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The Fall of Violence and the Reconfiguration of Urban Neighborhoods

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ABSTRACT Over the past few decades, U.S. cities have changed dramatically, largely because of two major trends: the fall of violence and the rise of urban inequality. Despite the attention given to each of these trends, little research has assessed how they are related to each other. This study is the first to generate causal evidence on the impact of violent crime on economic residential segregation. We document the effect of the crime drop on economic segregation in 500 U.S. cities between 1990 and 2010, using exogenous shocks to city crime rates to identify causal effects. We find that declining violent and property crime reduced low-income household segregation but had no effect on affluent households. Our findings indicate that the crime decline has not overturned the trend toward rising economic segregation but has slowed its pace. Additional analyses suggest that declining crime reduced low-income household segregation by drawing more White and college-educated residents to the poorest neighborhoods of 1990. We also find suggestive evidence that declining violence led poor households to migrate out of low-income neighborhoods, reflecting a pattern of gentrification. Descriptive analyses of tract-level data from five cities show that neighborhoods with sharper declines in violence became less socioeconomically disadvantaged. Despite continued rising economic inequality, the crime decline has had its greatest impact on concentrated poverty, long seen as one of the most harmful dimensions of urban inequality.

KEYWORDS Violent crime • Economic segregation • Urban inequality

Introduction

The relationship between violence and various forms of neighborhood change has been a central concern for urban sociology since the work of Du Bois (1899/1996) in Philadelphia and the studies on community organization and crime by sociologists of the Chicago school (Park et al. 1925; Shaw and McKay 1942). Decades later, the growth in neighborhood violence was central to debate among researchers studying the rise of concentrated poverty and racial segregation in the postindustrial city (Anderson 1999; Massey and Denton 1993; Wilson 1987). More recently, gentrification scholars have focused on how the decline in violence has driven neighborhood demographic change (Hyra 2017; Pattillo 2010). The ongoing sociological

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tradition highlights the role of violence in shaping segregation, neighborhood poverty, and population change.

Over the past few decades, U.S. cities have experienced dramatic changes driven by two major trends: a decline in violence and a rise in urban inequality. From 1990 to 2010, the national homicide rate was halved, with cities such as New York, Los Angeles, Dallas, Fort Worth, and San Diego seeing violence drop by 50% to 80% (Federal Bureau of Investigation 2011; Friedman et al. 2017). From the 1960s to the early 1990s, city life was synonymous with violence, and half of major U.S. cities had extreme murder rates of 20 per 100,000 residents or higher. Although violence remains high in some neighborhoods, nearly every major city has seen declines, with urban centers such as New York, Los Angeles, and Washington, DC, transformed by falling crime rates. Even with the upticks in violence in the second half of the 2010s, most cities are far safer than their historical highs three decades ago.

Over the same period, rising economic inequality in the U.S. population has become manifest in urban neighborhoods as the sorting of high- and low-income households into separate communities has risen sharply since the 1970s (Reardon and Bischoff 2011; Reardon et al. 2018). The 1990s saw a renewed interest in urban life: high-income, college-educated households returned to central-city neighborhoods, and visible signs of urban inequality emerged, including gentrification, exploding home values, gated communities, and rising rents (Couture and Handbury 2017; Ehrenhalt 2012; Ellen and O'Regan 2008).

The decline in violence and rise in inequality mark a significant shift in American urban life. Yet, despite a long tradition linking violence, neighborhood change, and urban poverty, little progress has been made in understanding how urban neighborhoods were reshaped by what Zimring (2006) called "the great American crime decline." Some studies have suggested that gentrification contributed to crime declines in specific neighborhoods (Autor et al. 2017; Papachristos et al. 2011). However, a larger body of research on neighborhood change and gentrification suggests that declining violence has reshaped central-city neighborhoods by attracting investment, amenities, and social services; raising property values; drawing affluent, highly educated White residents; and displacing low-income racial and ethnic minorities (Ehrenhalt 2012; Ellen et al. 2019; Florida 2017; Hyra 2017).

Despite three decades of declining violence and significant socioeconomic changes in cities, we lack credible estimates of how the crime drop has reshaped urban neighborhoods. Additionally, there is no national evidence on how violence influences economic segregation or the mechanisms of neighborhood sorting across the socioeconomic spectrum. Addressing these questions is essential for understanding how declining violence interacts with local housing markets to reshape city neighborhoods.

Building on a large strand of research showing that violent crime plays a central role in the sorting of city residents, this article presents evidence on the impact of declining violence on economic segregation and poverty concentration. Using temporal shocks to city crime rates from 1990 to 2010, we identify causal effects in a sample of 500 municipalities. This period, marked by widespread declines in violence, allows us to leverage exogenous crime rate shocks induced by the federal Community Oriented Policing Services (COPS) program. Prior research found that COPS fund distribution timing was exogenous to preexisting crime and demographic trends (Evans and Owens 2007). We use the number of officers hired through COPS

(1990–2008) as an instrumental variable (IV) for crime changes (1990–2010) in a two-way fixed-effects framework, observing each municipality in 1990, 2000, and 2010. Our analyses confirm that COPS fund timing was unrelated to prior crime or demographic trends. Further tests that assess the possibility of an omitted variable that would invalidate the COPS IV strategy and overturn our results show that such an omitted variable is highly unlikely to exist.

A murder rate decline of 1 standard deviation (SD) predicts a 0.56-SD decline in the segregation of low-income households. Estimates of changes in violent and property crime rates yield similar effect sizes. These findings indicate that although the crime decline has not reversed the trend toward rising economic segregation, it has slowed its pace. In cities where crime declined more substantially, the segregation of poor households has grown more slowly and has even reversed in some cities. We find no evidence that crime rate changes affected the segregation of affluent households. This pattern is consistent with neighborhood-level descriptive evidence showing that the largest changes in violence during the 1990s and 2000s occurred in low-income neighborhoods (Friedson and Sharkey 2015).

In additional analyses, we examine demographic changes in neighborhoods with high poverty rates in 1990. We find that as violent crime rates fell from 1990 to 2010, the concentration of White and college-educated residents in the poorest neighborhoods increased, but the concentration of poor residents in those neighborhoods decreased. Although the estimates of changes in the concentration of poor households in low-income neighborhoods are not statistically significant, this pattern could reflect the gentrification and displacement documented in several cities across the nation.

In five cities (Chicago, Denver, New York, Philadelphia, and Portland), we examine neighborhood-level dynamics underlying the citywide changes in our main results. These analyses indicate that tracts with faster crime declines saw increases in White and college-educated residents, decreases in poverty rates, and rising median household incomes.

Falling violence has led to a reconfiguration of urban neighborhoods, making cities more economically integrated. Although urban inequality has continued to rise even as violence has fallen, the crime decline has had its greatest impact on reducing concentrated poverty, which has long been thought of as one of the most harmful dimensions of urban inequality.

Theory and Evidence on Crime and Neighborhood Change

The link between crime and spatial patterns of sorting and neighborhood change has long been central to criminological and demographic research. Early Chicago school of sociology scholars developed an ecological model to explain high delinquency rates in low-income neighborhoods (Park et al. 1925; Shaw and McKay 1942). These observations inspired extensive research on how concentrated disadvantage and residential segregation predict crime and disorder (Krivo et al. 2009; Sampson et al. 1997; Shihadeh and Flynn 1996). Whereas early ecological approaches focused on how neighborhood change influenced crime, later research examined crime's impact on neighborhood demographic changes. Morenoff and Sampson (1997:34) highlighted this reverse relationship between crime and neighborhood change, noting that "although Shaw and McKay based their explanation of neighborhood delinquency rates on an ecological model of urban change, they neglected to analyze the role that crime played as an engine of that change." Morenoff and Sampson found that White, higher income residents tend to leave neighborhoods more quickly as violence increases. This perspective views crime as a community-level factor that erodes the socioeconomic fabric of neighborhoods, driving demographic shifts.

Besides driving neighborhood change, research shows that violence casts a long shadow over communities, impacting all residents, regardless of direct involvement with crime (Sharkey 2018). Exposure to community violence affects children's cognition and grades, shapes parenting styles, and discourages investments from families, businesses, teachers, and officials. Violence alters neighborhoods by deterring public space use, undermining businesses, weakening labor markets, and increasing law enforcement presence.

Violence can directly and indirectly drive or reinforce economic segregation and poverty concentration. Directly, it impacts poverty by influencing schools, youth cognitive development, and local labor market opportunities. Indirectly, it shapes neighborhood selection, discouraging entry by families with more residential options and prompting out-migration among those with the resources to leave. Urban economics research, drawing on neighborhood choice models (Brueckner et al. 1999; McFadden 1974), has found that declining crime rates encourage high-income households to choose central-city neighborhoods because they value the amenities in those neighborhoods, such as upscale restaurants (Ellen et al. 2019; O'Sullivan 2005).

The various mechanisms of neighborhood change were visible between the 1960s and the early 1990s, when large-scale urban out-migration allowed crime scholars to generate evidence on how different demographic changes were shaped by crime and disorder at the metropolitan level. Several studies documented how the out-migration of upper income and White residents to the suburbs in the 1960s and 1970s, known as "white flight," was partially a response to increases in violent crime rates in central-city neighborhoods (Grubb 1982; Liska and Bellair 1995; Marshall 1979; Sampson and Wooldredge 1986; South and Crowder 1997). The same processes influenced the out-migration of middle-class Black individuals from central-city neighborhoods within the boundaries of historically Black enclaves (Wilson 1987).

Cullen and Levitt (1999) conducted one of the most convincing studies of the effects of crime and urban out-migration. Using exogenous variation in criminal justice severity as an instrument for changes in crime in the 1970s and 1980s, they found that a 10% crime increase led to a 1% decline in central-city populations. Individuals with higher levels of education and families with children were the most likely to relocate to suburbs as crime rose. Ellen and O'Regan (2008) extended this work, analyzing the 1990s crime decline. Although they found no link between crime and net population changes, they showed that lower crime rates were associated with higher rates of population retention, slowing urban flight.

More recently, Ellen et al. (2019) used geocoded data from the 1990 and 2000 Decennial Censuses and the 2010, 2011, and 2012 American Community Survey to examine household moves across 200 metropolitan areas. They found that crime reductions increased the likelihood of high-income, college-educated households moving into low-income, minority, central-city neighborhoods instead of suburban areas.

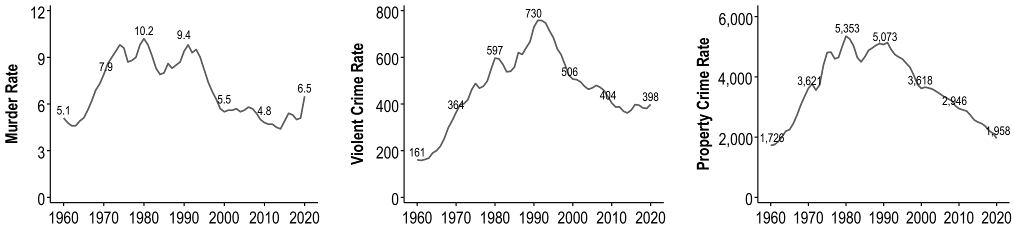

Fig. 1 Trends in national crime rates (number per 100,000 residents), 1960–2020. *Source:* FBI's Uniform Crime Reporting Program.

