217222	217222	217222
Pre-reform treated mean	.176	.176	.315	.315
Accuracy			.308 (0.053)	.309 (0.051)
False negative rate			.932 (0.01)	.932 (0.01)
False positive rate			.091 (0.007)	.091 (0.007)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Estimates based on probation spells starting 1-3 years before the reform and 0-11 years after.

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	Technical Revocation		Arrest	
	(1)	(2)	(3)	(4)
Post-reform	-0.00387***	-0.00412***	-0.0118***	-0.0112***
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Similar racial disparities across variety of robustness exercises

Single difference estimates show same patterns link

Insensitive to time window used around the reform link

No racial differences in arrests by crime severity link

Race gaps not explained by offender Xs link

Same gaps after CRVs eliminated for misdemeanants link

Larger declines in incarceration for any reason for black felony probationers link

Constructing a decomposition

Letting $B_i \in \{0,1\}$ be an indicator for race, we can use this to decompose differences in technical incarceration[1]

$$\underbrace{Pr(R_i(0)=1|B_i=1) - Pr(R_i(0)=1|B_i=0)}_{\text{difference in technical revokes}} =$$

$$\sum_{k=0}^{1} \underbrace{Pr(Y_i(0)=k|B_i=0)}_{\text{white risk}}[\underbrace{Pr(R_i(0)=1|Y_i(0)=k,B_i=1) - Pr(R_i=1|Y_i(0)=k,B_i=0)}_{\text{difference in targeting}}]$$

$$+\underbrace{Pr(R_i(0)=1|Y_i(0)=k,B_i=1)}_{\text{black targeting}}[\underbrace{Pr(Y_i(0)=k|B_i=1) - Pr(Y_i(0)=k|B_i=0)}_{\text{difference in risk}}]$$

[1] Suppressing conditioning on being a "potential complier" with $R_i(1)=0$.

Decomposition shows targeting responsible for disparity

	Overall rates		Decomposition	
	White	Black	Gap	Share of explained
Probability of technical revoke				
$Pr(R_i(0) = 1)$	0.039	0.082	0.043	100.0%
Distribution of risk				
$Pr(Y_i(0) = 1)$	0.313	0.376	0.063	9.8%
$Pr(Y_i(0) = 0)$	0.687	0.624	-0.063	-13.3%
True / false positive rates				
$Pr(R_i(0) = 1 \mid Y_i(0) = 1)$	0.070	0.068	-0.002	-1.5%
$Pr(R_i(0) = 1 \mid Y_i(0) = 0)$	0.025	0.091	0.066	104.9%

Notes: Estimates based on core diff-in-diff model. Oaxaca calculates contribution of differences in risk using black targeting rates as baseline, and differences in targeting using white risk as baseline.

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What is the social return revoking a rule-breaker?

If state incarcerates someone for rule breaking, it pays the incarceration costs

If not, they might commit a costly crime; will also have to incarcerate

The social return to revoking individual i is therefore:

$$V_i = \underbrace{-J_i}_{\text{Cost of revoke}} + \underbrace{Pr(Y_i(0) = 1 | R_i = 0)}_{\text{pr(offend) if not revoked}}$$
$$[\underbrace{E[U(Y_i(0)) | R_i = 0, Y_i(0) = 1]}_{\text{Cost of crime if not revoked}} + \underbrace{J_i'}_{\text{Cost of new sentence}}]$$

We can calculate a "break-even" valuation of crime $E[U(Y_i(0)) | R_i = 0, Y_i(0) = 1]$ to justify revokes affected by the reform

What other costs / benefits might be relevant?

Costs of rule-driven incarceration

- Incarceration costs

Benefits of rule-driven incarceration

- Reduced crime

Note: http://www.ncpolicywatch.com/wp-content/uploads/2018/01/Court-Fines-and-Fees-Criminalizing-Poverty-in-NC.pdf

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- Incarceration costs
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- Long run impacts on offenders
- Court costs
- Racial inequity

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Benefits of rule-driven incarceration

- Reduced crime
- Collection of fees and fines
- Deterrent effects
- Long run impacts on offenders

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Break-even valuations by sub-population

	(1) $\triangle$ rev. $	(2) $\triangle$ indir. $	(3) Break-even	(4) Break-even (fel. only)	(5) Cost LB	(6) Cost UB
All	-633***	223	42,618***	104,818**	16,757	177,546
	(25)	(119)	(11,800)	(35,112)	(39,858)	(120,517)
Non-black	-423***	232	21,272*	41,025*	1,316	41,051
	(33)	(129)	(10,246)	(20,473)	(41,011)	(124,545)
Black	-888***	309	47,976*	179,263	30,206	331,070
	(39)	(227)	(18,673)	(111,261)	(63,898)	(194,954)
Non-black men	-504***	226	27,115*	45,461*	-14,106	32,563
	(41)	(166)	(12,837)	(21,828)	(44,689)	(140,121)
Black men	-1,004***	407	40,401*	132,548	32,373	330,335
	(48)	(301)	(18,363)	(84,530)	(69,830)	(211,819)

Source: Estimates based on core diff-in-diff sample with same controls. Graph Crime type

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Source: Estimates based on core diff-in-diff sample with same controls. Graph Crime type

Similar results in richer multi-period model

One period model shows rules target criminal risk, but are less accurate for black offenders

But one-period model is very simplified

- Rule breaking occurs *throughout* a probation spell, not all at beginning
- Effectiveness of rules thus depend on both distribution of risk and targeting conditional on risk over duration
- A lot of crime happens after one year

Paper extends to a three-year multi-period model and finds similar effects Details

Behaviors or biased responses?

Bias could arise because behaviors differ in the two populations, or because responses to behavior differ

Weight of evidence suggests these results are about behavior

- Response to violations shows no race gap
- Race gaps large for violations with / without discretion
- No match effects in probationer-officer race
- Officer decisions guided by detailed response matrix

Moreover, effects of the reform persist—not undone by biased officers finding new ways to penalize black probationers

Where do we go from here?

So far, I have shown that rules affected by the reform identify riskier probationers, but target black offenders much more aggressively

But important questions remain:

- Are we sure there was no behavioral response?
- What would happen if we reduced technical rules further?
- And what can we say about the information in specific *types* of rule violations?

These questions can't be answered using reduced-form evidence alone

So I next introduce more structure to tackle them

Contents

Goal: Estimate distribution of unobserved hazards for each behavior

Each individual has a latent risk in each spell s for being

- Arrested for new crime: Y_{is}^*
- Revoked for technical rule breaking: R_{is}^*

We want to measure:

1. How does each risk evolve over a spell (i.e., duration dependence)?
2. Are some people more likely to exhibit a behavior than others (i.e., heterogeneity)?
3. Are people who break rules more likely to be arrested as well (i.e., correlated risks)?

This is hard because observed changes in behavior over time conflate all three factors

I do this with a logit approximation to discrete time hazard

Approximate discrete hazard for each risk with a logit (Cox 1970, Efron 1988), i.e.:

$$Pr(Y_{is}^* = t | Y_{is}^* \geq t, X_{is}, U_i^Y) = \Lambda\left(\theta_0^Y(t) + X_{ist}'\beta^Y + U_i^Y\right) \tag{1}$$

$$Pr(R_{is}^* = t | R_{is}^* \geq t, X_{is}, U_i^R) = \Lambda\left(\theta_0^R(t) + X_{ist}'\beta^R + U_i^R\right) \tag{2}$$

1. $\theta_0^j(t)$ is the discrete hazard at duration t for outcome j
2. X_{ist} are covariates such as age, spell indicators, criminal history, etc.
3. U_i^Y and U_i^R are unobserved, individual-specific heterogeneity

X_{ist} can include indicator for being post-reform

Key source of identification: Repeated spells

U_i^Y and U_i^R have no s or t subscripts (Honoré 1993, Abbring van den Berg 2003)

- If $U_i^Y = 0 \; \forall i$, then Y_{i1}^* should be independent of Y_{i2}^* conditional on X
- But if short Y_{i1}^* predicts short Y_{i2}^*, that implies i has high U_i^Y
- Same logic applies across risks, i.e., if Y_{i1}^* predicts R_{i2}^*

Implies model is identified without any variation from the reform itself

- No need to *impose* exclusion restriction; can test if arrest risk increases post-reform
- Can also throw out this variation entirely and see if answer changes

