Online Appendix

Smartphone Data Reveal Neighborhood-Level Racial Disparities in Police Presence

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February 16, 2023

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A Other Data Sources

Census demographics data. Census block group and city characteristics data come from American Community Survey (ACS) 2013-2017 5-year estimates. We collect data on each block group's racial composition (% Black, Hispanic, and Asian), population, median household income, percent college graduates, and census form mail return rate. We also collect city level data on racial composition (% Black, White, Hispanic, and Asian).

Homicide data. Homicide data is collected by The Washington Post and covers homicide information (including latitude-longitude location, arrest decision, victim demographics) in 50 of the largest U.S. cities from 2007 to 2017 (Rich 2020). For several cities, the homicide data is not available for the whole decade: for example, in New York City, data are provided in 2016 and 2017 only (so we collected NYC homicide data between 2013 to 2016 from NYC open data portal); for San Antonio, data are only available between 2013 to 2016. The definition of homicide follows the FBI's Uniform Crime Reporting Program, including murder and non-negligent manslaughter while excluding suicides, accidents, justifiable homicides, and deaths caused by negligence. We use records of homicides to measure crime-driven demand for policing given the high accuracy of homicide reporting.

Law Enforcement Management and Administrative Statistics (LEMAS) data. The LEMAS data contains information on police officers' demographics, salaries, and functions, and agencies' duties, structures, and policies for 3499 local law enforcement agencies in 2016 (Bureau of Justice Statistics 2016). We obtain the racial composition of full time sworn officers and supervisors for 21 cities' police departments to compare with the imputed race of smartphone users. Among the 21 cities, the Indianapolis Metropolitan police department is not included in the LEMAS data, while the Phoenix and the San Antonio Police Departments have missing data on officers' and supervisors' race, respectively.

FBI Uniform Crime Report (UCR) - Law Enforcement Officers Killed or Assaulted (LEOKA) data. UCR-LEOKA data contains measures of officers that are killed or assaulted and total officer employment as of October 1st of each year at the departmental level (Kaplan 2020). We compare the police officer counts in the 2017 UCR-LEOKA data with the smartphone measure of patrol officers.

NYPD Officer Home Zip Code data. Data on NYPD police officers' home zip code comes from Bell (2016) through submission of a Freedom of Information Law (FOIL) request to the NYPD. The data reports the number of police officers that live in a specific zip code and patrol in a specific precinct. We calculate the total number of police officers that live in a zip code across all precincts to compare with the police officer counts that we infer to "live" in that zipcode from the smartphone location data.

Police Enforcement Action data. We collect 6 cities' geocoded data on police arrests in 2017 from each city's open data portal.¹ We collect geocoded data on police stops in nine cities from multiple sources, including open data portals for New York City, Philadelphia and Denver, Stanford Open Policing Project (Pierson et al. 2020) for Columbus, Nashville, Houston, San Antonio, and Oklahoma City and Ba et al. (2021) for Chicago. We collect 2017 stop data for most cities, and for cities in which 2017 data are not available, we use data closest to 2017: for Chicago, we use data in 2015; for Columbus and Oklahoma City, we use data in 2016. We match the latitude-longitude location of a police action to a census block group and aggregate the total number of stops or arrests during a year in a block group. Note that a small fraction of police action data are missing location information. While the missing records usually account for less than 5% of the observations for most cities, 13.49% of the stop records have missing location information for the Chicago Police Department.

B Alternative Crime-driven Demand Measures

In this section, we explore the robustness of policing disparity estimates to alternative crimedriven demand measures. In Table A.3, we measure crime-driven demand using homicide data from 2013 to 2016, and include the average homicide count and distance to the nearest homicide between 2013 and 2016 in the regression. The estimates are quantitatively similar

¹The 6 cities are: New York City, Los Angeles, Chicago, Dallas, Austin, Washington.

when using multiple years of homicide data. It is worth noting that while including information on older homicides does allow researchers to differentiate between neighborhoods without homicides in 2016, it is not obvious that police "should" do the same. Given the potential negative consequences of police interaction, particularly for young Black people (Rios, 2011), failing to update patrol patterns to reflect current, rather than past, violence may itself be a component of anti-Black bias in addition to a proxy for neighborhood demand for police.

