Online Appendix

The Fall of Violence and the Reconfiguration of Urban Neighborhoods

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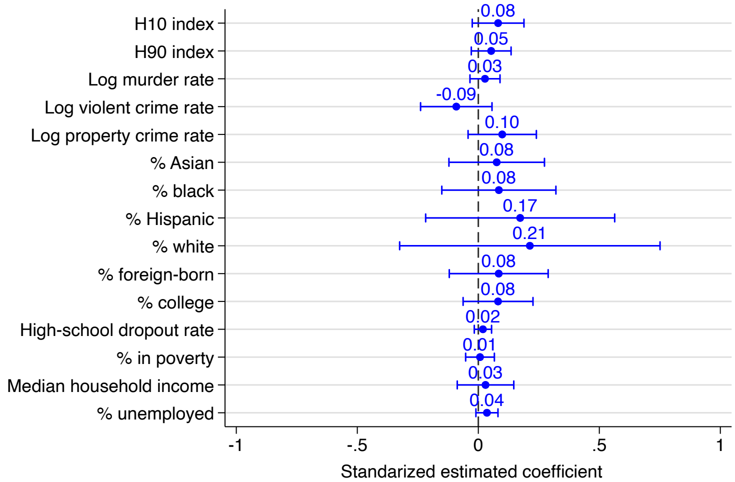
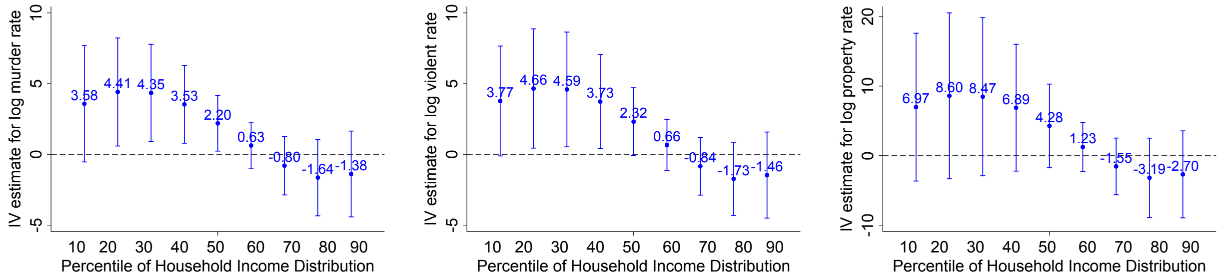
Figure A1: Estimated coefficients from a regression of 1990-2000 changes in COPS funding on 1980-1990 changes in crime rates and demographics



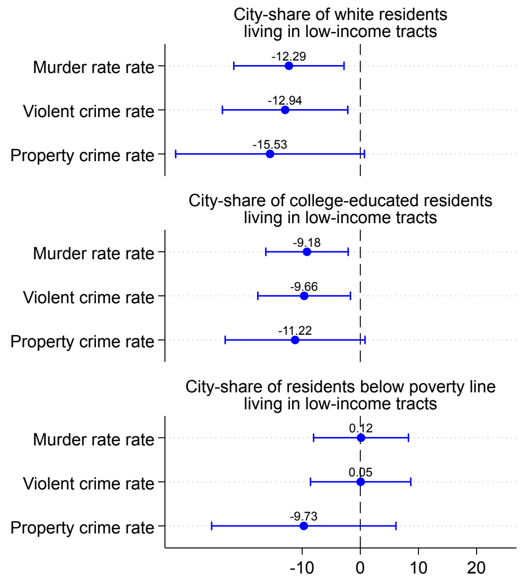
Estimated coefficients from an OLS regression of 1990-2000 changes in officers hired with COPS funding on 1980-1990 changes in segregation, crime, and demographics (all variables have been standardized to have mean 0 and SD 1). Standard errors are robust to heteroskedasticity. Error bars are 95% confidence intervals.

