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Community and the Crime Decline: The Causal Effect of Local Nonprofits on Violent Crime

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Abstract

Largely overlooked in the theoretical and empirical literature on the crime decline is a long tradition of research in criminology and urban sociology that considers how violence is regulated through informal sources of social control arising from residents and organizations internal to communities. In this article, we incorporate the "systemic" model of community life into debates on the U.S. crime drop, and we focus on the role that local nonprofit organizations played in the national decline of violence from the 1990s to the 2010s. Using longitudinal data and a strategy to account for the endogeneity of nonprofit formation, we estimate the causal effect on violent crime of nonprofits focused on reducing violence and building stronger communities. Drawing on a panel of 264 cities spanning more than 20 years, we estimate that every 10 additional organizations focusing on crime and community life in a city with 100,000 residents leads to a 9 percent reduction in the murder rate, a 6 percent reduction in the violent crime rate, and a 4 percent reduction in the property crime rate.

Keywords

violence, nonprofits, community, systemic model, instrumental variables

Since violent crime in the United States began to fall rapidly in the middle of the 1990s, sociologists, criminologists, and economists have proposed a wide range of theories to explain the crime drop. Some of the most well-known theories focus on exogenous changes in society that are thought to have influenced the number of potential offenders, including changes in the rate of abortions, the prevalence of lead exposure, or the age structure of the population (Aizer and Currie 2017; Levitt 2004; Reyes 2007; Zimring 2006). Another group of theories focuses on externally imposed shifts in policing and criminal justice policy that were designed to respond to the problem of violence, including changes in the size of police forces, the tactics of policing, and the scale of incarceration (Levitt 2002; Travis, Western, and Redburn 2014; Zimring 2011). The common assumption shared by most of these theories is that the decline of violence was driven primarily by

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forces external to the communities that were most affected by violent crime in the 1990s and earlier.

Largely overlooked in the theoretical and empirical literature on the crime decline is a long tradition of research in criminology and urban sociology that considers how violence is regulated through informal sources of social control internal to communities. The "systemic" model of community organization and crime focuses on the set of actors, organizations, and institutions that influence the level of social cohesion within a neighborhood and the degree to which communities are able to solve common problems and realize shared objectives (Bursik 1999; Bursik and Grasmick 1993; Sampson 2012; Sampson, Raudenbush, and Earls 1997). This model has been extremely influential in the study of cross-neighborhood variation in violence and crime, but it has been largely missing in debates about what caused "The Great American Crime Decline" (Zimring 2006).

In this article, we incorporate one key dimension of the systemic model into the literature on the crime decline by presenting national evidence on the role that local organizations played in reducing crime. Our focus is on local nonprofits formed to confront violent crime and build stronger communities. Our goal is to present causal evidence on the impact of these organizations on crime and violence in U.S. cities.

Because community organizations are formed at least partly in response to social problems like violence, it is not possible to rely on cross-sectional data and standard analytic methods to identify the effect of nonprofit formation on crime rates. To account for the endogeneity of nonprofit formation, we use variation in the prevalence of nonprofits across cities and over time in a fixed-effects framework and adapt an instrumental variable (IV) strategy to identify the causal effect of nonprofits on crime.

The fixed-effects approach relies only on change in the number of nonprofits formed within cities, thus eliminating the possibility that an association between nonprofits and violence could be explained by any fixed, unobserved characteristic of cities that might affect both the number of nonprofits in the city and the violent crime rate. The instrumental variable approach relies on variation in the formation of nonprofits driven by a factor that has no direct relationship to the crime rate within the city. Specifically, we use the formation of nonprofits focused on the arts and humanities, medical research, and environmental protection as an instrument for the formation of nonprofits related to violence, crime, and community-building. Our core assumption is that changes in the prevalence of arts, medical, and environmental nonprofits have no direct effect on crime and violence but are associated with changes in the prevalence of nonprofits designed to address violence and rebuild communities—which, for simplicity, we refer to as "community" nonprofits—through common mechanisms of funding availability. Under this assumption, we can make causal inferences about the impact of community nonprofits on changes in crime and violence.

Drawing on a panel of 264 cities spanning more than 20 years, we estimate the effect on violent crime, homicide, and property crime of year-to-year changes and long-term changes in the formation of community nonprofits. Our models of long-term change over more than two decades indicate that every 10 additional community nonprofits in a city with 100,000 residents leads to a 12 percent reduction in the homicide rate, a 10 percent reduction in the violent crime rate, and a 7 percent reduction in the property crime rate. When we model year-to-year changes in the prevalence of community nonprofits, we find that every 10 additional nonprofits per 100,000 residents leads to a 9 percent decline in the murder rate, a 6 percent decline in the violent crime rate, and a 4 percent decline in the property crime rate.

LOCAL ORGANIZATIONS AND THE GREAT CRIME DECLINE

Explanations of the Crime Decline

From the early 1990s to the 2010s, the national homicide rate was cut roughly in half, and rates of aggravated assault, robbery, sexual assault, motor vehicle theft, and larceny fell by roughly similar amounts. Although there was substantial geographic variation in the amount of change, the rate of violence fell, to some degree, in just about every major city across the country. The homicide rate fell by at least 50 percent in more than a third of the largest U.S. cities, including Atlanta, Dallas, Denver, Los Angeles, New York, and Washington, DC (Federal Bureau of Investigation 2015). Even in places that continue to have high levels of violence, like Oakland and New Orleans, the homicide rate fell by 25 to 50 percent.[1]

Only recently have most cities begun to publish crime data at the level of neighborhoods or blocks, so it is not possible to know how communities within cities have changed since the beginning of the 1990s. However, Friedson and Sharkey (2015) analyze data from six cities with neighborhood-level data on crime going back at least a decade, and show that the greatest changes in community violence took place in the poorest, most segregated, and most violent neighborhoods in all six cities (see also Ellen and O'Regan 2009). Although it is not possible to generalize beyond these cities, the evidence available indicates that the forces responsible for the decline of violence had their greatest impact in the most violent neighborhoods of each city.

The range of forces and policy changes that have been proposed as potential explanations for the decline of violence are diverse, and few have received strong and unequivocal empirical support. The most prominent explanations for the drop in violence, including changes in abortion law and to environmental policy that reduced air lead levels, aggressive policing and prosecution of minor offenses, and the establishment of longer sentences for criminal offenders, all represent policy shifts driven or implemented by actors outside the communities where violence is most prevalent.[2]

To be clear, our goal in this article is not to adjudicate between different hypotheses for the crime decline. The methods we utilize are designed to generate a causal estimate of the effect of a single factor, and they do not allow us to make comparisons of the relative impact of multiple potential causes. Our intent in reviewing the existing literature is to highlight the evidence that has been brought to bear on the impact of various factors on the crime decline, and to point out that most of the common explanations focus on changes driven by actors, institutions, or policies external to the communities that were most affected by the crisis of violence that peaked in the early 1990s. Our strategy is designed to identify the impact of an additional factor that is very different from most common explanations of the crime drop: the formation of local nonprofit organizations.

Local Organizations and the Fight against Violence from Within

The focus on external forces that contributed to the crime decline stands in contrast to many observers' accounts that document extensive efforts by local organizations and community leaders to organize residents in an effort to confront the problem of violence. These examples typically come from case studies conducted in specific communities. But considered together, they reveal a local mobilization against violence that has been largely ignored in debates about the national drop in violent crime.

Von Hoffman (2003), for instance, documents the work of community activists in South Central Los Angeles who organized to hire and train formerly incarcerated residents to clean up sidewalks and maintain the streets, build over 100 units of affordable housing in their community, and coordinate 57 block groups to ensure that street alleys were not used for dumping or drug dealing. Putnam, Feldstein, and Cohen (2004) interviewed residents and leaders from organizations like Valley Interfaith in the Rio Grande Valley and the Dudley Street Neighborhood Initiative (DSNI) in Boston to understand how years of organizing and advocacy had slowly generated change in their communities. The DSNI built affordable homes designed for community residents, provided jobs to young people in newly-developed community gardens and a greenhouse, and waged campaigns to clean up abandoned lots, build new community centers, and stop outsiders from dumping trash on the streets of the Dudley Triangle. These efforts were designed to change the neighborhood from a dangerous, run-down, anonymous set of streets into an urban village, where the streets were clean and safe, and where people knew their neighbors and looked out for each other (see also Medoff and Sklar 1994).

Journalist Robert Snyder (2014) describes how community groups worked to transform Washington Heights in Manhattan, a section of New York City that was overtaken by gang violence and drug distribution. Organizations like Alianza Dominicana, the Community League of West 159th Street, the Dominican Women's Development Center, and the Asociación Comunal de Dominicanos Progresistas organized and marched to bring resources and political attention to the fight against violence. Mothers Against Violence, Friends of Fort Tryon Park, and the New York Restoration Project worked to clean up, maintain, and retake public parks within Washington Heights that had been dominated by drug dealers and addicts.

The literature on the causes of the crime decline mostly ignores the work of neighbors who led the effort to keep young people safe within their communities, groups of residents who came together to transform abandoned lots and turn them into parks and gardens, business owners who agreed to tax themselves in order to enhance security in the area around their establishments, and social service providers who developed programs shown to reduce young people's involvement with violence. Although not all of these activities were formal, organized efforts, most were carried out by groups that utilized a common organizational form: the nonprofit. When activist Juanita Tate expanded her efforts to organize neighbors on each block of what used to be called South Central Los Angeles, she established Concerned Citizens of South Central Los Angeles (Von Hoffman 2003). When the business owners on Hollywood Boulevard decided they needed enhanced security and sanitation, they formed the Hollywood Entertainment District, one of many business improvement districts that formed as nonprofit entities with the primary goal of keeping public spaces safe in order to improve profits (Hollywood Entertainment District 2015).

The stories from these individuals and the organizations they created provide a different perspective on the national crime decline. Instead of seeing the drop in violent crime solely as the result of a set of external processes, forces, and policies imposed on communities where violence was concentrated, their stories expand the focus to the role that communities played in responding to the challenge of violence through the development of local efforts and local organizations.