To provide a direct measure of demand for police services as well as suspicion of criminal activity, in Table A.4, we control for the number of 311 calls in New York City where the geocoded 311 calls data are made publicly available. In the case of New York City, we do not find evidence suggesting that the number of 311 calls explain the police presence disparity in Black neighborhoods, regardless of controlling for the total number of calls (Column 3), or calls handled specifically by NYPD (Column 4), or calls handled by the nine major agencies (Column 5). In contrast, conditional on neighborhood socioeconomic characteristics, the number of 311 calls explains away roughly 60% of the enhanced police time in Hispanic neighborhoods, and all additional police time in Asian neighborhoods.

C Sensitivity to Visitors' Foot Traffic

We demonstrate that our results are not sensitive to foot traffic from non-residents in two ways. First, we examine police presence during non-working hours by excluding pings between 9 am to 5 pm on weekdays, shown in Table A.5. We observe a strikingly similar pattern as in Table 1, suggesting that the estimates are not driven by daytime foot traffic. Second, we complement the above analysis by removing block groups that are likely to have large levels of visitor foot traffic in one city, New York City, that accounts for the largest number of block groups (N = 6,226) among the 21 cities. We exclude block groups in Precinct 1 (Wall Street), 6 (the West Village), 8 (Penn Station, Grand Central), 14 (Midtown South) and 18 (Midtown North). Comparing the estimates of exposure disparities where we include every block group in NYPD precincts (column 1-2) or exclude block groups in five NYPD precincts (column 3-4) in Table A.6, suggests that our results are insensitive to the exclusion of precincts with potentially high levels of non-residential foot traffic.

D Disparities over the course of a shift

Officers begin each shift at a station and, after receiving specific instructions about their daily tasks (in a process known as "roll call"), leave to patrol their beat with relatively little real-time oversight. Enforcement activity generally peaks midway through an officer's shift, suggesting that the way officers spend their patrol time may vary over the course of a day (Chalfin and Goncalves 2021). Appendix Figure A.7 plot how the share of time officers spend in more Hispanic and more Black places increases as their shift rolls out. The difference between how much time officers spend in more Hispanic versus Whiter places increases from the first hour of the shift through the third hour. In places where more Black people live, the disparities in police time are most pronounced halfway through a shift and then decline.

Figures and Tables





Notes: The spatial pattern of smartphone pings is categorized as either Home, Other, or Work. Smartphone is "at home" if the ping location is at the Home Geohash-7 (a 152 x 152 m grid); "at Work" if the ping location is in any police stations' building boundaries. Pings observed at locations other than "Home" and "Work" are classified as "Other".







Notes: Total Officer Counts on the y-axis reports the number of officers (with arrest powers) in each city's police department on October 1st, 2017 from Uniform Crime Report (UCR) data. Patrol Smartphone Counts reports the number of smartphones that have at least one "shift" during 2017. Correlation coefficient between the two measures is reported.



Figure A.3: LEMAS Police Force Racial Composition vs. Smartphone Racial Composition

Notes: Police % White (Black, Hispanic, Asian) represents measures of racial composition of police officers from LEMAS data. Smartphone: % White (Black, Hispanic, Asian) denotes the smartphone-imputed racial composition for likely patrol officers based on home blocks.

Figure A.4: Police Officer Validation, a Residence-based Check for NYPD Officers at the Zip Code Level



Notes: This figure presents a binned scatter plot of the number of smartphones from NYPD that we infer "live" in a zip code vs. the actual number of NYPD police officers living in a zip code, both transformed in arsinh values. We include all zip codes in the FOIL request data, with zip codes grouped into 20 equal-sized bins. Correlation coefficient between the two measures (in arsinh values) is reported.



Figure A.5: Number of Arrests vs. Police Hours Across Block Groups

Notes: Each panel presents a binned scatter plot of the number of arrests vs. the police hours observed in the block groups, with both variables measured in arsinh values. Block groups are grouped into 20 equal size bins. Correlation coefficient between the two measures (in arsinh values) is reported in each panel.