Figure A2: Instrumental variable fixed effects estimates of the impact of changes in crime rates on changes in segregation of households at different income percentiles (unweighted regressions)



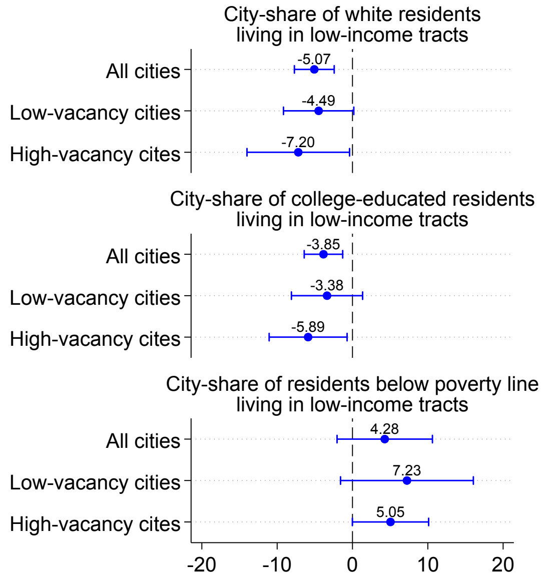
This figure is the unweighted counterpart to Figure 3. Each point estimate and 95% confidence interval come from a separate 2SLS fixed effects regression of the form described in Equations (2.1) and (2.2). The coefficients shown are the second-stage estimates. Each regression estimates impacts of changes in the crime rate on changes in the segregation of households with incomes at or below the income percentile indicated in the x-axis. Segregation indices range from 0 to 100. Crime rates are log-transformed. All regressions include place and year fixed effects and the same set of controls than those shown in Table 4. Standard errors are robust to heteroskedasticity.

Figure A3: Instrumental variable fixed effects estimates of the impact of changes in crime on changes in the concentration of different demographic groups in low-income neighborhoods (unweighted regressions)



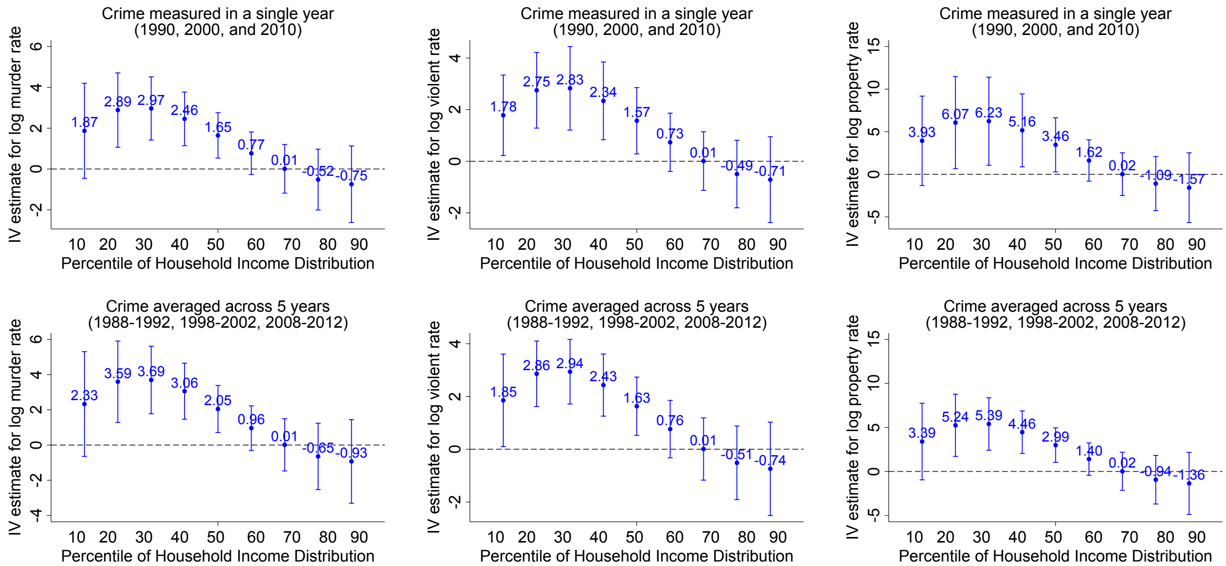
This figure is the unweighted counterpart to Figure 4. These models assess the change in the concentration of white (top panel), college-educated (middle panel), and poor (bottom panel) residents in neighborhoods that were low-income in 1990. Low-income neighborhoods are the set of tracts in the bottom quantile of the city-specific household income distribution in 1990. Our measure of concentration is the city-share of white, college-educated, and poor residents living in the neighborhoods that were low-income in 1990. Each point estimate and 95% confidence interval come from a separate 2SLS fixed effects regression of the form described in Equations (2.1) and (2.2). The coefficients shown are the second-stage estimates. City-share outcomes range from 0 to 100. Crime rates are log-transformed. All regressions include place and year fixed effects and the same set of controls than those shown in Table 4. All models include 1990 population weights. Standard errors are robust to heteroskedasticity.