The Systemic Model and the Role of Community Organizations

The systemic model of community argues that "neighborhood life is shaped by the structure of formal and informal networks of association" (Bursik and Grasmick 1993:x). From this perspective, the degree of social cohesion and informal social control within communities arises from local networks of organizations, institutions, and residents who work together to uphold common values and shared expectations of behavior (Sampson 2012). The systemic model relates closely to the theory of social disorganization and crime put forward by Shaw and McKay (1942) and refined and extended in more recent work (Bursik 1988; Sampson and Groves 1989; Sampson et al. 1997).[3] In its original form, Shaw and McKay argued that structural features of neighborhoods, such as residential mobility, ethnic heterogeneity, and poverty, undermine the ties that bind together residents through informal associations and involvement with neighborhood institutions, in turn diminishing the community's capacity to work collectively to confront common challenges like crime and violence. The strongest empirical tests of the model demonstrate how collective efficacy, defined as a community's sense of "social cohesion combined with shared expectations for social control" (Sampson 2012:27), mediates the relationship between neighborhood characteristics like concentrated disadvantage and neighborhood levels of violence (Kubrin and Wo 2015; Sampson et al. 1997).

Neighborhood institutions and organizations are a core component of the systemic model and are central to the processes that create social capital, which can be thought of as the overall level of social trust and the degree of engagement with community-oriented activities and organizations (Lin 1999; Putnam 1993). Community-oriented organizations can establish or strengthen ties between residents and connect individuals to other residents, organizations, or community resources, facilitating voluntary associations, improving social cohesion and informal social control, and building interpersonal trust (Bursik 1989; Small 2009).

Organizations within a community are embedded within larger networks of public and private agencies and organizations extending across a city's neighborhoods and beyond the city limits. These extra-local networks connect communities to external sources of influence, resources, and political power, all of which strengthen the capacity to achieve common goals and values (Bursik and Grasmick 1993; Sampson 2012; Vargas 2016). Communities with stronger internal and external ties, higher levels of social cohesion, and greater informal social control are more likely to be able to regulate activity in public spaces and control the threat of violence.

In examining the role of community organizations in crime prevention, Skogan (1988) distinguishes between actions that focus directly on reducing criminal activity in the neighborhood (e.g., requesting more policing or engaging in collective surveillance practices) and actions that tackle the underlying social and economic factors that lead to crime (e.g., providing employment opportunities). These crime-reducing efforts emerge from communities' ability to capture problem-solving resources and from the activation of a series of mechanisms of informal internal control. Skogan's model suggests that the pathway linking community organizations with community violence runs not only through informal social control and social cohesion, it is also direct.

Many neighborhood organizations are actively engaged in efforts to control crime and violence directly by developing programs for young people in a community, hiring staff to work against violence, or through the provision of private security (LaFree 1998a). A growing body of evidence demonstrates the role that such programs can play in reducing individual violence. Research exploiting exogenous variation in attendance at schools run by the Harlem Children's Zone in Manhattan, or participation in activities of "Becoming A Man," administered by Youth Guidance in Chicago, shows substantial reductions in individual children's involvement in crime and violence (Cook et al. 2015; Dobbie and Fryer 2011; Hartmann and Depro 2006; Heller et al. 2013). Efforts to clean up neighborhoods or improve the physical infrastructure can bring more people on to the streets and increase surveillance of public spaces, in turn reducing criminal activity. For example, the Pennsylvania Horticultural Society's greening project, which randomly designated vacant lots in Philadelphia to be converted into green spaces, removing trash and debris and planting grass and trees, has led to a decrease in gun assaults citywide as well as a decrease in total crime in the half-mile area around vacant lots that have been greened (Branas et al. 2011; Garvin, Cannuscio, and Branas 2013).

Despite this body of evidence and the strong theoretical focus on organizational life within communities, this aspect of social disorganization theory has received less empirical attention than other components. Research shows that the prevalence of resident engagement with community organizations is inversely associated with rates of violence (Sampson and Groves 1989), but measures of overall organizational density are often only weakly or indirectly associated with rates of crime and violence (Morenoff, Sampson, and Raudenbush 2001; Peterson, Krivo, and Harris 2000).

We propose two explanations for this partial disconnect between theory and evidence.

From a theoretical perspective, many studies use measures of organizational density that include a wide range of establishments and organizations that have no direct relationship to crime and violence. These studies are designed to capture the indirect connection between organizational density and crime through the pathway of informal social control (see Morenoff et al. 2001). But they are not designed to capture the direct effect of community organizations on crime. Rather than examining all organizations within a neighborhood, we focus on local nonprofit organizations that proliferated in the early 1990s with the specific goal of building stronger communities and confronting the problems of crime and violence.

From a methodological perspective, no studies that we know of have dealt with the endogeneity of community organization formation. Because community organizations are formed at least partly in response to social problems like crime and violence, a basic regression of violent crime on the prevalence of anti-violence nonprofits would likely lead to a positive relationship.[4] This positive association does not mean that nonprofit organizations lead to higher levels of violence, of course, but it does mean that standard analytic approaches are likely to generate biased estimates of the causal effect of organizations on crime. We address this problem in multiple ways. First, by using city fixed-effects specifications, we focus on short-term changes in the formation of local nonprofits and examine how these changes affect crime rates in the following year. The possibility that unobserved characteristics of cities are generating bias in our results, or that shifts in crime are leading to the formation of more nonprofits, are both mitigated with this approach. Second, our instrumental variable approach utilizes variation in the formation of community organizations that is unrelated to the problem of crime and violence, and thus robust to the problem of endogeneity. Previous quantitative articles that examine the relationship between local organizations and crime have not dealt with the endogeneity of nonprofit formation, and thus we believe this is the first study that provides a plausible causal estimate of the impact of such organizations on crime.

DATA SOURCES

Our analysis draws on crime data from the Uniform Crime Reports (UCR), demographic data from the decennial Census and American Community Surveys, and nonprofit organization data from the National Center for Charitable Statistics (NCCS).

The FBI releases annual estimates of various crimes in the UCR.[5] We focus on Part I offenses, which are aggregated into two categories: violent crimes (aggravated assault, forcible rape, murder, and robbery) and property crimes (arson, burglary, larceny-theft, and motor vehicle theft). We generate city-level crime rates per 100,000 residents for violent crime, property crime, and murder between the years 1991 to 2014.[6]

To measure city demographic characteristics and economic conditions, we use data from the 1990 and 2000 Censuses (Summary File 1) and the 2009 to 2013 American Community Survey (five-year estimates). Specifically, we construct the following controls: population density, percent of Asian residents, percent of African American residents, percent of Hispanic residents, percent of residents of other race,[7] percent of residents older than age 25 with less than a high school diploma, percent of residents older than age 25 with a bachelor's degree or more, percent foreign-born, percent of males age 15 to 24, percent of residents living in poverty, percent unemployed, and percent employed in the manufacturing sector. We use linear interpolation to generate demographic controls for the years in between 1990, 2000, and 2013.

Finally, we use data on nonprofit organizations released annually by the National Center for Charitable Statistics (NCCS), a part of the Center on Nonprofits and Philanthropy at the Urban Institute. NCCS provides various datasets with a host of information about nonprofits, such as number of employees, revenue and expenses, and nonprofit status categorized by type of organization. NCCS data are based on information provided by tax-exempt nonprofit organizations to the Internal Revenue Service. Our analysis uses data from the Cumulative Master File (CMF), released as a subset of the Business Master Files (BMF), which contain descriptive information of all active organizations that have registered for tax-exempt status with the IRS. The BMF includes active and registered public charities, private foundations, 501(c) (other), 501(c)3, and other exempt organizations such as social welfare organizations and trade unions, but the CMF subset limits the data to all 501(c) organizations only. We further limit our data to 501(c)3 organizations specifically. 501(c)3 organizations are tax-exempt charitable organizations that are recognized by the IRS as qualifying for nonprofit status.[8]

As of February 2013, there were around 1.7 million registered 501(c)3 organizations in the United States. The CMF provides data on the name and address of each organization, whether it meets the public support test (i.e., whether the organization received substantial support from the general public), when it obtained its tax-exempt status, and other descriptive information. The NCCS categorizes all nonprofits using the National Taxonomy of Exempt Entities Core Code (NTEE-CC) system, a classification system that specifies the broad subsector an organization belongs to (e.g., education), its activity area (e.g., higher education), and its specific subcategory (e.g., four-year colleges). Each organization is also assigned a confidence level of A, B, or C. This rating corresponds to how confident one can be that a given nonprofit is correctly classified, ranging from highly confident (A) to fairly confident (C). In the full CMF dataset, 50 percent of nonprofits have confidence level A, 42 percent have confidence level B, and 8 percent have confidence level C.

We limit our analysis to organizations operating in the 300 largest cities in the United States that were registered between 1990 and 2013. We rely on each organization's NTEE-CC classification to identify nonprofits whose activities focused on confronting violent crime and building stronger communities. We label these organizations as "community" nonprofits. Within this broad category of community nonprofits, we distinguish between five types of organizations: nonprofits focusing on crime prevention, nonprofits that focus on neighborhood development, nonprofits running substance abuse prevention programs, nonprofits that provide job training and workforce development programs for disadvantaged populations, and nonprofits that provide recreational and social activities for children and youth. For the instrumental variable analyses, we create a separate category of nonprofits that includes organizations focused on the arts, medical research, and environmental protection. We exclude from the arts group nonprofits that promote cultural and educational activities for local communities and youth. In the online supplement, we provide a detailed description of the NTEE-CC codes that fall within the five types of community organizations and within the group of nonprofits that configure the instrumental variable.[9]

The key explanatory variable is the cumulative number of nonprofits that remained active in a given year. The definition of "active" organizations is based on an organization's inclusion in the NCCS data files, as the dataset we use excludes any defunct organizations (NCCS 2013). Because only active nonprofits are included in the data, we argue that using the cumulative figures is a reasonable strategy to model year-to-year changes in nonprofit formation. The alternative strategy of using newly-formed nonprofits would not allow us to account for nonprofits that close in a given year, and it would be more likely to contain measurement error because of the difficulty in pinpointing the start of operations for a nonprofit.[10]

We combine data on nonprofits, crime, and demographics for the largest 300 cities in the country (ranked using 2010 population counts), restricting the sample to cities for which we have data on all variables for the start and end years (1990 and 2013) and for at least eight more years in between. The final dataset includes 264 cities with complete data for 10 years or more. Among them, 234 cities have data for all years from 1990 to 2013.