Figure A.6: Number of Stops vs. Police Hours Across Block Groups

Notes: Each panel presents a binned scatter plot of number of stops vs. the police hours observed in the block groups, with both variables transformed in arsinh values. Block groups are grouped into 20

equal-sized bins. Correlation coefficient between the two measures (in arsinh values) is reported in each panel.



Figure A.7: Racial Disparity in Police Presence over the Course of a Shift

(a) Black-White Disparity

Notes: Figure plots coefficients of % Black (Hispanic) share from a regression where police presence in each hour of the shift is regressed against the % Black, % Hispanic and % Asian, with city fixed effects included.



Figure A.8: Supervisor: % Black vs. Officer: % Black



Figure A.9: City-specific Estimates of Black-White Disparity

Notes: "No Control" ("With Controls") condition plots the coefficient for % Black in the OLS regression: $arsinh(Hour_i) = \beta_0 + \beta_1 Race_i + \epsilon_i$

 $(arsinh(Hour_i) = \beta_0 + \beta_1 Socioeconomics_i + \beta_2 Crime_i + \beta_3 Race_i + \epsilon_i)$. Race include % Black, % Hispanic and % Asian. Socioeconomics include log population, % college graduates, median household income, census form return rate. Crime include distance to nearest homicide and homicide count in 2016.

	(1)	(2)	(3)	(4)
VARIABLES	Police: % White	Police: % Black	Police: % Hispanic	Police: % Asia
Smartphone: % White	0.577^{***} (0.107)			
City % White	0.718^{***} (0.129)			
Smartphone: % Black	· · ·	0.614^{***} (0.159)		
City % Black		0.446^{***} (0.140)		
Smartphone: % Hispanic			0.873^{***} (0.190)	
City % Hispanic			0.191 (0.131)	
Smartphone: % Asian			× ,	0.647^{***} (0.147)
City % Asian				-0.0628 (0.131)
Constant	-0.0270 (0.0503)	-0.00939 (0.0176)	-0.0280^{**} (0.00977)	-0.000590 (0.00296)
Observations	19	19	19	19
R-squared	0.910	0.909	0.936	0.947

Table A.1: Racial Composition: Smartphone Measure vs. LEMAS

Notes: Police % White (Black, Hispanic, Asian) represents measures of racial composition of police officers from LEMAS data. Smartphone: % White (Black, Hispanic, Asian) denotes the smartphone-imputed racial composition of likely patrol officers based on home blocks. City % White (Black, Hispanic, Asian) denotes the share of population that is identified as White (Black, Hispanic, Asian) in the city. Robust standard errors are reported in parentheses: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Variable	Obs	Mean	Std. Dev.	Min	Max
Police Presence:					
Hour	23799	26.685	201.754	0	14683.32
$\operatorname{arsinh}(\operatorname{Hour})$	23799	2.483	1.428	0	10.288
Number of Shifts	23799	70.34	129.557	0	5306
arsinh(Number of Shifts)	23799	4.246	1.261	0	9.27
Neighborhood Characteristics:					
% Black	23682	.237	.31	0	1
% Hispanic	23682	.287	.284	0	1
% Asian	23682	.084	.137	0	.983
Population	23799	1425.74	820.84	0	18369
% College Graduates	23679	.338	.251	0	1
Median Household Income (1K)	22526	62.553	38.174	2.499	250.001
Census Form Return Rate	23671	.736	.088	0	1
Distance to nearest 2016 homicide (km)	23799	1.331	1.612	.001	23.759
Homicide Count 2016	23799	.152	.472	0	7

