Do Police Maximize Arrests or Minimize Crime? Evidence from racial profiling in U.S. cities

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What is the objective of discretionary police stops?

- Arrest maximization: uncover crime
- Crime minimization: prevent crime

Information about objective is necessary to identify sources of discrimination in the data

Identifying sources of discrimination

- Existing approach:

    1. Model an agent that uses statistical discrimination **in order to meet objective**
    2. Then allow for taste-based discrimination, stereotypes, incorrect beliefs, etc.

    $\implies$ Derive empirical test that allows one to reject statistical discrimination as only source of discrimination

- When police use racial profiling to stop and search: what is the objective?

Identifying sources of discrimination in policing

A problem

- Existing empirical tests assume that police maximize arrests (Knowles, Persico and Todd 2001, Dharmapala and Ross 2004, Anwar and Fang 2006, Antonovics and Knight 2009, Marx 2017, Hernández-Murrillo and Knowles 2004)
- These tests are *invalid* if police minimize crime instead

  (Manski 2005 and 2006, Dominitz and Knowles 2006, Durlauf 2005, Harcourt 2004)
- No alternative empirical test under assumption of crime minimization

This paper

- Derive an empirical test to identify police objectives

  Arrest Max vs. Crime Min

1. Compare models of alternative police objectives
   - Comparative statics for observable outcomes differ
2. Test predictions using city-level data

   Outcomes of interest:
   - Racial discrepancies in arrest rates
   - Police spending

Model

1. $t = 0$, Local government chooses total number of police searches to minimize costs of crime and policing

2. $t = 1$, Individuals choose to commit crime or not
   - Differ by race ($j = 1, 2$) and income ($y_{ij} \sim F_j$)
   - Can commit crime instead of legal earning opportunity, but with risk of arrest

   $$\implies \text{Commit crime iff } y_{ij} \leq y_j^*(p_j)$$

3. $t = 1$, Police officers allocate searches across two groups
   - Either solve Crime Minimization Problem (CMP)
   - Or Arrest Maximization Problem (AMP)

(Crime choice and police search as in Knowles, Persico, and Todd 2001, Manski 2005, 2006, Dominitz and Knowles 2006)

Police Search

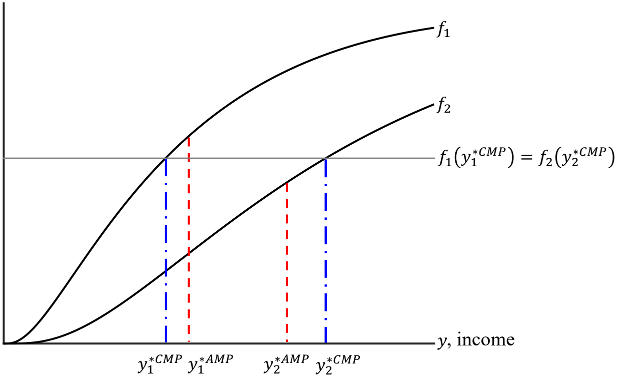
Choose p_1 and p_2 subject to budget constraint

1. If police minimize crime,

   Equate marginal effect on crime, $f_1(y_1^*(p_1)) = f_2(y_2^*(p_2))$

2. If police maximize arrests,

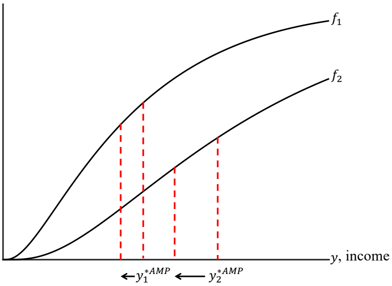
   Equate crime rates, $F_1(y_1^*(p_1)) = F_2(y_2^*(p_2))$



Arrest Max

$\uparrow n_1 \implies \uparrow$ Police spending

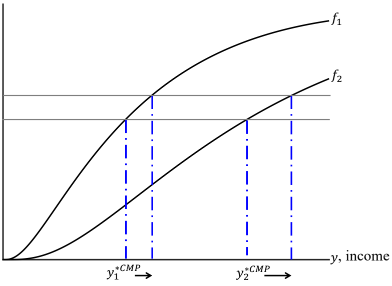
$\implies \downarrow$ Distance between arrest rates