Trends in Nonprofit Growth and Crime

Table 1 shows the mean and standard deviation for crime, nonprofit, and demographic variables for 1990, 2000, and 2013 and for the change from 1990 to 2013. For each of the five categories of community organizations (crime prevention, neighborhood development, substance abuse, workforce development, and youth), we show the cumulative number of nonprofits per 100,000 residents that were active in 1990, 2000, and 2013. In the 264 cities in our sample, the number of community nonprofits per 100,000 residents almost quadrupled in this period, growing from 13.83 to 51.95. Nonprofits focusing on neighborhood development grew from 5.50 to 22.51 per 100,000 residents from 1990 to 2013. Nonprofits providing recreational and social activities for youth grew from 4.72 to 18.72 per 100,000 residents from 1990 to 2013. Although smaller in absolute terms, the growth in the other three types of community nonprofits was also substantial in relative terms. Crime prevention nonprofits grew from 1.33 to 4.86 per 100,000 residents, nonprofits providing access to substance abuse programs grew from 1.42 to 3.64 per 100,000 residents, and workforce and job training organizations increased from .86 to 2.22 per 100,000 residents. Similarly, the number of nonprofits focused on the arts, medical research, and environmental preservation increased from 23.76 per 100,000 residents in 1990 to 65.18 in 2013.

Figure 1 shows annual growth in all community nonprofits along with annual growth in nonprofits focused on the arts, medical research, and environmental protection. The figure shows that growth in these two sets of nonprofits followed similar trends from 1990 to 2013. Figure 2 displays the annual growth for each of the five types of community nonprofits, and shows that the growth in community organizations was driven primarily by the increase in neighborhood development and youth-related organizations.

Salamon (2003) argues that the overall growth in the nonprofit sector was driven by federal funding for community organizations in the 1990s, a period in which government support for nonprofits rebounded after years of cutbacks in funding for organizations focused on social and human services, education and training, community development, and health care. In the late 1990s and 2000s, the growth of the nonprofit sector continued but at a slower rate. The slowdown in growth rates could be partially attributed to the budget cuts in discretionary programs during the George W. Bush administration and to the economic downturn of 2008.

For comparison, Figure 3 shows trends in murder, violent crime, and property crime rates for the 264 cities in our sample. Between 1990 and 2013, during the same time that the number of nonprofit organizations grew, the murder rate per 100,000 residents was cut by more than half, declining from 21.58 at its peak in 1991 to 9.52 in 2013. The violent crime rate per 100,000 residents declined from 1,463 to 674 between 1990 and 2013, and property crimes dropped from 7,957 to 3,801 crimes per 100,000 residents. The simple conclusion from these graphs is that violent and property crimes began to fall sharply very close to the time at which the nonprofit sector was expanding rapidly. The empirical strategy that we present is designed to assess whether the two trends are causally related within cities.

ANALYTIC APPROACH

Estimating the causal effect of community nonprofits on crime rates is complicated by two sources of bias. First, if cities adjust their rate of nonprofit formation on the basis of crime rates, and the creation of these nonprofits leads to declines in crime, we are confronted with a circular causal chain in which it is impossible to pin down the direction of the causal arrow. If nonprofit formation is

Table 1. Population-Weighted Descriptive Statistics

	1990	2000	2013	Change 1990 to 2013
Nonprofits per 100,000				
Community organizations	13.83	29.34	51.95	38.12
	(6.98)	(15.35)	(28.47)	(24.15)
Crime prevention	1.33	2.83	4.86	3.53
	(1.16)	(2.16)	(3.59)	(2.76)
Neighborhood development	5.50	12.95	22.51	17.01
	(3.90)	(8.73)	(16.39)	(14.05)
Substance abuse	1.42	2.55	3.64	2.22
	(.98)	(1.50)	(2.04)	(1.54)
Workforce development	.86	1.44	2.22	1.36
	(.85)	(1.18)	(1.62)	(1.19)
Youth	4.72	9.57	18.72	14.00
	(2.58)	(4.67)	(8.48)	(7.35)
Arts, medical, and environmental	23.76	42.64	65.18	41.42
	(15.55)	(28.31)	(41.30)	(28.16)
Crime Rates per 100,000				
Murder	20.24	11.63	9.52	–10.68
	(14.92)	(9.45)	(8.93)	(11.75)
Violent	1463.89	934.08	674.08	–787.88
	(865.71)	(497.67)	(379.91)	(770.57)
Property	7957.73	5201.05	3801.99	–4128.38
	(2371.92)	(2087.07)	(1552.56)	(2102.98)
Demographics				
Population density	6868.31	7393.04	7707.42	839.11
	(6941.72)	(7468.97)	(7679.96)	(1192.14)
% Asian	4.71	6.08	7.68	2.98
	(5.05)	(6.24)	(7.47)	(3.38)
% Black	21.50	22.14	21.51	.01
	(17.14)	(18.08)	(17.59)	(5.11)
% Hispanic	16.80	21.86	25.89	9.10
	(15.89)	(17.73)	(18.58)	(6.51)
% Other race	.68	3.02	3.15	2.47
	(.70)	(1.49)	(1.66)	(1.17)
% White	56.32	46.90	41.75	–14.56
	(19.14)	(18.83)	(17.38)	(8.10)
% Less than high school	26.24	23.31	17.58	–8.66
	(8.63)	(8.23)	(6.46)	(5.24)
% College	22.51	26.13	31.06	8.56
	(7.57)	(8.92)	(10.17)	(4.61)
% Foreign-born	14.34	19.12	20.60	6.26
	(12.24)	(13.42)	(12.73)	(4.06)
% Males age 15 to 24	8.02	7.70	7.67	–0.35
	(1.50)	(1.39)	(1.49)	(0.88)
% Poverty	17.19	17.34	20.71	3.52
	(6.02)	(5.68)	(5.98)	(3.06)
% Unemployed	5.01	4.75	6.83	1.82
	(1.41)	(1.34)	(1.74)	(1.26)
% Manufacturing	14.87	11.32	8.54	–6.33
	(5.66)	(5.08)	(3.81)	(2.91)

Note: All means and standard deviations are computed using 1990 population weights. The sample includes the 264 cities used in the analyses.

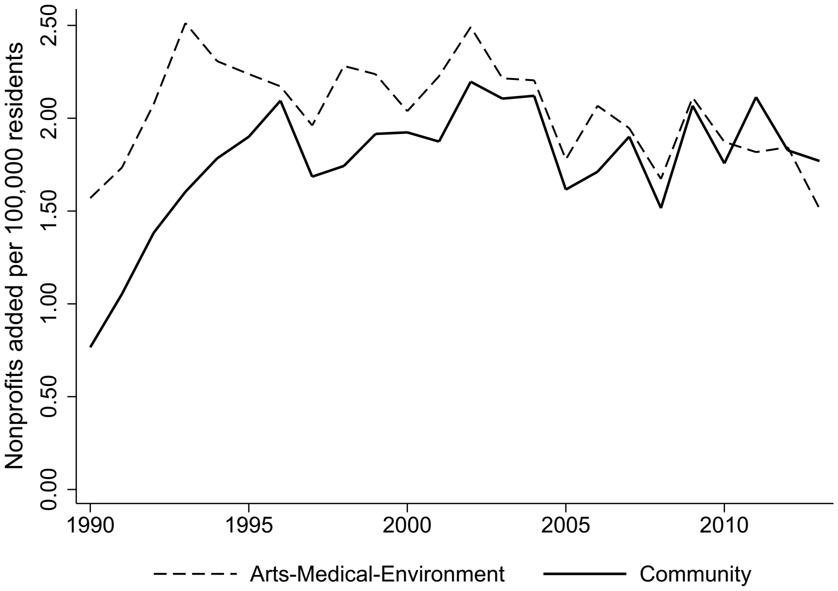

Figure 1. Annual Growth Rate in Community and Arts, Medical, and Environmental Nonprofits

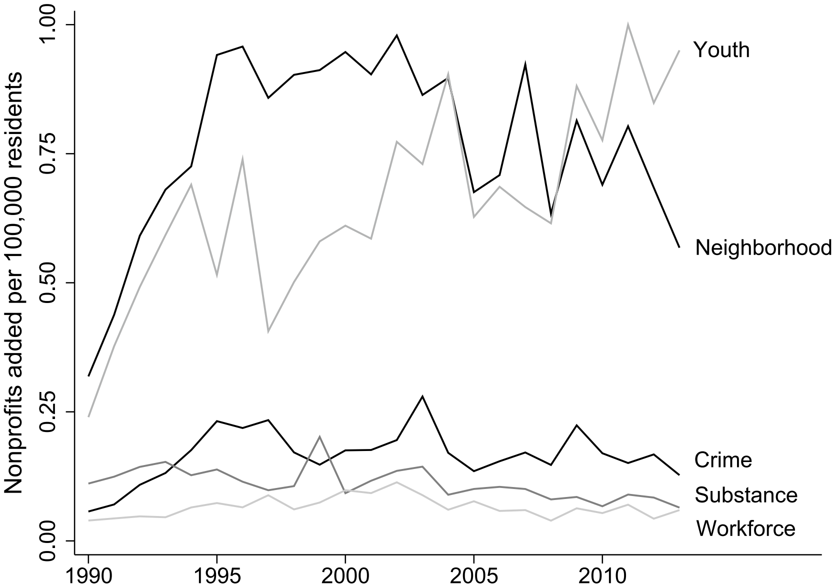

Figure 2. Annual Growth Rate for Different Types of Community Nonprofits

endogenously determined in this way, it would pose a simultaneity bias problem that interferes with identification of the impact of nonprofits on crime.[11]

The second source of bias is the traditional case of an omitted variable. In this case, an unobserved factor that causes both changes in the rate of nonprofit formation and changes in crime rates may lead to the wrong conclusion that the former caused the latter. One example of an omitted variable would be improving economic conditions. Thriving cities may offer more employment opportunities that reduce the incentives to commit crimes,

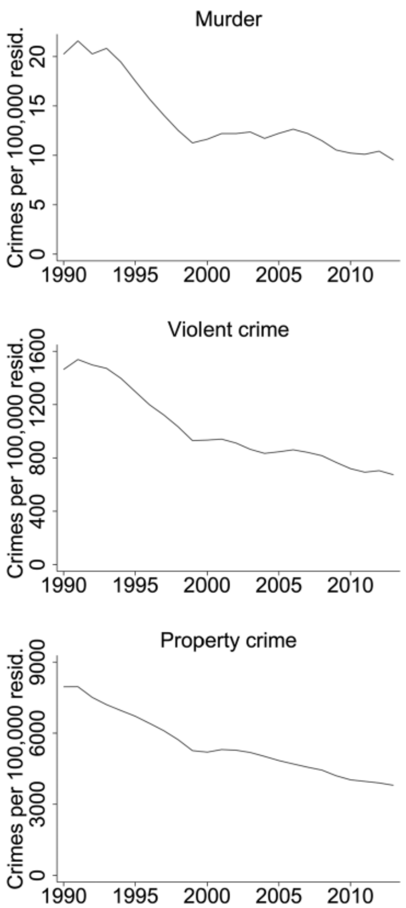

Figure 3. Trends in Crime Rates

thereby reducing the rate of crime. At the same time, local economic growth may lead to expansion of the nonprofit sector via donations from corporations operating in the city. In this case, crime rates would decline when nonprofits are formed, although a causal link between the two does not exist.