Figure A4: Instrumental variable fixed effects estimates of the impact of changes in violent crime on changes in the concentration of different demographic groups in low-income neighborhoods in low- and high-vacancy cities



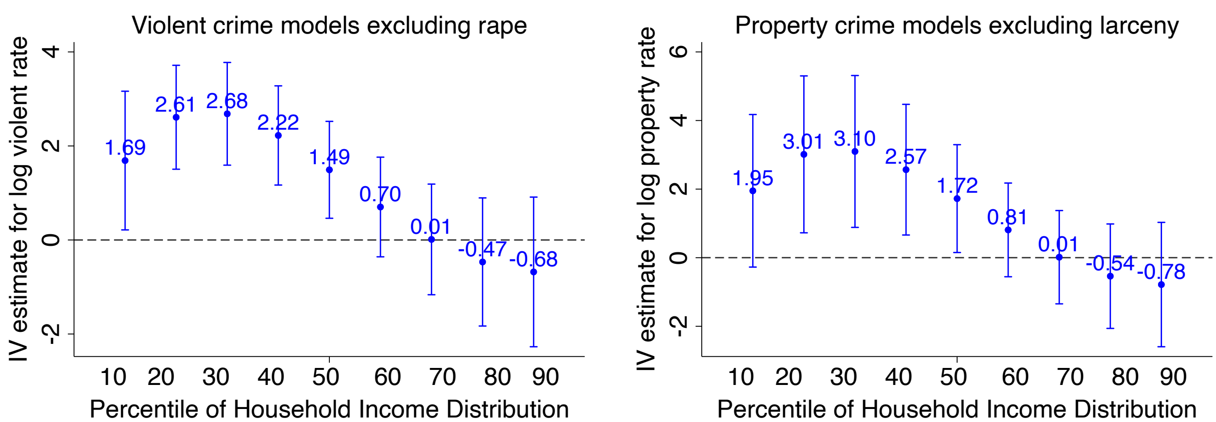
These models assess the change in the concentration of white (top panel), college-educated (middle panel), and poor (bottom panel) residents in neighborhoods that were low-income in 1990. Low-income neighborhoods are the set of tracts in the bottom quantile of the city-specific household income distribution in 1990. Our measure of concentration is the city-share of white, college-educated, and poor residents living in the neighborhoods that were low-income in 1990. We run separate models for cities where the rate of vacant housing units was below 9 percent (low-vacancy cities) and for cities where it was 9 percent and higher (high-vacancy cities). Each point estimate and 95% confidence interval come from a separate 2SLS fixed effects regression of the form described in Equations (2.1) and (2.2). The coefficients shown are the second-stage estimates. City-share outcomes range from 0 to 100. Crime rates are log-transformed. All regressions include place and year fixed effects and the same set of controls than those shown in Table 4. All models include 1990 population weights. Standard errors are robust to heteroskedasticity.