Falling Violence and Rising Inequality

We present national trends in murder, property crime, and violent crime from 1960 to 2019. Figure 1 shows that between 1960 and 1980, the murder rate doubled (from 5.1 to 10.2 per 100,000 residents), property crime more than doubled (from 1,726 to 5,353 per 100,000), and violent crime tripled (from 161 to 597 per 100,000). After a brief decline between 1980 and 1985, crime rates surged again during the crack cocaine epidemic (1985–1990). By 1990, the murder rate was 9.4, property crime was 5,073, and violent crime was 730 per 100,000 residents.

The 1990–2010 period marked one of the most dramatic transformations in recent urban history. During these two decades, the murder rate dropped by 49% (from 9.4 to 4.8 per 100,000 residents), property crime declined by 42% (from 5,073 to 2,946), and violent crime declined by 45% (from 730 to 404). Most cities saw declines during the 1990–2010 period, with some experiencing declines of 50% to 80% (e.g., New York, Los Angeles, Dallas, Fort Worth, and San Diego). Although the national murder rate rose after 2014, focusing on 1990–2010 allows us to leverage the sharp drop in violence across cities to examine our research questions.

The trends reported by the FBI match health department records, hospital data, and self-reported victimization rates from the National Crime Victimization Survey (NCVS) (Sharkey 2018). Data from the NCVS show a 75% decline in violent victimization from 1993 to 2015, with the poorest populations experiencing the greatest absolute reductions. At the neighborhood level, violence declined in both poor and nonpoor neighborhoods, with the most violent communities seeing the largest drops. Analyzing data from six cities with neighborhood-level crime data going back at least a decade, Friedson and Sharkey (2015) found that the steepest declines occurred in the poorest, most segregated, and most violent neighborhoods.[1] By all measures, "the great American crime decline" (Zimring 2006) represents one of the most dramatic changes for U.S. cities in the last two decades.

[1] In a similar analysis that uses a different sample of cities, Krivo et al. (2018) examined the crime trajectories of census tracts and found that predominantly Black tracts were more likely to experience increases in burglary and homicide rates between 1999 and 2013. These tract-level findings are plausible within the city-level context that Friedson and Sharkey (2015) studied. Citywide, racial minorities and low-income individuals might have experienced declines in their exposure to violent crime, but this pattern is consistent with a subset of predominantly Black tracts having experienced net crime gains.

As violence declined, rising economic inequality was also reshaping U.S. cities. The nation's Gini index, a key measure of income inequality, rose from 0.39 in 1970 to 0.46 in 2014 (U.S. Census Bureau 2015). This increase was driven by growing incomes at the top of the distribution: between 1970 and 2010, the income ratio between the 90th and 50th percentiles grew by 30%, whereas the ratio between the 10th and 50th percentiles shrank by 7% (Autor et al. 2008). Consequently, the share of income earned by the top 10% rose from 33% in 1970 to 45% in 2006 (Atkinson et al. 2011).

Cities and neighborhoods have mirrored the rise in economic inequality. Since 1970, low-income households have been less likely to share neighborhoods with middle- and high-income households, the number of households in low- or high-income neighborhoods has doubled, and the share in middle-income neighborhoods has dropped from 65% to 44%. Income segregation remained stable in the 1970s, rose in the 1980s, dipped slightly in the 1990s, and increased again in the 2000s, with overall income segregation growing by 1.2 SDs from 1970 to 2009 (Reardon and Bischoff 2011; for a discussion on measurement problems in the study of income segregation growth since 2000, see Logan et al. 2018).

The rise in economic segregation is largely driven by affluent households and increasing median incomes in their neighborhoods (Reardon et al. 2015). From 1980 to 2010, the share of upper income households in majority upper income tracts grew from 9% to 18%, and the share of lower income households in majority lower income tracts rose marginally from 23% to 25% (Fry and Taylor 2012). Owens (2016) showed that the growth in income segregation has been driven largely by the residential choices of families with children.

While affluent households distanced themselves economically, college-educated and mostly White residents increasingly moved into low-income, central-city neighborhoods. Gentrification, which began in some East Coast cities (e.g., New York and Boston) in the 1980s, surged in the 1990s and accelerated in the 2000s (Ellen and O'Regan 2008; Ellen and Torrats-Espinosa 2019). Among low-income central-city neighborhoods, 14% saw large median income gains in both the 1990s and 2000s. The share of college-educated residents rose in 25% and 35% of such neighborhoods in the 1990s and 2000s, respectively, and the share of non-Hispanic White residents grew in 7% and 18%, respectively (Ellen and Ding 2016).[2]

A key issue in gentrification is whether low-income residents are displaced as higher income households move in and rents rise. The lack of nationally representative data makes this topic contentious. Studying participants in the Section 8 Housing Choice Voucher Program, Ellen and Torrats-Espinosa (2020) found little evidence that rising rents push voucher holders to higher poverty neighborhoods. Other studies suggest that low-income households leave gentrifying neighborhoods at similar or lower rates than other neighborhoods, indicating that gentrification might not directly drive displacement (Freeman and Braconi 2004). To contribute to this debate, we explore whether high-poverty neighborhoods lost low-income households as the city's crime rates declined.

[2] Ellen and Ding (2016) defined a neighborhood as "low-income" if the census tract was at the bottom 40th percentile of the median income distribution in its metropolitan area. They defined "large relative gains" as more than 10-percentage-point increases in the ratio of the census tract value to the metropolitan area average (e.g., an increase in tract median income from 60% to 75% of the average metropolitan income).

The trends in income residential segregation and the gentrification of low-income neighborhoods paint a conflicting picture of how U.S. cities have been reshaped in the last 30 years. On the one hand, the rise in income segregation can be interpreted as a story about how low- and high-income households have become less likely to live near each other. On the other hand, the national focus on gentrification and the absence of evidence on the large-scale displacement of the poor suggest that poor sections of cities have become more economically integrated as high-income households have moved to low-income neighborhoods. One of our goals in this study is to reconcile these two stories, which seem to be at odds with each other.

These profound changes in the configuration of urban neighborhoods have occurred as cities experienced one of the steepest and most sustained declines in violence in U.S. history. Although some attention has been given to the relationship between declining violence and neighborhood change during this period of rising economic inequality (Ehrenhalt 2012; Ellen et al. 2019; Florida 2017; Hyra 2017), no research has assessed whether the fall of urban violence has had a causal impact on the demographic and socioeconomic shifts in city neighborhoods.

Data

To provide evidence on the impact of declining violence on economic segregation and poverty concentration, we use city-level data from the census and crime records from the FBI's Uniform Crime Reporting Program. We focus on changes between 1990 and 2010, a period in which we can leverage an instrumental strategy to isolate causal effects. Our sample includes the largest 500 municipalities (based on their population in 2010) for which Uniform Crime Reporting data were available.[3]

Income Segregation

We measure within-city income segregation using the information theory index (H), which indicates the degree to which households with incomes below a given percentile in the household income distribution are segregated from households with incomes at or above that percentile.[4] Our main focus is on estimating the impact of changes in crime on changes in the segregation of households with incomes at the bottom and the top of the income distribution, respectively. To do so, we compute indices of segregation of poverty (H10) and segregation of affluence (H90). H10 measures the residential segregation of households with incomes below the 10th percentile of the household income distribution from households at or above the 10th percentile. Analogously, H90 measures the residential segregation of households with

[3] To be included in our sample, a city must have available crime data for 1989, 1990, 1999, 2000, 2009, and 2010.

[4] For comprehensive reviews of the strengths and limitations of the H index and other commonly used indices of segregation, see Reardon and Firebaugh (2002) and Reardon and O'Sullivan (2004).

incomes below the 90th percentile of the household income distribution from households at or above the 90th percentile.[5]

We use tract-level data from the 1990 and 2000 censuses and five-year estimates from the 2006–2010 American Community Survey to compute indices of within-city income residential segregation in 1990, 2000, and 2010. We use the Longitudinal Tract Data Base crosswalks to hold tract boundaries fixed at their 2010 delineations. To map tracts onto municipalities, we calculate the centroid of each tract and assign a tract to a given municipality if the tract centroid is inside the municipality boundary. We use Reardon's (2011) methodology to estimate city-specific income percentiles from tract-level counts of households with incomes within brackets defined by the census.[6] Following Reardon et al.'s (2018) recommendations, we correct the bias in our segregation estimates arising from differences in sampling rates in the census and the American Community Survey.

The H indices range from 0 to 100, with 0 being a city with no segregation and 100 being a city with total segregation. The value of the index can be interpreted as the percentage of the variation in income between tracts rather than within tracts (Owens et al. 2016). For example, the H10 index for Chicago in 1990 was 14, indicating that 14% of the variation in the number of households with incomes below the 10th percentile was between tracts and that the remaining 86% was within tracts. By 2010, the segregation of poor households in Chicago had declined substantially, with only 9% of the variation in the number of households with incomes below the 10th percentile occurring between tracts.

Figure 2 shows trends in poverty (H10) and affluence (H90) segregation for the 500 cities in our sample. The thick blue lines show national trends, and the thin gray lines represent individual cities. In any given year, the poor are less segregated than the affluent, meaning that low-income households are more likely to live alongside middle- and high-income households than the reverse. Trends in our sample align with metropolitan-level patterns (Owens 2016; Reardon and Bischoff 2011; Reardon et al. 2018): segregation rose from 1980 to 1990, dipped in the 1990s, and rose again in the 2000s. H10 and H90 indices grew from 6.61 and 10.36, respectively, in 1980 to 8.51 and 14.39 in 2010. City-specific lines reveal substantial variation in income segregation trends, which our empirical approach leverages to examine how changes in violence influenced segregation and neighborhood dynamics.

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[5] Because the H index is binary, H90 can be interpreted as the segregation of households with incomes below the 90th percentile from the rest or as the segregation of households with incomes at or above the 90th percentile from the rest. The two statements are equivalent. We prefer the latter because it better conveys the notion of measuring the degree to which the most affluent households are segregated from the rest.

[6] One advantage of the H index over other measures of income segregation is that it is computed from households' ranks in the income distribution rather than from their actual income levels, making it less sensitive to changes in the shape of the income distribution that could arise from increasing income inequality over time (Reardon 2011). Although examining the segregation of households, for example, earning less than $20,000 and households earning $20,000 or more in a cross section of cities could be informative, estimating trends over time for that metric of segregation would be complicated by the fact that the distribution of household income might have widened in times of increasing income inequality. The use of city-specific percentile ranks addresses this issue because the share of households below a given percentile remains constant over time.