To deal with these endogeneity concerns, we propose three empirical strategies that build on each other and are discussed in detail below. In addition, we conduct a set of robustness tests, where we test whether our findings are sensitive to alternative model specifications. In the robustness tests section, we also look at whether other explanations for the crime decline, such as incarceration rates or the size of police forces, may be biasing our results.

Modeling Long-Term Changes in Nonprofit Formation

We start by estimating a model of long-term changes in crime rates as a function of long-term changes in nonprofits per capita between 1990 and 2013. We control for a number of demographic and socioeconomic changes taking place simultaneously with the growth of community nonprofits, allowing us to exploit temporal variation in crime rates and nonprofit growth while accounting for key time-varying confounders. The model takes the following form:

$$\Delta Crime_i = \alpha + \delta_{OLS}\, \Delta Community_i + \theta\, Community1990_i + \boldsymbol{\Delta X}_i' \boldsymbol{\beta} + e_i \quad (1)$$

We specify Equation 1 separately to examine changes in the murder rate, violent crime rate, and property crime rate. $\Delta Crime_i$ is the change in the log of crime rate between 1990 and 2013 for city i; $\Delta Community_i$ is the change in the cumulative number of community nonprofits per 100,000 residents between 1990 and 2013 in city i; and θ *Community* 1990_i is the number of community nonprofits per 100,000 residents that were active in 1990 in city i. $\boldsymbol{\Delta X}_i'$ is a vector of sociodemographic controls for city i that include changes between 1990 and 2013 in the following characteristics: population density, percent of Asian residents, percent of African American residents, percent of Hispanic residents, percent of residents of other race (excluding non-Hispanic white), percent of residents older than age 25 with less than a high school diploma, percent of residents older than 25 with a bachelor's degree or more, percent foreign-born, percent of males age 15 to 24, percent of residents living in poverty, percent unemployed, and percent employed in the manufacturing sector.[12]

The estimation of parameters in Equation 1 uses Ordinary Least Squares (OLS). The parameter of interest is δ_{OLS}, and it captures the change in the log of the crime rate between 1990 and 2013 associated with a change in one community nonprofit per 100,000 residents.

Standard errors are robust to heteroscedasticity, and all models include city population weights from 1990. The sample for the long-term analyses includes 264 cities.

Although the vector of demographic controls $\Delta X_i'$ accounts for a rich set of changes taking place simultaneously during this period, the results may still be susceptible to two sources of bias. First, we cannot rule out the possibility that we left out some omitted variables that are correlated with the change in crimes rates and the change in community nonprofits. Similarly, any association captured by δ_{OLS} could be a product of reverse causality.

Our next empirical strategy enables us to directly address simultaneity bias and other endogeneity concerns. We develop an instrumental variable approach inspired by Levitt's (2002) analyses of the impact of police on crime. To estimate the impact of police officers per capita on crime rates, Levitt proposed using the number of municipal firefighters per capita as an instrument for the size of the police force. Levitt argued that changes in the level of firefighters and in the level of police officers were related, because both are influenced by the power of public sector unions, citizen tastes for government services, and a mayor's decisions and approach to these public services. However, the prevalence of firefighters is unlikely to have a direct impact on crime once the factors that affect firefighters and crime rates are accounted for (e.g., changes in the local economy, fiscal conditions within the city). If the prevalence of firefighters is associated with the prevalence of police officers, and has no association with crime, then it meets the main criteria for an instrumental variable and can be used to identify the causal effect of police officers on crime.

In the spirit of Levitt's approach, we use the change in the number of nonprofits that focus on the arts, medical research, and environmental protection as an instrument for the change in community nonprofits. We argue that changes in the prevalence of nonprofits that have nothing to do with crime and violence are associated with changes in the prevalence of nonprofits related to crime and violence through common mechanisms of funding availability, but these nonprofits have no direct impact on crime and violence once the full set of control variables are included in the model.[13]

To be a valid instrument, the change in nonprofits focusing on the arts, medical research, and environmental protection must meet three assumptions or conditions. First, the relevance condition requires that the instrument has to induce a change in the endogenous variable, community nonprofits, and that this change has to translate into a sufficiently strong correlation between them. Second, the exogeneity assumption requires that the change in nonprofits focusing on the arts, medical research, and environmental protection should be uncorrelated with prior crime trends in the city. In other words, the values that the instrument takes on should be allocated as if they were randomly assigned, conditional on other variables included in the model. Third, the exclusion restriction states that the instrument can only affect crime rates through its effect on the treatment variable, community nonprofits.

We show that there is a strong correlation between changes in nonprofits focusing on the arts, medical research, and environmental protection and changes in community nonprofits, which gives direct evidence on the validity of the relevance condition.[14] In Table S1 in the online supplement, we examine whether lagged crime rates explain the growth in the number of nonprofits that focus on the arts, medical research, and environmental protection. We find no evidence that the growth in these nonprofits is correlated with prior trends in crime rates. Finally, we argue that the instrument meets the exclusion restriction because nonprofits focusing on the arts, medical research, and environmental protection target populations and issues that are unrelated to the problem of neighborhood violence.[15]

If the instrumental variable assumptions are satisfied, it is possible to estimate the causal effect of changes in community nonprofits on crime rates. This approach yields an estimate of the local average treatment effect (LATE) of community nonprofits on crime. The estimated impact is local in the sense that it is only estimated for the subset of cities for which the instrument induces a change in community nonprofits (Angrist, Imbens, and Rubin 1996). The notion of a local treatment effect should be kept in mind when we evaluate and compare the size of the instrumental variable estimates.

The system of equations used in the instrumental variable estimation takes the following form:

$$\Delta\, Community_i = \pi_1\, \Delta ArtMedEnv_i + \theta\, Community1990_i + \boldsymbol{\Delta X_i'}\, \boldsymbol{\beta} + \eta_i \tag{2.1}$$

$$\Delta Crime_i = \pi_2\, \Delta ArtMedEnv_i + \theta\, Community1990_i + \boldsymbol{\Delta X_i'}\, \boldsymbol{\beta} + e_i \tag{2.2}$$

In Equation 2.1, the first stage, $\Delta Community_i$ is the change in community nonprofits per 100,000 residents in city i between 1990 and 2013; $\Delta ArtMedEnv_i$ is the change in the number of arts, medical, and environmental nonprofits per 100,000 residents in city i between 1990 and 2013; and π_1 captures the impact of changes in the prevalence of arts, medical, and environmental nonprofits on the change in the prevalence of community nonprofits. In Equation 2.2, the reduced form, π_2, captures the impact of changes in the prevalence of arts, medical, and environmental nonprofits on the change in crime rates. Both equations control for the prevalence of community nonprofits in 1990 and include the same set of demographic controls as in Equation 1. If the assumptions outlined in the previous section are met, the causal estimate of the impact of the change in community nonprofits on the change in crime rates, δ_{IV}, can be obtained by dividing the reduced-form estimate over the first-stage estimate ($\delta_{IV} = \pi_2 / \pi_1$).[16]

Modeling Year-to-Year Changes in Nonprofit Formation

In the next set of models, we use a city fixed-effects approach that exploits year-to-year variation in crime rates and in community nonprofits per capita between 1990 and 2013. This approach essentially allows each city to act as its own control by removing any bias that may arise from time-invariant, systematic differences between cities. Our fixed-effects models also control for a set of time-varying characteristics, such as change in population density or unemployment within a city, to account for potential confounders that may be correlated with changes in crime rates and in nonprofit formation. Although the set of time-varying covariates accounts for changes in sociodemographic and labor market conditions, it is possible that other unobserved factors that change over short periods of time could generate bias in our results. The model specification has the following form:

$$Crime_{it+1} = \delta_{OLS}\, Community_{it} + \boldsymbol{X_{it}'}\boldsymbol{\beta} + \boldsymbol{Z_i'}\,\gamma + \boldsymbol{W_t'}\,\boldsymbol{\theta} + e_{it} \tag{3}$$

In Equation 3, $Crime_{it+1}$ is the log of the crime rate in city i in year t + 1; $Community_{it}$ is the cumulative number of community nonprofits per 100,000 residents that were active in city i in year t; $\boldsymbol{X_{it}'}$ is a set of demographic controls for city i in year t analogous to that of Equation 1; $\boldsymbol{Z_i'}$ is a set of city fixed-effects; and $\boldsymbol{W_t'}$ is a set of year fixed-effects. Nonprofits per capita and demographic controls are lagged one year with respect to crime rates to partially address endogeneity concerns. The city fixed-effects control for all time-invariant characteristics of the cities, and the year fixed-effects account for time and secular trends that are common to all cities in our sample. In one of the robustness checks, we allow these time trends to be specific to each of the four Census regions. The parameter of interest is δ_{OLS}, which estimates the association between changes in nonprofits per capita and changes in crime rates. Standard errors are clustered by city, and all models include city population weights from the 1990 Census.

