Economics 250a
Racial Disparities and Discrimination

Reading List

Note: there is a huge literature on this topic in economics and in other social sciences. This lecture will focus on a few selected issues. The first four papers are review articles. The next two are key papers that have a large impact on current research. The last 3 are recent papers on race and crime.

Joseph Altonji and Rebecca Blank. "Race and Gender in the Labor Market." In O. Ashenfelter and D. Card, Handbook of Labor Economics volume 3. Elsevier, 1999. This is good background material. Be aware that the tables are not very reliable!

Kerwin Charles and Jonathan Guryan. "Studying Discrimination: Fundamental Challenges and Recent Progress." Annual Review of Economics 3 (2011): 479-511.

Roland Fryer. "Racial Inequality in the 21st Century: The Declining Significance of Discrimination." In O. Ashenfelter and D. Card, Handbook of Labor Economics volume 4B. Elsevier, 2011.

Lang, Kevin and Jee-Yeon Lehmann. "Racial Discrimination in the Labor Market: Theory and Empirics." Journal of Economics Literature 50 (2012): 959-1006.

Coate, Stephen and Glenn Loury. "Will Affirmative Action Policies Eliminate Negative Stereotypes?" American Economic Review 82 (1993): 1220-1240.

Marianne Bertrand and Sendhil Mullainathan. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimiation." American Economic Review 94 (2004): 991-1013.

Anwar, Shamena, Patrick Bayer and Randi Hjalmarsson. "The Impact of Jury Race in Criminal Trials." Quarterly Journal of Economics (2014): 1-39.

Roland Fryer, “An Empirical Analysis of Racial Differences in Police Use of Force”. Unpublished, June 2016.

Steven Raphael and Sandra Rozo. “Racial Disparities in the Acquisition of Juvenile Arrest Records”. Unpublished October 2016.

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1. Basic Patterns

Typically black men have about 20-25% lower annual earnings than whites, whereas black women have 5-10% lower annual earnings. Some of the gap is due to education.

	Years of Educ	%College or More
white men	14.1	36.8
black men	13.3	20.5
white women	14.4	41.0
black women	13.7	27.0

Using the March 2012/2013 CPS I estimated some simple models for log hourly wages with and without controls for education (years plus dummy for college+) and experience (cubic). These models exclude immigrants and are limited to people age 21-62:

For men, the differences (relative to white non-Hispanics) are:

	unadjusted	adjusted
black	-0.24	-0.14
hispanic	-0.19	-0.01

For women, the differences (relative to white non-Hispanics) are:

	unadjusted	adjusted
black	-0.10	-0.02
hispanic	-0.14	0.01

Notice the BW gap for women almost disappears if we control for education, whereas for men we still see a 10-15% gap. In his Handbook chapter Fryer (table 2) shows results for NLSY97 sample in 2006/7 (when they are in their 20s). The patterns are similar to those in the CPS. Based on these patterns, Fryer argues that the "big problem" facing black workers is education; though one can still see a 10% or so gap for black men. We will come back to this later in the lecture.

Wage models fit to earlier years of CPS data show some narrowing of the BW gap for both men and women from 1965 to 1975 (or so) and in the 1990s – see LL, Figure 1 and the figure from Card-DiNardo. The early convergence is often attributed to a combination of reduced discrimination, explicit government policies, and improved education quality for blacks born after 1930 or so. However, different analysts reach different conclusions about the relative size of these effects. There is also some argument about differential withdrawal of black men from the labor market after the mid-1960s (ie, "selection bias" in the earnings of black men). Black women tend to have higher employment rates than white women so this is not a factor for them.

2. Models of Discrimination and Racial Gaps

a. Becker's model

The "classic" Becker model of discrimination is one in which employers face horizontal supply curves of workers of both races, and have a distaste for hiring black workers. Employer j maximizes an objective like:

$$f(L_a + L_b) - w_a L_a - (w_b + d_j) L_b$$

where L_a and L_b are employment of whites and blacks, respectively, w_a and w_b are their market wages, and d_j is the "disrimination coefficient" of employer j. Note we have assumed B and W are equally productive. This firm acts as if black workes "cost" $w_b + d_j$. So if $d_j > w_a - w_b$ this employer hires only whites, whereas if $d_j < w_a - w_b$ it hires only blacks.

In the market equilibrium, B's are employed at all-black firms with the lowest levels of d_j. If total demand by firms with $d_j = 0$ is less than the supply of B's then the black wage is forced down until the last B is hired. The market-wide wage gap is determined by d_{j^m} where j^m is the most discriminatory firm that hires B's: the "marginal" hiring firm. Notice that this means that even at non-discriminating firms, B's are paid their lower market wage (and are a bargain): so none of the infra-marginal all-black firms would be even interested in hiring a white worker.

The stark Becker model is obviously not a good one to take to the data from the last few decades. (The ideas were written up in the 1950s, when there were many 100% segregated firms). Clearly, we rarely see any firms that hire only B's and (among larger employers in areas with reasonable numbers of B's) very few that have hire only W's. One "problem" for the Becker model is that since the 1960's, firms *cannot* legally justify paying a lower wage to equally productive B and W workers by arguing that B's have lower market wages. Of course productivity is rarely observable so...

Nevertheless, Charles and Guryan (JPE, 2008) try to test this model by looking at how the BW wage gap in a state varies with the strength of discriminatory preferences exhibited by whites in the b^{th} percentile of the distribution of discriminatory preferences, where b is the share of black workers in the area.

b. Statistical Discrimination

In the late 1960's Arrow proposed a model of "discrimination" based on imperfect information. Let p_i represent the true productivity of worker i and assume that among W's, $p_i \sim N(\mu_a, \sigma_a^2)$, whereas among B's, $p_i \sim N(\mu_b, \sigma_b^2)$. Suppose that employers don't observe p perfectly but instead observe a noisy version:

$$q_i = p_i + \eta_i$$

where $\eta_i \sim N(0, \sigma_\eta^2)$. If employers pay wages equal to expected productivity then the wage for a B with observed productivity q will be:

$$w_i = (1 - \lambda_b)\mu_b + \lambda_b q_i$$

where $\lambda_b = \sigma_b^2/(\sigma_b^2 + \sigma_\eta^2)$, whereas the wage paid to a white worker with the same observed productivity will be:

$$w_i = (1 - \lambda_a)\mu_a + \lambda_a q_i$$

where $\lambda_a = \sigma_a^2/(\sigma_a^2 + \sigma_\eta^2)$. In the simplest case where $\sigma_a^2 = \sigma_b^2$, the $\lambda's$ are equal, but if $\mu_b < \mu_a$ a B worker will receive a lower wage than a W with the same q.

Another interesting case is the one where $\mu_b = \mu_a$ but $\sigma_a^2 < \sigma_b^2$ (or alternatively, the noise component is more variable for B's). In this case, $\lambda_b < \lambda_a$ so B's wages are less sensitive to their observed productivity. This can reduce the dynamic incentives for B's to invest in skills - an idea formalized in Coate and Loury. Some people think this is an important explanation for the lower level of schooling among B's. Importantly, however, the observed return to schooling is usually (if anything) higher for B's than W's. For example, in the March 2012/2013 CPS samples, running log wages on education and a cubic in experience by gender/race group we get the following "returns" to schooling:

white men:	0.121 (0.001)
black men:	0.123 (0.004)
white women:	0.124 (0.001)
black women:	0.137 (0.003)

Of course the model is really about skills that are not directly observed, so one might be interested in seeing the "return" to cognitive skills by race.

c. Discrimination in a Search Model

Dan Black (JOLE, 1995) proposed a very simple equilibrium search model with some discriminating employers that illustrates another "market level" form of discrimination. Here I follow LL's explanation of the model. The model is a **wage posting** model with the following assumptions:

- flow value of unemployment = 0; cost of search is k
- jobs last forever once found; no discounting
- all workers have productivity p
- worker meets one firm per period. The firm makes a take-it or leave-it wage offer w_a or w_b depending on race, which searcher can accept or reject
- value of a job is $w + \alpha$ where $\alpha \sim F(\alpha)$
- a fraction θ of firms will not hire B's

Value functions for unemployed workers (taking w_a, w_b as fixed):
for W: $V^a = -k + E\max\{w_a + \alpha, V^a\}$
for B: $V^b = -k + \theta V^b + (1-\theta)E\max\{w_b + \alpha, V^b\}$
Re-arranging we get 2 equations:

$$\begin{aligned} k &= \int_{V^a - w_a} (w_a + \alpha - V^a)dF(\alpha) \\ k &= (1-\theta)\int_{V^b - w_b} (w_b + \alpha - V^b)dF(\alpha) \end{aligned}$$

If $w_b \leq w_a$ we must have $V^b < V^a$ when $\theta > 0$.