Figure A5: Instrumental variable fixed effects estimates of the impact of changes in crime rates on changes in segregation of households at different income percentiles (crime rates averaged over one and five years)



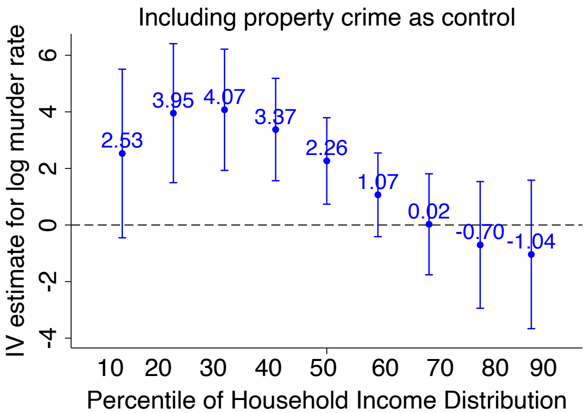
Each point estimate and 95% confidence interval come from a separate 2SLS fixed effects regression of the form described in Equations (2.1) and (2.2). The coefficients shown are the second-stage estimates. Each regression estimates impacts of changes in the crime rate on changes in the segregation of households with incomes at or below the income percentile indicated in the x-axis. Segregation indices range from 0 to 100. Crime rates are log-transformed. All regressions include place and year fixed effects and the same set of controls than those shown in Table 4. Standard errors are robust to heteroskedasticity.

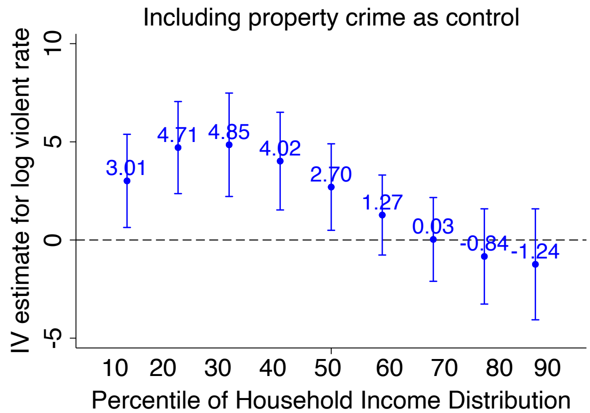
Figure A6: Instrumental variable fixed effects estimates of the impact of changes in crime rates on changes in segregation of households at different income percentiles (excluding rape and larceny)



Each point estimate and 95% confidence interval come from a separate 2SLS fixed effects regression of the form described in Equations (2.1) and (2.2). The coefficients shown are the second-stage estimates. Each regression estimates impacts of changes in the crime rate on changes in the segregation of households with incomes at or below the income percentile indicated in the x-axis. Segregation indices range from 0 to 100. Crime rates are log-transformed. All regressions include place and year fixed effects and the same set of controls than those shown in Table 4. Standard errors are robust to heteroskedasticity.

Figure A7: Instrumental variable fixed effects estimates of the impact of changes in crime rates on changes in segregation of households at different income percentiles (adding property crime rate as control)





Each point estimate and 95% confidence interval come from a separate 2SLS fixed effects regression of the form described in Equations (2.1) and (2.2). The coefficients shown are the second-stage estimates. Each regression estimates impacts of changes in the crime rate on changes in the segregation of households with incomes at or below the income percentile indicated in the x-axis. Segregation indices range from 0 to 100. Crime rates are log-transformed. All regressions include place and year fixed effects and the same set of controls than those shown in Table 4. Standard errors are robust to heteroskedasticity.