Although the set of time-varying covariates included in these models account for changes in sociodemographic and labor market conditions, it is possible that other unobserved factors that change over short periods of time could generate bias in our results. To address this possibility, we again rely on the instrumental variables strategy described previously. As before, we use the change in nonprofits dedicated to the arts, medical research, and environmental protection as an instrument for changes in community nonprofits in an instrumental variable framework. The system equations used in the IV estimation take the following form:

$$Community_{it} = \pi_1 \ ArtMedEnv_{it} + \boldsymbol{X}_{it}' \beta + \boldsymbol{Z}_i' \gamma + \boldsymbol{W}_t' \theta + \eta_{it} \quad (4.1)$$

$$Crime_{it+1} = \pi_2 \ ArtMedEnv_{it} + \boldsymbol{X}_{it}' \beta + \boldsymbol{Z}_i' \gamma + \boldsymbol{W}_t' \theta + e_{it} \quad (4.2)$$

In Equation 4.1, the first stage, we regress year-to-year changes in community nonprofits on year-to-year changes in nonprofits dedicated to arts, medical research, and environmental protection. In that equation, π_1 captures the impact of year-to-year changes in the prevalence of arts, medical, and environmental nonprofits on the change in the prevalence of community nonprofits. In Equation 4.2, the reduced form, we regress year-to-year changes in crime rates on year-to-year changes in nonprofits dedicated to arts, medical research, and environmental protection. π_2 captures the impact of year-to-year changes in the prevalence of arts, medical, and environmental nonprofits on the change in crime rates in the following year. The first-stage and reduced-form equations include the same set of demographic controls and city and year fixed-effects as the OLS specification represented by Equation 3. As in the instrumental variable estimation described earlier, the causal estimate of the impact of the change in community nonprofits on the change in crime rates, δ_{IV}, is obtained by dividing the reduced-form estimate over the first-stage estimate ($\delta_{IV} = \pi_2 / \pi_1$).[17] Standard errors are clustered by city, and all models include city population weights from the 1990 Census. The sample for the year-to-year analyses includes 6,043 city-year observations.[18]

In a series of robustness tests, we examine the sensitivity of our OLS and IV estimates to the following alternative model specifications and sample restrictions: excluding population weights, replacing the year fixed-effects with a set of region-by-year fixed-effects, including a lagged dependent variable in the right-hand side, restricting the analyses to the 100 largest cities, excluding the 100 largest cities from the sample, and controlling for state incarceration rates and police officers per capita in the city.

RESULTS

The Impact of Long-Term Changes in the Prevalence of Community Nonprofits

Table 2 displays OLS and IV estimates for the models of long-term change represented in Equations 1, 2.1, and 2.2. Columns 1 to 3 show OLS estimates for changes in murder rate, violent crime rate, and property crime rate. We find that 10 additional community nonprofits per 100,000 residents are associated with a 6 percent decrease in the murder rate, a 6 percent decrease in the violent crime rate, and a 5 percent decrease in the violent property crime rate. Considering that the standard deviation for the change in community nonprofits per 100,000 residents active between 1990 and 2013 is 24.15, a one standard deviation increase in community nonprofits per 100,000 residents is associated with a 14 percent decline in the murder and violent crime rates and with a 12 percent decline in the property crime rate. These effect sizes are substantial given the means and standard deviations for the change in the different crime categories reported in Table 1.

Columns 4 to 7 show results from the IV estimation. The first stage, which tests how strongly our instrumental variable predicts changes in community nonprofits, is reported in Column 4. We find that the number of community nonprofits per 100,000 residents

Table 2. Long-Term Change Estimates for Community Nonprofits

	OLS			IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Murder	Violent	Property	Community Nonprofits	Murder	Violent	Property
Δ Community nonprofits	−.006**	−.006**	−.005***		−.012***	−.010***	−.007***
	(.002)	(.002)	(.001)		(.003)	(.003)	(.002)
Δ Arts, medical, environ. nonprofits				.607***			
				(.057)			
1990 community nonprofits	.007	.014**	.012**	.224	.013*	.018**	.014***
	(.005)	(.005)	(.004)	(.156)	(.006)	(.006)	(.004)
Δ Population density	−.000***	−.000***	−.000***	−.010***	−.000***	−.000***	−.000***
	(.000)	(.000)	(.000)	(.001)	(.000)	(.000)	(.000)
Δ % Asian	−.010	−.003	−.008	−.100	−.012	−.005	−.008
	(.017)	(.014)	(.009)	(.330)	(.016)	(.013)	(.008)
Δ % Black	.027**	.026**	.013**	−.146	.021*	.021*	.011*
	(.009)	(.009)	(.005)	(.262)	(.009)	(.009)	(.005)
Δ % Hispanic	.006	−.001	.003	−.264	.002	−.003	.001
	(.011)	(.009)	(.006)	(.271)	(.011)	(.009)	(.006)
Δ % Other race	.084*	.039	.004	−2.468**	.068*	.027	−.003
	(.034)	(.028)	(.017)	(.782)	(.033)	(.029)	(.018)
Δ % Less than high school	−.013	−.016	−.006	−1.108***	−.018	−.020	−.008
	(.013)	(.012)	(.006)	(.212)	(.013)	(.011)	(.006)
Δ % College	.015	−.014	.004	−1.582***	.016	−.013	.004
	(.012)	(.010)	(.008)	(.407)	(.012)	(.010)	(.008)
Δ % Foreign-born	.011	.026	.009	1.208***	.015	.028	.010
	(.017)	(.018)	(.010)	(.309)	(.017)	(.017)	(.010)
Δ % Males age 15 to 24	.095	.069	.004	−1.294	.097*	.070	.004
	(.049)	(.041)	(.026)	(.845)	(.049)	(.040)	(.025)
Δ % Poverty	.033	.016	.008	−1.058*	.032	.015	.008
	(.019)	(.015)	(.012)	(.455)	(.020)	(.015)	(.011)
Δ % Unemployed	−.013	−.057	.009	4.256***	.004	−.044	.016
	(.038)	(.033)	(.022)	(1.092)	(.038)	(.034)	(.023)
Δ % Manufacturing	.028	.050***	.029**	.704*	.032*	.053***	.031**
	(.016)	(.015)	(.010)	(.301)	(.016)	(.015)	(.010)
F-test IV				112.226			
Observations	264	264	264	264	264	264	264
Adj. R^2	.458	.435	.541	.798	.442	.423	.533

Note: Heteroskedasticity-robust standard errors in parentheses. All models include 1990 population weights.
**p* < .05; ***p* < .01; ****p* < .001 (two-tailed tests).

grows by 6.07 nonprofits for each 10 additional nonprofits focused on the arts, medical research, and environmental protection. This first-stage relationship is very strong, as the Wald test on the excluded instrument indicates (F-statistic = 112.26). Columns 5 to 7 show the second-stage estimates for murder rate, violent crime rate, and property crime rate; in other words, these columns display our estimates of the causal impact of community nonprofits on different types of crime under the assumptions described previously about our instrumental variable. We find that 10 additional community nonprofits per

Table 3. OLS and IV Fixed-Effects Estimates for All Community Nonprofits

	OLS			IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Murder	Violent	Property	Community Nonprofits	Murder	Violent	Property
Community non-profits	–.005***	–.004*	–.004**		–.009***	–.006*	–.004*
	(.001)	(.002)	(.001)		(.002)	(.003)	(.002)
Arts, medical, environ. nonprofits				.584***			
				(.049)			
Population density	–.000***	–.000***	–.000***	–.010***	–.000***	–.000***	–.000***
	(.000)	(.000)	(.000)	(.001)	(.000)	(.000)	(.000)
% Asian	–.009	–.012	–.007	–.726*	–.015	–.015	–.007
	(.014)	(.013)	(.008)	(.295)	(.015)	(.014)	(.008)
% Black	.020**	.020*	.010*	–.379	.015	.018*	.010*
	(.007)	(.008)	(.005)	(.254)	(.008)	(.008)	(.005)
% Hispanic	–.003	–.007	–.000	–.426	–.007	–.009	–.001
	(.010)	(.009)	(.006)	(.266)	(.010)	(.009)	(.006)
% Other race	.028	.005	–.018	–1.014	.024	.004	–.019
	(.026)	(.021)	(.016)	(.592)	(.026)	(.021)	(.016)
% Less than high school	–.009	–.007	.006	–1.328***	–.013	–.009	.005
	(.011)	(.011)	(.007)	(.207)	(.011)	(.011)	(.007)
% College	.006	–.011	.001	–1.311***	.009	–.009	.001
	(.011)	(.010)	(.007)	(.393)	(.011)	(.011)	(.007)
% Foreign-born	.023	.029	.010	1.657***	.029	.031	.011
	(.015)	(.018)	(.010)	(.273)	(.016)	(.019)	(.011)
% Males age 15 to 24	.064	.064*	.029	–1.162	.066*	.065*	.029
	(.032)	(.028)	(.021)	(.674)	(.033)	(.028)	(.021)
% Poverty	.019	.015	–.014	–.058	.022	.017	–.014
	(.013)	(.013)	(.009)	(.294)	(.014)	(.013)	(.009)
% Unemployed	.016	–.034	.018	2.424***	.023	–.030	.019
	(.024)	(.023)	(.016)	(.594)	(.025)	(.023)	(.016)
% Manufacturing	.035*	.060***	.032**	.768**	.041**	.062***	.032**
	(.014)	(.015)	(.010)	(.247)	(.014)	(.015)	(.010)
F-test IV				142.595			
Observations	6,043	6,043	6,043	6,043	6,043	6,043	6,043
Adj. R^2	.433	.599	.623	.917	.404	.580	.605
City fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered by city in parentheses. All models include 1990 population weights.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

100,000 residents lead to a 12 percent decrease in the murder rate, a 10 percent decrease in the violent crime rate, and a 7 percent decrease in the property crime rate. Translating these point estimates to standard deviation changes, we find that a one standard deviation increase in community nonprofits per 100,000 residents leads to a 29 percent decline in the murder rate, a 24 percent decline in the violent crime rate, and a 17 percent decline in the property crime rate.