More

Estimation details

Estimate using all data up to 3 years post reform completely separately by race and gender, discretizing to week level and using:

- 4 types for set of $\{U_i^Y, U_i^R\}$ (Heckman and Singer 1984)
- Flexible polynomial for baseline hazards
- Include a simple time trend in intercept of duration polynomial rather than controls

Also estimate version with continuous heterogeneity modeling:

$$\begin{pmatrix} U_i^Y \\ U_i^R \end{pmatrix} \sim N(\alpha, \Sigma) \tag{3}$$

Estimation results for men

	Black men		Non-black men	
	Arrest	Revoke	Arrest	Revoke
Duration	-0.14 (0.11)	3.79 (0.17)	-0.84 (0.11)	2.95 (0.16)
Duration^2	-2.10 (0.70)	-21.99 (1.22)	2.00 (0.70)	-19.45 (1.20)
Duration^3	5.56 (1.79)	42.82 (3.43)	-4.06 (1.77)	39.34 (3.37)
Duration^4	-5.35 (1.97)	-38.73 (4.04)	4.58 (1.94)	-36.78 (4.00)
Duration^5	1.75 (0.77)	13.25 (1.68)	-1.98 (0.76)	12.94 (1.68)
Has 2 spells	0.84 (0.01)	0.76 (0.02)	1.21 (0.01)	1.09 (0.02)
Second spell	-0.18 (0.03)	0.09 (0.04)	-0.34 (0.03)	-0.02 (0.05)
Second spell x dur.	-0.07 (0.12)	-0.02 (0.21)	0.02 (0.12)	0.14 (0.20)
Second spell x dur.^{2}	0.21 (0.71)	-1.68 (1.34)	-0.36 (0.65)	-2.42 (1.21)
Second spell x dur.^{3}	-0.43 (1.72)	5.11 (3.57)	0.51 (1.57)	6.90 (3.18)
Second spell x dur.^{4}	0.31 (1.84)	-5.51 (4.13)	-0.12 (1.67)	-7.42 (3.62)
Second spell x dur.^{5}	-0.05 (0.72)	2.00 (1.71)	-0.09 (0.65)	2.79 (1.48)
Calendar time	-0.02 (0.01)	-0.23 (0.02)	0.05 (0.01)	-0.04 (0.02)
Calendar time^2	-0.00 (0.01)	-0.15 (0.01)	0.02 (0.01)	-0.08 (0.01)
Age	-2.52 (0.13)	-3.39 (0.20)	-2.91 (0.13)	-2.07 (0.23)
Age^2	4.17 (0.29)	6.75 (0.43)	5.51 (0.27)	4.37 (0.48)
Age^3	-2.04 (0.16)	-3.53 (0.24)	-2.92 (0.15)	-2.50 (0.27)
Post reform	0.05 (0.01)	-0.50 (0.03)	0.04 (0.01)	-0.39 (0.03)

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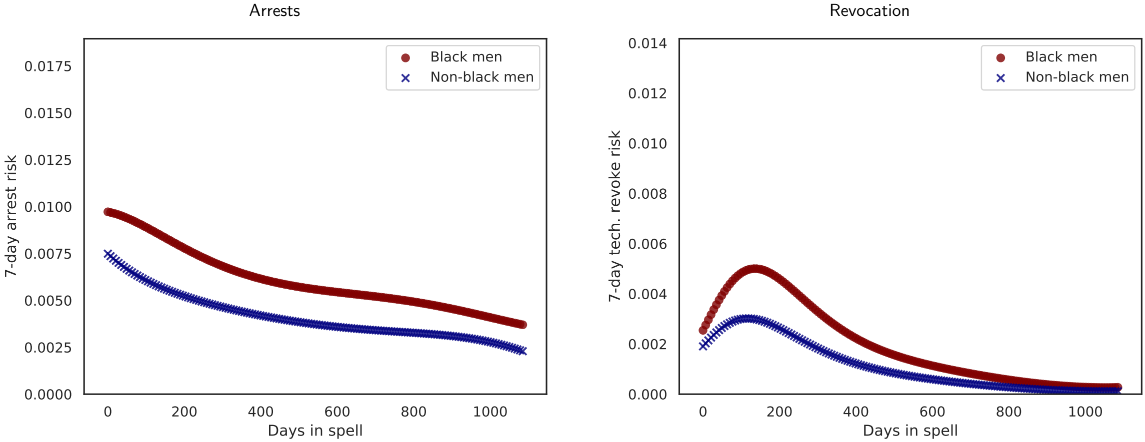
Hazards reflect both race gaps



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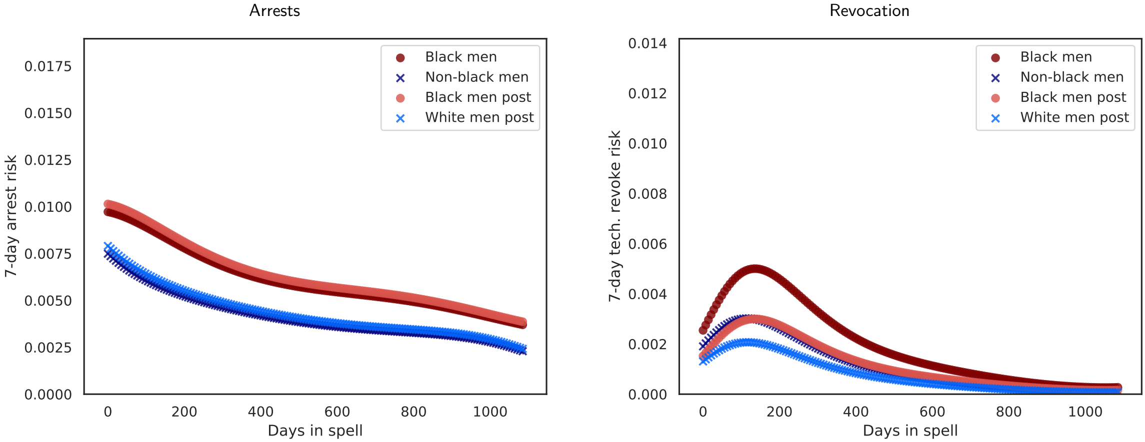
Second spell x dur.^{2}	0.21 (0.71)	-1.68 (1.34)	-0.36 (0.65)	-2.42 (1.21)
Second spell x dur.^{3}	-0.43 (1.72)	5.11 (3.57)	0.51 (1.57)	6.90 (3.18)
Second spell x dur.^{4}	0.31 (1.84)	-5.51 (4.13)	-0.12 (1.67)	-7.42 (3.62)
Second spell x dur.^{5}	-0.05 (0.72)	2.00 (1.71)	-0.09 (0.65)	2.79 (1.48)
Calendar time	-0.02 (0.01)	-0.23 (0.02)	0.05 (0.01)	-0.04 (0.02)
Calendar time^2	-0.00 (0.01)	-0.15 (0.01)	0.02 (0.01)	-0.08 (0.01)
Age	-2.52 (0.13)	-3.39 (0.20)	-2.91 (0.13)	-2.07 (0.23)
Age^2	4.17 (0.29)	6.75 (0.43)	5.51 (0.27)	4.37 (0.48)
Age^3	-2.04 (0.16)	-3.53 (0.24)	-2.92 (0.15)	-2.50 (0.27)
Post reform	0.05 (0.01)	-0.50 (0.03)	0.04 (0.01)	-0.39 (0.03)

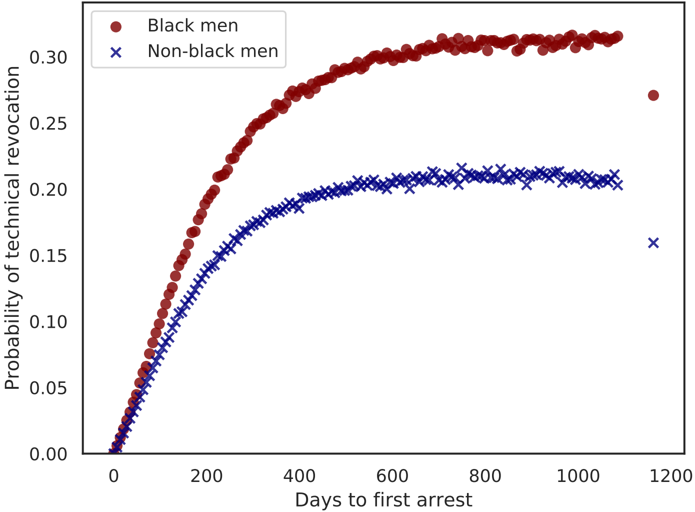
Economically small behavioral responses for offending