What do firms do? Firms have monopsonistic power and can offer a wage below p and take the chance that the worker has a high value of α. Since jobs last forever and there is no discounting the optimal strategy for a firm faced with a white applicant is to maximize

$$\pi^a = (1 - F(V^a - w_a))(p - w_a)$$

while for an unpredjudiced firm faced with a black applicant, the firm will maximize

$$\pi^b = (1 - F(V^b - w_b))(p - w_b)$$

The FOC's imply:

$$\begin{aligned} p - w_a &= \frac{1 - F(V^a - w_a)}{f(V^a - w_a)} = m(V^a - w_a) \\ p - w_b &= \frac{1 - F(V^b - w_b)}{f(V^b - w_b)} = m(V^b - w_b) \end{aligned}$$

Now assume that $m()$ is strictly decreasing (Note m is the "Mills ratio" and will be decreasing if F is log-concave, a standard assumption in such problems). Then the solutions must have $w_b < w_a$.

The economic idea is that if some firms won't hire B's, then non-discriminating firms have more market power over B's, and set a lower wage. Note that in this model (as in the Becker model) the presence of the discriminating firms conveys a benefit to non-discriminators

d. Rational Sterotype Models

Coate and Loury develop a model with workers investing in skills (or not) and firms partially observing productivity and deciding how to assign workers, in which there can be multiple equilibria.[1] In a "low" equilibrium, firms expect a low level of investment, and so require a very high signal in order to assign workers to a high-productivity job. Given that high bar, most workers find it optimal not to invest. In the "high" equilibrium, firms expect a high level of investment, and so have a relatively low threshold for the observed signal to assign workers to a high-productivity job. Given that lower bar, most workers find it optimal to invest.

The following "sketch" of their model is from LL.

- workers are in one of 2 groups

- workers have a cost of investment $c \sim U[0, 1]$. Worker sees c and decides to invest or not. Workers who invest are "qualified" (q). Rest are unqualified (u).

[1] The possibility of multiple equilibrium plays a large role in the statistical discrimination literature because the game is to think of models where (1) no one has direct animus against B's; (2) B's and W's are fundamentally the same; (3) everyone is rational; and yet (4) B's choose lower levels of human capital investment and end up getting paid less. If this is true than a "big push" could get us to a new equilibrium.

- firm sees group and a signal θ. CDF of the signal is $F_q(\theta)$ for qualified and $F_u(\theta)$ for unqualified, with $F_q(\theta) < F_u(\theta)$ – so low values of θ are more likely for U's

- firm has 2 jobs: "easy" (job 0) is appropriate for q or u. The "hard" job (job 1) is only appropriate for q's. Worker is paid a wage w if assigned to the hard job (and 0 if assigned to the easy job).

- firm has priors π_a and π_b that members of the 2 groups are qualified

- firm will assign a worker with prior π to the high task if $\theta \geq s^*(\pi)$, where s^* is a decreasing function (higher π means a lower standard). (See CL, equation 1 and 2 for long derivation, based on posterior prob of being qualified, given θ, and payoff to firm of correct vs incorrect assignment).

- given standard s a worker who is qualified gets the hard job with probability $(1 - F_q(s))$, while if he were unqualified the probability is $(1 - F_u(s))$. So the benefit of investing is $w(F_u(s) - F_q(s))$, and a worker with cost c will invest if

$$w[F_u(s) - F_q(s)] > c.$$

Notice that its as if a worker has only 1 chance to get hired for the better job.

If $c \sim U[0, 1]$, then fraction who invest is

$$\pi^* = w[F_u(s(\pi)) - F_q(s(\pi))]$$

Since $F_u(s)$ and $F_q(s)$ are S-shaped functions with $F_q(s)$ underneath, the rhs of this equation is increasing and then decreasing in s (i.e. inverse-U shaped).

In equilibrium we must have:

$$\pi = w[F_u(s^*(\pi)) - F_q(s^*(\pi))]$$

This can have multiple solutions (see Figure at the end of lecture), so there can be both High and Low equ.

3. Some Important Recent Papers

a. Bertrand and Mullainathan – the "names" paper

This is a carefully designed audit study that has inspired many later studies on lots of different issues using a similar design. (BM were not the first to send randomized applications but they did a very good job and had a lot of power int their design).

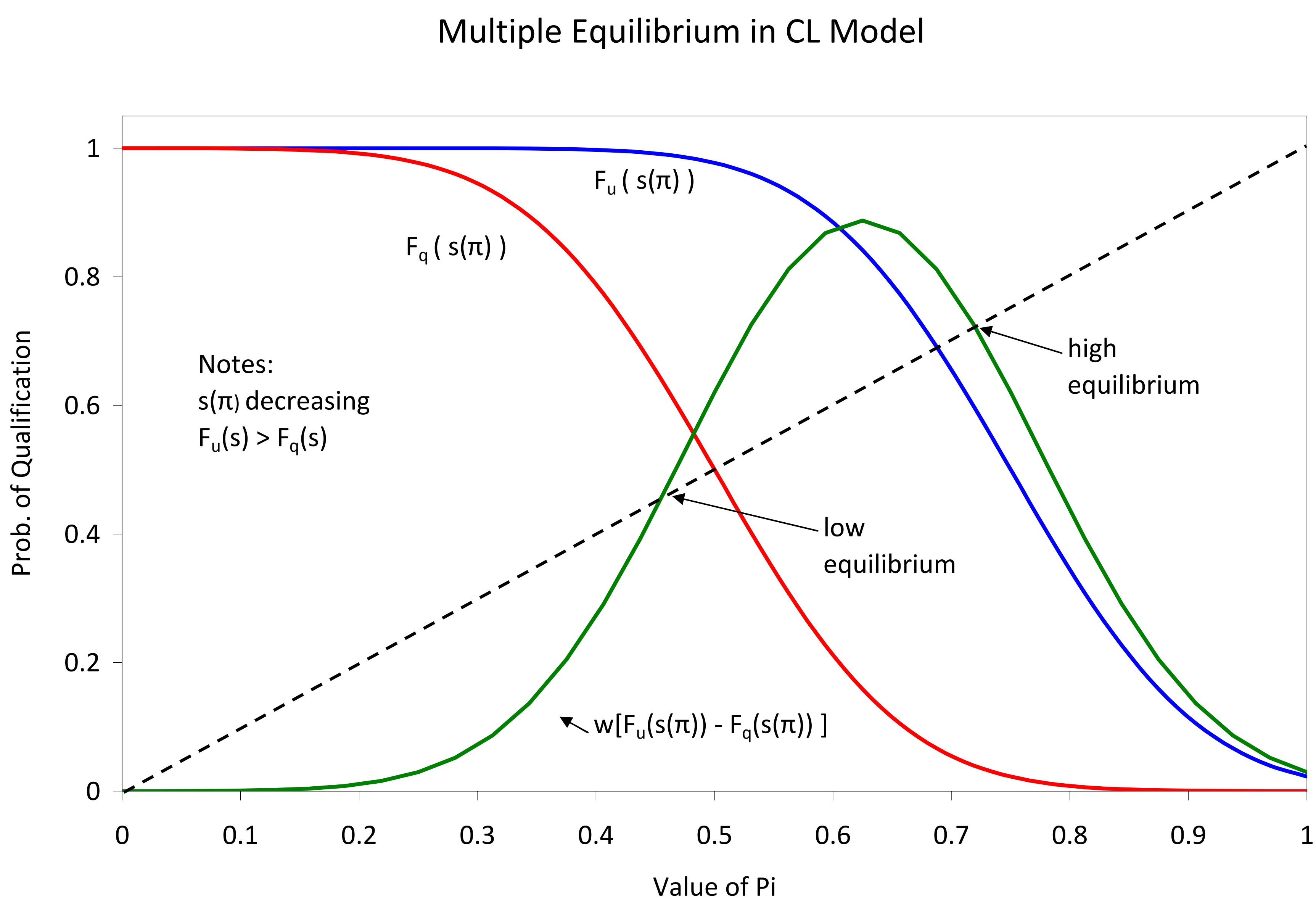
The paper is important because it seems to establish with a strong research design that blacks and whites are NOT treated equally by firms. Nevertheless, some authors have tried to argue that BM's use of black names as a signifier of race is confounded by the fact that black names also signify "low SES".

c) Three Recent crime papers

Anwar, Bayer and Hjalmarsson (QJE, 2012) - the "black jury" paper.