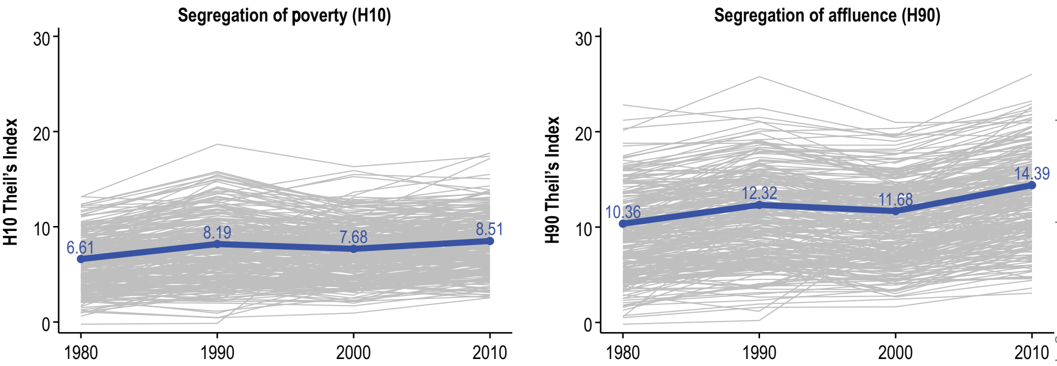

Fig. 2 Trends in segregation of poverty and affluence, 1980–2010. The H10 and H90 Theil information indices are computed from tract-level counts of households with incomes in the income brackets used in the censuses of 1980, 1990, and 2000 and the 2006–2010 American Community Survey. We extrapolate from income brackets to income percentiles using Reardon's (2011) method. All income segregation indices are bias-corrected, as recommended by Reardon et al. (2018). The H10 index captures the residential segregation of households with incomes at or below the 10th percentile of the household family income distribution. The H90 index captures the residential segregation of households with incomes at or above the 90th percentile of the household family income distribution. Each value plotted in the graph is the population-weighted average of the H10 and H90 indices of all cities in our sample ($N = 500$) in the corresponding year.

Reardon and Bischoff (2011) attributed the decrease in poverty segregation during the 1990s to the demolition of high-density public housing and the rise of scattered-site and mixed-income housing. Although these housing policies likely contributed, their limited scale suggests they are not the sole explanation. One overlooked factor is the decline in community violence. As Figure 1 shows, violent crime dropped sharply from 1990 to 2000, with the murder rate falling from 9.4 to 5.5 per 100,000 residents. During this period, poverty segregation also declined from 8.19 to 7.68 (Figure 2), aligning with evidence of shifting low-income neighborhood composition in the 1990s (Ellen and O'Regan 2008).

Note that these figures represent national averages and that the correlation between declines in crime and poverty segregation in the 1990s was more pronounced in specific cities. For example, in Houston, the murder rate dropped from 30.8 to 12.8 murders per 100,000 residents, and the segregation of poverty declined from 10.7 to 8.7. Similarly, in Detroit, the murder rate decreased from 59.3 to 43.2, and the segregation of poverty declined from 6.7 to 4.6. In Baltimore, the murder rate dropped from 36.1 to 29 murders per 100,000 residents, and the segregation of poverty declined from 11.6 to 9.7.

Crime

We use crime data at the law enforcement agency level from the FBI's Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest from 1989, 1990, 1999, 2000, 2009, and 2010 to compute two-year averages that we match to measures of segregation for 1990, 2000, and 2010. We use the Law Enforcement

Table 1 Descriptive statistics

	1990	2000	2010
Segregation of Poverty (H10)	8.19	7.68	8.51
	(3.44)	(2.80)	(2.67)
Segregation of Affluence (H90)	12.32	11.68	14.39
	(5.10)	(4.68)	(5.05)
Murder Rate	15.20	9.57	8.66
	(12.64)	(8.48)	(7.78)
Violent Crime Rate	2,190.94	2,043.26	1,831.64
	(1,136.10)	(1,148.87)	(1,122.11)
Property Crime Rate	7,534.08	5,086.10	4,019.41
	(2,433.59)	(2,182.44)	(1,632.38)
COPS Officers	0.00	59.08	62.29
	(0.00)	(134.49)	(136.81)
Population Density	2.25	2.46	2.58
	(2.56)	(2.75)	(2.81)
Males Aged 15–24	8.09	7.78	7.63
	(1.97)	(1.96)	(1.95)
Asian	4.52	5.96	7.27
	(5.29)	(6.65)	(7.66)
Black	17.62	18.20	18.03
	(16.23)	(16.91)	(16.46)
Hispanic	16.76	21.85	24.93
	(16.72)	(18.49)	(19.06)
Foreign-born	13.61	18.52	19.71
	(11.83)	(13.04)	(12.59)
College Degree	22.99	26.82	30.60
	(8.71)	(10.19)	(11.03)
High School Dropout	13.41	11.85	7.18
	(5.02)	(4.78)	(2.79)
Poverty Rate	16.11	16.14	17.99
	(6.62)	(6.28)	(6.17)
Unemployment Rate	4.73	4.49	5.04
	(1.41)	(1.41)	(1.38)
Black–White Dissimilarity Index	0.53	0.51	0.54
	(0.21)	(0.21)	(0.17)

Notes: Income segregation measures are computed from tract-level counts from the 1990 and 2000 censuses and the 2006–2010 American Community Survey. Tract boundaries are held constant across decades using 2010 delineations. Crime rates in 1990 are two-year averages for 1989 and 1990. Crime rates in 2000 are two-year averages for 1999 and 2000. Crime rates in 2010 are two-year averages for 2009 and 2010. COPS officers represent the cumulative number of officers hired from the program's start until the corresponding year. Demographics are computed from place-level data from the 1990 and 2000 censuses and the 2006–2010 American Community Survey. Segregation indices range from 0 to 100. Crime rates are in number of crimes per 100,000 residents. SDs are shown in parentheses.

Agency Identifiers Crosswalk (Bureau of Justice Statistics 2018) to aggregate law enforcement agency–level crime reports to the city level.[7] Our focus is on Type 1 offenses, which we group into murder (murder and nonnegligent manslaughter), all

[7] Most cities include only one law enforcement agency. However, crime reports in large cities, such as New York, originate from several law enforcement agencies (e.g., New York City Police Department, Metropolitan Police Department). We aggregate crime reports of all agencies whose jurisdiction is inside the city

violent crimes (murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault), and property crimes (burglary, larceny-theft, and motor vehicle theft).[8] We compute murder, violent, and property crime rates for every 100,000 residents in the city. We log-transform all crime rates to reduce skewness and facilitate the interpretation of regression coefficients.[9] Table 1 shows means and SDs for income segregation, crime rates, and the cumulative number of officers hired through the COPS program, as well as the demographic controls included in our models for 1990, 2000, and 2010 for the 500 sample municipalities.[10]

Empirical Strategy

Ordinary Least-Squares (OLS) Estimation

Our empirical strategy is designed to estimate the impact of changes in crime on changes in residential segregation between 1990 and 2010. We leverage the panel structure of our data, where each of the 500 municipalities is observed in 1990, 2000, and 2010, in a two-way fixed-effects setup that estimates the effect of within-municipality changes in crime on within-municipality changes in income residential segregation. Our baseline regression equation is as follows:

$$Seg_{it}^{p} = \delta_{OLS}^{p} Crime_{it} + \mathbf{X}_{it}'\boldsymbol{\beta} + \boldsymbol{\theta}_i + \boldsymbol{\zeta}_t + e_{it}. \tag{1}$$

Seg_{it}^{p} is the income residential segregation of households with income below percentile p in city i in year t; $Crime_{it}$ is the log crime rate in city i in year t; $\mathbf{X}_{it}'$ is a vector of controls that accounts for demographic conditions in city i in year t, including population density, the share of males aged 15–24, the share of non-Hispanic Asian residents, the share of non-Hispanic Black residents, the share of Hispanic residents, the share of foreign-born residents, the share of college-educated residents, the high school dropout rate, the poverty rate, the unemployment rate, and the Black–White dissimilarity index of racial segregation; $\boldsymbol{\theta}_i$ is a set of city fixed effects that accounts

limits, as defined by the Law Enforcement Agency Identifiers Crosswalk. We exclude from these counts any reports from agencies whose jurisdictions straddle city boundaries (e.g., state police departments).

[8] We consider the impact of violent and property crimes in line with research on violence and neighborhood change that has focused on both types of crimes (Cullen and Levitt 1999). Changes in the property crime rate are more likely to be measured with error, given well-documented patterns of misreporting across agencies. The IV estimation will mitigate attenuation bias that could arise from this measurement error.

[9] All results we present are robust to fitting models without log-transforming crime rates, to measuring crime rates in single years (1990, 2000, and 2010) and as five-year averages (see Figure A5), to excluding rapes and larcenies from the violent and property crime counts (see Figure A6), and to controlling for property crime in the violent crime and murder models (see Figure A7; all figures and tables designated with an "A" appear in the online appendix).

[10] As many have noted (Kaplan 2021; Maltz and Targonski 2002), Uniform Crime Reporting data imperfectly measure actual crime rates and require meticulous, agency-specific validation owing to inconsistent reporting issues. Unfortunately, given the years our study covers, we cannot use alternative crime data sources, such as the National Incident-Based Reporting System (NIBRS). Inconsistent reporting is more prevalent in small police departments (Maltz and Targonski 2002). This inconsistency constitutes a form of measurement error, which our IV strategy aims to minimize. Additionally, our models separately assess the effect of murder rate changes, which is less likely to suffer from misreporting issues.

for all time-invariant attributes of the city; ζ_t is a set of year fixed effects that accounts for common temporal trends affecting all cities; and e_{it} is an idiosyncratic error term. δ^p_{OLS} estimates the relationship between changes in crime rates and changes in the segregation of households with incomes below percentile p. We specify separate equations that estimate the association between changes in income residential segregation and changes in the property crime rate, changes in the violent crime rate, and changes in the murder rate. Although our main focus is on changes in the segregation of households with incomes below the 10th percentile (H10) and the segregation of households with incomes at or above the 90th percentile (H90), we report estimates at all percentiles of the income distribution. All models include city population weights and heteroskedasticity-robust standard errors. Models without population weights, shown in the online appendix, yield the same results.

A potential critique of our approach is that we measure crime changes at the city level but draw conclusions about neighborhood-level population changes. Ideally, our models would link neighborhood crime changes to population shifts, but such data are limited to a few cities and years. Nonetheless, prior theory and evidence support connecting city-level crime changes to neighborhood processes. Rising city crime rates can create fear and insecurity (Skogan 1986), prompting selective migration as those with the means to move to safer neighborhoods do so, increasing segregation (Liska and Bellair 1995; Sampson and Wooldredge 1986; South and Crowder 1997). Conversely, declining crime can attract new residents to previously stigmatized neighborhoods, fostering diversity and integration (Ellen et al. 2019). Thus, city-level crime changes can influence neighborhood dynamics, as reflected in citywide segregation patterns.