Estimation results for men

	Black men		Non-black men	
	Arrest	Revoke	Arrest	Revoke
Type locations				
Type 1	-7.04 (0.00)	-6.99 (0.08)	-7.57 (0.00)	-8.55 (0.18)
Type 2	-5.44 (0.00)	-7.24 (0.09)	-5.86 (0.00)	-6.21 (0.04)
Type 3	-5.39 (0.00)	-5.46 (0.09)	-5.86 (0.00)	-8.04 (0.06)
Type 4	-3.50 (0.05)	-6.07 (0.20)	-3.74 (0.07)	-6.57 (0.13)
Type shares				
Type 1	0.11 (0.00)		0.07 (0.00)	
Type 2	0.60 (0.03)		0.24 (0.01)	
Type 3	0.21 (0.03)		0.62 (0.02)	
Type 4	0.08 (0.00)		0.07 (0.00)	

Model detects strong racial disparities



Notes: Figure plots estimates of $Pr(R_i^* < Y_i^* | Y_i^* = k)$, or the likelihood of technical revocation before time k among probationers who would be otherwise be rearrested at time k, from simulating outcomes in the competing risks model. Observables are held constant at their mean levels for men in the sample and simulations use the estimated race-gender specific distributions of unobserved heterogeneity.

Validation and extensions

Model does good job fitting diff-in-diff moments Link

Fits empirical hazards Link

Fits joint distribution of failures across spells Link

Continuous heterogeneity changes little

- Correlation between unobserved components of risk is 65% higher for non-black offenders

Now extend to multiple TV types

Do different rule violations have different information?

Can address this by extending the model to accommodate more risks:

1. Arrested for new crime
2. Drug violation
3. Cash fees / fines violation
4. Reporting violation
5. Any other violation

Implementation

Could switch to a 5-outcome competing risks model

But this would throw out useful information

Instead, decompose revokes into rule-breaking and punishments

$$Pr(R^*_{is} = t | R^*_{is} \geq t) = Pr(V^k_{ist} = 1 | R^*_{is} \geq t) Pr(I_{ist} = 1 | V^k_{ist} = 1, R^*_{is} \geq t) \tag{4}$$

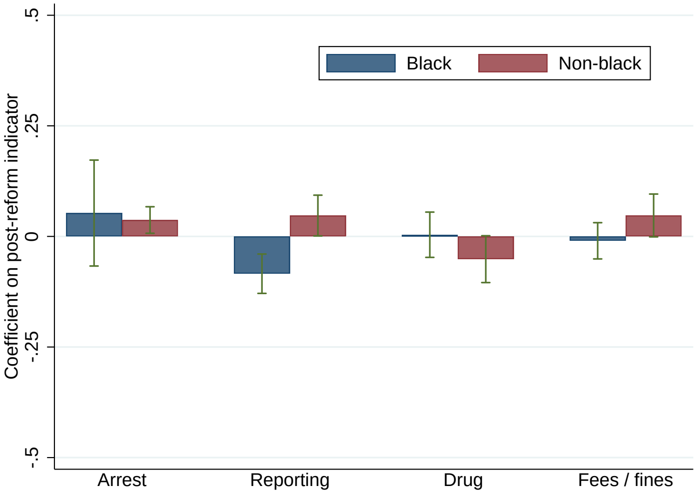
1. $V^k_{ist} = 1$ if i breaks a technical rule of type k at duration t in spell s
2. $I_{ist} = 1$ if revoked as a result

Both modeled with same logit structure

$$Pr(V^k_{ist} = 1 | X_{ist}, U_i^{V^k}, R^*_{is} \geq t) = \Lambda\left(\theta_0^{V^k}(t) + X'_{ist}\beta^{V^k} + U_i^{V^k}\right) \tag{5}$$

$$Pr(I_{ist} = 1 | V^k_{ist} = 1, X_{ist}, U_i^{V^k}, R^*_{is} \geq t) = \Lambda\left(\theta_0^{I}(t) + X'_{ist}\beta^{I}\right) \tag{6}$$

Violations also show limited behavioral responses



Results can also compare performance of rules

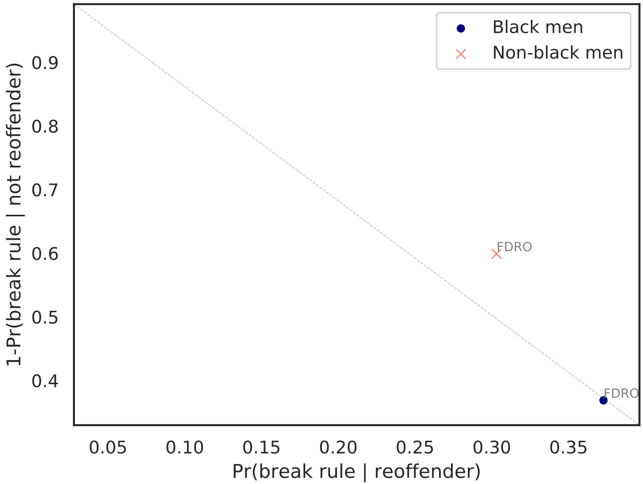
For each violation type, can simulate:

- Share of three-year *reoffenders* who break rule (true positive)
- Share of three-year *non-reoffenders* who do not break rules (true negative)

More targeted rules have more reoffenders and fewer non-reoffenders break them

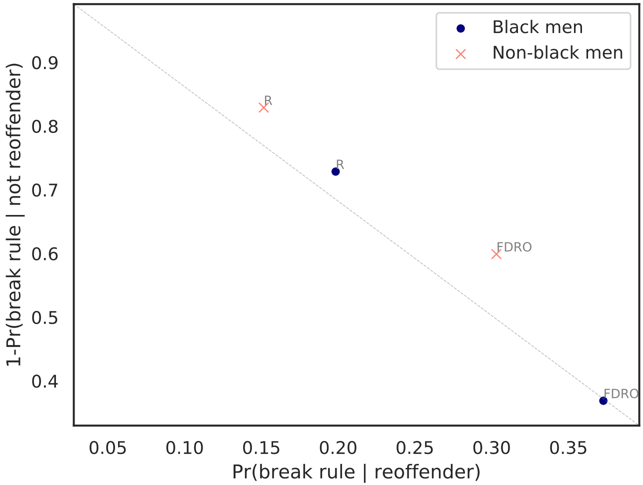
Can do the same exercise for combinations of rules (e.g., drug + reporting)

All rules are worse indicators of risk for black offenders



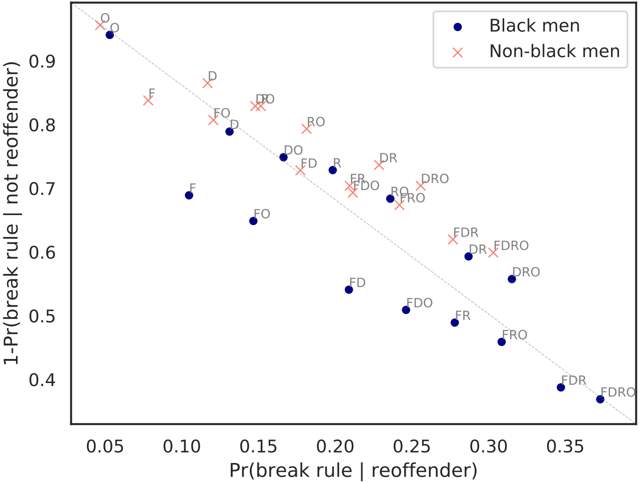
Notes: Figure plots estimates of the share of potential offenders over a three year period who break technical rules before they offend (x-axis) against the share of non-offenders who do not break technical rules. Each point is labeled with a combination of "F" for fees / fines violations, "D" for drug / alcohol violations, "R" for reporting violations, and "O" for all other.