Fryer's "Use of Force" paper

Raphael and Rozo's "Juvenile arrest" paper Black men are disproportion-

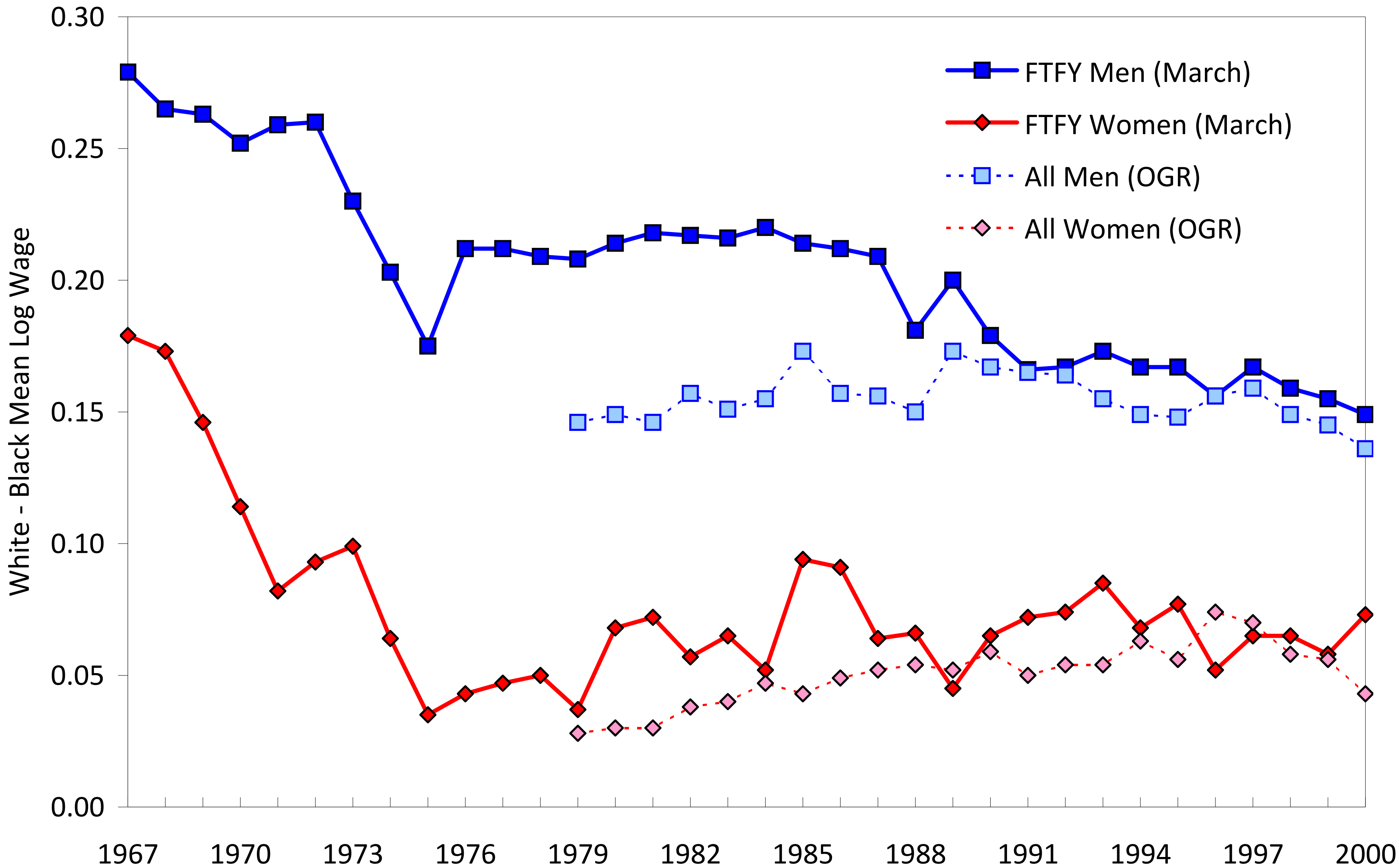

Multiple Equilibrium in CL Model
Prob. of Qualification
Value of Pi
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
F_u (s(π))
F_q (s(π))
Notes:
s(π) decreasing
$F_u(s) > F_q(s)$
high
equilibrium
low
equilibrium
w[F_u(s(π)) - F_q(s(π))]

ately involved in criminal justice (arrests, incarcerations, etc), and there is a concern that this factor hurts their labor market outcomes, especially with the ready availability of information about past criminal records.

ABH is a carefully designed jury study that shows that when there are more blacks in a jury, a black defendent is less likely to be convicted. The instrument is the presence of any black in the jury pool, which they show seems to pass standard exogeneity/design tests. The paper is one of several out there now which show that black defendents are treated differently.

Fryer's "use of force" paper uses data from several sources – including the NYC stop and frisk program – to examine the probability of a police use of force, **conditional on an interaction.** He finds that P(use of force|stop) is higher for blacks and hispanics in NYC. Interestingly, he does not find that blacks or Hispanics are more likely to be found with a weapon, conditional on the level of force.

Figure 13: White-Black Wage Gaps (from Card-DiNardo)



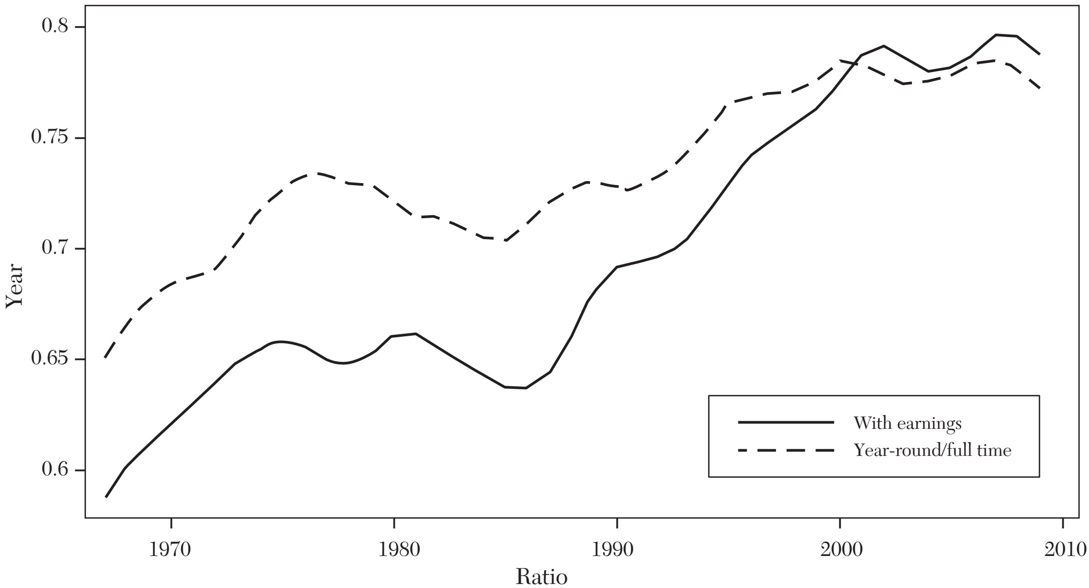


Figure 1. Ratio of Median Earnings: Black Men/White Men, 1967–2009

declining labor force participation of black men (Brown 1984; Chandra 2000; Juhn 2003). In addition, early improvements can also be credited to both the rise in the relative level of educational attainment (Smith and Welch 1989) and the relative quality of the schools attended by blacks (Card and Krueger 1993). Nevertheless, it is difficult to come up with plausible estimates of the effects of human capital that would fully explain the wage convergence in the 1960s and early 1970s. On the other hand, they make the absence of further convergence in the late 1970s and much of the 1980s even more surprising.