Crime Min

$\uparrow n_1 \implies \updownarrow$ Police spending

$\implies \uparrow$ Distance between arrest rates



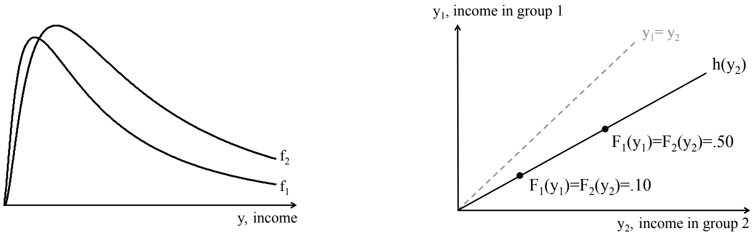
Characterizing equilibria

- Use quantile-quantile function to characterize equilibria:

$$h(y_2) \equiv F_1^{-1}(F_2(y_2))$$

  - F_2 is a 'stretch' of F_1 if $h' < 1$
  - F_2 is a 'shrink' of F_1 if $h' > 1$

Figure: Income densities and the quantile-quantile function when F_2 is a stretch of F_1



Propositions 1 & 2

Outcome, X	F_2 is a stretch or shrink of F_1	Sign of $\partial X/\partial n_1$: Arrest Max	Sign of $\partial X/\partial n_1$: Crime Min
Police Spending	Stretch	+	+/-
	Shrink	-	+/-
Distance between arrest rates	Stretch	-	+
	Shrink	+	-

Data

A panel of U.S. cities observed in 2002, 2007, 2012, 2017 (3,633 city-years)

- Police Spending: Census of Governments
  - Exclude capital and construction spending
- Arrests: Uniform Crime Reports (FBI)
  - Focus on arrests for drug sale
- Income and other covariates: American Community Survey, Census

Measuring $h'(.)$

Let group 1 be the Black population and group 2 be the White population

$$hprime = \frac{\text{50th income \%tile, Black} - \text{10th income \%tile, Black}}{\text{50th income \%tile, White} - \text{10th income \%tile, White}}$$

$$stretch = 1 \text{ if } hprime < 1$$

$$shrink = 1 \text{ if } hprime > 1$$

Empirical Specifications

$$y_{ct} = \beta_0 + \beta_1 pblack_{ct} + \beta_2 pblack_{ct} \times shrink_{ct} + \beta_3 shrink_{ct} + \beta_4 hprime_{ct}$$
$$+ X'_{ct}\gamma + \theta_c + \phi_t + \epsilon_{ct}$$

$$y_{ct} = \pi_0 + \pi_1 pblack_{ct} + \pi_2 pblack_{ct} \times hprime_{ct} + \pi_3 hprime_{ct}$$
$$+ X'_{ct}\gamma + \theta_c + \phi_t + \epsilon_{ct}.$$

Outcome in city c, time t	Arrest Max	Crime Min
Police Spending	$\beta_1 > 0$	$--$
	$\beta_1 + \beta_2 < 0$	$--$
Distance between arrest rates	$\beta_1 < 0$	$\beta_1 > 0$
	$\beta_1 + \beta_2 > 0$	$\beta_1 + \beta_2 < 0$

Empirical Results: Distance between arrest rates

Table 1, Panel B: City and year fixed effects

	Predicted Sign AMP	Predicted Sign CMP	(1)	(2)	(3)
Percent Black	$-$	$+$	-11.44**	-12.09**	-17.17***
			(4.91)	(4.88)	(6.51)
Percent Black $\times$ *shrink*	$+$	$-$		1.77	
				(1.49)	
Percent Black $\times$ *hprime*	$+$	$-$			6.40*
					(3.66)
hprime	$+/-$	$+/-$	-0.13	-0.06	-0.75
			(0.57)	(0.57)	(0.50)
shrink	$+/-$	$+/-$	-0.23	-0.43	
			(0.27)	(0.31)	
N			3633	3633	3633
R^2			0.56	0.56	0.56
Dependent variable mean			2.46	2.46	2.46
p-value for $H_0 : \beta_1 + \beta_2 = 0$				0.038	
p-value for $H_0 : \pi_1 + \pi_2 = 0$					0.024

Note: Arrest rates are arrests per 1,000 population. Standard errors clustered at the city level are in parentheses. All regressions include city and year fixed effects and the following covariates: population, population squared, population density, Theil index of residential segregation, median household income, poverty rate, percent Hispanic, percent Asian, percent American Indian/Alaska Native, percent unemployed, percent without a high school diploma, percent with a bachelors degree or higher, percent age 24 and younger, percent age 65 and older, and percent female.