The Impact of Year-to-Year Changes in Nonprofit Formation

In the next set of models, represented by Equations 3, 4.1, and 4.2, we use year-to-year variation in the cumulative number of nonprofits to

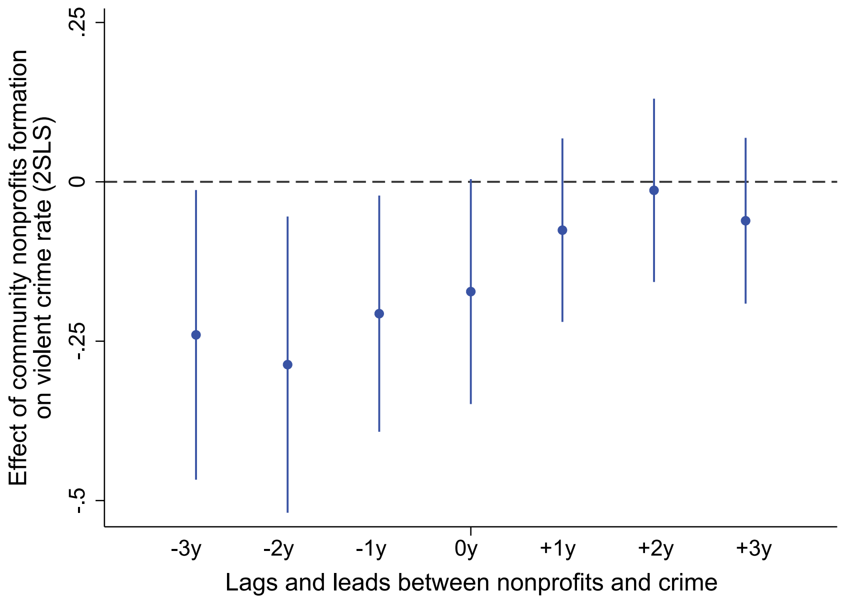

Figure 4. IV Estimates of Community Nonprofits on Violent Crime Rate

examine their impact on crime rates in the following year. We report OLS and IV results in Table 3. The OLS estimates reported in Columns 1 to 3 indicate that 10 additional community nonprofits per 100,000 residents are associated with a 5 percent decline in the murder rate, a 4 percent decline in the violent crime rate, and a 4 percent decline in the property crime rate. A one standard deviation increase in the cumulative number of community nonprofits per 100,000 residents is associated with a 12 percent decline in the murder rate and with a 10 percent decline in the violent and property crime rates.

Columns 4 to 7 in Table 3 show results from the IV models. In the first stage, we find that 10 additional nonprofits per 100,000 residents that focused on the arts, medical research, or environmental preservation are associated with an increase of 5.84 additional community nonprofits per 100,000 residents (F-statistic = 142.60). Again, these results indicate that our instrumental variable strongly predicts year-to-year changes in community nonprofits. Second-stage results show that 10 additional community nonprofits per 100,000 residents lead to a 9 percent decline in the murder rate, a 6 percent decline in the violent crime rate, and a 4 percent decline in the property crime rate. Translating these magnitudes to standard deviation changes, we find that a one standard deviation increase in the number of community nonprofits results in a 22 percent decrease in the murder rate, a 14 percent decrease in the violent crime rate, and a 10 percent decrease in the property crime rate.[19]

Figure 4 shows IV estimates of the impact of newly added community nonprofits on violent crime rates when adding different lags and leads to the measure of nonprofits. Each of the point estimates and 95 percent confidence intervals displayed in Figure 4 come from separate regressions in which nonprofits are measured from three years before crime rates (−3y) up to three years after (+3y). Consistent with our theoretical predictions, the creation of nonprofits affects future crime rates (estimates −3y to −1y) but not the other way around (estimates +1y to +3y). This finding is reassuring, because it confirms that crime in a given year is not affected by the formation of nonprofits created in future years, and thus it provides more evidence that the underlying relationship between community nonprofits and crime is not driven by some unobserved change occurring within cities.

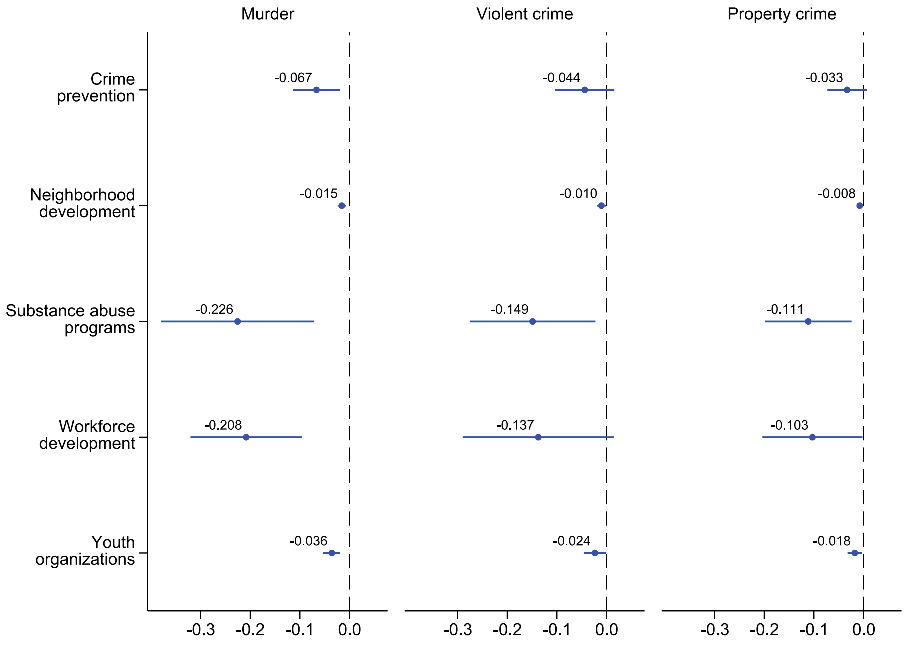

Figure 5. IV Estimates for Different Types of Community Nonprofits

The Impact of Different Types of Community Nonprofits

In an effort to generate some insight into the specific types of nonprofits that have the greatest impact on crime, we estimate separate IV fixed-effects models for each of the five types of organizations that compose the broader category of community nonprofits. We use the same model specification and the same sample of cities and years as the models shown in Table 3. Figure 5 displays point estimates and 95 percent confidence intervals for the impact of each nonprofit type on the murder rate (left column), violent crime rate (central column), and property crime rate (right column). These estimates are much less precise because of the smaller number of nonprofits in each category, so comparisons between different types of organizations should be interpreted with caution.

Each additional nonprofit focused on substance abuse per 100,000 residents leads to a 23 percent decline in the murder rate, a 15 percent decline in the violent crime rate, and an 11 percent decline in the property crime rate. Similarly, each additional nonprofit focused on workforce development per 100,000 residents leads to a 21 percent decline in the murder rate, a 14 percent decline in the violent crime rate, and a 10 percent decline in the property crime rate.[20]

Despite the larger impact that these two types of community nonprofits had in absolute terms, it should be noted that most of the growth in community nonprofits during the period of our study came from organizations focused on neighborhood development, youth programs, and crime prevention. The IV estimates for these three nonprofit types are much closer to the overall estimate for all community nonprofits, as Figure 5 shows. Thus, although programs focusing specifically on substance abuse and job training may have had the largest impact on crime for each additional nonprofit added, the broader set of programs focusing on strengthening communities and fighting crime may have had a larger overall impact on the decline of violence across U.S. cities.

Tests of Robustness

We conducted a series of additional analyses to test the robustness of our results. Table 4 shows results from a number of alternative

Table 4. Robustness to Alternative Model Specifications and Sample Choices

	Murder		Violent		Property	
	OLS	IV	OLS	IV	OLS	IV
(1) Baseline	−.005***	−.009***	−.004*	−.006*	−.004**	−.004*
	(.001)	(.002)	(.002)	(.003)	(.001)	(.002)
(2) Without population weights	−.004**	−.009***	−.004***	−.006	−.003**	−.002
	(.001)	(.002)	(.001)	(.003)	(.001)	(.002)
(3) Region-by-year fixed-effects	−.005**	−.008**	−.004	−.004	−.003*	−.004*
	(.001)	(.002)	(.002)	(.002)	(.001)	(.002)
(4) Lagged dependent variable	−.004**	−.006**	−.002	−.002	−.003**	−.003*
	(.001)	(.002)	(.001)	(.002)	(.001)	(.001)
(5) Only 100 largest cities	−.004*	−.007*	−.003	−.006	−.005*	−.003
	(.002)	(.003)	(.003)	(.004)	(.002)	(.002)
(6) Excluding 100 largest cities	−.005**	−.009*	−.005***	−.004	−.003**	−.005**
	(.002)	(.004)	(.002)	(.003)	(.001)	(.002)
(7) Adding state incarceration	−.005**	−.009**	−.005**	−.008**	−.005***	−.005**
	(.002)	(.003)	(.002)	(.003)	(.001)	(.002)
(8) Adding police (1992 to 2008)	−.004*	−.009**	−.006*	−.009*	−.006**	−.007**
	(.002)	(.003)	(.002)	(.004)	(.002)	(.002)

Note: Standard errors clustered by city in parentheses. All models include 1990 population weights.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$ (two-tailed tests).

model specifications and sample restrictions. Each cell corresponds to a separate model from which we report only the point estimates and standard errors for δ_{OLS} and δ_{IV}. All models include the same set of covariates and fixed-effects shown in Table 3. For comparison, we show the baseline estimates from Table 3 in the first row.

In the second row, we estimate OLS and IV models without city population weights and obtain qualitatively the same results (although the coefficients in some IV models are imprecisely estimated). In the third row, we replace the year fixed-effects with a set of year-by-region fixed-effects to account for different time trends across Census regions. We find that the baseline estimates remain virtually the same after we allow for this alternative fixed-effects specification. The fourth row reports results using a lagged dependent variable specification (i.e., including the log of crime rate in year $t - 1$ in the right-hand side of the equation) and shows that the sign of the impact is preserved across all models, but the point estimates shrink slightly and some are imprecisely estimated.

In the fifth row, we restrict the analyses to the largest 100 cities and obtain point estimates consistent with those in the baseline models. However, the smaller sample size yields larger confidence intervals. Results in the sixth row are based on models that exclude the 100 largest cities from the analyses; they show qualitatively similar results, suggesting that baseline estimates are not driven by changes that took place in the most populated cities in the country.