The very large gains made by black men after the mid-to-late 1980s cannot be accounted for by nonearners in the Current Population Survey (CPS) since there was little change during this period. While the the proportion of black men age 22–64 who were in prison or jail (and thus not in the CPS sample) grew (Western 2006, table 1.1; Western and Pettit 2005), the increase in incarceration rates cannot explain the large convergence from a black–white earnings ratio of 0.62 in 1987 to 0.77 in 2000. Moreover, Neal (2006) shows that skill convergence between young black and white men stopped and may even have reversed itself among those born after 1960. Thus, overall skill convergence should have slowed after 1990, making it difficult to explain why earnings convergence reasserted itself.

3.2 *Employment Differentials*

Much less attention has been paid to racial employment and unemployment differentials than to wage differentials although the former are in many ways more dramatic. In 2008, the labor force participation rate of black men age 25–54 was 83.7 percent compared with 91.5 percent among white men. The unemployment rate was 9.1 percent

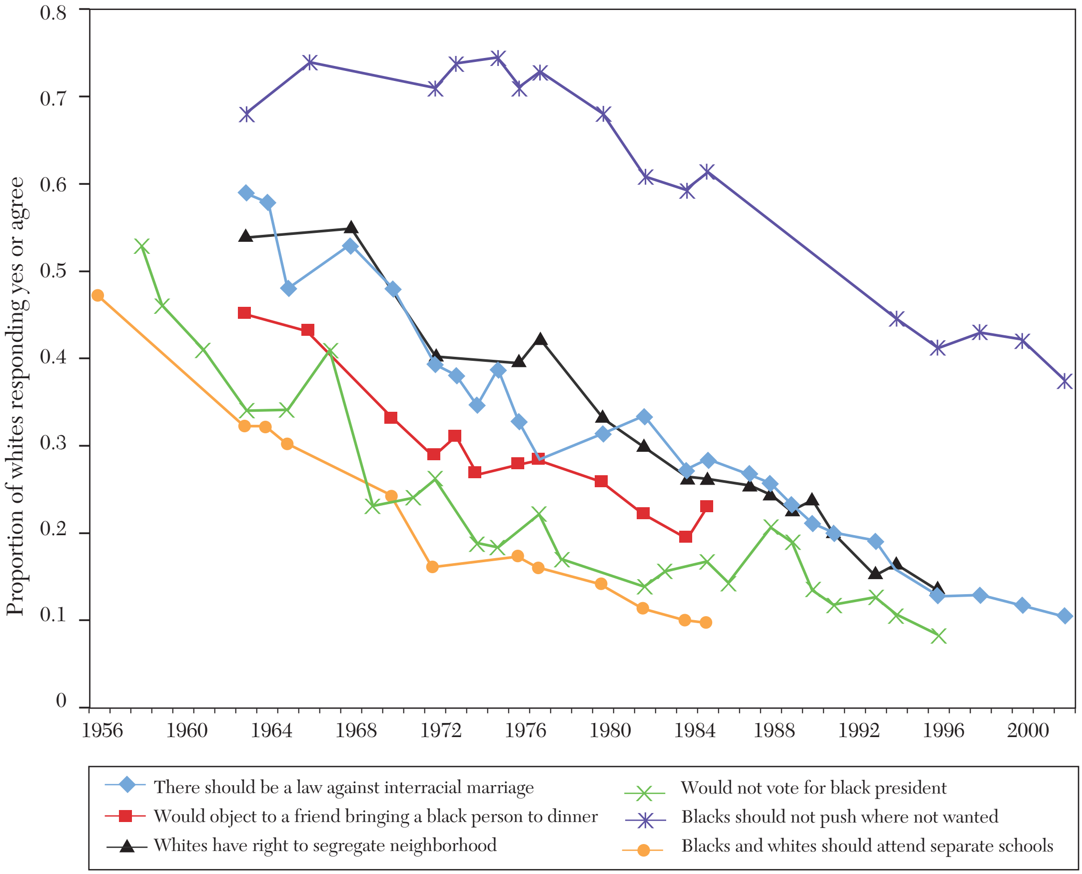


Figure 3. Trends in Prejudice Measures, 1956–2003.

against blacks. Figure 3 documents the decline in prejudice as measured by national polls and surveys.[15] The data show large declines since the 1950s and 1960s in whites' expression of prejudiced views on school segregation, social interaction, and blacks in politics. While we cannot completely discount the possibility that whites are merely becoming more cautious in expressing what are now socially unacceptable views, there is behavioral evidence to support the change. In the late 1950s, over half of whites said they would not vote for a black president. The evidence of the 2008 election suggests that this proportion has declined significantly.

In 1958, 94 percent of Americans disapproved of marriage between a white and a black. By 2007, this figure was 17 percent.[16]

[15] Survey responses are drawn from the General Social Society Survey 1972–2008 and Naemi, Mueller, and Smith (1989).

[16] http://www.gallup.com/poll/28417/most-americans-approve-interracial-marriages.aspx, downloaded January 5, 2010.

Table 1
Mean Call-Back Rates By Racial Soundingness of Names [a]

	Call-Back Rate for White Names	*Call-Back Rate for African American Names*	*Ratio*	*Difference (p-value)*
Sample:				
All sent resumes	**10.06%** [2445]	**6.70%** [2445]	**1.50**	**3.35%** (.0000)
Chicago	**8.61%** [1359]	**5.81%** [1359]	**1.48**	**2.80%** (.0024)
Boston	**11.88%** [1086]	**7.83%** [1086]	**1.52**	**4.05%** (.0008)
Females	**10.33%** [1868]	**6.87%** [1893]	**1.50**	**3.46%** (.0001)
Females in administrative jobs	**10.93%** [1363]	**6.81%** [1364]	**1.60**	**4.12%** (.0001)
Females in sales jobs	**8.71%** [505]	**6.99%** [529]	**1.25**	**1.72%** (.1520)
Males	**9.19%** [577]	**6.16%** [552]	**1.49**	**3.03%** (.0283)

[a] Notes:

1. The table reports, for the entire sample and different subsamples of sent resumes, the call-back rates for applicants with a White sounding name (column 1) and an African American sounding name (column 2), as well as the ratio (column 3) and difference (column 4) of these call-back rates. In brackets in each cell is the number of resumes sent in that cell.
2. Column 4 also reports the p-value for a test of proportion testing the null hypothesis that the call-back rates are equal across racial groups.

Table 2
Distribution of Call-Backs By Employment Ad [a]

Equal Treatment:	*No Call-back*	*1W+1B*	*2W+2B*
87.37%	82.56%	3.46%	1.35%
[1162]	[1098]	[46]	[18]
Whites Favored (WF):	*1W+0B*	*2W+0B*	*2W+1B*
8.87%	5.93%	1.50%	1.43%
[118]	[79]	[20]	[19]
African Americans Favored (BF):	*1B+0W*	*2B+0W*	*2B+1W*
3.76%	2.78%	0.45%	0.53%
[50]	[37]	[6]	[7]
Ho: WF=BF			
p=.0000			

[a] Notes:

1. This table documents the distribution of call-backs at the employment ad level. "No Call-Back" is the fraction of ads for which none of the fictitious applicants received a call-back. "1W+1B" is the fraction of ads for which exactly one White and one African American applicant received a call-back. "2W+2B" is the fraction of ads for which exactly two White applicants and two African American applicants received a call-back. "Equal Treatment" is defined as the sum of "No Call-Back," "1W+1B," "2W+2B." "1W+0B" is the fraction of ads for which exactly one White applicant and no African American applicant received a call back. "2W+0B" is the fraction of ads for which exactly two White applicants and no African American applicant received a call-back. "2W+1B" is the fraction of ads for which exactly two White applicants and one African American applicant received a call-back. "Whites Favored" is defined as the sum of "1W+0B," "2W+0B," and "2W+1B." "1B+0W" is the fraction of ads for which exactly one African American applicant and no White applicant received a call-back. "2B+0W" is the fraction of ads for which exactly two African American applicants and no White applicant received a call-back. "2B+1W" is the fraction of ads for which exactly two African American applicants and one White applicant received a call-back. "African Americans Favored" is defined as the sum of "1B+0W," "2B+0W," and "2B+1W."
2. In brackets in each cell is the number of employment ads in that cell.