IV Estimation

One limitation of the estimation strategy represented in Eq. (1) is that the association captured by δ_{OLS} could be driven by endogenous crime rate changes, measurement error, or reverse causality in which changes in income segregation lead to changes in crime rates.[11] To account for these identification threats, we employ an IV strategy that exploits the timing of grants that law enforcement agencies received under the COPS program as a citywide exogenous shock to crime rates.

IV regression requires finding a variable Z, the instrument, that is related to the treatment variable T and that it is only related to the outcome variable Y through the change that Z induces on T. If these conditions are met, we can use the predicted values of T from a regression of T on Z to estimate the causal effect of T on Y. The first condition (i.e., the instrument is related to the treatment variable), known as the *relevance condition*, can be tested in the data by examining the direction and strength of the association between the instrument and the treatment variable. The second con-

[11] Measurement error might arise if some police departments underreport crime rates to the FBI. If such underreporting is driven by an omitted variable (e.g., smaller departments devoting less resources to report to the FBI), the OLS estimates will be biased. Because, as we argue, the timing of the receipt of the COPS grant is uncorrelated with any other changes affecting cites and police departments, we can rely on the IV estimation to address confounding related to how crime rates are measured in the FBI data.

dition (i.e., the instrument is only related to the outcome via its association with the treatment variable), known as the *exclusion restriction*, cannot be formally tested in the data. However, we can provide suggestive evidence that rules out the possibility that the instrument is affecting the outcome through pathways other than the one running through the treatment. Before we present evidence on the extent to which these two assumptions hold in our setting, we provide an overview of the COPS program.

The COPS program, established in 1994 under the Violent Crime Control and Law Enforcement Act, funded 75% of the cost to hire or rehire entry-level officers. Evans and Owens (2007) demonstrated that COPS grants causally reduced violent and property crimes from 1990 to 2001, with no correlation between grant timing and prior crime trends. Interviews with police agency representatives revealed that the application process was simple, with low barriers and minimal paperwork for subsequent grants. Funds were often disbursed arbitrarily, with the COPS office occasionally soliciting applications. Thus, fund allocation was unpredictable, particularly in the program's early years.

In light of this evidence, we use the number of officers hired through the COPS program in each municipality as an instrument for crime rates (for similar uses of the COPS instrument, see Sharkey and Torrats-Espinosa 2017; Torrats-Espinosa 2020). This setup exploits the quasi-random shock to crime rates that the COPS grants induced through two channels: (1) not all police departments applied or received funds when the program started in 1994; and (2) the COPS office awarded the grants in subsequent years up until 2008 in a seemingly idiosyncratic way that had little to do with crime trends unfolding across cities (Evans and Owens 2007). Because the program started in 1994, COPS hiring in 1990 was zero for all cities. For 2000, the COPS instrument is the cumulative number of officers hired through the program up to that year. For 2010, the instrument is the cumulative number of officers hired through the program up to 2008. Starting in 2009, the COPS office changed the way grants were awarded, assigning each application a "fiscal need score" and a "crime score" and allocating the funds on the basis of those scores. Such allocation criteria make the exclusion restriction less plausible for years after 2008. Therefore, we focus on 1990–2010 throughout our analyses.

We conduct the IV estimation using the following two-stage least-squares (2SLS) system of equations:

$$Crime_{it} = \pi_1 COPS_{it} + \mathbf{X}'_{it}\boldsymbol{\beta} + \boldsymbol{\theta}_i + \boldsymbol{\zeta}_t + \eta_{it}, \tag{2.1}$$

$$Seg^p_{it} = \pi^p_2 COPS_{it} + \mathbf{X}'_{it}\boldsymbol{\beta} + \boldsymbol{\theta}_i + \boldsymbol{\zeta}_t + e_{it}. \tag{2.2}$$

$Crime_{it}$ is the log crime rate in city i in year t; Seg^p_{it} is the level of income residential segregation of households with incomes below percentile p in city i in year t; $COPS_{it}$ is the cumulative number of officers hired through the COPS program in city i up to year t; and $\mathbf{X}'_{it}$, $\boldsymbol{\theta}_i$, $\boldsymbol{\zeta}_i$ are the same vectors of demographic controls and fixed effects included in Eq. (1). We measure COPS officer hiring cumulatively because police agencies retained the police officers that were hired through the COPS grants in each year (Evans and Owens 2007). Our results are robust to using the COPS grant amount (in millions of dollars) instead of the number of officers hired through the grants as an instrument for crime rates.

Equation (2.1) estimates the impact of changes in the instrument on changes in crime rates, π_1. Equation (2.2) is the reduced-form equation, and it estimates the direct effect of the instrument on the residential segregation of households with incomes below percentile p, π_2^p. The IV estimate of the impact of crime rates on the residential segregation of households with income below percentile p, δ_{IV}^p, is obtained by dividing the corresponding reduced-form estimate over the first-stage estimate ($\delta_{IV}^p = \pi_2^p/\pi_1$). As in any IV strategy, δ_{IV}^p represents an estimate of the local average treatment effect (LATE) specific to the instrument that induced the exogenous shock to the treatment variable (Angrist et al. 1996). In our case, the LATE is the estimated change in segregation resulting from an exogenous shock to the size of police departments that alters crime rates. However, a different research design leveraging a different exogenous shock to crime rates could produce a different LATE.

We specify separate equations to estimate the causal effect of changes in property crime rate, violent crime rate, and murder rate on income residential segregation. As before, we focus on the impact of changes in crime on changes in the H10 and H90 indices, but we present evidence at all percentiles. All models include city population weights and heteroskedasticity-robust standard errors. We use population weights in models reported in the main text. Unweighted results, which align closely with the weighted results, are available in the online appendix.

Before we show the OLS and IV results, we discuss evidence on the extent to which the relevance condition and exclusion restriction assumptions for the IV estimation hold in our setting. The relevance condition requires that larger increases in citywide per capita COPS hiring should translate into larger crime drops in the city. The validity of this condition can be tested by examining the estimate for π_1 in the first-stage equation. In Table 2, we show that for every 10 additional officers hired through the COPS program, the murder rate declined by 1.3%, the violent crime rate decreased by 1.6%, and the property crime rate declined by 0.8%. Importantly, in all three models, the F statistic for the Wald test on the IV is well above 10, indicating a strong first stage that avoids small sample bias associated with the "weak instrument" problem (Stock and Yogo 2005).

The exclusion restriction assumes that COPS grants affected income segregation only through changes in crime. This assumption would be violated if grants were allocated on the basis of prior trends in crime, income segregation, or related demographic changes. For instance, if cities with declining crime or improving economic trends before the program began were more likely to receive grants, the exclusion restriction would not hold. To test this possibility, Figure A1 regresses 1990–2000 changes in COPS funding on 1980–1990 changes in murder rates, crime rates, income segregation, and included demographics (all figures and tables designated with an "A" appear in the online appendix). The results show no evidence that prior changes in these attributes predicted grant allocation, supporting the validity of the exclusion restriction.

In Figure A8, we further assess the exclusion restriction assumption by testing sensitivity to unmeasured confounding. As stated earlier, the IV estimate, δ_{IV}^p, is obtained by dividing two causal effects: the causal effect of the instrument on crime, π_1 (obtained in the first-stage regression), and the causal effect of the instrument on segregation, π_2^p (obtained in the reduced-form regression). Therefore, for the δ_{IV}^p estimate to be unbiased, both the π_1 and the π_2^p estimates must be free of bias. A number of tests allow for the assessment of bias due to unmeasured confounding in a regres-

Table 2 First-stage estimates of officers hired through the COPS program on changes in crime rates

	Murder (1)	Violent Crime (2)	Property Crime (3)
COPS Officers (in 10s)	–0.013**	–0.016**	–0.008**
	(0.002)	(0.003)	(0.002)
Population Density	–0.327**	–0.357*	–0.426**
	(0.091)	(0.174)	(0.104)
Males Aged 15–24	0.044†	–0.003	0.029
	(0.025)	(0.022)	(0.024)
Asian	–0.022*	–0.032*	–0.009
	(0.011)	(0.015)	(0.013)
Black	0.026**	0.024**	0.016*
	(0.006)	(0.009)	(0.007)
Hispanic	–0.005	–0.030**	–0.013
	(0.007)	(0.010)	(0.008)
Foreign-born	0.005	0.022	0.014
	(0.011)	(0.013)	(0.012)
College Degree	0.005	–0.028*	–0.004
	(0.008)	(0.012)	(0.007)
High School Dropout	0.019**	–0.000	–0.006
	(0.007)	(0.012)	(0.012)
Poverty Rate	0.014	0.016	0.007
	(0.010)	(0.011)	(0.009)
Unemployment Rate	0.011	–0.052	–0.033
	(0.021)	(0.035)	(0.033)
Black–White Dissimilarity Index	0.488*	0.414	0.376†
	(0.193)	(0.258)	(0.207)
Number of Observations	1,500	1,500	1,500
Adjusted R^2	.475	.162	.275
F Statistic IV	43.0	22.3	17.2

Notes: Standard errors, shown in parentheses, are robust to heteroskedasticity. Crime rates are log-transformed. All models include city fixed effects, year fixed effects, and population weights. Results without population weights are reported in Table A1. The sample includes 500 cities observed in 1990, 2000, and 2010.

†$p<.10$; *$p<.05$; **$p<.01$

sion setting. We use the test developed by Oster (2019) to assess 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 create bias in the estimate of the COPS effect 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 first-stage equation. The same logic would apply to the assessment of bias in the reduced-form equation: the test quantifies 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 reduced-form equation. Results from the Oster test for the first-stage and reduced-form equations, reported in Figure A8, show that a confounder that would overturn our findings is unlikely to exist.

Results

The Impact of Crime on Income Segregation

We begin by reporting OLS associations estimated via the two-way fixed-effects model represented by Eq. (1). Table 3 shows OLS estimates of the association between changes in rates of murder (columns 1 and 2), violent crime (columns 3 and 4), and property crime (columns 5 and 6) and changes in the segregation of both poverty (H10) and affluence (H90). Only models estimating the relationship between changes in murder and changes in income segregation yield significant associations. For each 10% decline in the murder rate, the segregation of poverty and affluence decreased by 0.04 points and 0.03 points (on a scale of 0–100), respectively; these figures translate to changes of 0.11 and 0.10 SDs for the segregation of poverty and affluence, respectively, for each SD change in the murder rate. Models without population weights (included in Table A2) show qualitatively similar results.