Prior research has linked the growth of police departments and the expansion of the criminal justice system to the crime decline. Given the relevance of these two factors in the debates around the crime decline, evaluating the sensitivity of our estimates when we account for them is a useful exercise. Including them is particularly important to test for any confounding effect. For example, if the size of the police force is causally linked to both nonprofit growth and crime rate, we would expect our estimated effect of nonprofits to change after controlling for this variable. In the last two rows of Table 4, we control for the incarceration rate at the state level and for the size of the police force in the city and find that both point estimates and standard errors remain qualitatively the same.[21] We interpret this finding as another indirect validation of our identification strategy and as evidence of the independent role that community organizations have played in reducing crime rates in U.S. cities. More broadly, results in Table 4 indicate that our main findings from Table 3 are robust to modeling the relationship between community nonprofit formation and crime rates in different ways.

DISCUSSION: MOBILIZATION FROM WITHIN

When violent crime reached its latest peak in the early 1990s, a range of actors at different levels of society mobilized to respond. Federal resources were used to bolster the number of police officers on the streets of poor neighborhoods, and legislation was passed at the state and federal levels to create mandatory minimum sentences for many different crimes and to treat juvenile offenders as adults. Schools installed metal detectors and security cameras, and private firms hired security guards to patrol their properties.

These changes were implemented mainly by actors and institutions outside the communities where the problem of violence was most acute. But another set of changes was occurring within these communities. As surveillance of urban neighborhoods intensified and the criminal justice system expanded its reach, residents and community leaders began to establish thousands of local organizations designed to strengthen their neighborhoods, provide support and safe spaces for young people, and confront violence. Beyond case studies of successful programs and specific neighborhoods that have changed over time, these local efforts to respond to the problem of violent crime have been overlooked in the literature on the decline of violence in the United States.

We consider the proliferation of community nonprofits to be among the most important shifts to occur in urban communities over this period, altering the physical and social environment in ways that have not been adequately studied at the national level. Strong social theory on community life suggests that local organizations are a core component of the informal networks that are essential to generating social cohesion and informal social control, and thus limiting violence (Sampson 2012). Yet the systemic model has not been incorporated into discussions of the crime decline. To be clear, our intent in this article is not to challenge existing theories of why violence fell. Rather, we bring attention to another set of changes that occurred across U.S. cities in the early 1990s, and we assess whether these changes had a causal impact on violent crime.

Understanding the impact of local organizations on violence and crime is challenging because these organizations are more likely to be established in neighborhoods where the problem of violence is most severe. A simple analysis assessing the association between anti-violence organizations and violent crime in a cross-section of cities or neighborhoods would likely lead to the conclusion that more organizations lead to more crime. This conclusion is clearly inaccurate, but it means that to understand the effect of local organizations on crime one needs to develop alternative approaches. We use longitudinal data and employ multiple analytic strategies to assess whether the growth in local nonprofits led to reductions in crime. We examine how long-term changes in the number of nonprofits focused on reducing violence and strengthening communities affected long-term changes in crime rates; we take advantage of short-term changes in the number of nonprofits designed to confront violence and build stronger communities and assess how these changes affected violent crime in the subsequent year; and we use variation in the number of local organizations driven not by the severity of the violence problem, but rather by shifts in the broader funding landscape that led to the formation of more nonprofits that had nothing to do with crime and violence.

These analytic strategies lead to the same conclusions. After accounting for the endogeneity of nonprofit formation, we find strong evidence that establishment of community nonprofits had a substantively meaningful negative effect on murder, violent crime, and property crime. Our estimates indicate that the addition of 10 community nonprofits per 100,000 residents leads to a 9 percent decline in the murder rate, a 6 percent decline in the violent crime rate, and a 4 percent decline in the property crime rate. The sizes of these effects are substantial if we take into account the growth in community nonprofits between 1990 and 2013 across all cities in our sample. Our results predict that in a city where the growth in community nonprofits was one standard deviation above the mean, this change would have resulted in a 22 percent decrease in the murder rate and a 14 and 10 percent decrease in violent and property crime rates, respectively. If we look at specific cities that experienced large declines in crime rates in the 1990s and 2000s, we find that these crime drops were accompanied by large increases in community nonprofits. For example, between 1990 and 2013, New York added 25 nonprofits per 100,000 residents, Los Angeles 36, Chicago 47, and Boston 56.

Although the article's primary contribution is to identify the causal effect of community organizations on violent crime, the evidence presented also has implications for research and policy on community violence. First, the findings suggest the need for a reintegration of criminological theory on crime and violence with the large literature on the crime decline in the United States. Social disorganization theory has received strong support in the empirical literature on cross-sectional variation in crime and violence (Weisburd and Piquero 2008), but much less attention has been devoted to temporal variation in the dimensions of communities that lead to greater or lesser social organization. For instance, little is known about how the emergence or departure of core community institutions and organizations affects collective efficacy within communities, and how such within-community changes affect social dynamics and patterns of crime and violence.[22]

Despite the prominence of social disorganization theory to the study of crime and violence in the United States, the theory has not been used to help explain the long-term decline of U.S. violence (Rosenfeld 2002). In our analysis, we consider only nonprofits focused on building stronger communities and confronting violence, but other important dimensions of the systemic model, including ties between residents, the strength of local networks, levels of social cohesion and trust, and levels of informal social control, have not been used to explain national trends in violence.[23] Although it is challenging to measure these dimensions of community life, our hope is that creative steps can be taken to generate measures within specific cities to assess whether the systemic model can help us better understand the decline of violence in the United States and beyond.

Although we focus on only one feature of communities, our emphasis on community-based organizations adds a new dimension to the vast literature on the crime decline in the United States. A review of the most prominent contributions to this literature would lead to the conclusion that local organizations played no role in helping bring about the long-term reduction of violence that has taken place since the early 1990s. For example, Zimring's (2006) seminal book on the crime drop of the 1990s provides an excellent review of the evidence on various theories of the crime decline and concludes it was likely some combination of improving economic conditions, shifts in the age of the population, improvement in policing tactics, and expansion of the incarcerated population that led to the crime drop. In another influential review, Levitt (2004) assesses evidence on a wide range of potential explanations and concludes that four factors—growth in the police, rise of incarceration, end of the crack epidemic, and legalization of abortion—fully account for the decline of violent crime. A more recent report from the Brennan Center for Justice features a state-level analysis of 13 factors that have been proposed as explanations for the crime drop, providing support for some theories already mentioned, such as the growth of police departments, and pointing to the importance of other factors rarely mentioned, such as the decline in alcohol consumption (Roeder, Eisen, and Bowling 2015).

Our analysis is not designed to assess or challenge any of the existing theories of the crime drop, but it does allow us to insert another factor into the active debates about the fall of violence. Nowhere in any of the most comprehensive, prominent, and influential overviews of the causes of the crime decline is there any discussion of the role played by local organizations established to control violence and build stronger communities. The absence of scholarly attention to community organizations is reflected in coverage of the crime decline from the popular press. For example, Levitt (2004) begins his review article by conducting a search of articles about the crime decline in the 10 largest U.S. newspapers in the 1990s, and finds that the vast majority focused on only a small number of potential explanations, including changes in policing, incarceration, the crack cocaine market, gun control laws, and economic conditions. An article in a popular criminal justice blog reviewed an updated list of theories that have been proposed over time, including the decline of lead exposure, the expansion of abortion, the growth of immigration, and even the spread of medication for depression and Attention Deficit Hyperactivity Disorder (Goldstein 2014). Again, no mention is made of local efforts to mobilize and confront violence.

The lack of attention to local organizations is likely attributable to the challenges in finding adequate data sources on such organizations and in specifying exactly what community organizations do to confront violent crime in their neighborhoods. Our analysis has not overcome all of these challenges. We aggregated together many different kinds of organizations from a large administrative dataset that does not allow us to examine the specific activities or programs that organizations administer. Our measure of the prevalence of local organizations makes the implicit assumption that the raw number of such organizations is what matters, yet it is more likely that the presence of energetic and effective organizational leadership and staff plays a larger role in determining whether organizations will have an impact on violence. More research needs to be done to understand the mechanisms underlying the findings in this article.

The dearth of national research on the impact of community organizations may be due entirely to the empirical challenges we discussed, but the absence of empirical attention to such organizations has implications for our understanding of why violence fell and for policy debates moving forward. With the exception of case studies documenting local organizations' efforts in specific cities (e.g., Kennedy 2011), debates about why violent crime fell in the United States have not adequately acknowledged the efforts made by groups of residents, activists, and community leaders who have worked to confront violence within their own neighborhoods. Because these organizations are frequently overlooked, the prevention of violence is implicitly presented as a social outcome that is dependent on the efforts, ideas, and resources of those external to the communities most affected by the problem of violence. This perspective discounts the many case studies documenting how residents and community leaders came together in The Bronx and Washington Heights in New York, the Dudley Triangle of Boston, the Rio Grande Valley in Texas, and thousands of other neighborhoods to retake public spaces for the use of residents, provide programs and services for young people, and work collectively to fight back against violent crime.

It is easy to romanticize the efforts of such organizations and assume they were effective without any formal evaluation. However, it is also easy to dismiss or overlook the work of local organizations, and to assume they did not play a meaningful role in reducing violence. We do not suggest that every nonprofit organization is effective at reducing violence, but a number of recent experimental evaluations provide strong evidence that local organizations administering high-quality programs—like summer jobs for teens, in-school programming combined with cognitive behavioral therapy, or intensive tutoring—can generate substantial effects on participants' involvement with violent or criminal activity (Cook et al. 2015; Heller et al. 2013). This research supports the more general point that local organizations have tremendous capacity to play central roles in the fight against violence.

As the practice of aggressive or violent policing and the expansion of the criminal justice system have met with growing protest, community-based organizations may become increasingly central to the effort to control violence within communities that are vulnerable to a rise in violent crime. We argue that the evidence presented in this article is thus relevant not only for understanding why violence fell in the 1990s, but also for reconsidering the set of actors and organizations that have the greatest potential to build stronger urban communities and control violent crime in the years to come.