All rules are worse indicators of risk for black offenders



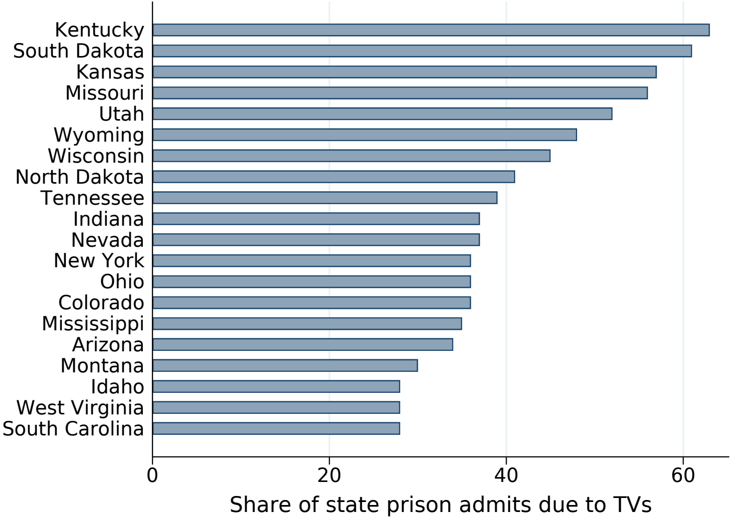
Notes: Figure plots estimates of the share of potential offenders over a three year period who break technical rules before they offend (x-axis) against the share of non-offenders who do not break technical rules. Each point is labeled with a combination of "F" for fees / fines violations, "D" for drug / alcohol violations, "R" for reporting violations, and "O" for all other.

All rules are worse indicators of risk for black offenders



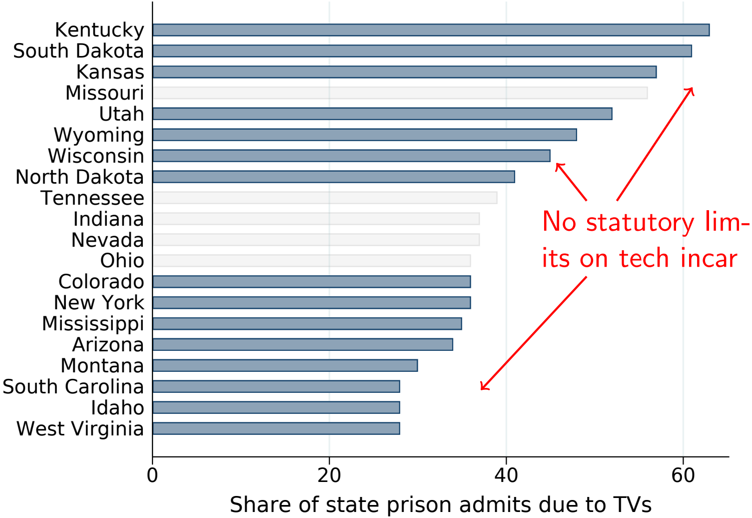
Notes: Figure plots estimates of the share of potential offenders over a three year period who break technical rules before they offend (x-axis) against the share of non-offenders who do not break technical rules. Each point is labeled with a combination of "F" for fees / fines violations, "D" for drug / alcohol violations, "R" for reporting violations, and "O" for all other.

Not a hypothetical: Technical rules are widespread



Source: The Council of State Governments Justice Center.

Not a hypothetical: Technical rules are widespread



Source: The Council of State Governments Justice Center.

Conclusion

Technical rules proxy for criminal risk, but target black offenders more aggressively

Relaxing them poses a tradeoff: more arrests but smaller disparities

Regardless of price of crime and equity, however, some rules are worse ideas

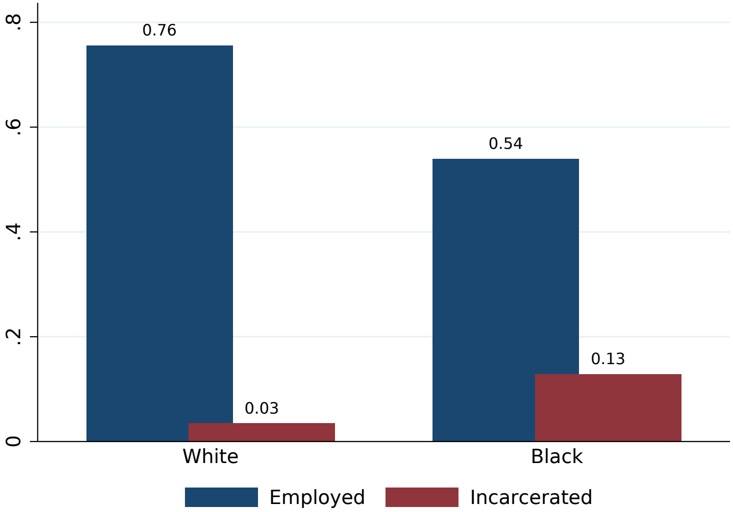
- NC's reform successful because it targeted some of those rules
- Potentially lots of room for other states to improve, too

Suggests disparate *impact* rather than *treatment* is an important channel for disparities

- Easier to address too – simple policy changes are effective
- Where else might disparate impact be driving big disparities?

Appendix

Criminal justice and labor market disparities tightly linked



Note: Figure constructed from the 2013-2017 5-year public use American Community Survey Data (Ruggles et al., 2019). Includes White and African-American men aged 18-40 with zero years of college education. → Back.

Meek Mill (Robert Williams): A timeline

- Jan 2007: Williams is arrested on drug and weapons charges.
- Aug 2008: Judge Genece Brinkley sentences Williams to two years in jail and eight years of probation.
- Oct 2012: Williams stopped by police due to tinted windows; arrested after officers smell marijuana.
- Nov 2012: In probation violation hearing, Williams passes two drug tests; Brinkley forbids him from touring.
- Dec 2012: Williams faces additional violations hearings for booking shows that violate restrictions on his travel.
- June 2013: Brinkley orders Williams to take etiquette courses after he disparages his probation officer online.
- July 2014: Brinkley sends Williams to jail for six months for continuing to travel for shows, testing positive for pain killers, and his behavior online.
- July 2015: Williams is barred from preforming and recording music for two months.
- Feb 2016: Brinkley extends Williams probation for several years, orders community service and an ankle monitor, and bars him from performing and recording.
- Mar 2017: Williams is charged with assault after a fight in the St. Louis airport; the case is later thrown out.
- Aug 2017: Williams is filmed popping a wheelie on a dirt bike. Police arrest him for reckless endangerment; charges later dismissed.
- Nov 2017: Williams sent to jail for two to four years for more probation violations, including drug tests and limited travel.

Source: Rolling Stone Back

What is probation?

- At sentencing, convicted offenders can be sent to jail or prison, placed on probation, or fined
- Probation means you go home, but risk incarceration for breaking certain rules over the probation period, which can be months to years
- In NC, these rules can include:
  - Commit no new crime
  - Do not leave the county without permission and submit to curfews
  - Report to a probation officer regularly
  - Pay a monthly fee and other costs (e.g., for your state-provided lawyer)
  - Find and keep a job or vocational training
  - Submit to warrantless searches
  - Abstain from drugs, submit to tests, and attend programs
  - Perform community service
  - Not associate with gang members or be present where gangs are active
  - Satisfy other conditions "reasonably related to rehabilitation"

Back

Criminology literature

This literature is nicely summarized in Wilson and Petersilia (2011) and in Sakoda (2019)

From Piehl and LoBuglio (2005):

- "There is little detailed, direct evidence on how much crime is averted by enforcement of violations of technical violations... The most pressing questions are whether technical violations predict criminal behavior and whether the structure of supervision itself makes it more difficult for ex-inmates to reintegrate into society...Unfortunately, the research literature does not provide clear lessons about how much and in what ways supervision matters directly to crime control."

Back

Who enforces the rules?