Notes: This table provides summary statistics of police presence and neighborhood characteristic variables across block groups in the 21 cities.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\operatorname{arsinh}(\operatorname{Hour})$	$\operatorname{arsinh}(\operatorname{Hour})$	$\operatorname{arsinh}(\operatorname{Hour})$	arsinh(Hour)	arsinh(Hour)
% Black	0.271***	0.493***	0.270***	0.258***	0.231***
	(0.0332)	(0.0353)	(0.0481)	(0.0508)	(0.0528)
BG % Black X Police: % Black				0.673*	2.769**
				(0.296)	(0.898)
BG % Black X Supervisor: % Black					-1.972*
				a a cardododo	(0.815)
% Hispanic	0.488***	0.362^{***}	0.259***	0.217***	0.193**
	(0.0348)	(0.0367)	(0.0563)	(0.0590)	(0.0600)
% Asian	0.379^{***}	0.276^{***}	-0.0300	-0.0592	-0.0512
	(0.0735)	(0.0783)	(0.0821)	(0.0836)	(0.0840)
Log Population			0.388^{***}	0.404^{***}	0.433^{***}
			(0.0210)	(0.0218)	(0.0225)
% College Graduates			1.175^{***}	1.224^{***}	1.249^{***}
			(0.0679)	(0.0704)	(0.0711)
Median Household Income (1K)			-0.00421***	-0.00403***	-0.00381^{***}
			(0.000395)	(0.000404)	(0.000406)
Census Form Return Rate			-1.189***	-1.243***	-1.299***
			(0.127)	(0.133)	(0.135)
Avg 13-16 Homicide Count			0.299***	0.299***	0.295***
			(0.0177)	(0.0185)	(0.0190)
Distance to nearest 13-16 homicide (km)			-0.159***	-0.167***	-0.168***
			(0.0104)	(0.0116)	(0.0121)
			· · · ·	· · · ·	· · · ·
Observations	23,682	23,682	22,521	20,961	20,112
R-squared	0.008	0.106	0.173	0.162	0.167
City FE	No	Yes	Yes	Yes	Yes

Table A.3: Disparities in Neighborhood Police Exposure (Controlling for Homicides from 2013-2016, Including NYC)