Table 4
Average Call-Back Rates
By Racial Soundingness of Names and Resume Quality [a]

Panel A: Subjective Measure of Quality

	Low	High	Ratio	Difference (p-value)
White Names	**8.80%**	**11.31%**	**1.29**	**2.51%**
	[1216]	[1229]		(.0391)
African American Names	**6.41%**	**6.99%**	**1.09**	**0.58%**
	[1216]	[1229]		(.5644)

Panel B: Predicted Measure of Quality

	Low	High	Ratio	Difference (p-value)
White Names	**5.04%**	**14.18%**	**2.81**	**9.14%**
	[834]	[804]		(.0000)
African American Names	**5.14%**	**8.58%**	**1.66**	**3.44%**
	[817]	[816]		(.0060)

[a] Notes:

1. Panel A reports the mean call-back rates for applicants with a White sounding name (raw 1) and African American sounding name (raw 2) depending on whether the resume was subjectively qualified as a lower quality (column 1) or higher quality (column 2). In brackets is the number of resumes sent for each race/quality group. Column 4 reports the p-value of a test of proportion testing the null hypothesis that the call-back rates are equal across quality groups within each racial group.

2. For Panel B, we use a third of the sample to estimate a probit regression of the call-back dummy on the set of resume characteristics as displayed in Table 3. We further control for a sex dummy, a city dummy, 6 occupation dummies and a vector of dummy variables for job requirements as listed in the employment ad (see Section 4.4 for details). We then use the estimated coefficients on the set of resume characteristics to estimate a predicted call-back for the remaining resumes (2/3 of the sample). We call "high quality" resumes the resumes that rank above the median predicted call-back and "low quality" resumes the resumes that rank below the median predicted call-back. In brackets is the number of resumes sent for each race/quality group. Column 4 reports the p-value of a test of proportion testing the null hypothesis that the call-back rates are equal across quality groups within each racial group.

Table 11
Call-Back Rates and Mother's Education by First Name[a]

White Female			African American Female		
Name	Call-back	Mother Education	Name	Call-back	Mother Education
Emily	8.3%	96.6%	Aisha	2.2%	77.2%
Anne	9.0%	93.1%	Keisha	3.8%	68.8%
Jill	9.3%	92.3%	Tamika	5.4%	61.5%
Allison	9.4%	95.7%	Lakisha	5.5%	55.6%
Sarah	9.8%	93.4%	Tanisha	6.3%	64.0%
Meredith	10.6%	97.9%	Latoya	8.8%	55.5%
Laurie	10.8%	81.8%	Kenya	9.1%	70.2%
Carrie	13.1%	80.7%	Latonya	9.1%	31.3%
Kristen	13.6%	93.4%	Ebony	10.5%	65.6%
Average		91.7%	Average		61.0%
Overall		83.9%	Overall		70.2%
Correlation	-.350	(p=.3558)	Correlation	-.326	(p=.391)
White Male			**African American Male**		
Name	Call-back	Mother Education	Name	Call-back	Mother Education
Neil	6.6%	85.7%	Rasheed	3.0%	77.3%
Geoffrey	6.8%	96.0%	Tremayne	4.3%	—
Brett	6.8%	93.9%	Kareem	4.7%	67.4%
Brendan	7.7%	96.7%	Darnell	4.8%	66.1 %
Greg	7.8%	88.3%	Tyrone	5.3%	64.0%
Todd	8.7%	87.7%	Jamal	6.6%	73.9%
Matthew	9.0%	93.1%	Hakim	7.3%	73.7%
Jay	13.2%	85.4%	Leroy	9.4%	53.3%
Brad	15.9%	90.5%	Jermaine	11.3%	57.5%
Average		91.7%	Average		66.7%
Overall		83.5%	Overall		68.9%
Correlation	-.276	(p=.472)	Correlation	-.619	(p=.102)

[a] Notes:

1. This table reports, for each first name used in the experiment, call-back rate and average mother education. Average mother education for a given first name is defined as the fraction of babies born with name in Massachusetts between 1970 and 1986 whose mother had at least completed a high school degree (see text for details). Within each sex/race group, first names are ranked by increasing call-back rate. In brackets in each cell is the number of resumes sent in that cell.
2. "Average" reports, within each race-gender group, the average mother education for all the babies born with one of the names used in the experiment. "Overall" reports, within each race-gender group, average mother education for all babies born in Massachusetts between 1970 and 1986 in that race-gender group. "Correlation" reports the Spearman rank order correlation betwen call-back rates and mother education *within* each race-gender group as well as the p-value for the test of independence.

TABLE I
SUMMARY STATISTICS

	All Cases		Black Defendants		White Defendants	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Defendant characteristics						
Black	0.44	0.50	1	0	0	0
Hispanic	0.04	0.20	0	0	0	0
White	0.51	0.50	0	0	1	0
Male	0.92	0.27	0.95	0.21	0.89	0.32
Case characteristics						
Total charges	2.99	3.57	2.79	2.33	3.26	4.55
Any drug charge	0.25	0.44	0.37	0.49	0.14	0.35
Any murder charge	0.05	0.22	0.06	0.25	0.05	0.21
Any robbery charge	0.09	0.29	0.15	0.36	0.05	0.21
Any other violent charge	0.31	0.46	0.31	0.46	0.30	0.46
Any property charge	0.23	0.42	0.21	0.41	0.25	0.43
Any sex charge	0.13	0.34	0.08	0.27	0.18	0.38
Any weapons charge	0.12	0.33	0.18	0.39	0.08	0.27
Any other charge	0.33	0.47	0.26	0.44	0.37	0.48
Dependant variables						
Proportion guilty convictions	0.670	0.439	0.686	0.432	0.641	0.450
Any guilty convictions	0.728	0.445	0.745	0.437	0.702	0.458
Pool and seated jury characteristics						
Number of seated jurors	7.11	0.483	7.12	0.476	7.11	0.496
Number in jury pool	27.3	7.3	26.9	7.0	27.6	7.6
Any black in pool	0.64	0.48	0.63	0.48	0.65	0.48
Any black on seated jury	0.28	0.45	0.29	0.45	0.26	0.44
Proportion black on seated jury	0.046	0.080	0.051	0.089	0.040	0.069
Proportion black in pool	0.039	0.040	0.040	0.043	0.038	0.038
Observations	785		333		379	

Notes: The first two columns report summary statistics for the full sample of 785 cases for which a jury was selected and the variable under consideration is defined. In particular, defendant race is defined for 774 cases, defendant gender for 776 cases, specific crime categories for 776 cases, total charges for 773 cases, the dependant variables for 750 cases, and the pool and seated jury variables for the full sample of 785 cases. The latter columns report summary statistics for cases with black defendants (n = 333) and white defendants (n = 379), respectively, in which a verdict of guilty or not guilty by the jury was returned for at least one of the charged offenses. Together, the observations in these columns make up the sample used in our main analysis. Summary statistics for the proportion variables (i.e., proportion guilty convictions, proportion black on seated jury, and proportion black in pool) were formed by measuring the proportion for each jury or jury pool and averaging across cases.

TABLE II
THE RELATIONSHIP BETWEEN THE RACIAL COMPOSITION OF THE JURY POOL AND DEFENDANT/CASE CHARACTERISTICS

	(1) Indicator for any blacks in pool	(2) Proportion of blacks in pool	(3) Proportion of whites in pool	(4) Proportion of other races in pool
Defendant characteristics				
Black	−0.008	0.003	−0.004	0.001
	[0.039]	[0.003]	[0.005]	[0.003]
Hispanic	0.005	0.004	−0.003	−0.001
	[0.088]	[0.008]	[0.011]	[0.006]
Male	0.043	0.006	−0.009	0.002
	[0.067]	[0.005]	[0.007]	[0.004]
Case characteristics				
Any drug charge	−0.029	−0.0003	0.004	−0.003
	[0.051]	[0.004]	[0.006]	[0.004]
Any murder charge	0.093	−0.002	−0.006	0.006
	[0.076]	[0.006]	[0.008]	[0.005]
Any other charge	0.007	0.002	−0.004	−0.0005
	[0.040]	[0.004]	[0.005]	[0.003]
Any other violent charge	0.0001	0.004	−0.004	−0.0003
	[0.042]	[0.004]	[0.005]	[0.003]
Any property charge	0.078	0.013***	−0.006	−0.008**
	[0.047]	[0.005]	[0.006]	[0.003]
Any robbery charge	−0.026	−0.005	0.004	0.0001
	[0.065]	[0.005]	[0.008]	[0.005]
Any sex charge	0.07	0.002	0.001	−0.004
	[0.058]	[0.005]	[0.006]	[0.004]
Any weapons charge	0.075	−0.001	0.001	0.0002
	[0.054]	[0.004]	[0.006]	[0.004]
Total charges	0.008*	5×10^{-5}	0.0002	−0.0003
	[0.003]	[0.000]	[0.000]	[0.000]
Constant	0.541***	0.028***	0.942***	0.029***
	[0.074]	[0.006]	[0.007]	[0.005]
Observations	771	771	771	771
F-statistic	1.40	1.13	0.68	1.07
R-squared	0.02	0.02	0.01	0.01

Notes: Each column reports parameter estimates and heteroskedasticity-robust standard errors from OLS regressions using the variable in the column heading as the dependent variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The crime categories are not mutually exclusive, so there is no omitted crime category. F-statistics jointly testing whether all coefficients equal 0 are reported in the second to last row of the table. Fourteen observations from the full sample shown in Table I were dropped due to one or more missing values for the various defendant and case characteristics.