Table 4 shows IV estimates of the effect of changes in rates of murder (columns 1 and 2), violent crime (columns 3 and 4), and property crime (columns 5 and 6). We find strong positive effects of changes in all three types of crime on changes in the segregation of poverty but no effects on changes in the segregation of the most affluent households. First, column 1 shows that for each 10% decline in the murder rate, the segregation of poverty decreased by 0.23 points (on a 0–100 scale). This figure represents a 0.56-SD change for a 1-SD change in the murder rate. Second, column 3 shows that for each 10% decline in violent crime, the segregation of poverty decreased by 0.18 points (on a 0–100 scale), representing a 0.55-SD change for a 1-SD change in violent crime. Finally, column 5 shows that for each 10% decline, the segregation of poverty decreased by 0.38 points (on a 0–100 scale), reflecting a 0.82-SD change for each SD change in the property crime rate. Table A3 reports results excluding population weights, which are qualitatively the same as those presented here.

The IV estimates are larger than the OLS ones, a difference that might arise for several reasons. The first one arises from the local nature of the IV estimate. Under the assumptions of valid first stage and exclusion restriction, and in the presence of heterogeneous treatment effects, the IV strategy identifies a LATE for the set of cities for which the instrument induces a change in crime rates that could differ from the average treatment effect for the entire population (Angrist et al. 1996). The second potential reason for the OLS–IV differences arises from the motivation of using an IV approach in the first place: the omitted variable bias problem. The OLS estimates are likely biased owing to the endogeneity of changes in crime rates. If the IV assumptions hold, the IV strategy will mitigate this bias and produce estimates that differ from the OLS ones. The third reason for the OLS–IV differences is that OLS estimates might suffer from attenuation bias owing to measurement error in crime rates. The IV strategy mitigates this bias, producing estimates that will be larger in absolute magnitude.

In Figure 3, we extend our analyses to all other deciles of the household income distribution. We use tract-level data on household income to compute citywide measures of segregation for households at the 10th to 90th percentiles (in 10-percentile increments) of the household income distribution. For completeness, we also report the analyses at the 10th and 90th percentiles in Table 4.

The point estimates and 95% confidence intervals shown in Figure 3 are generated from separate IV regressions of the change in the segregation of households at

Table 3 OLS fixed-effects estimates of changes in crime and income segregation

	H10 (1)	H90 (2)	H10 (3)	H90 (4)	H10 (5)	H90 (6)
Log Murder Rate	0.427**	0.328*				
	(0.128)	(0.137)				
Log Violent Crime Rate			0.135	–0.072		
			(0.107)	(0.078)		
Log Property Crime Rate					0.078	0.011
					(0.051)	(0.054)
Population Density	1.102*	0.427	0.924	0.155	0.869	0.218
	(0.535)	(0.547)	(0.587)	(0.502)	(0.564)	(0.508)
Males Aged 15–24	–0.022	0.040	–0.004	0.052	–0.008	0.053
	(0.085)	(0.095)	(0.086)	(0.096)	(0.086)	(0.096)
Asian	0.048	–0.164**	0.044	–0.171**	0.041	–0.169**
	(0.044)	(0.047)	(0.045)	(0.047)	(0.044)	(0.047)
Black	–0.009	0.040	0.001	0.053	0.004	0.051
	(0.041)	(0.036)	(0.039)	(0.035)	(0.040)	(0.036)
Hispanic	–0.003	–0.024	0.002	–0.023	0.000	–0.022
	(0.032)	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)
Foreign-born	–0.028	0.194**	–0.029	0.196**	–0.028	0.195**
	(0.047)	(0.052)	(0.048)	(0.053)	(0.048)	(0.053)
College Degree	–0.043	0.060	–0.035	0.062	–0.038	0.063
	(0.062)	(0.047)	(0.060)	(0.047)	(0.062)	(0.047)
High School Dropout	–0.083**	–0.091*	–0.074*	–0.083*	–0.073*	–0.083*
	(0.032)	(0.040)	(0.031)	(0.040)	(0.031)	(0.040)
Poverty Rate	0.083†	0.038	0.084†	0.039	0.084†	0.039
	(0.047)	(0.050)	(0.048)	(0.050)	(0.048)	(0.050)
Unemployment Rate	0.162	–0.169	0.174	–0.167	0.170	–0.164
	(0.115)	(0.120)	(0.118)	(0.121)	(0.117)	(0.121)
Black–White Dissimilarity Index	3.300**	0.526	3.493**	0.781	3.539**	0.732
	(0.872)	(1.060)	(0.865)	(1.069)	(0.864)	(1.070)
Number of Observations	1,500	1,500	1,500	1,500	1,500	1,500
Adjusted R^2	.164	.497	.156	.494	.154	.493

Notes: Standard errors, shown in parentheses, are robust to heteroskedasticity. Segregation indices range from 0 to 100. Crime rates are log-transformed. All models include population weights. Results without population weights are reported in Table A2. The sample includes 500 cities observed in 1990, 2000, and 2010.

†$p<.10$; *$p<.05$; **$p<.01$

a given percentile on the change in the log of murder, violent crime, and property crime rates. The point estimate on the far left in each coefficient's plot represents the causal effect of changes in crime on changes in the segregation of households with incomes below the 10th percentile, the next point estimate represents the causal effect of changes in crime on changes in the segregation of households with incomes below the 20th percentile, and so forth. We find that the fall in crime between 1990 and 2010 led to a decline in the segregation of households with incomes below the 50th percentile but had no effect on the segregation of households with incomes at or above the 60th percentile. This pattern is consistent with evidence showing that low-income neighborhoods experienced the largest declines in violence (Friedson and Sharkey 2015). It is also consistent with evidence showing that the drivers of urban revival and

Table 4 IV fixed-effects estimates of changes in crime on changes in residential segregation of poor (H10) and affluent (H90) households

	H10 (1)	H90 (2)	H10 (3)	H90 (4)	H10 (5)	H90 (6)
Log Murder Rate	2.296†	–0.919				
	(1.342)	(1.186)				
Log Violent Crime Rate			1.840*	–0.736		
			(0.828)	(0.877)		
Log Property Crime Rate					3.844	–1.538
					(2.352)	(1.925)
Population Density	2.333†	–0.395	2.239*	–0.357	3.220†	–0.749
	(1.257)	(0.960)	(0.905)	(0.841)	(1.824)	(1.366)
Males Aged 15–24	–0.095	0.089	0.012	0.046	–0.106	0.093
	(0.106)	(0.104)	(0.093)	(0.093)	(0.137)	(0.108)
Asian	0.081	–0.186**	0.088†	–0.189**	0.065	–0.180**
	(0.055)	(0.052)	(0.053)	(0.048)	(0.066)	(0.051)
Black	–0.070†	0.081†	–0.056	0.076†	–0.074	0.083†
	(0.042)	(0.047)	(0.038)	(0.041)	(0.049)	(0.049)
Hispanic	–0.017	–0.015	0.027	–0.033	0.023	–0.031
	(0.036)	(0.034)	(0.031)	(0.033)	(0.043)	(0.035)
Foreign-born	–0.032	0.197**	–0.060	0.208**	–0.074	0.214**
	(0.044)	(0.054)	(0.051)	(0.051)	(0.063)	(0.055)
College Degree	–0.063	0.073	–0.001	0.048	–0.037	0.063
	(0.064)	(0.048)	(0.045)	(0.046)	(0.059)	(0.046)
High School Dropout	–0.128**	–0.061	–0.083*	–0.079*	–0.062	–0.088*
	(0.040)	(0.044)	(0.035)	(0.037)	(0.054)	(0.042)
Poverty Rate	0.080†	0.040	0.083*	0.039	0.088	0.037
	(0.046)	(0.050)	(0.048)	(0.050)	(0.055)	(0.050)
Unemployment Rate	0.136	–0.151	0.256†	–0.199	0.286	–0.211
	(0.104)	(0.126)	(0.133)	(0.129)	(0.196)	(0.145)
Black–White Dissimilarity Index	2.093	1.331	2.452*	1.187	1.767	1.461
	(1.323)	(1.221)	(1.069)	(1.083)	(1.690)	(1.333)
Number of Observations	1,500	1,500	1,500	1,500	1,500	1,500

Notes: Standard errors, shown in parentheses, are robust to heteroskedasticity. Segregation indices range from 0 to 100. Crime rates are log-transformed. All models include population weights. Results without population weights are reported in Table A3. The sample includes 500 cities observed in 1990, 2000, and 2010.

†$p<.10$; *$p<.05$; **$p<.01$

neighborhood change in the 1990s and 2000s were young and middle-aged adults who had not reached their full earnings potential (Couture and Handbury 2017; Ehrenhalt 2012). If this was the group moving into low-income neighborhoods in greater numbers as cities became safer, but more affluent households did not move in response to falling crime rates, we should expect to see more economic integration at the bottom half of the income distribution but not much change at the top of the distribution.

These findings provide an overlooked explanation for the decline in economic segregation during the 1990s. Although some cities saw reductions as a result of the demolition of high-rise public housing (Reardon and Bischoff 2011), the steep national decline in crime from the early 1990s to 2000 was felt across most major cities. During this period, the murder rate dropped by 42%, and victimization rates saw their

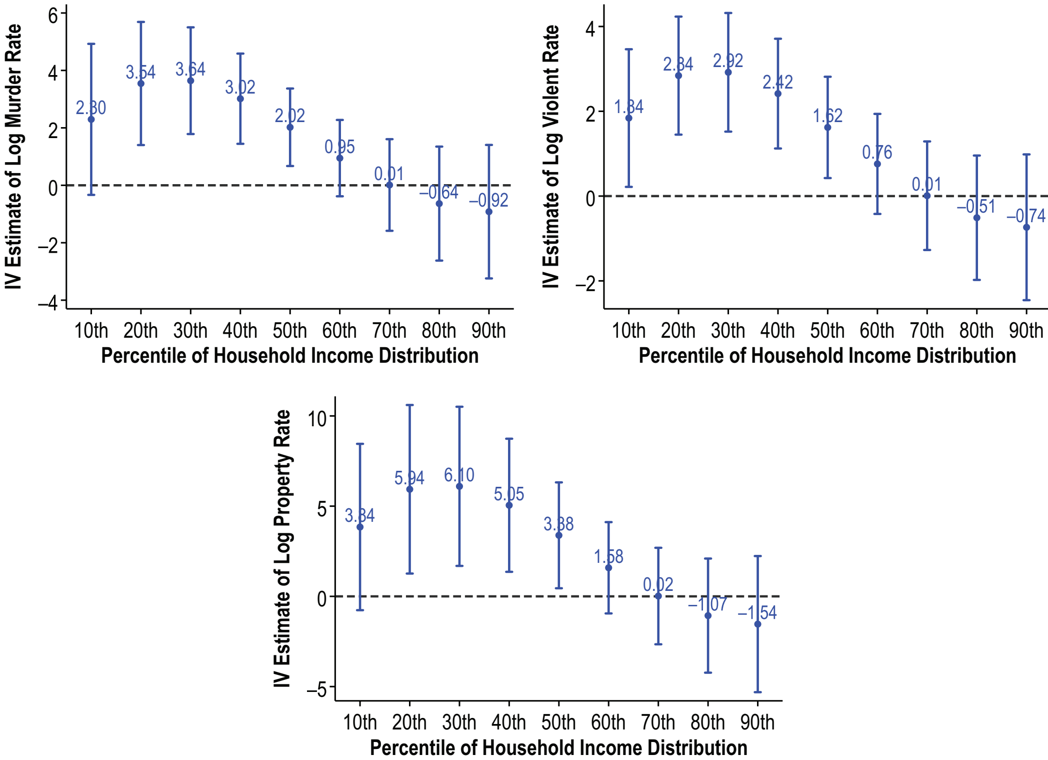

Fig. 3 IV fixed-effects estimates of the impact of changes in crime rates on changes in the segregation of households at different income percentiles. Each point estimate and 95% confidence interval comes from a separate 2SLS fixed-effects regression, as described in Eqs. (2.1) and (2.2). The coefficients shown are the second-stage estimates. Each regression estimates the impacts of changes in the crime rate on changes in the segregation of households with incomes at or below the income percentile indicated on 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 set of controls shown in Table 4. All models include population weights. Results from unweighted regressions are shown in Figure A2. Standard errors are robust to heteroskedasticity.

sharpest declines, dramatically improving city life and sparking renewed interest in central-city neighborhoods (Ellen and O'Regan 2008). Many of these neighborhoods, which attracted middle- and high-income households, previously had high poverty rates, leading to increased economic integration but also raising concerns about gentrification and displacement. In the next section, we examine how the migration of college-educated and White residents into the poorest 1990 neighborhoods influenced income segregation and whether these changes displaced low-income residents.