Notes: This table presents OLS estimates of exposure disparity among census block groups (BGs) across 21 cities (Column 1, 2, 4, 5) and within cities (Column 3, 6). The dependent variable is police hours observed in BGs (excluding pings moving faster than 50 mph), transformed in arsinh values. All race variables (including neighborhood racial composition, Police: % Black and Supervisor: % Black) are mean-centered. Household income is measured in thousands of dollars, census return rates range from 0-1. Robust standard errors are reported in parentheses: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)
% Black	0.194**	0.577***	0.570***	0.605***	0.660***
	(0.0666)	(0.0839)	(0.0797)	(0.0825)	(0.0785)
% Hispanic	0.129 +	0.727***	0.265^{*}	0.393^{***}	0.296^{**}
	(0.0712)	(0.106)	(0.106)	(0.109)	(0.104)
% Asian	-0.143	0.269*	0.365**	0.229+	0.0771
	(0.111)	(0.122)	(0.113)	(0.118)	(0.103)
Log Population		0.455***	0.113*	0.242***	0.0894*
~~~		(0.0488)	(0.0459)	(0.0486)	(0.0403)
% College Graduates		1.707***	1.158***	1.464***	0.185
		(0.136)	(0.128)	(0.133)	(0.132)
Median Household Income (1K)		-0.00150*	-0.000998	-0.000891	-0.00239***
		(0.000735)	(0.000680)	(0.000706)	(0.000665)
Census Form Return Rate		-0.322	$1.2(6^{+++})$	$0.871^{**}$	$0.817^{**}$
Distance to accurat 2016 hominite (low)		(0.250)	(0.207)	(0.273)	(0.200)
Distance to nearest 2016 nomicide (km)		$-0.130^{-1.1}$	-0.123	-0.131	-0.0894
Hamisida Count 2016		(0.0200)	(0.0247) 0.419***	(0.0202) 0.459***	(0.0238) 0.272***
Holmeide Count 2010		(0.0868)	(0.412)	(0.0846)	(0.0770)
arginh(311 Calle NVPD)		(0.0808)	(0.0650)	(0.0840)	(0.0779)
arshin(311 Galis - 1(11 D)				(0.0245)	(0.0751)
arginh(311 Calle - HPD)				(0.0240)	(0.0251)
arshin(511 Gails - 111 D)					(0.0119)
arsinh(311  Calls - DOT)					0.325***
					(0.0237)
arsinh(311 Calls - DEP)					0.0898***
					(0.0254)
arsinh(311 Calls - DSNY)					-0.0614**
(011 0000 1000)					(0.0237)
arsinh(311 Calls - DOB)					0.0853***
( )					(0.0214)
arsinh(311 Calls - DPR)					-0.138***
,					(0.0186)
arsinh(311 Calls - DOHMH)					0.184***
					(0.0195)
arsinh(311 Calls - DHS)					0.300***
					(0.0149)
asinh(Total 311 Calls)			$0.716^{***}$		
			(0.0321)		
Observations	6,226	5,821	5,821	5,821	5,821
R-squared	0.003	0.080	0.171	0.119	0.288

Table A.4: Disparities in Neighborhood Police Exposure (Controlling for Number of 311 Calls)

Notes: This table presents OLS estimates of exposure disparity among census block groups (BGs) in NYC. In column 5, we control for the number of calls handled by the top 9 agencies: NYPD, Housing Preservation and Development (HPD), Department of Transportation (DOT), Department of Environmental Protection (DEP), Department of Sanitation (DSNY), Department of Buildings (DOB), Department of Parks & Recreation (DPR), Department of Health and Mental Hygiene (DOHMH), Department of Homeless Services (DHS) respectively. Robust standard errors in parentheses: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.</li>

	(1)	(2)	(3)	(4)	(5)
VARIABLES	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)
% Black	$0.333^{***}$	$0.527^{***}$	$0.368^{***}$	$0.348^{***}$	$0.348^{***}$
	(0.0318)	(0.0337)	(0.0458)	(0.0490)	(0.0513)
BG % Black X Police: % Black				0.434	1.208
				(0.287)	(0.869)
BG % Black X Supervisor: % Black					-0.755
					(0.785)
% Hispanic	$0.501^{***}$	$0.379^{***}$	$0.260^{***}$	$0.199^{***}$	$0.179^{**}$
	(0.0330)	(0.0349)	(0.0541)	(0.0571)	(0.0581)
% Asian	$0.455^{***}$	$0.281^{***}$	-0.0540	-0.0876	-0.0785
	(0.0693)	(0.0739)	(0.0782)	(0.0799)	(0.0802)
Log Population			$0.401^{***}$	$0.411^{***}$	$0.434^{***}$
			(0.0202)	(0.0210)	(0.0216)
% College Graduates			$0.991^{***}$	$1.033^{***}$	$1.054^{***}$
			(0.0645)	(0.0676)	(0.0684)
Median Household Income (1K)			-0.00372***	-0.00375***	-0.00356***
			(0.000374)	(0.000384)	(0.000387)
Census Form Return Rate			$-1.318^{***}$	$-1.360^{***}$	$-1.416^{***}$
			(0.121)	(0.127)	(0.130)
Distance to nearest 2016 homicide (km)			-0.106***	-0.108***	$-0.105^{***}$
			(0.00624)	(0.00697)	(0.00719)
Homicide Count 2016			$0.182^{***}$	$0.182^{***}$	$0.182^{***}$
			(0.0195)	(0.0204)	(0.0209)
Observations	$23,\!682$	$23,\!682$	22,521	20,961	20,112
R-squared	0.010	0.109	0.167	0.146	0.151
City FE	No	Yes	Yes	Yes	Yes

Table A.5:	Disparities	in Neighborhood	Police Exposure	(During No	on-working Hours)