Empirical Results: Police Spending

Table 2, Panel B: City and year fixed effects

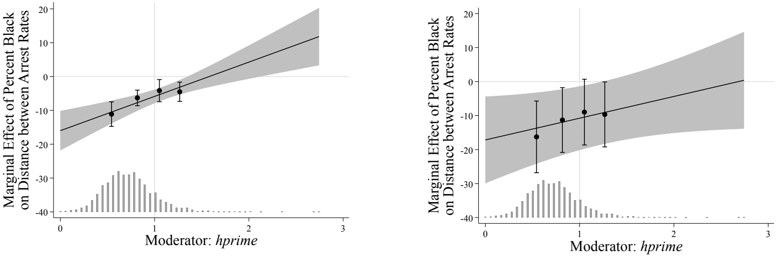
	Predicted Sign AMP	Predicted Sign CMP	(1)	(2)	(3)
Percent Black	$+$	$+/-$	-17.61*	-18.69*	-14.60
			(10.45)	(10.57)	(11.91)
Percent Black $\times$ *shrink*	$-$	$+/-$		2.92	
				(1.86)	
Percent Black $\times$ *hprime*	$-$	$+/-$			-3.32
					(8.54)
hprime	$+/-$	$+/-$	-0.70	-0.57	-0.62
			(0.78)	(0.79)	(0.59)
shrink	$+/-$	$+/-$	-0.11	-0.43	
			(0.45)	(0.52)	
N			3633	3633	3633
R^2			0.98	0.98	0.98
Dependent variable mean			27.63	27.63	27.63
p-value for $H_0 : \beta_1 + \beta_2 = 0$				0.125	
p-value for $H_0 : \pi_1 + \pi_2 = 0$					0.093

Note: Police spending is direct police expenditures in 1 million USD. Standard errors clustered at the city level are in parentheses. All regressions include city and year fixed effects and the following covariates: population, population squared, population density, Theil index of residential segregation, median household income, poverty rate, percent Hispanic, percent Asian, percent American Indian/Alaska Native, percent unemployed, percent without a high school diploma, percent with a bachelors degree or higher, percent age 24 and younger, percent age 65 and older, and percent female.

Distance between Arrest Rates

A. State fixed effects

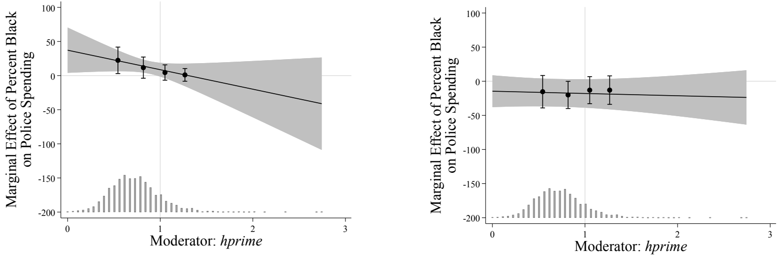
B. City fixed effects



Note: This figure shows the estimated marginal effect of percent Black on the distance between arrest rates at different levels of *hprime*. All regressions include year fixed effects and time-varying covariates. Standard errors allow for clustering at the city level. The black solid line shows the marginal effect implied by the linear interaction estimates from estimating equation **??**, and the gray area indicates the 95% confidence interval. The black circles indicate point estimates from the binning estimator and the whiskers indicate 95% confidence intervals. The distribution of *hprime* is shown with histograms along the x-axes. The theoretical models predict that the sign of the marginal effect will change at *hprime* $= 1$, indicated with a vertical gray line.

Police Spending

C. State fixed effects   D. City fixed effects



Note: This figure shows the estimated marginal effect of percent Black on police spending at different levels of *hprime*. All regressions include year fixed effects and time-varying covariates. Standard errors allow for clustering at the city level. The black solid line shows the marginal effect implied by the linear interaction estimates from estimating equation **??**, and the gray area indicates the 95% confidence interval. The black circles indicate point estimates from the binning estimator and the whiskers indicate 95% confidence intervals. The distribution of *hprime* is shown with histograms along the x-axes. The theoretical models predict that the sign of the marginal effect will change at $hprime = 1$, indicated with a vertical gray line.

Robustness Checks: Empirical

- Patterns do not hold for placebo outcomes or income measures
- Analysis with other racial groups (Asian, American Indian/Alaskan Native)
- Alternative explanations
  - Racial animus
  - Racial composition of police force
  - City mayor's political party, race
  - Racial profiling laws
- Robust to omitted variables (Altonji Elder and Taber, 2005; Oster, 2017)
  - Based on explanatory power of observables, it is unlikely that the unbiased coefficients in the regression of distance between arrest rate would fail to reject the crime minimization model.

Robustness Checks: Theoretical extensions

- Taste-based discrimination, other forms of discrimination
- Diminishing marginal returns in arrest maximization problem
- Non-monolithic police behavior
- Political model of police spending
- Racial profiling bans

Conclusion

- Model of profiling with endogenous police resources yields empirical test for police objectives
- U.S. city-level data are consistent with predictions of arrest maximization, inconsistent with those of crime mininimization
- Supports the validity of existing tests that use arrest maximization assumption to identify types of discrimination