- Paid $\sim$ \$30-40k per year, mostly have 4-year degrees
- Supervise mixed case load of roughly 60-80 offenders at a time
- Conduct interviews, searches, testing, and arrests
- Carry guns and pepper spray
- In NC, 48% female and 37% black

Back

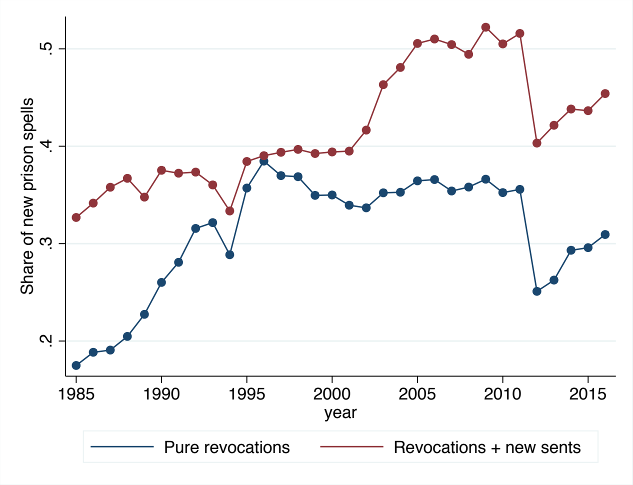
Probation officer response grid

		SUPERVISION LEVEL					
		L1*	**L2**	**L3**	**L4**	**L5**	**MINIMUM RESPONSE HIERARCHY**
TYPE OF NONCOMPLIANCE	**S1** (public safety)	*A*	*A*	*A*	*A*	*A*	**A** PVR + arrest*
	S2 (new crime behavior or conviction)	*A/ B/C*	*A/ B/C*	*B/C*	*B/C*	*B/C*	**B** Delegated Authority Quick Dip*
	S3 (reoccur/multiple)	*A/ B/C*	*B/C*	*B/C*	*B/C/D*	*B/C/D*	**C** PVR + cite* Contempt* Modify/extend* Delegated authority-non quick dip* Increase searches Increase drug screens Increase contacts
	S4 (nonrecurring)	*C*	*C*	*D*	*D*	*D*	**D** Refer to treatment CPPO reprimand Modify payment schedule Initiate contact PPO reprimand
	S5 (non-willful)	*D*	*D*	*D*	*D*	*D*	

*** CPPO approval required for responses marked (*) and all responses to violations by L1 offenders**

Source: 2017 NC Community Corrections Policy Manual. Back to behaviors

Probation is an important driver of incarceration in NC



Source: Author's calculations based on DPS data. Back

Black probationers get more administrative violations...

	Outcome: Any administrative violation					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.171***	0.186***	0.174***	0.147***	0.139***	0.102***
	(0.00173)	(0.00185)	(0.00187)	(0.00186)	(0.00198)	(0.00377)
N	314514	314514	314514	314514	314514	89012
R-squared	0.0296	0.0440	0.0618	0.0951	0.109	0.0899
Y white mean	0.501	0.501	0.501	0.501	0.501	0.501
Demographics		Yes	Yes	Yes	Yes	Yes
Sentence			Yes	Yes	Yes	Yes
Criminal hist				Yes	Yes	Yes
Zip code FE					Yes	Yes
Test scores						Yes
Logit coefficient	0.714	0.789	0.753	0.655		
Logit AME	0.169	0.184	0.172	0.145		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all probationers starting spells in 2006-2010 and aged 16-45 at the start of their spell. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration.Test score controls include last math and reading standardized test scores (normalized to have mean 0 and standard deviation 1 in the full population) observed from grades 3 to 8.

Back

...and drug violations...

	Outcome: Any drug violation					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.0596***	0.0655***	0.0638***	0.0461***	0.0437***	0.0214***
	(0.00161)	(0.00171)	(0.00172)	(0.00173)	(0.00183)	(0.00389)
N	314514	314514	314514	314514	314514	89012
R-squared	0.00438	0.0227	0.0353	0.0529	0.0637	0.0620
Y white mean	0.251	0.251	0.251	0.251	0.251	0.251
Demographics		Yes	Yes	Yes	Yes	Yes
Sentence			Yes	Yes	Yes	Yes
Criminal hist				Yes	Yes	Yes
Zip code FE					Yes	Yes
Test scores						Yes
Logit coefficient	0.296	0.333	0.327	0.241		
Logit AME	0.0591	0.0653	0.0632	0.0456		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all probationers starting spells in 2006-2010 and aged 16-45 at the start of their spell. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration. Test score controls include last math and reading standardized test scores (normalized to have mean 0 and standard deviation 1 in the full population) observed from grades 3 to 8.

Back

...and absconding violations...

	Outcome: Any absconding violation					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.0412***	0.0487***	0.0416***	0.0241***	0.0165***	0.0142***
	(0.00133)	(0.00142)	(0.00143)	(0.00143)	(0.00152)	(0.00316)
N	314514	314514	314514	314514	314514	89012
R-squared	0.00310	0.0168	0.0255	0.0484	0.0612	0.0644
Y white mean	0.143	0.143	0.143	0.143	0.143	0.143
Demographics		Yes	Yes	Yes	Yes	Yes
Sentence			Yes	Yes	Yes	Yes
Criminal hist				Yes	Yes	Yes
Zip code FE					Yes	Yes
Test scores						Yes
Logit coefficient	0.302	0.362	0.308	0.189		
Logit AME	0.0408	0.0482	0.0407	0.0243		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all probationers starting spells in 2006-2010 and aged 16-45 at the start of their spell. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration. Test score controls include last math and reading standardized test scores (normalized to have mean 0 and standard deviation 1 in the full population) observed from grades 3 to 8.

Back

...and more likely to get revoked...

	Outcome: Any arrest					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.0626***	0.0690***	0.0561***	0.0285***	0.0302***	0.0309***
	(0.00172)	(0.00182)	(0.00184)	(0.00183)	(0.00194)	(0.00402)
N	314514	314514	314514	314514	314514	89012
R-squared	0.00421	0.0284	0.0453	0.0786	0.0891	0.0741
Y white mean	0.330	0.330	0.330	0.330	0.330	0.330
Demographics		Yes	Yes	Yes	Yes	Yes
Sentence			Yes	Yes	Yes	Yes
Criminal hist				Yes	Yes	Yes
Zip code FE					Yes	Yes
Test scores						Yes
Logit coefficient	0.272	0.308	0.253	0.134		
Logit AME	0.0622	0.0688	0.0554	0.0283		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all probationers starting spells in 2006-2010 and aged 16-45 at the start of their spell. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration. Test score controls include last math and reading standardized test scores (normalized to have mean 0 and standard deviation 1 in the full population) observed from grades 3 to 8.

Back

...but not more likely to get revoked condition on violations

	Outcome: Revoked (conditional on violation)				
	(1)	(2)	(3)	(4)	(5)
Black	-0.00357*	0.00952***	0.00384	-0.0106***	0.00275
	(0.00182)	(0.00196)	(0.00197)	(0.00195)	(0.00210)
N	289505	289505	289505	289505	289505
R-squared	0.0000133	0.0227	0.0309	0.0559	0.405
Dep. var white mean	0.399	0.399	0.399	0.399	0.399
Demographic controls		Yes	Yes	Yes	Yes
Sentence controls			Yes	Yes	Yes
Criminal history controls				Yes	Yes
Violations FE					Yes
Logit coefficient	-0.0149	0.0411	0.0174	-0.0454	
Logit AME	-0.00357	0.00963	0.00403	-0.0103	

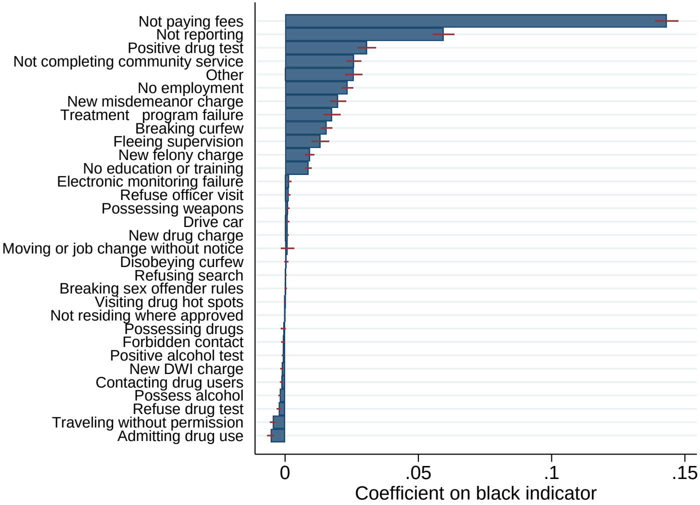
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all violation hearings disposed between 2006-2010 for probationers aged 16-45 at the start of their spell. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration. Violations FE are fixed effects for the unique set of violations disposed.