Demographic Changes in High-Poverty Neighborhoods

Declines in poverty segregation can result from shifts in the economic status of non-moving households or, more commonly, from class-specific migration that reshapes neighborhoods. Specifically, these declines might stem from low-income households moving out of poor neighborhoods or middle- and high-income households moving in. Both processes likely contribute, but understanding their relative importance clarifies how low-income communities have changed as crime has fallen. If out-migration by low-income residents drives these declines, it raises concerns about displacement due to rising property values and rents. Conversely, if middle- and high-income households move into low-income neighborhoods without reducing the prevalence of low-income residents, concerns about gentrification and displacement might be less pressing.

In the next analyses, we examine how different types of migration contributed to the decline in poverty segregation. We focus on census tracts in the bottom quintile of median household income in 1990, labeling them as *low-income neighborhoods*. For these neighborhoods, we track three outcomes: changes in the city's share of college-educated residents, non-Hispanic White residents, and residents below the poverty line. Table A4 shows that the share of college-educated residents in low-income neighborhoods rose from 9% in 1990 to 10.3% in 2010, and the share of non-Hispanic White residents increased slightly from 9.3% to 9.8%. Meanwhile, the share of city residents in poverty living in these neighborhoods declined from 46.2% in 1990 to 34.1% in 2010.

The choice of examining how college-educated and poor residents have become more or less concentrated in the neighborhoods that were among the poorest in 1990 is a strategy to assess the importance of the residential choices of households with different incomes. We use college-educated residents as a proxy for middle- and upper income residents; we use residents with income below the poverty line as a proxy for low-income residents. This approach is commonly used in research on gentrification and urban inequality (Ellen and Ding 2016; Freeman 2005; Moretti 2012).[12] Because much of the debate on gentrification is connected to discussions about neighborhood racial change (Ellen and O'Regan 2011; Hwang and Sampson 2014), we also examine how the concentration of non-Hispanic White residents living in low-income neighborhoods changed as crime dropped.

IV estimates for changes in the composition of low-income neighborhoods are reported in Figure 4. (Figure A3 shows the same results without weighting regressions by city population.) We find that falling crime rates led to an increased concentration of White and college-educated residents in neighborhoods that were low income in 1990 and a decrease in the concentration of low-income residents in those same neighborhoods. Each 10% decline in the murder rate led to a 0.61-percentage-point increase in the city's share of non-Hispanic White residents living in high-poverty neighborhoods and a 0.45-percentage-point increase in the city's share of college-educated residents living in high-poverty neighborhoods. When we examine changes in the city's share of households with incomes below the poverty line living in low-income neighborhoods, we find a statistically nonsignificant positive impact, suggesting that poor residents out-migrated from low-income neighborhoods as violence fell. Results estimating the impact of changes in the violent and property crime rates yield similar magnitudes, as shown by the rest of the coefficients plotted in Figure 4.

[12] A regression of the change in the H10 index on the change in the share of college-educated residents that lived in tracts that were at least 30% poor in 1990 yields a statistically significant coefficient of –0.37. This result means that, on average, for each 1-percentage-point increase in the share of college-educated residents living in tracts that were high poverty in 1990, the segregation of poverty declined by 0.37 points (on a 0–100 scale).

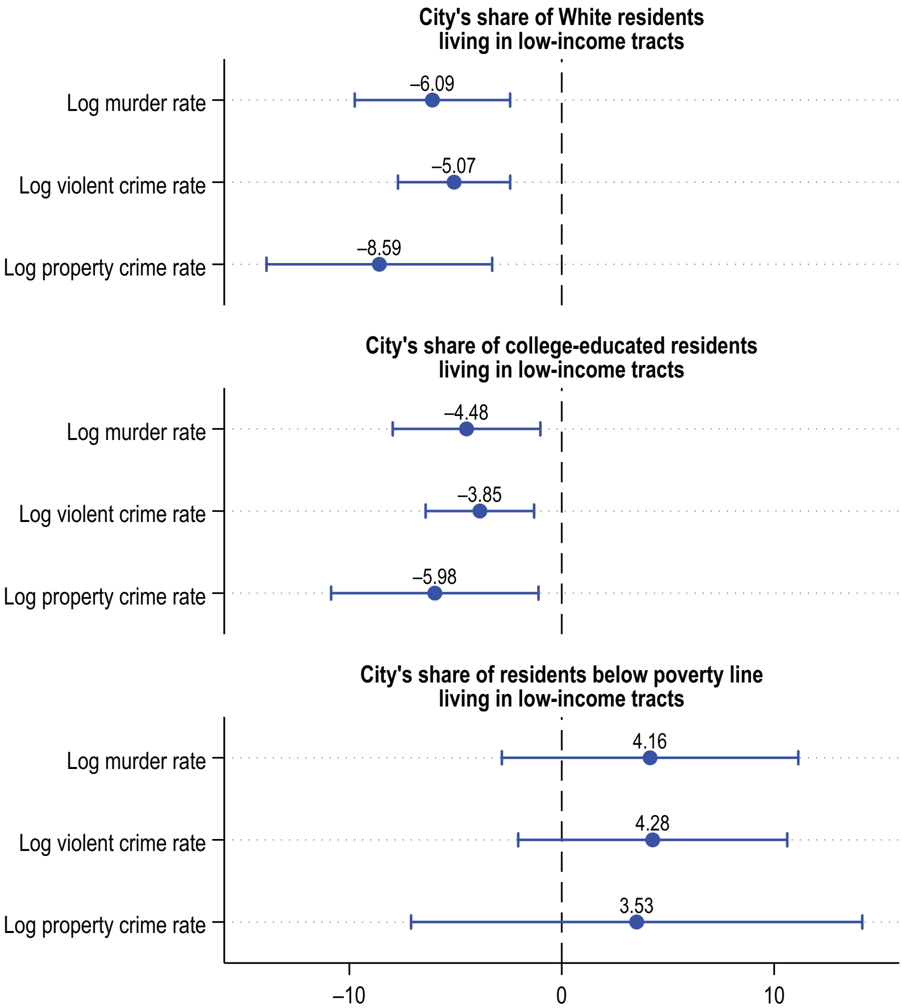

Fig. 4 IV fixed-effects estimates of the impact of changes in crime on changes in the concentration of different demographic groups in low-income neighborhoods. These models assess the change in the concentration of White (top panel), college-educated (middle panel), and poor (bottom panel) residents in neighborhoods that were low income in 1990. Low-income neighborhoods are the tracts in the bottom quantile of the city-specific household income distribution in 1990. Our measure of concentration is the city's 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 comes from a separate 2SLS fixed-effects regression, as described in Eqs. (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 set of controls shown in Table 4. All models include 1990 population weights. Results from unweighted regressions are shown in Figure A3. Standard errors are robust to heteroskedasticity.

These findings help us explain a possible mechanism driving our earlier findings on changes in income residential segregation shown in Figure 3. Figure 4 suggests that the decline in poverty segregation associated with the decline in violence shown in Figure 3 is driven by population turnover, whereby some low-income residents were replaced by White residents with higher income levels. The magnitudes in Figure 4 are modest, and the impacts on the displacement of poor households are unclear. Still, they are consistent with prior quantitative, ethnographic, and journalistic evidence documenting that the crime decline was an important contributing factor in the repopulation of low-income, central-city neighborhoods in recent decades (Ehrenhalt 2012; Ellen et al. 2019). This increased inflow of higher income White residents into low-income neighborhoods appears to have contributed to the out-migration of some low-income households from those neighborhoods, a pattern of gentrification documented elsewhere (Hwang and Ding 2020).

The empirical evidence on displacement in gentrifying neighborhoods is not conclusive, with some studies indicating that low-income residents do not move out at higher rates when high-income households move into their neighborhoods (Ellen and O'Regan 2011; Freeman 2005). However, an increasing number of journalistic accounts have documented the negative effects of gentrification on the displacement and well-being of original residents. It is plausible that the impact of gentrification on displacement varies across housing markets, with low-income households experiencing more pressure to move out of low-income neighborhoods if the housing supply in those neighborhoods is more limited. In fact, most of the stories highlighting the negative effects of gentrification on displacement come from cities that had a more limited supply of housing units in high-poverty neighborhoods in 1990, such as New York City, San Francisco, and Seattle. In 1990, only 5.7% of all housing units in tracts with a poverty rate of 30% or higher in New York City were vacant. In Seattle, that figure was 6.8%. Conversely, the vacancy rate in high-poverty neighborhoods was 18.1% in Atlanta and 20.4% in New Orleans.

In Figure A4, we assess the extent to which the patterns shown in Figure 4 vary across housing markets. We divide the sample of cities into those with low vacancy rates in low-income neighborhoods in 1990 and those with high vacancy rates in low-income neighborhoods in 1990. We use the 1990 median vacancy rate of 9% in low-income neighborhoods in the 500 municipalities in our sample to divide cities into these two groups, and we estimate IV models of the impact of changes in violent crime on changes in the same outcomes as those shown in Figure 4. We find that the impacts on the concentration of poor households in low-income neighborhoods are driven by cities with a more limited availability of housing units in low-income neighborhoods. In those cities, some low-income households appear to have been displaced as crime rates fell and White and college-educated residents moved in.