TABLE IV
REDUCED-FORM BENCHMARK REGRESSIONS

	(1)	(2)	(3)	(4)
Dependent variable	Any guilty conviction		Proportion guilty convictions	
Black defendant	0.150***	0.164***	0.156***	0.160***
	[0.056]	[0.058]	[0.055]	[0.057]
Any black in pool	0.069	0.105**	0.063	0.090*
	[0.048]	[0.051]	[0.047]	[0.050]
Black defendant * any black in pool	−0.168**	−0.166**	−0.174**	−0.155**
	[0.070]	[0.074]	[0.069]	[0.072]
Constant	0.656***	0.627***	0.600***	0.576***
	[0.039]	[0.041]	[0.038]	[0.040]
Includes controls for:				
Gender/age of pool	No	Yes	No	Yes
County dummy	No	Yes	No	Yes
Year of filing dummies	No	Yes	No	Yes
Observations	712	712	712	712
R-squared	0.01	0.07	0.01	0.08

Notes: The dependent variable for each regression is shown in the row heading. All regressions are estimated on the main analysis sample using OLS and heteroskedasticity-robust standard errors are reported in brackets. The gender of the jury pool is measured as the proportion of the pool that is female, and the age of jury pool is controlled for with the proportion of the pool that is age 40 or less, and proportion of the pool that is between the ages of 40 and 60. For each of the controls (including county and year of filing dummies) both a demeaned version of the control variable and the interaction of this demeaned variable with whether the defendant is black are included in the specification. Because the control variables are demeaned, the coefficients on the variables reported in the table can be interpreted as the estimated effect at the mean and are comparable across columns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

age and adding year dummies addresses the possibility that crime patterns or convictions rates may be trending systematically over time. In all cases, the additional control variables described above are fully interacted with the defendant's race. This allows for the possibility that these control variables have a differential effect for black and white defendants, just as we have allowed for the racial composition of the jury pool.[24]

The point estimates for the three key coefficients are remarkably robust and statistically significant in the specification that includes controls. For expositional convenience, we use the specification reported in column (2) as our *benchmark* specifi-

24. In addition, each control variable is demeaned (prior to being interacted), which ensures that the main coefficients in Table IV are reported at the sample mean in each specification and therefore comparable; that is, there is no need to look at the coefficients on the interaction variables included in the vector of controls.

Table 2A

Racial Differences in Non-Lethal Use of Force, NYC Stop Question and Frisk,Any Use of Force

	White Mean	Black	Hispanic	Asian	Other Race
	(1)	(2)	(3)	(4)	(5)
No Controls	0.153	1.534***	1.582***	1.044	1.392***
		(0.144)	(0.149)	(0.119)	(0.121)
+ Baseline Characteristics		1.480***	1.517***	1.010	1.346***
		(0.146)	(0.146)	(0.122)	(0.114)
+ Encounter Characteristics		1.655***	1.641***	1.059	1.452***
		(0.155)	(0.157)	(0.133)	(0.121)
+ Civilian Behavior		1.456***	1.513***	1.049	1.368***
		(0.128)	(0.136)	(0.124)	(0.107)
+ Fixed Effects		1.173***	1.120***	0.951	1.057**
		(0.034)	(0.026)	(0.033)	(0.028)
Observations			4,927,467		

Notes: This table reports odds ratios by running logistic regressions. The sample consists of all NYC stop and frisks from 2003-2013 with non-missing use of force data. The dependent variable is an indicator for whether the police reported using any force during a stop and frisk interaction. The omitted race is white, and the omitted ID type is other. The first column gives the unconditional average of stop and frisk interactions that reported any force being used for white civilians. Columns (2) through (5) report logistic estimates for black, hispanic, asian and other race civilians respectively. Each row corresponds to a different empirical specification. The first row includes solely racial group dummies. The second row adds controls for gender and a quadratic in age. The third row adds controls for whether the stop was indoors or outdoors, whether the stop took place during the daytime, whether the stop took place in a high crime area or during a high crime time, whether the officer was in uniform, civilian ID type, and whether others were stopped during the interaction. The fourth row adds controls for civilian behavior. The fifth row adds precinct and year fixed effects. Each row includes missings in all variables. Standard errors clustered at the precinct level are reported in parentheses.

Table 9
Weapon Found,
Conditional on Force Used

	White Mean	Coefficient on Black	Coefficient on Hispanic	Observations
	(1)	(2)	(3)	(4)
At Least Hands	0.036	-0.013^{***}	-0.008^{**}	1,028,625
		(0.004)	(0.003)	
At Least Pushing to Wall	0.036	-0.002	-0.000	253,643
		(0.002)	(0.002)	
At Least Using Handcuffs	0.040	-0.000	0.000	118,527
		(0.002)	(0.003)	
At Least Drawing a Weapon	0.053	0.003	0.001	58,443
		(0.004)	(0.004)	
At Least Pushing to Ground	0.054	0.005	0.002	51,083
		(0.004)	(0.005)	
At Least Pointing a Weapon	0.083	-0.011	-0.007	19,505
		(0.010)	(0.010)	
At Least Using Spray/Baton	0.092	-0.013	0.007	1,745
		(0.027)	(0.033)	

Notes: This table reports OLS estimates. The sample consists of all NYC stop and frisks from 2003-2013 in which use of force and outcome variable were non-missing. The dependent variable is a binary variable that is coded as 1 whenever a weapon was found on the civilian and 0 if weapon was not found. Each row looks at the fraction of white civilians carrying weapons and racial differences in carrying weapons for black civilians versus white civilians and hispanic civilians versus white civlians, conditional on at least a force level being used. We control for gender, a quadratic in age, civilian behavior, whether the stop was indoors or outdoors, whether the stop took place during the daytime, whether the stop took place in a high crime area or during a high crime time, whether the officer was in uniform, civilian ID type, whether others were stopped during the interaction, and missings in all variables. Precinct and year fixed effects were included in all regressions. Standard errors clustered at the precinct level are reported in parentheses.

Figure 3: Booking Rates by Age and Race, All Juvenile Arrests and First Arrests

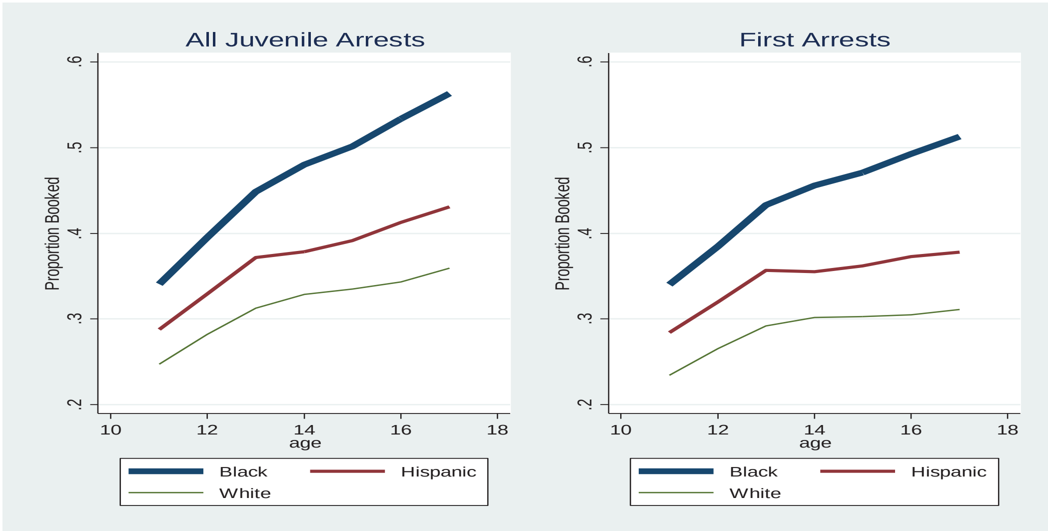


Figure 4: Arrest Status by Arrest Sequence and Race/Ethnicity for those Youth Arrested at Least Four Times