Back Back to behaviors

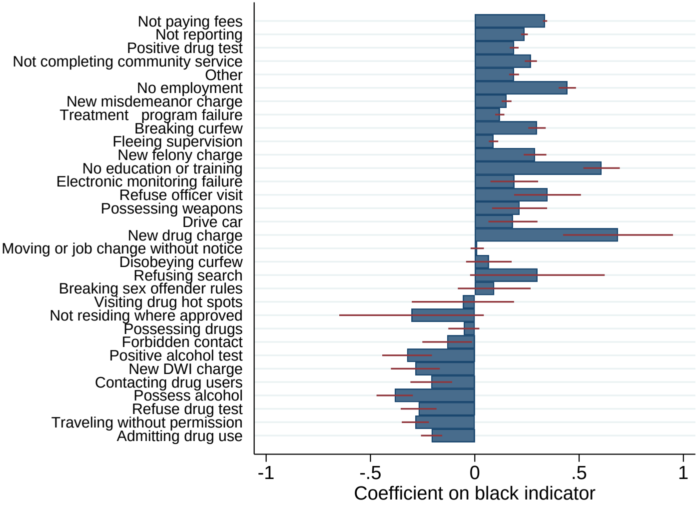
Financial fines account for most of black effects



Note: Graph plots the coefficient from a regression of an indicator for any violation of the listed type within three years on a dummy for black. Controls and sample are the same as in column (5) of previous table.

Back Proportional effects Officer race Back to behaviors

Other effects proportionally larger



Note: Graph plots the coefficient from a regression of an indicator for any violation of the listed type within three years on a dummy for black divided by the white mean for the outcome. Controls and sample are the same as in column (5) of previous table.

Back

What about other impacts of the reform?

Option for short confinement spells (CRVs) in response to violations

If CRVs are used exclusively as substitute for revokes, still estimate a clear causal effect:

Index potential outcomes by R_i and C_i (for CRV). If $Pr(C_i = 1|R_i(1) = R_i(0) = 0) = 0$, then:

$$
\begin{aligned}
E[Y_i(1-R_i)|Z_i=1] - E[Y_i(1-R_i)|Z_i=0] &= E[Y_i(0,1)|R_i(1) < R_i(0), C_i(1)=1]Pr(C_i(1)=1, R_i(1) < R_i(0)) \\
&+ E[Y_i(0,0)|R_i(1) < R_i(0), C_i(1)=1]Pr(C_i(1)=0, R_i(1) < R_i(0)) \\
&= E[Y_i(0,C_i)|R_i(1) < R_i(0)]Pr(R_i(1) < R_i(0))
\end{aligned}
$$

Racial differences still indicative of disparate impacts of revocation vs. alternative policy

Back

Extension to difference in differences

Potential outcomes depend on Z_i and treatment R_i as $Y_i(R_i, Z_i)$

Let T_i indicate treatment group membership. Assume

- Common trends for controls and always-takers:
  $E[Y_i(0,1)|T_i = 0, Z_i = 1] - E[Y_i(0,0)|T_i = 0, Z_i = 0] =$
  $E[Y_i(0,1)|R_i(0) = 0, T_i = 1, Z_i = 1] - E[Y_i(0,0)|R_i(0) = 0, T_i = 1, Z_i = 0]$
- Stable complier shares: $(R_i(1), R_i(0)) \perp\!\!\!\perp Z_i | T_i$

Then the DiD reduced form on $Y_i(1 - R_i)$ identifies:

$$\underbrace{Pr(Y_i(0,1) = 1, R_i(1) = 0, R_i(0) = 1) \mid T_i = 1, Z_i = 1)}_{\text{Object of interest}} -$$

$$\underbrace{(E[Y_i(0,1)|T_i = 0, Z_i = 1] - E[Y_i(0,0)|T_i = 0, Z_i = 0])\,(1 - Pr(R_i(1) = 0, R_i(0) = 0|T_i = 1))}_{\text{Bias term}}$$

Back

Proof

First note that under the maintained assumptions:

$$
\begin{aligned}
E[Y_i(1-R_i)|T_i=1,Z_i=1] &= E[Y_i(0,1)|R_i(1)=0,\,T_i=1,Z_i=1]Pr(R_i(1)=0|T_i=1,Z_i=1)\\
&= E[Y_i(0,1)|R_i(1)=0,R_i(0)=1,\,T_i=1,Z_i=1]Pr(R_i(1)=0,R_i(0)=1|T_i=1)\\
&+ E[Y_i(0,1)|R_i(1)=0,R_i(0)=0,\,T_i=1,Z_i=1]Pr(R_i(1)=0,R_i(0)=0|T_i=1)\\
E[Y_i(1-R_i)|T_i=1,Z_i=0] &= E[Y_i(0,0)|R_i(1)=0,R_i(0)=0,\,T_i=1,Z_i=0]Pr(R_i(1)=0,R_i(0)=0|T_i=1)
\end{aligned}
$$

Because controls have $Pr(R_i=0|T_i=0)\approx 1$, we have:

$$
E[Y_i(1-R_i)|T_i=0,Z_i=1]-E[Y_i(1-R_i)|T_i=0,Z_i=0]=E[Y_i(0,1)|T_i=0,Z_i=1]-E[Y_i(0,0)|T_i=0,Z_i=0]
$$

Putting these together shows that:

$$
\begin{aligned}
DiD = {} & E[Y_i(0,1)|R_i(1)=0,R_i(0)=1,\,T_i=1,Z_i=1]Pr(R_i(1)=0,R_i(0)=1|T_i=1)\\
&+ Pr(R_i(1)=0,R_i(0)=0|T_i=1)[E[Y_i(0,1)|R_i(1)=0,R_i(0)=0,\,T_i=1,Z_i=1]\\
&- E[Y_i(0,0)|R_i(1)=0,R_i(0)=0,\,T_i=1,Z_i=0]]-E[Y_i(0,1)|T_i=0,Z_i=1]+E[Y_i(0,0)|T_i=0,Z_i=0]
\end{aligned}
$$

Back

Relationship between risk objects

Accuracy and error rates are related as follows:

$$
\begin{aligned}
Pr(Y_i(0) = 1|R_i = 1) &= Pr(R_i = 1|Y_i(0) = 1)\frac{Pr(Y_i(0) = 1)}{Pr(R_i = 1)} \\
&= \frac{1 - Pr(R_i = 0|Y_i(0) = 1)}{1 - Pr(R_i = 0|Y_i(0) = 1) + Pr(R_i = 1|Y_i(0) = 0)\frac{Pr(Y_i(0)=0)}{Pr(Y_i(0)=1)}}
\end{aligned}
$$

Back

Single difference estimates of impacts of reform

	Black		Non-black	
	(1)	(2)	(3)	(4)
	Revoke	Arrest	Revoke	Arrest
Post-reform	-0.0730***	0.0118**	-0.0420***	0.0180***
	(0.00294)	(0.00391)	(0.00241)	(0.00336)
N	52397	52397	65335	65335
Pre-reform treated mean	.175	.311	.132	.258
Demographic controls	Yes	Yes	Yes	Yes
Criminal history FE	Yes	Yes	Yes	Yes
Accuracy		.171 (.052)		.459 (.079)
False negative		.961 (.012)		.932 (.012)
False positive		.106 (.007)		.035 (.006)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Includes all treated probation spells beginning 1-2 years before the reform and 0-1 years afterwards. Back

Impact of data window

	Not-black			Black		
	(1)	(2)	(3)	(4)	(5)	(6)
	1yr	2yr	3yr	1yr	2yr	3yr
Post-reform	-0.0036	-0.0067***	-0.0081***	-0.0036	-0.011***	-0.019***
	(0.0026)	(0.0019)	(0.0016)	(0.0039)	(0.0028)	(0.0024)
Treated	-0.0041	-0.00033	0.0019	-0.044***	-0.046***	-0.049***
	(0.0029)	(0.0021)	(0.0017)	(0.0038)	(0.0027)	(0.0022)
Post-x-treat	0.021***	0.018***	0.017***	0.015**	0.023***	0.028***
	(0.0041)	(0.0029)	(0.0024)	(0.0054)	(0.0038)	(0.0032)
N	165936	328784	488779	109764	217222	319596
R-squared	0.073	0.073	0.073	0.083	0.081	0.079
$\bar{Y}_{treat}$	.258	.265	.268	.311	.315	.318
Accuracy	.523	.55	.587	.205	.309	.365
False negative	.924	.931	.929	.957	.932	.918
False positive	.031	.026	.023	.096	.091	.089
Demo controls	Yes	Yes	Yes	Yes	Yes	Yes
Criminal hist FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Estimates based on probation spells starting / finishing as listed in table. Back