Table A1: First-stage fixed effects estimates of changes in COPS officer hiring on changes in crime (unweighted regressions)

	(1) Murder	(2) Violent	(3) Property
COPS officers (in 10s)	-0.014***	-0.013***	-0.007**
	(0.003)	(0.004)	(0.003)
Population density	-0.231**	-0.430***	-0.450***
	(0.110)	(0.158)	(0.153)
% Males 15-24	0.012	0.008	0.013
	(0.019)	(0.021)	(0.023)
% Asian	-0.030**	-0.028	-0.006
	(0.013)	(0.019)	(0.021)
% Black	0.022***	0.023**	0.011
	(0.006)	(0.009)	(0.009)
% Hispanic	-0.009	-0.021*	-0.015
	(0.009)	(0.012)	(0.012)
% Foreign-born	0.007	0.005	0.007
	(0.012)	(0.018)	(0.021)
% College degree	-0.003	-0.006	-0.005
	(0.008)	(0.010)	(0.009)
% High-school dropout	0.020***	-0.006	-0.008
	(0.007)	(0.015)	(0.017)
Poverty rate	0.009	0.026**	0.016
	(0.010)	(0.010)	(0.011)
Unemployment rate	-0.006	-0.108**	-0.067
	(0.023)	(0.045)	(0.047)
B-W Dissim. Index	0.507**	0.262	0.297
	(0.214)	(0.270)	(0.279)
Observations	1,500	1,500	1,500
Adj. R^2	0.176	0.052	0.122
F-Stat IV	17.7	10.4	5.1

This table is the unweighted counterpart to Table 2. * 0.10 ** 0.05 *** 0.01. Crime rates are log-transformed. Standard errors are robust to heteroskedasticity. The sample includes 500 cities observed in 1990, 2000, and 2010.

Table A2: OLS fixed effects estimates of changes in crime and changes in income segregation (unweighted regressions)

	(1) H10	(2) H90	(3) H10	(4) H90	(5) H10	(6) H90
Log murder crime	0.230**	0.273**				
	(0.100)	(0.113)				
Log violent crime			0.069	-0.013		
			(0.048)	(0.058)		
Log property crime					0.058*	0.029
					(0.035)	(0.049)
Population density	1.051***	0.219	1.025**	0.146	1.021**	0.165
	(0.403)	(0.483)	(0.400)	(0.473)	(0.399)	(0.475)
% Males 15-24	-0.102	-0.135	-0.100	-0.132	-0.100	-0.133
	(0.073)	(0.095)	(0.074)	(0.094)	(0.074)	(0.094)
% Asian	-0.014	-0.139***	-0.019	-0.148***	-0.020	-0.147***
	(0.035)	(0.042)	(0.035)	(0.042)	(0.035)	(0.042)
% Black	-0.018	0.047	-0.014	0.054*	-0.013	0.053*
	(0.029)	(0.032)	(0.028)	(0.032)	(0.028)	(0.032)
% Hispanic	-0.009	0.017	-0.009	0.014	-0.010	0.015
	(0.023)	(0.028)	(0.024)	(0.028)	(0.024)	(0.028)
% Foreign-born	0.037	0.119***	0.038	0.121***	0.038	0.121***
	(0.036)	(0.042)	(0.036)	(0.042)	(0.036)	(0.042)
% College degree	-0.014	0.029	-0.014	0.028	-0.014	0.029
	(0.035)	(0.039)	(0.035)	(0.040)	(0.035)	(0.040)
% High-school dropout	-0.064***	-0.028	-0.059**	-0.023	-0.059**	-0.022
	(0.024)	(0.031)	(0.025)	(0.031)	(0.025)	(0.031)
Poverty rate	-0.016	0.055	-0.015	0.058	-0.015	0.057
	(0.042)	(0.045)	(0.042)	(0.045)	(0.042)	(0.045)
Unemployment rate	0.119	-0.118	0.125	-0.122	0.121	-0.118
	(0.090)	(0.106)	(0.092)	(0.108)	(0.091)	(0.107)
B-W Dissim. Index	2.638***	1.605*	2.739***	1.751**	2.741***	1.739**
	(0.719)	(0.864)	(0.719)	(0.869)	(0.719)	(0.869)
Observations	1,500	1,500	1,500	1,500	1,500	1,500
Adj. R^2	0.177	0.379	0.174	0.375	0.174	0.375

This table is the unweighted counterpart to Table 3. * 0.10 ** 0.05 *** 0.01. Segregation indices range from 0 to 100. Crime rates are log-transformed. Standard errors are robust to heteroskedasticity. The sample includes 500 cities observed in 1990, 2000, and 2010.