Descriptive Neighborhood-Level Evidence

Our theory assumes that the citywide changes in economic segregation we document stem from neighborhood-level dynamics. Data limitations prevent subcity analyses for all sample cities, but we address this shortcoming by collecting tract-level crime data from Chicago, Denver, New York, Philadelphia, and Portland to estimate OLS

Table 5 Tract-level regressions of 2000–2015 demographic changes on changes in violent crime in Chicago, Denver, New York City, Philadelphia, and Portland

	Share White		Share College-Educated		Share in Poverty		Household Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change Log Violent Crime	−0.077**	−0.047**	−0.050**	−0.044**	0.028**	0.017*	−0.101**	−0.059**
	(0.008)	(0.004)	(0.003)	(0.003)	(0.008)	(0.007)	(0.027)	(0.021)
1990 Levels								
Share Black		0.179**		−0.041**		−0.000		−0.163**
		(0.007)		(0.006)		(0.005)		(0.046)
Share Asian		0.071**		−0.140**		0.043*		−0.459**
		(0.025)		(0.028)		(0.020)		(0.097)
Share Hispanic		0.231**		−0.032*		0.004		−0.238†
		(0.014)		(0.013)		(0.012)		(0.122)
Share in poverty		0.134**		0.046		−0.151**		0.365
		(0.030)		(0.034)		(0.026)		(0.236)
Share college-educated		0.235**		0.076**		−0.074**		0.649**
		(0.023)		(0.022)		(0.014)		(0.096)
Share no high school		−0.030		0.030		−0.043†		0.502*
		(0.041)		(0.035)		(0.025)		(0.232)
Median household income		−0.000*		−0.000**		−0.000		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Number of Observations	3,581	3,581	3,581	3,581	3,581	3,581	3,581	3,581
Adjusted R^2	.089	.422	.065	.119	.077	.143	.045	.115

Notes: Standard errors, shown in parentheses, are robust to heteroskedasticity. Outcome variables are changes from 2000 to 2015, measured with data from the 2000 census and the 2011–2015 American Community Survey, respectively. Changes in median household income are measured as changes in the log of inflation-adjusted incomes. Tract boundaries are held constant at their 2000 delineations. Changes in logged violent crime rates are measured in different periods for each city owing to data limitations: changes in violent crime are from 1995 to 2007 in Chicago, 1995 to 2007 in Denver, 2001 to 2008 in New York City, 1998 to 2006 in Philadelphia, and 1995 to 2002 in Portland. All models include city fixed effects.

†$p<.10$; *$p<.05$; **$p<.01$

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models assessing demographic changes linked to violent crime changes. Specifically, we regress 2000–2015 tract-level changes in the share college-educated, the share non-Hispanic White, the poverty rate, and log median household income on tract-level changes in log violent crime rates. Changes in violent crime are from 1995 to 2007 in Chicago, 1995 to 2007 in Denver, 2001 to 2008 in New York City, 1998 to 2006 in Philadelphia, and 1995 to 2002 in Portland. As noted earlier, changes in the outcome variable are measured from 2000 to 2015 in all cities. We report models that show the bivariate association between changes in violent crime and changes in the outcome and models that control for 1990 levels in neighborhood demographics (shares non-Hispanic Black, non-Hispanic Asian, Hispanic, living in poverty, with a college degree, and with less than high school, as well as median household income). We do not control for 1990–2000 changes in those demographics to avoid inducing posttreatment bias. We estimate these models by pooling all five cities and adding city fixed effects. We report results from these models in Table 5.

With the caveat that these tract-level models are descriptive and can speak only to noncausal associations, we find that as crime rates fell, neighborhoods became Whiter and more affluent. For each 1% decline in the violent crime rate in the census tract, the percentage of non-Hispanic White residents in the tract increased by 0.05 percentage points, the percentage of residents with a college degree in the tract increased by 0.04 percentage points, the percentage of residents living below the poverty line in the tract decreased by 0.02 percentage points, and the median household income increased by 6%. In SD changes, we find that a 1-SD decline in the violent crime rate predicts a 0.16-SD increase in the share of non-Hispanic White residents, a 0.20-SD increase in the share of residents with a college degree, a 0.11-SD decrease in the poverty rate, and a 0.08-SD increase in the median household income.

Discussion

In the late 1980s and early 1990s, one could persuasively argue that the two most pressing problems facing U.S. cities were violence and concentrated poverty. The classic urban ethnographies from that era depicted streets where the possibility of violence structured interpersonal interactions and where the threat of violence lingered in the background of every public space, from parks to sidewalks to schools (Anderson 1999; Klinenberg 2002; Kotlowitz 1992; Pattillo-McCoy 1999). An enormous literature documented the rise and consequences of concentrated poverty, culminating in large-scale federal efforts to tear down high-poverty public housing projects and disperse residents into low-poverty neighborhoods (Briggs et al. 2010; Cisneros and Engdahl 2009; Wilson 1987).

Theory and evidence link the rise of community violence with neighborhood sorting, disinvestment, neighborhood change, and rising urban inequality (Peterson and Krivo 2010; Sharkey and Sampson 2015), but urban sociologists have generated much less evidence on sorting and change when violence declines. In the decades since the era of extreme violence, cities have changed dramatically as the problem of urban violence has become much less severe. Murder, property crime, and violent crime rates have fallen across the nation since 1990. In major cities, such as New York and Los Angeles, violence has fallen much further. Even cities that still feature extreme levels of violence, such as Atlanta and Chicago, have seen meaningful reductions in violence since the early 1990s.

Yet, whereas violence has fallen sharply, concentrated poverty has changed much less. The segregation of poverty declined temporarily in the 1990s but rose again in the 2000s. The growth in urban inequality has been accompanied by the visibility of new problems, such as gentrification, in neighborhoods of prominent cities that had been abandoned decades earlier. And at the top of the distribution, the segregation of city residents into high-income communities has risen steadily. These trends lead to questions that we attempted to address empirically. How are the problems of urban violence and concentrated poverty related? More specifically, did the drop in crime impact economic segregation in U.S. cities? If so, through what processes of neighborhood change did this effect operate?

Our results provide strong evidence on two of these questions and partial evidence on the third. We find that the segregation of poor households has grown more slowly in cities where crime declined more substantially, and in some cities, it has reversed. Our main results indicate that the impact of the crime drop on the segregation of poverty is causal. This finding does not mean that the crime drop has reversed the rise of economic segregation; instead, it implies that the fall of violence has slowed. If violence never declined, we would expect that the long-term trend of rising concentrated poverty documented in the classic studies of urban poverty would have accelerated more quickly.

Just as important as the overall relationship between violence and economic segregation are the mechanisms driving the relationship. If declining violence reduces concentrated poverty through gentrification and displacement of the poor, for instance, we might question the benefits of the crime drop for low-income urban populations. Although our ability to generate conclusive evidence on the processes of neighborhood change is limited, we show that the overall decline in income segregation across the country as a whole appears to be driven by the combination of college-educated residents moving into neighborhoods that had the highest poverty rates in 1990 and some low-income households moving out of those same neighborhoods—a pattern that reflects gentrification. We also find heterogeneity in cities with different housing market conditions. In cities with tighter housing markets in 1990, inflows of middle- and high-income households into low-income neighborhoods led to some displacement of poor residents living in those neighborhoods. These findings are consistent with the ethnographic literature on gentrification in "hot" real estate markets, such as San Francisco and Washington, DC.

Our study clarifies the relationship between these two trends that have had such a profound impact on U.S. cities over the past few decades. It shows that the crime drop has not been sufficient to reverse the pattern of rising urban inequality and has had no impact on the trend of high-income households moving into areas of concentrated affluence. However, the fall of violence has affected segregation at the bottom of the distribution, reducing the level of concentrated poverty in urban neighborhoods. Given what is known about the consequences of concentrated poverty, we consider this finding to be important for the study of urban inequality. A large body of evidence indicates that concentrated poverty harms the life chances of children (Sharkey and Faber 2014) and that children growing up in metropolitan areas with higher levels of income segregation are less likely to move up in the income distribution as adults (Chetty et al. 2014).

One limitation of our study is that it cannot assess how neighborhood-level changes in crime rates affect household location decisions. The poorest and most violent neighborhoods experienced the largest relative drops in violence in the 1990s and 2000s (Friedson and Sharkey 2015). Our city-level findings suggest that demographic changes in these neighborhoods drive the shifts in economic segregation indicated by our models. Future studies should test this hypothesis using research designs that exploit exogenous shocks to crime rates at the neighborhood level.

The pathway from reduced crime to household residential decisions involves complex individual-level perceptions and information processes—a mechanism that future research should explore. Areas with more effective communication channels, such as active community organizations or local news outlets, might experience stronger effects as residents become more aware of the improved safety. For instance, neighborhoods with community groups that actively publicize crime reduction might attract new residents more rapidly. In contrast, neighborhoods with a long-standing reputation for high crime might see slower demographic shifts despite safety improvements because it takes longer for these new realities to reshape public perceptions. Additionally, households with different socioeconomic statuses might process these signals differently; for example, higher income households might be more responsive to crime reduction signals owing to greater access to information. Households with children might require even stronger signals of improved safety before considering relocation to areas previously known for higher crime rates.

Furthermore, large shocks to crime rates, such as those triggered by a major federal effort to increase police hiring, may have rapidly reduced crime and attracted new residents. However, more sustainable, community-driven initiatives may take longer to produce visible effects. Assessing the effectiveness of different interventions will require additional data sources that allow for measuring changes in segregation at shorter intervals. Census data limit us to examining changes over 10-year periods. However, consumer credit databases, which include household locations and incomes, could enable year-to-year assessments of the relationship between crime changes and residential mobility (for a study of gentrification using consumer credit data from Philadelphia, see Hwang and Ding 2020).

Our broader conclusion is that the benefits of the crime drop extend well beyond the individual lives saved or the positive effects on the life chances of individuals who no longer live in violent environments (Sharkey and Torrats-Espinosa 2017). Declining violence changes residential decision-making, bringing new residents into areas of high poverty. In some cities with tight housing markets, this process of change can lead to rising rents and out-migration of the poor. In such places, public policies must ensure that residents can remain in their communities as those areas become safer. However, in cities with sufficient housing supply, declining violence does not visibly push low-income residents out of their neighborhoods. Instead, falling violence slows economic segregation and leads to a shift in the configuration of urban neighborhoods. ■

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References

Anderson, E. (1999). *Code of the street: Decency, violence, and the moral life of the inner city*. New York, NY: W. W. Norton & Company.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association, 91,* 444–455.

Atkinson, A. B., Piketty, T., & Saez, E. (2011). Top incomes in the long run of history. *Journal of Economic Literature, 49,* 3–71.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in U.S. wage inequality: Revising the revisionists. *Review of Economics and Statistics, 90,* 300–323.

Autor, D., H., Palmer, C. J., & Pathak, P. A. (2017). *Gentrification and the amenity value of crime reductions: Evidence from rent deregulation* (NBER Working Paper 23914). Cambridge, MA: National Bureau of Economic Research.