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Notes

1. It is beyond the scope of this article to expand beyond the United States, but trends in crime look broadly similar in Canada, Australia, and many Western European nations (Dijk, Kesteren, and Smit 2007; Farrell, Tilley, and Tseloni 2014; Rosenfeld and Messner 2009; Zimring 2006). We note, too, the finding in Salamon and colleagues (2013) of general growth of the nonprofit sector between the late 1990s and mid-2000s in seven of eight countries for which longitudinal data are available: the United States, Japan, Canada, Belgium, Thailand, Norway, and Australia. These similarities are not sufficient to make any conclusions, but they do suggest that the broad trends on which we focus may be relevant outside the United States.
2. We acknowledge the arguments made by Forman (2017) and Fortner (2015) documenting support for more punitive criminal justice policy within the black community and among black politicians. These arguments are designed to help explain the growth of a more aggressive and expansive criminal justice system, an example of an externally imposed set of policy shifts to respond to crime and violence. Their arguments are not designed to help explain why crime fell.
3. We use the term social disorganization because it is identified with a long tradition of criminological theory. However, decades of ethnographic research has demonstrated that the idea that low-income neighborhoods are socially disorganized is incorrect (Stack 1975; Venkatesh 2006; Whyte 1943). In his criminology textbook published in 1947, Sutherland used the term "differential social organization" instead of social disorganization. See also Sampson (2012) for a discussion of the term and its history.
4. This is in fact true in our data. If we regress crime rates on the number of nonprofits per capita using a cross-section of cities, we obtain a significant, positive relationship.
5. Given that UCR data are based on crime being reported by police departments, it is possible that part of any demonstrated effect may be explained by a decreased willingness to make arrests and report crime brought about by police partnerships with community organizations. This is less of a concern with the measure of the murder rate, which is measured with high reliability and is less sensitive to changes in reporting patterns (Mosher, Miethe, and Hart 2010). Another limitation of the UCR data is that they only contain crimes reported or known to law enforcement agencies, as opposed to actual levels of crimes. This measurement error issue is less of a concern because crime rates are our dependent variable.
6. As we will describe, nonprofits are lagged one year with respect to crime rates. This means the nonprofit and demographic data include years 1990 to 2013, whereas the crime data include years 1991 to 2014.
7. The excluded group is non-Hispanic white residents.
8. Organizations with more than $5,000 in annual gross receipts are required to register with the IRS to obtain 501(c)3 status; religious organizations, such as churches, are not required to register regardless of their annual gross receipts.
9. The NTEE-CC codes enable us to identify and classify community nonprofits with a high degree of precision. However, based on the organization names listed in the CMF dataset, there are some nonprofits outside the NTEE-CC codes that we use to define community nonprofits that seem to be engaged in crime-prevention activities. To capture those, we search for nonprofits that have specific keywords in their organization name (e.g., crime, violence, recidivism). In the online supplement, we

provide the list of keywords that we use to supplement the NTEE-CC codes. We were careful in choosing keywords that fit our definition of community nonprofits, but we acknowledge that some of the keywords may capture organizations that are somewhat irrelevant. We assessed the sensitivity of our estimates by excluding nonprofits that were captured by the keyword search, and we obtained the same results.

10. The NCCS defines active organizations as those that are providing services to the community during a given year. Prior to 2006, the IRS verified this status by mailing postcards to registered nonprofits every three years. As the NCCS documentation acknowledges, it is possible that some defunct organizations that have not formally dissolved may be included in the data, although we have no reason to believe that some areas or nonprofit sectors would be more systematically affected by any overestimation of the number of active nonprofits.
11. Perhaps the most comparable example of a scenario in which simultaneity bias complicates the identification of causal effects is in estimation of the size of the police force on crime rates. In that case, potential criminals choose whether to commit a crime based on the number of police officers in the city, and at the same time, cities adjust the number of police officers based on the city's crime rate.
12. Changes in community nonprofits and changes in crime rates are measured by averaging rates from 1990 to 1992 and from 2010 to 2013, and then computing the change between these two periods.
13. One could make the case that the change in the number of nonprofits focusing on the arts, medical research, and environmental protection is picking up changes in economic growth in the city (we thank a reviewer for raising this point). If this was the case, we should see a strong bivariate correlation between economic growth and changes in the instrument. In results available upon request, we examine this correlation in the fixed-effects framework that we use in our main analyses. Specifically, we regress the number of arts, medical, and environmental nonprofits per 100,000 residents on unemployment rate (a proxy for economic growth), city fixed-effects, and year fixed-effects. We find a weak, non-significant relationship between unemployment rate and our instrument.
14. We follow the convention in the literature and consider the instrument to be strong enough if the F-statistic from a Wald test on the instrumental variable is larger than 10 in the first-stage regression (Stock and Yogo 2005). As Tables 2 and 3 show, the F-test on the instrument in the first-stage regressions yields F-statistics that are well above this value.
15. The exclusion restriction could also be violated if an increase in arts, medical, and environmental nonprofits brings about demographic shifts that affect crime rates. For example, if highly educated workers are attracted by the kind of activities these nonprofits support and promote in the city, the increase in the number of more skilled workers in the city could affect crime rates if that leads to the gentrification of certain neighborhoods or to local economic growth. We consider this scenario less plausible in fixed-effects specifications that focus on within-city, year-to-year changes in nonprofits. Furthermore, the set of time-varying controls will account for socioeconomic and demographic changes that could open backdoor paths between our instrument and crime rates.
16. Another way of describing the instrumental variable estimation is by showing the first- and second-stage equations. In that case, we would use the predicted values of the change in crime obtained in the first-stage equation and plug them into the second-stage equation (i.e., the second stage uses only the variation in the endogenous variable that is induced by the instrument in the first stage). This approach would yield point estimates identical to the ones we obtain from our approach, but the standard errors would be incorrectly estimated.
17. As in Equations 2.1 and 2.2, the estimation procedure described in Equations 4.1 and 4.2 is done in one step, which yields the correct standard errors.
18. This is an unbalanced panel of cities. We focus on the same 264 cities that feature in the analyses of long-term changes. To be included in the sample, a city must meet the following criteria: (1) the city is among the 300 largest cities in the country (in terms of 2010 population); (2) it has at least 10 years of complete data on crime, nonprofits, and demographics; and (3) two of these ten years must be 1990 and 2013. Among the 264 cities that meet these conditions, 234 have complete data for the entire 24-year span between 1990 and 2013. The choice of focusing on cities that have at least 10 years with complete data is arbitrary. However, results remain the same if we lower this restriction to cities that have at least five years of complete data (with two of them being 1990 and 2013). Results are also robust to using the sample of 234 cities for which we have complete data for the 24 years.
19. IV estimates are robust to excluding the vector of demographic controls, suggesting that changes in population characteristics do not drive our results. We include them in the estimation because they help us build a stronger first stage by removing residual variation in crime rates, and they increase the precision of the second-stage estimates. In Table S2 in the online supplement, we show OLS and IV results using year-to-year variation in the number of newly added nonprofits in a given year, instead of using the cumulative number of nonprofits active in the year. We obtain OLS point estimates that are qualitatively similar to those reported in Table 3 but larger in magnitude.

20. All point estimates for each nonprofit type shown in Figure 5 are larger than the estimate we obtain when we combine them under the broad category of community nonprofits (Table 3). To be clear, each of the five nonprofit types and the broad category of community nonprofits enter the models in the same scale (nonprofits per 100,000 residents), and all community nonprofits fall under one of the five types shown in Figure 5. If we reduce these five categories to two, X_1 and X_2, the broad category of community nonprofits that adds all of them together can be defined as $X_T = X_1 + X_2$. Because X_1 and X_2 include all possible types of nonprofits in X_T, X_1 and X_2 can be represented as shares of X_T. That is, $X_1 = p\,X_T$ and $X_2 = (1-p)\,X_T$, where p and $1-p$ are the shares for X_1 and X_2, respectively. Knowing this, we can write the OLS coefficients on X_1 and X_2, β_1 and β_2, which are obtained from separate regressions of Y on X_1 and X_2, as functions of the OLS coefficient we obtain from a regression on Y on X_T, β_T, as follows:

$$\beta_1 = \frac{Cov(Y,X1)}{Var(X)} = \frac{Cov(Y,pX_T)}{Var(pX_T)} = \frac{pCov(Y,X_T)}{p^2\,Var(X_T)} = \frac{1}{p} * \frac{Cov(Y,X_T)}{Var(X_T)} = \frac{\beta_T}{p}$$

and by symmetry,

$$\beta_2 = \frac{\beta_T}{1-p}$$

where p and $1-p$ are the shares of X_T that X_1 and X_2 represent. In other words, the coefficients on the individual types of nonprofits are scaled versions of the coefficient on the broad community nonprofit category, where the scaling factors are the inverse of the shares that each nonprofit type represents. The extension to the five-nonprofit case follows directly from the derivation above. The same result applies to the IV coefficients. A straightforward way of showing the relationships between β_1 and β_2 and β_T in the IV case is by expressing the IV coefficients as $\beta_{IV} = \frac{Cov(X,Z)}{Cov(Y,Z)}$, where Z is the instrumental variable.

21. For incarceration, we use the state incarceration rate from the National Prisoner Statistics Program from the Bureau of Justice Statistics. For size of the police force, we use the number of sworn police officers per capita from the Census of State and Local Law Enforcement Agencies from 1992, 1996, 2000, 2004, and 2008. We chose not to include these two controls in our main set of results for two reasons. First, data on incarceration at the city level are not available, so we have to use state-level measures, which we believe are inadequate indicators of the incarcerated population in a given city and year. Second, data on size of the police force are not available over the full period, so our sample becomes smaller and the timeframe for the analysis shrinks substantially when we include this measure.

22. As an example, Sampson and colleagues (2005) find that the density of nonprofit organizations in a neighborhood, or what they call organizational infrastructure, is the most important predictor of variation in collective action. We argue that this type of research should be extended to consider community-level changes in organizational infrastructure, collective efficacy and collective action, and crime and violence. There is also a need to generate evidence on how changes in organizational infrastructure and collective efficacy interact with changes in formal policing, a topic that has received little attention in the literature.

23. LaFree's (1998b) argument about the decline of core institutions within U.S. society is an exception, although the argument does not focus on neighborhood-level institutions and organizations and has not been applied to the decline of violence.

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