Table A3: Instrumental variable fixed effects estimates of changes in crime on changes in residential segregation of poor (H10) and affluent (H90) households (unweighted regressions)

	(1) H10	(2) H90	(3) H10	(4) H90	(5) H10	(6) H90
Log murder crime	3.576*	-1.383				
	(2.096)	(1.547)				
Log violent crime			3.775*	-1.460		
			(1.982)	(1.552)		
Log property crime					6.969	-2.696
					(5.423)	(3.192)
Population density	1.875**	-0.189	2.673**	-0.498	4.186	-1.083
	(0.849)	(0.692)	(1.265)	(0.955)	(3.006)	(1.713)
% Males 15-24	-0.142	-0.116	-0.132	-0.120	-0.193	-0.096
	(0.100)	(0.089)	(0.111)	(0.088)	(0.197)	(0.106)
% Asian	0.085	-0.188***	0.084	-0.188***	0.020	-0.163**
	(0.079)	(0.062)	(0.090)	(0.061)	(0.141)	(0.069)
% Black	-0.094	0.085*	-0.102	0.088	-0.093	0.085
	(0.060)	(0.051)	(0.065)	(0.055)	(0.100)	(0.061)
% Hispanic	0.019	0.003	0.065	-0.015	0.095	-0.026
	(0.038)	(0.031)	(0.057)	(0.042)	(0.112)	(0.062)
% Foreign-born	0.016	0.130***	0.019	0.129***	-0.009	0.140**
	(0.051)	(0.045)	(0.069)	(0.049)	(0.135)	(0.069)
% College degree	-0.005	0.025	0.009	0.020	0.021	0.015
	(0.042)	(0.041)	(0.047)	(0.042)	(0.076)	(0.050)
% High-school dropout	-0.132**	0.005	-0.039	-0.031	-0.005	-0.044
	(0.056)	(0.046)	(0.059)	(0.037)	(0.121)	(0.058)
Poverty rate	-0.045	0.070	-0.111	0.095*	-0.126	0.101
	(0.055)	(0.047)	(0.074)	(0.057)	(0.119)	(0.070)
Unemployment rate	0.139	-0.128	0.525*	-0.278	0.586	-0.301
	(0.106)	(0.116)	(0.289)	(0.204)	(0.504)	(0.266)
B-W Dissim. Index	0.888	2.471**	1.712	2.153**	0.632	2.570
	(1.543)	(1.242)	(1.487)	(1.074)	(3.117)	(1.685)
Observations	1,500	1,500	1,500	1,500	1,500	1,500

This table is the unweighted counterpart to Table 4. * 0.10 ** 0.05 *** 0.01. Segregation indices range from 0 to 100. Crime rates are log-transformed. Standard errors are robust to heteroskedasticity. The sample includes 500 cities observed in 1990, 2000, and 2010.

Table A4: Descriptive statistics for outcomes used in the analysis of demographic changes in neighborhoods that started as low-income in 1990

	1990	2000	2010
College-educated	8.99	8.88	10.31
	(7.53)	(7.20)	(7.62)
Living in poverty	46.25	38.62	34.13
	(13.68)	(12.68)	(12.59)
Non-Hispanic white	9.35	8.82	9.79
	(8.83)	(8.62)	(8.77)