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Notes: This table presents OLS estimates of exposure disparity among census block groups (BGs) across 21 cities (Column 1, 2, 4, 5) and within cities (Column 3, 6). The dependent variable is police hours observed in BGs (during non-working hours), transformed in arsinh values. All race variables (including neighborhood racial composition, Police: % Black and Supervisor: % Black) are mean-centered. Household income is measured in thousands of dollars, census return rates range from 0-1. Robust standard errors are reported in parentheses: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.</p>

	(1)	(2)	(3)	(4)
VARIABLES	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)	arsinh(Hour)
% Black	$0.194^{**}$	$0.577^{***}$	$0.257^{***}$	$0.539^{***}$
	(0.0666)	(0.0839)	(0.0665)	(0.0838)
% Hispanic	0.129 +	$0.727^{***}$	$0.184^{**}$	$0.618^{***}$
	(0.0712)	(0.106)	(0.0710)	(0.105)
% Asian	-0.143	$0.269^{*}$	-0.116	0.204 +
	(0.111)	(0.122)	(0.111)	(0.120)
Log Population		$0.455^{***}$		$0.428^{***}$
		(0.0488)		(0.0479)
% College Graduates		$1.707^{***}$		$1.567^{***}$
		(0.136)		(0.137)
Median Household Income (1K)		-0.00150*		-0.00240***
		(0.000735)		(0.000704)
Census Form Return Rate		-0.322		-0.190
		(0.250)		(0.251)
Distance to nearest 2016 homicide (km)		$-0.156^{***}$		$-0.161^{***}$
		(0.0266)		(0.0265)
Homicide Count 2016		$0.464^{***}$		$0.451^{***}$
		(0.0868)		(0.0857)
Observations	6,226	5,821	6,062	5,672
R-squared	0.003	0.080	0.005	0.073

Table A.6: Disparities in NYC Neighborhood Police Exposure

Notes: This table presents the OLS regression estimates of the disparity in police presence among census block groups (BGs) in New York City. Column 1 and 2 include the full sample; column 3 and 4 exclude BGs in Precinct 1 (Wall Street), 6 (the West Village), 8 (Penn Station, Grand Central), 14 (Midtown South) and 18 (Midtown North). The dependent variable is the police hours observed in census block groups (excluding pings moving faster than 50 mph), transformed in arsinh values. Household income is measured in thousands of dollars, census form return rates range from 0-1. Robust standard errors are reported in parentheses: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

		1.2	1.2		( ) <b>(</b>	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	arsinh(Hour)	arsinh(Number of stops)	arsinh(Stops/Hours)	arsinh(Hour)	arsinh(Number of stops)	arsinh(Stops/Hours)
% Black	$0.447^{***}$	1.322***	$0.646^{***}$	$0.534^{***}$	0.986***	$0.465^{***}$
	(0.0425)	(0.0349)	(0.0360)	(0.0573)	(0.0482)	(0.0499)
% Hispanic	0.186***	1.069***	0.581***	0.449***	0.819***	0.388***
*	(0.0486)	(0.0417)	(0.0406)	(0.0700)	(0.0601)	(0.0603)
% Asian	0.305**	0.384***	0.0488	0.217*	0.0357	-0.0167
	(0.0965)	(0.0689)	(0.0575)	(0.102)	(0.0763)	(0.0666)
Log Population	()	()	()	0.421***	0.329***	-0.0421 +
0 1				(0.0283)	(0.0231)	(0.0221)
% College Graduates				1.420***	0.520***	-0.564***
				(0.0845)	(0.0737)	(0.0720)
Median Household Income (1K)				-0.00360***	-0.00307***	0.00180***
				(0.000544)	(0.000448)	(0.000388)
Census Form Return Rate				-1.240***	-1.112***	0.238+
				(0.159)	(0.133)	(0.127)
Distance to nearest 2016 homicide (km)				-0.0971***	-0.0871***	0.00554
Distance to nearest 2010 nonneite (iiii)				(0.0101)	(0.0117)	(0.0115)
Homicide Count 2016				0.235***	0.325***	0.113***
Holmoldo Codine 2010				(0.0252)	(0.0202)	(0.0241)
				(0.0252)	(0.0202)	(0.0241)
Observations	13,969	13,969	13,912	13,176	13,176	13,123
R-squared	0.032	0.762	0.662	0.095	0.774	0.659
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7: Disparities in Neighborhood Police Exposure and Downstream (Stop) Disparities

Notes: This table presents OLS estimates of disparities in exposure, stops, and stops per hour among census block groups (BGs) across 9 cities: New York City, Chicago, Houston, Philadelphia, San Antonio, Oklahoma City, Denver, Columbus, Nashville. All race variables (including neighborhood racial composition, Police: % Black and Supervisor: % Black) are mean-centered. Household income is measured in thousands of dollars, census return rates range from 0-1. Robust standard errors are reported in parentheses: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.</li>

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