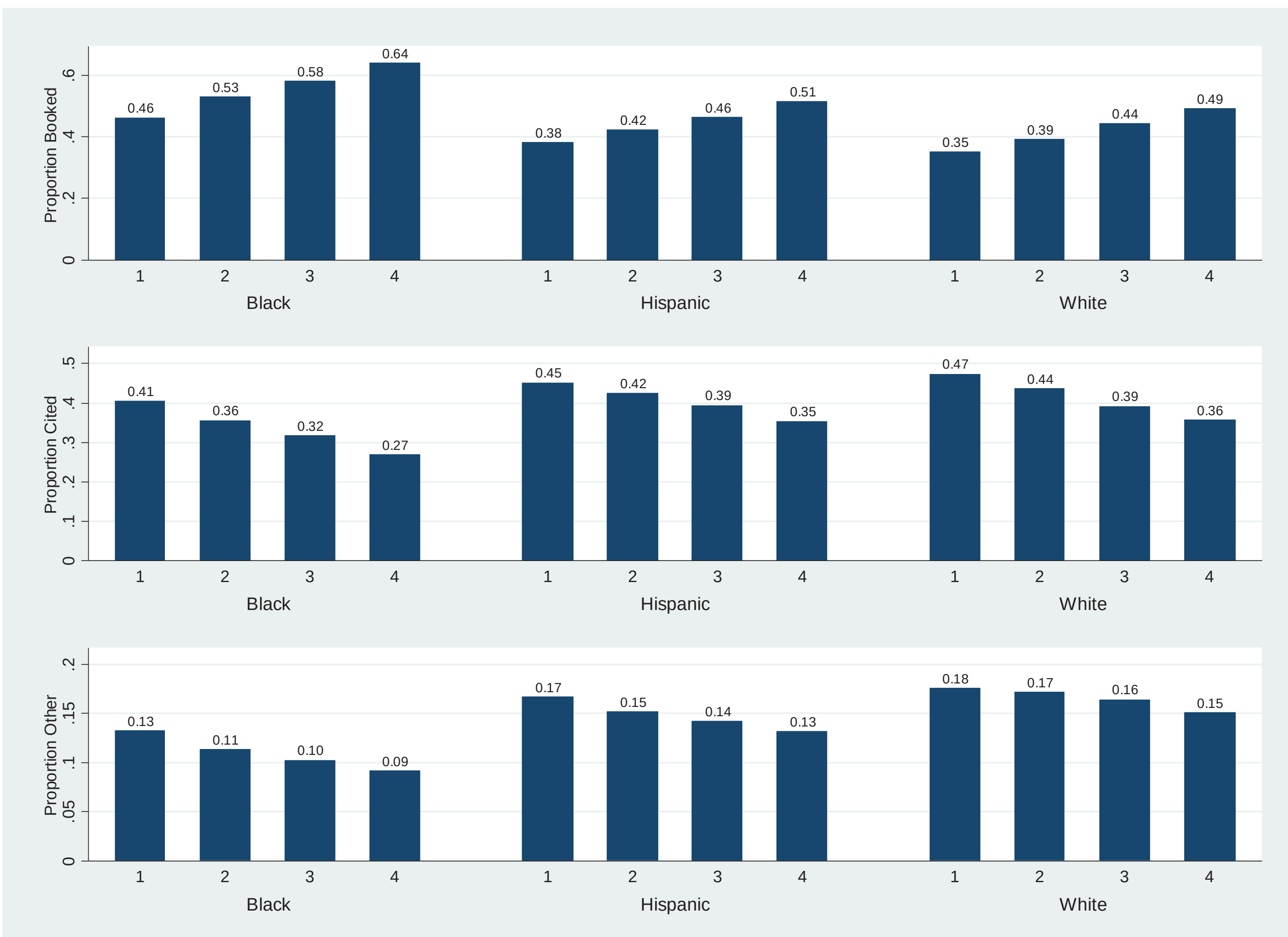


Figure 5: Proportion Booked at First Arrest by Arrest Date Relative to 18th Birthday of the Arrestee and the Proportion Booked at Second Arrest by First-Arrest Arrest Date Relative to the 18th Birthday of the Arrestee

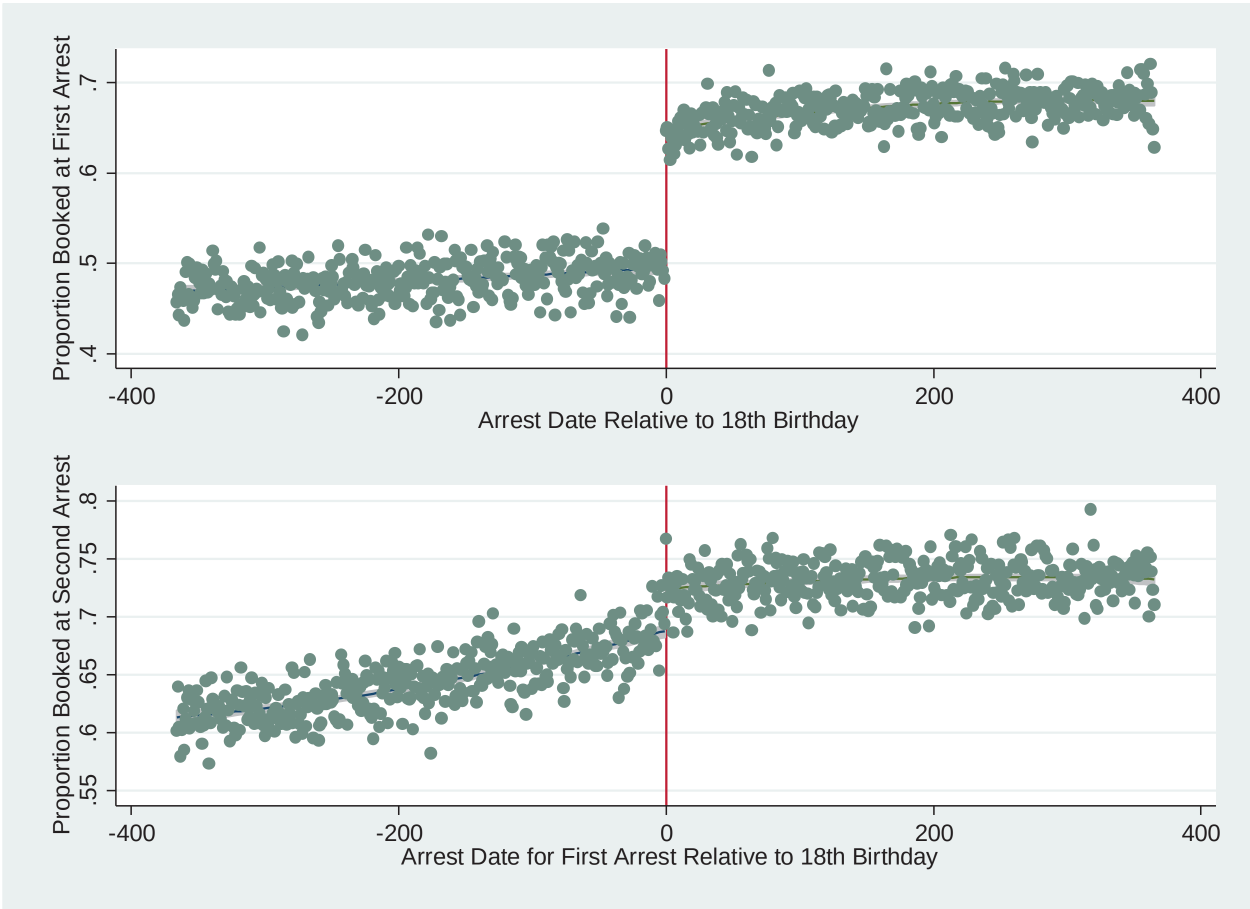


Figure 7: Proportion Booked by Race and Date of Arrest Relative to the Arrestee's Birthday for Black, White, and Hispanic Youth: All Offenses and by Broad Offense Category