Effects of reform by crime type

	Black			Not-black		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Misd/fel	Fel	Any	Misd/fel	Fel
Post-reform	-0.0112***	-0.00926***	0.00212	-0.00666***	-0.00191	0.00324***
	(0.00281)	(0.00274)	(0.00168)	(0.00190)	(0.00178)	(0.000963)
Treated	-0.0464***	-0.0408***	-0.00280	-0.000334	0.00161	0.00745***
	(0.00268)	(0.00262)	(0.00163)	(0.00207)	(0.00195)	(0.00110)
Post-x-treat	0.0233***	0.0207***	0.00558*	0.0179***	0.0178***	0.00929***
	(0.00383)	(0.00374)	(0.00237)	(0.00295)	(0.00279)	(0.00163)
N	217222	217222	217222	328784	328784	328784
$\bar{Y}_{treat}$	.315	.291	.092	.265	.227	.063
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Criminal hist	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Includes all treated and untreated probation spells beginning 1-3 years before the reform and 0-2 years afterwards. Back

Triple difference estimates

	(1) Arrest	(2) Revoke	(3) Arrest	(4) Revoke	(5) Arrest	(6) Revoke	(7) Arrest	(8) Revoke	(9) Arrest	(10) Revoke
Treat-x-post	0.0201***	-0.0366***	0.0129	-0.0388***	0.0192*	-0.0341***				
	(0.00304)	(0.00175)	(0.00784)	(0.00496)	(0.00786)	(0.00496)				
Treat-x-post-x-black	0.00311	-0.0394***	0.00185	-0.0375***	-0.000708	-0.0356***	-0.00110	-0.0352***	-0.00283	-0.0323***
	(0.00501)	(0.00279)	(0.00497)	(0.00278)	(0.00504)	(0.00284)	(0.00513)	(0.00292)	(0.00563)	(0.00311)
N	546006	546006	546006	546006	546006	546006	546006	546006	546006	546006
Demographics			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Criminal history					Yes	Yes	Yes	Yes	Yes	Yes
Probation district							Yes	Yes		
Residence zipcode									Yes	Yes

Notes: Includes all treated and untreated probation spells beginning 1-3 years before the reform and 0-2 years afterwards. Back

Impact on misdemeanants after elimination of CRVs

	Black		Non-black	
	(1)	(2)	(3)	(4)
	Revoke	Arrest	Revoke	Arrest
Post-reform	-0.00413***	-0.0203***	-0.00285***	-0.00175
	(0.000847)	(0.00445)	(0.000487)	(0.00292)
Treated	0.173***	-0.0460***	0.120***	-0.00647*
	(0.00282)	(0.00412)	(0.00209)	(0.00319)
Post-x-treat	-0.0795***	0.0261***	-0.0284***	0.0180***
	(0.00398)	(0.00664)	(0.00307)	(0.00494)
N	78124	78124	128281	128281
Pre-reform treated mean	.189	.299	.135	.254
Demographic controls	Yes	Yes	Yes	Yes
Criminal history FE	Yes	Yes	Yes	Yes
Accuracy		.391 (.083)		.9 (.182)
False negative		.907 (.019)		.912 (.016)
False positive		.086 (.011)		.004 (.008)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Includes all misdemeanor treated and all untreated probation spells beginning 1-2 years before the reform or in 2016, after CRVs were eliminated for misdemeanor probationers by the legislature. Post is indicator for starting probation after December 1, 2011, the date JRA reforms took effect. Back

Impact on total felony technical incarceration

	Black				Non-black			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tech Inc	Any Tech Inc	2SLS Inc	2SLS Any	Tech Inc	Any Tech Inc	2SLS Inc	2SLS Any
Post-reform	-1.414***	-0.00772***	-0.670	-0.00554***	-0.432	-0.00383***	-0.329	-0.00356***
	(0.401)	(0.000763)	(0.444)	(0.000875)	(0.310)	(0.000446)	(0.319)	(0.000466)
Treated	16.50***	0.0851***	2.282	0.0433***	17.95***	0.0913***	6.449***	0.0608***
	(0.856)	(0.00271)	(1.169)	(0.00316)	(0.887)	(0.00267)	(1.807)	(0.00434)
Post-x-treat	-10.04***	-0.0295***			-6.324***	-0.0168***		
	(1.221)	(0.00360)			(1.317)	(0.00368)		
Revoked			200.3***	0.588***			168.9***	0.448***
			(22.44)	(0.0561)			(32.83)	(0.0799)
N	139820	139820	139819	139820	226376	226377	226377	226377
Pre-reform treated mean	25.064	.117			25.021	.12		
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Criminal history FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Includes all felony treated and all untreated probation spells beginning 1-3 years before the reform and 0-2 years afterwards. Back

Accommodating the real world

In real world, probationers can commit crimes or break rules throughout spell:

- $R_i \in \{0, 1, \ldots, \infty\}$ indicates time to revoke
- $Y_i \in \{0, 1, \ldots, \infty\}$ indicates time to reoffending

Index potential revocation by the reform as $R_i(0), R_i(1)$ and potential reoffending by R_i so that $Y_i = Y_i(R_i)$.

Can estimate:

$$\begin{aligned}
\text{Accuracy} &= Pr(Y_i(R_i(1)) = k | R_i(0) < k, R_i(1) > k) \\
\text{Type-I error} &= Pr(R_i(0) < k | Y_i(R_i(1)) > k, R_i(1) > k) \\
\text{Type-II error} &= Pr(R_i(0) > k | Y_i(R_i(1)) = k, R_i(1) > k)
\end{aligned}$$

Back

Proof of dynamic results

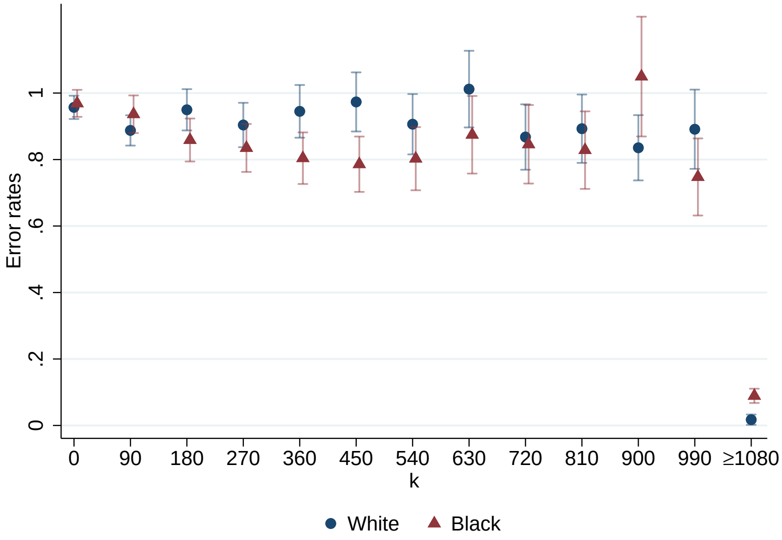
Note that the period k reduced form yields:

$$
\begin{aligned}
&E[1\{Y_i = k\}1\{R_i > k\}|Z_i = 1] - E[1\{Y_i = k\}1\{R_i > k\}|Z_i = 0] \\
&= Pr(Y_i = k, R_i > k|Z_i = 1) - Pr(Y_i = k, R_i > k|Z_i = 0) \\
&= Pr(Y_i(R_i(1)) = k, R_i(0) > k, R_i(1) > k) \\
&+ Pr(Y_i(R_i(1)) = k, R_i(0) < k, R_i(1) > k) \\
&- Pr(Y_i(R_i(0)) = k, R_i(0) > k, R_i(1) > k)
\end{aligned}
$$