Briggs, X. d. S., Popkin, S. J., & Goering, J. (2010). *Moving to opportunity: The story of an American experiment to fight ghetto poverty*. New York, NY: Oxford University Press.

Brueckner, J. K., Thisse, J.-F., & Zenou, Y. (1999). Why is central Paris rich and downtown Detroit poor? An amenity-based theory. *European Economic Review, 43,* 91–107.

Bureau of Justice Statistics. (2018). *Law enforcement agency identifiers crosswalk, United States, 2012* (ICPSR 35158) [Dataset]. United States Department of Justice. Retrieved from https://www.icpsr.umich.edu/web/NACJD/studies/35158

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics, 129,* 1553–1623.

Cisneros, H. G., & Engdahl, L. (2009). *From despair to hope: Hope VI and the promise of public housing in America's cities*. Washington, DC: Brookings Institution Press.

Couture, V., & Handbury, J. (2017). *Urban revival in America, 2000 to 2010* (NBER Working Paper 24084). Cambridge, MA: National Bureau of Economic Research.

Cullen, J. B., & Levitt, S. D. (1999). Crime, urban flight, and the consequences for cities. *Review of Economics and Statistics, 81,* 159–169.

Du Bois, W. E. B. (1996). *The Philadelphia Negro: A social study*. Philadelphia: University of Pennsylvania Press. (Original work published 1899)

Ehrenhalt, A. (2012). *The great inversion and the future of the American city*. New York, NY: Vintage.

Ellen, I. G., & Ding, L. (2016). Guest editors' introduction: Advancing our understanding of gentrification. *Cityscape, 18*(3), 3–8.

Ellen, I. G., Horn, K. M., & Reed, D. (2019). Has falling crime invited gentrification? *Journal of Housing Economics, 46,* 101636. https://doi.org/10.1016/j.jhe.2019.101636

Ellen, I. G., & O'Regan, K. (2008). Reversal of fortunes? Lower-income urban neighbourhoods in the U.S. in the 1990s. *Urban Studies, 45,* 845–869.

Ellen, I. G., & O'Regan, K. M. (2011). How low-income neighborhoods change: Entry, exit, and enhancement. *Regional Science and Urban Economics, 41,* 89–97.

Ellen, I. G., & Torrats-Espinosa, G. (2019). Gentrification and fair housing: Does gentrification further integration? *Housing Policy Debate, 29,* 835–851.

Ellen, I. G., & Torrats-Espinosa, G. (2020). Do vouchers protect low-income households from rising rents? *Eastern Economic Journal, 46,* 260–281.

Evans, W. N., & Owens, E. G. (2007). COPS and crime. *Journal of Public Economics, 91,* 181–201.

Federal Bureau of Investigation. (2011). *Crime in the United States, 2010* [Dataset]. U.S. Department of Justice. Retrieved from https://ucr.fbi.gov/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/tables/10tbl01.xls

Florida, R. (2017). *The new urban crisis: How our cities are increasing inequality, deepening segregation, and failing the middle class—and what we can do about it*. London, UK: Hachette Book Group.

Freeman, L. (2005). Displacement or succession? Residential mobility in gentrifying neighborhoods. *Urban Affairs Review, 40,* 463–491.

Freeman, L., & Braconi, F. (2004). Gentrification and displacement: New York City in the 1990s. *Journal of the American Planning Association, 70,* 39–52.

Friedman, M., Grawert, A. C., & Cullen, J. (2017). *Crime trends, 1990–2016* (20 Years report). New York, NY: Brennan Center for Justice at New York University School of Law. Retrieved from https://www.brennancenter.org/sites/default/files/publications/Crime%20Trends%201990-2016.pdf.

Friedson, M., & Sharkey, P. (2015). Violence and neighborhood disadvantage after the crime decline. *Annals of the American Academy of Political and Social Science, 660,* 341–358.
Fry, R., & Taylor, P. (2012). *The rise of residential segregation by income* (Report). Pew Research Center. Retrieved from https://www.pewresearch.org/wp-content/uploads/sites/3/2012/08/rise-of-residential-income-segregation-2012.2.pdf
Grubb, W. N. (1982). The flight to the suburbs of population and employment, 1960–1970. *Journal of Urban Economics, 11,* 348–367.
Hwang, J., & Ding, L. (2020). Unequal displacement: Gentrification, racial stratification, and residential destinations in Philadelphia. *American Journal of Sociology, 126,* 354–406.
Hwang, J., & Sampson, R. J. (2014). Divergent pathways of gentrification: Racial inequality and the social order of renewal in Chicago neighborhoods. *American Sociological Review, 79,* 726–751.
Hyra, D. S. (2017). *Race, class, and politics in the cappuccino city*. Chicago, IL: University of Chicago Press.
Kaplan, J. (2021). *Uniform Crime Reporting (UCR) program data: A practitioner's guide*. CrimRxiv. https://doi.org/10.21428/cb6ab371.f1bc7339
Klinenberg, E. (2002). *Heat wave: A social autopsy of disaster in Chicago*. Chicago, IL: University of Chicago Press.
Kotlowitz, A. (1992). *There are no children here: The story of two boys growing up in the other America*. New York, NY: Anchor Books.
Krivo, L. J., Peterson, R. D., & Kuhl, D. C. (2009). Segregation, racial structure, and neighborhood violent crime. *American Journal of Sociology, 114,* 1765–1802.
Krivo, L. J., Vélez, M. B., Lyons, C. J., Phillips, J. B., & Sabbath, E. (2018). Race, crime, and the changing fortunes of urban neighborhoods, 1999–2013. *Du Bois Review: Social Science Research on Race, 15,* 47–68.
Liska, A. E., & Bellair, P. E. (1995). Violent-crime rates and racial composition: Convergence over time. *American Journal of Sociology, 101,* 578–610.
Logan, J. R., Foster, A., Ke, J., & Li, F. (2018). The uptick in income segregation: Real trend or random sampling variation? *American Journal of Sociology, 124,* 185–222.
Maltz, M. D., & Targonski. J. (2002). A note on the use of county-level UCR data. *Journal of Quantitative Criminology, 18,* 297–318.
Marshall, H. (1979). White movement to the suburbs: A comparison of explanations. *American Sociological Review, 44,* 975–994.
Massey, D. S., & Denton, N. A. (1993). *American apartheid: Segregation and the making of the underclass.* Cambridge, MA: Harvard University Press.
McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). New York, NY: Academic Press.
Morenoff, J. D., & Sampson, R. J. (1997). Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. *Social Forces, 76,* 31–64.
Moretti, E. (2012). *The new geography of jobs*. New York, NY: Houghton Mifflin Harcourt.
Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics, 37,* 187–204.
O'Sullivan, A. (2005). Gentrification and crime. *Journal of Urban Economics, 57,* 73–85.
Owens, A. (2016). Inequality in children's contexts: Income segregation of households with and without children. *American Sociological Review, 81,* 549–574.
Owens, A., Reardon, S. F., & Jencks, C. (2016). Income segregation between schools and school districts. *American Educational Research Journal, 53,* 1159–1197.
Papachristos, A. V., Smith, C. M., Scherer, M. L., & Fugiero, M. A. (2011). More coffee, less crime? The relationship between gentrification and neighborhood crime rates in Chicago, 1991 to 2005. *City & Community, 10,* 215–240.
Park, R. E., Burgess, E. W., & McKenzie, R. D. (1925). *The city*. Chicago, IL: University of Chicago Press.
Pattillo, M. (2010). *Black on the block: The politics of race and class in the city*. Chicago, IL: University of Chicago Press.
Pattillo-McCoy, M. (1999). *Black picket fences: Privilege and peril among the Black middle class* (1st ed.). University of Chicago Press.
Peterson, R. D., & Krivo, L. J. (2010). *Divergent social worlds: Neighborhood crime and the racial–spatial divide.* New York, NY: Russell Sage Foundation.

Reardon, S. F. (2011). *Measures of income segregation* (Working paper). Stanford Center for Education Policy Analysis. Retrieved from https://cepa.stanford.edu/content/measures-income-segregation

Reardon, S. F., & Bischoff, K. (2011). Income inequality and income segregation. *American Journal of Sociology, 116,* 1092–1153.

Reardon, S. F., Bischoff, K., Owens, A., & Townsend, J. B. (2018). Has income segregation really increased? Bias and bias correction in sample-based segregation estimates. *Demography, 55,* 2129–2160.

Reardon, S. F., & Firebaugh, G. (2002). Measures of multigroup segregation. *Sociological Methodology, 32,* 33–67.

Reardon, S. F., & O'Sullivan, D. (2004). Measures of spatial segregation. *Sociological Methodology, 34,* 121–162.

Reardon, S. F., Fox, L., & Townsend, J. (2015). Neighborhood income composition by household race and income, 1990–2009. *Annals of the American Academy of Political and Social Science, 660,* 78–97.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277,* 918–924.

Sampson, R. J., & Wooldredge, J. D. (1986). Evidence that high crime rates encourage migration away from central cities. *Sociology and Social Research, 70,* 310–314.

Sharkey, P. (2018). The long reach of violence: A broader perspective on data, theory, and evidence on the prevalence and consequences of exposure to violence. *Annual Review of Criminology, 1,* 85–102.

Sharkey, P., & Faber, J. W. (2014). Where, when, why, and for whom do residential contexts matter? Moving away from the dichotomous understanding of neighborhood effects. *Annual Review of Sociology, 40,* 559–579.

Sharkey, P., & Sampson, R. J. (2015). Violence, cognition, and neighborhood inequality in America. In R. K. Schutt, L. J. Seidman, & M. S. Keshavan (Eds.), *Social neuroscience: Brain, mind, and society* (pp. 320–339). Cambridge, MA: Harvard University Press.

Sharkey, P., & Torrats-Espinosa, G. (2017). The effect of violent crime on economic mobility. *Journal of Urban Economics, 102,* 22–33.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago, IL: University of Chicago Press.

Shihadeh, E. S., & Flynn, N. (1996). Segregation and crime: The effect of Black social isolation on the rates of Black urban violence. *Social Forces, 74,* 1325–1352.

Skogan, W. (1986). Fear of crime and neighborhood change. *Crime and Justice, 8,* 203–229.

South, S. J., & Crowder, K. D. (1997). Residential mobility between cities and suburbs: Race, suburbanization, and back-to-the-city moves. *Demography, 34,* 525–538.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* (pp. 80–108). New York, NY: Cambridge University Press.

Torrats-Espinosa, G. (2020). Crime and inequality in academic achievement across school districts in the United States. *Demography, 57,* 123–145.

U.S. Census Bureau. (2015). *Annual social and economic supplements* [Dataset]. Available from https://www.census.gov/data/datasets/time-series/demo/cps/cps-asec.html

Wilson, W. J. (1987). *The truly disadvantaged: The inner city, the underclass, and public policy* (1st ed.). Chicago, IL: University of Chicago Press.

Zimring, F. E. (2006). *The great American crime decline*. New York, NY: Oxford University Press.

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