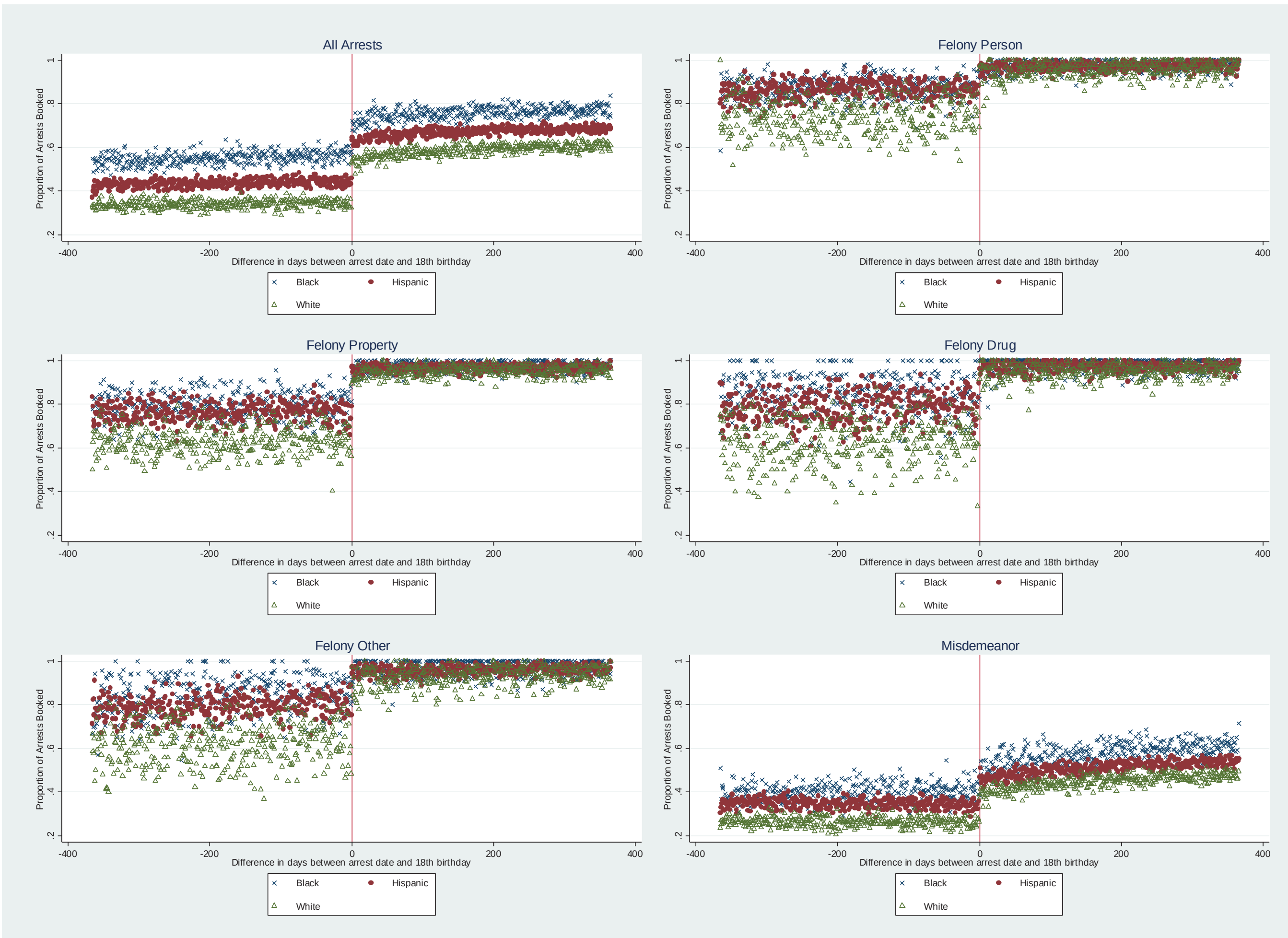


Table 4
IV Estimates of the Effect of a Prior Booking on the Likelihood that the Current Arrest is Booked Exploiting the Discontinuous Increases in Bookings Occurring at the Age of 18

Sample	Specification (1)	Specification (2)	Specification (3)
All Arrests	0.239 (0.024)[a]	0.117 (0.027)[a]	0.112 (0.026)[a]
Felony arrests	0.045 (0.017)[a]	0.055 (0.027)[b]	0.043 (0.025)[c]
Misdemeanor arrests	0.388 (0.034)[a]	0.164 (0.039)[a]	0.150 (0.036)[a]
Black	0.202 (0.065)[a]	0.110 (0.072)	0.109 (0.066)[c]
White	0.246 (0.037)[a]	0.161 (0.038)[a]	0.139 (0.036)[a]
Hispanic	0.224 (0.039)[a]	0.048 (0.051)	0.072 (0.045)
Male	0.204 (0.025)[a]	0.083 (0.028)[a]	0.075 (0.027)[a]
Female	0.460 (0.069)[a]	0.342 (0.092)[a]	0.331 (0.082)[a]

Standard errors are in parentheses. Estimates are based on a just-identified 2SLS model where the first stage includes the arrest date for the first arrest relative to the arrestees 18th birthday, the date variable squared, a dummy for over 18, interaction terms between the dummy and the quadratic function for the running variable and various additional covariates. Specification (1) only includes these variables. Specification (2) adds dummy variables for race and ethnicity, gender, the first arrest offense (roughly 76 categories), and the current arrest offense (roughly 72 categories). The final specification adds over 700 fixed effects for arresting agency.

a. Statistically significant at the one percent level of confidence.
b. Statistically significant at the five percent level of confidence.
c. Statistically significant at the ten percent level of confidence.

Table 5
Linear Probability Models Estimates of Racial/Ethnic Disparities in the Likelihood that a Juvenile Arrest is Booked

	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.163[a]	0.164[a]	0.092[a]	0.088[a]	0.082[a]	0.039[a]
	(0.024)	(0.023)	(0.019)	(0.019)	(0.017)	(0.004)
Hispanic	0.061[a]	0.055[a]	0.064[a]	0.062[a]	0.058[a]	0.016[a]
	(0.018)	(0.018)	(0.015)	(0.015)	(0.014)	(0.004)
Asian	-0.019	-0.019	-0.031	-0.032	-0.027	-0.009
	(0.028)	(0.028)	(0.023)	(0.023)	(0.022)	(0.006)
Other	0.019	0.015	0.022	0.023	0.023	0.005
	(0.020)	(0.020)	(0.016)	(0.016)	(0.015)	(0.006)
Prior Arrests						
Felony Person	-	-	-	0.051[a]	-0.089[a]	0.009
				(0.007)	(0.007)	(0.006)
Felony Property	-	-	-	0.049[a]	-0.070[a]	0.013[a]
				(0.006)	(0.006)	(0.004)
Felony Drug	-	-	-	0.053[a]	-0.068[a]	0.011
				(0.007)	(0.008)	(0.008)
Felony Other	-	-	-	0.039[a]	-0.067[a]	0.008[a]
				(0.007)	(0.006)	(0.004)
Misdemeanor	-	-	-	0.002	-0.042[a]	0.007[a]
				(0.005)	(0.004)	(0.003)
Status	-	-	-	-0.011[c]	-0.017[a]	-0.007[a]
				(0.006)	(0.004)	(0.003)
Prior Bookings						
One	-	-	-	-	0.252[a]	0.087[a]
					(0.017)	(0.007)
Two	-	-	-	-	0.370[a]	0.107[a]
					(0.022)	(0.012)
Three	-	-	-	-	0.457[a]	0.107[a]
					(0.024)	(0.015)
Four +	-	-	-	-	0.608[a]	0.094[a]
					(0.033)	(0.023)
Demographics/year	No	Yes	Yes	Yes	Yes	Yes
Current Offense	No	No	Yes	Yes	Yes	Yes
Agency	No	No	No	No	No	Yes

Note: Standard errors are in parentheses and are clustered by arresting law enforcement agency. All models are estimated on 1,349,477 observations and include a constant term. "White" is the omitted race/ethnicity category. Specifications including demographic/year controls include single-year age dummies, a dummy for male, and year-of-arrest dummies. Specifications including controls for current offense include 274 fixed effects for the most serious charge. Specifications including controls for agency include 708 agency-fixed effects.

a. Statistically significant at the one percent level of confidence.
b. Statistically significant at the five percent level of confidence
c. Statistically significant at the ten percent level of confidence.