Assume $Y_i(k) > k$ unless $k = \infty$ and $R_i(0) > k \rightarrow Y_i(R_i(1)) > k$

Then first and third terms cancel leaving us with $Pr(Y_i(R_i(1)) = k, R_i(0) < k, R_i(1) > k)$

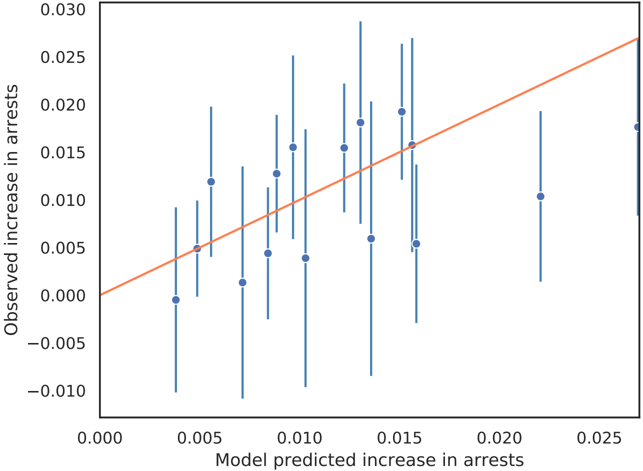
Revokes target black offenders more harshly at all horizons



Multi-period version of Oaxaca tells same story

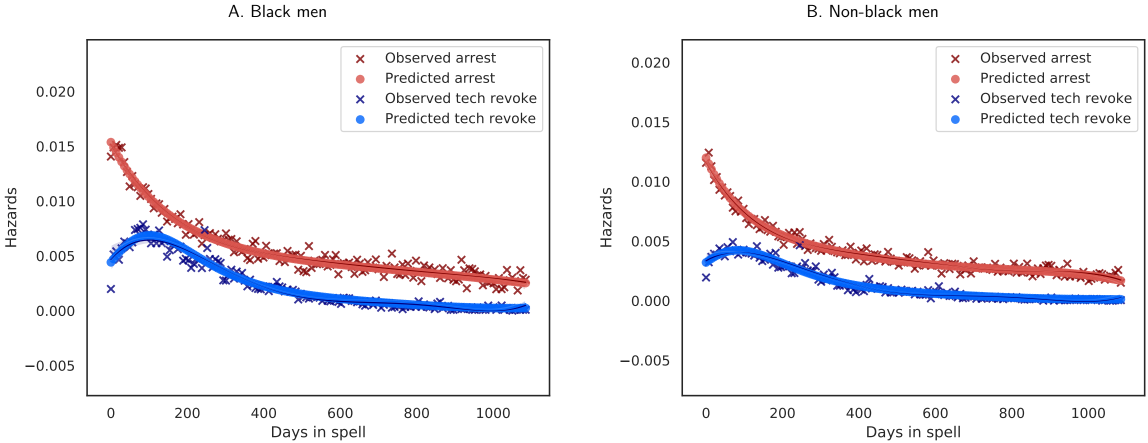
	Overall rates		Decomposition	
	Non-black	Black	Difference	Share of gap
Probability of technical revoke in 1080 days				
$Pr(R_i(0) \leq 1080)$	0.045	0.100	0.055	100.0%
Distribution of risk				
$Pr(Y_i(0) \leq 360)$	0.312	0.364	0.05	6.7%
$Pr(Y_i(0) \leq 720)$	0.426	0.488	0.063	10.4%
$Pr(Y_i(0) \leq 1080)$	0.497	0.560	0.062	11.4%
$Pr(Y_i(0) > 1080)$	0.503	0.440	-0.062	-10.0%
Total contribution				1.4%
Probability of revoke conditional on risk				
$Pr(R_i(0) < 360 \mid Y_i(0) < 360)$	0.070	0.077	0.007	4.6%
$Pr(R_i(0) < 720 \mid Y_i(0) < 720)$	0.063	0.105	0.042	33.9%
$Pr(R_i(0) < 1080 \mid Y_i(0) < 1080)$	0.072	0.109	0.036	33.6%
$Pr(R_i(0) < 1080 \mid Y_i(0) \geq 1080)$	0.017	0.089	0.072	65.1%

Model fits diff-in-diff moments well



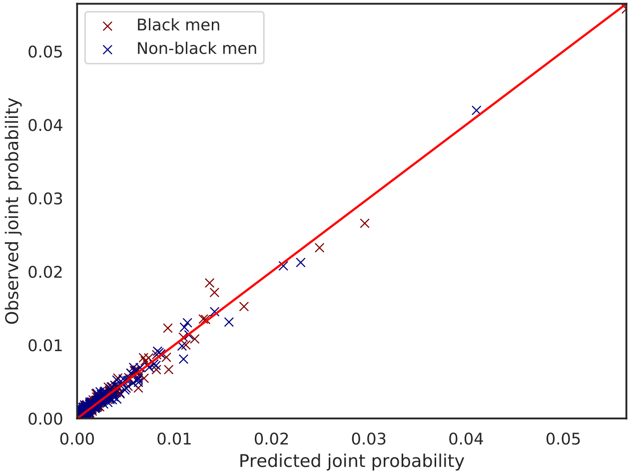
Notes: Figure compares difference-in-difference estimates of increase in observed arrests at 90, 180, 270, and 360 days for each race-by-gender group to the MMPH model's predictions of the same object. Vertical lines reflect 95% confidence intervals, while the orange line lies on a 45 degree angle. The diff-in-diff estimates are constructed using the sample sample and specification as in the reduced-form analysis and with no covariates included. Model predictions come from simulating observed arrests at each horizon with and without the "post" coefficients on technical violation risk. Back

Model fit to empirical hazards (pre-reform)



Notes: Figures plot empirical hazards and model predicted hazards for first year of spells starting at least one year before reform. Back

Fit to joint distribution of exits across spells



Notes: Figure plots observed vs. predicted frequencies of all possible exit combinations across two spells, discretizing to quarters. One cell, for example, is the joint probability of exiting due to rearrest in the first quarter of both spells. Another is the probability of exiting due to arrest in the 3rd quarter of the first spell, and due to technical incarceration in the 4th quarter of the second spell. Back

Officer race matters little

	Outcome: Any outcome in spell							
	(1) Adm	(2) Adm	(3) Drug	(4) Drug	(5) Rev.	(6) Rev.	(7) Tech rev.	(8) Tech rev.
Black	0.092***	0.092***	0.026***	0.024***	0.040***	0.041***	0.031***	0.033***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Black x black off		0.0016		0.0069*		-0.0048		-0.0048
		(0.004)		(0.003)		(0.003)		(0.003)
N	300733	300733	300733	300733	300733	300733	300733	300733
W mean	0.37	0.37	0.18	0.18	0.21	0.21	0.12	0.12
Demo	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sent	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crim hist	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Off FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all probationers starting spells in 2006-2010 and aged 16-45 at the start of their spell. Officer race is the race of the first officer assigned and only observations with a valid race are used. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration.

Back Back to behaviors

But black probationers also more likely to offend

	Outcome: Any arrest					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.0626***	0.0690***	0.0561***	0.0285***	0.0302***	0.0309***
	(0.00172)	(0.00182)	(0.00184)	(0.00183)	(0.00194)	(0.00402)
N	314514	314514	314514	314514	314514	89012
R-squared	0.00421	0.0284	0.0453	0.0786	0.0891	0.0741
Y white mean	0.330	0.330	0.330	0.330	0.330	0.330
Demographics		Yes	Yes	Yes	Yes	Yes
Sentence			Yes	Yes	Yes	Yes
Criminal hist				Yes	Yes	Yes
Zip code FE					Yes	Yes
Test scores						Yes
Logit coefficient	0.272	0.308	0.253	0.134		
Logit AME	0.0622	0.0688	0.0554	0.0283		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions include all probationers starting spells in 2006-2010 and aged 16-45 at the start of their spell. Demographic controls include gender, 20 quantiles of age, and district fixed effects. Sentence controls fixed effects for the offense class of their focal conviction and a linear control for the length of their supervision spell. Criminal history controls include fixed effects for prior convictions and revokes and a linear control for previous incarceration duration. Test score controls include last math and reading standardized test scores (normalized to have mean 0 and standard deviation 1 in the full population) observed from grades 3 to 8.

Back