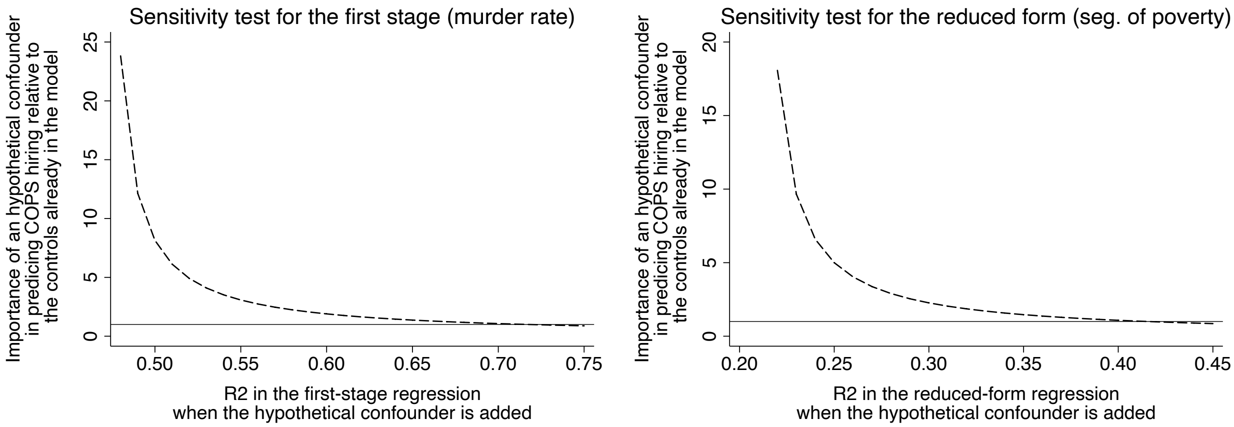
Each mean and SD represent the percentage of the total number of individuals of each group in the city who lived in neighborhoods that were low-income in 1990. Low-income neighborhoods are census tracts who were at the bottom quintile of their city household income distribution in 1990.

Oster's test for unobservable selection

Figure A8 reports results from the Oster (2019) test for the first-stage regression (left) and the reduced-form equations (right). The test assesses the magnitude of an unobserved covariate that, if added to the first-stage and reduced-form equations, would yield no impact of the COPS instrument on crime and segregation. The test estimates two characteristics of the hypothetical unobserved covariate that could be creating bias in the estimate of COPS on crime in the first-stage equation: the predictive power that this covariate would have on predicting the COPS instrument and its importance in predicting crime rates, relative to the full set of covariates already included in the model. And the same logic would apply to the assessment of bias in the reduced-form equation: the test would quantify the predictive power that the omitted variable would have on predicting the COPS instrument and its importance in predicting income segregation, relative to the full set of covariates already included in the model.

The y-axis represents the strength that a hypothetical confounder would have in predicting the COPS instrument, relative to the 11 covariates already included in the model (a value of 1 means that the unmeasured confounder is as predictive of the COPS instrument as the 11 covariates combined). The x-axis represents the R2 from a hypothetical regression including the 11 covariates, city and year fixed effects, and the unmeasured confounder. The black curve represents the pairs of x and y values that would make the association between the COPS instrument and the outcome equal to zero. For example, looking at the test for the first-stage equation (left), for the true association between the COPS instrument and murder to be zero, there should exist an unobserved covariate that when added to the first-stage regression increases the R2 from .47 (as shown in Table 2) to .50 and is ten times more predictive of the murder rate than the 11 controls included in the first stage regression. Or, moving to the far right of the curve, an unobserved covariate that would make the first-stage association go away would have to increase the R2 from .47 to .71 and be equally predictive of changes in crime as the 11 controls included in the first stage regression. Such scenarios appear to be highly implausible.

Figure A8: Oster's test for unobservable selection



The y-axis represents the strength that a hypothetical confounder would have in predicting the COPS instrument, relative to the 11 covariates already included in the model (a value of 1 means that the unmeasured confounder is as predictive of the COPS instrument as the 11 covariates combined). The x-axis represents the R^2 from a hypothetical regression including the 11 covariates, city and year fixed effects, and the unmeasured confounder. The black curve represents the pairs of x and y values that would make the association between the COPS instrument and murder (left) and segregation of poverty (right) equal to zero.