CRIMINOLOGY

VOLUNTARY ORGANIZATIONS AND NEIGHBORHOOD CRIME: A DYNAMIC PERSPECTIVE*

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KEYWORDS: neighborhood crime, voluntary organizations, organizational life course, social services, social capital

Although numerous theories suggest that voluntary organizations contribute to lower crime rates in neighborhoods, the evidence for this proposition is weak. Consequently, we propose a dynamic perspective for understanding the relationship between voluntary organizations and neighborhood crime that involves longitudinal analyses and the measurement of the age of organizations. By using longitudinal data on a sample of census blocks (N = 87,641) located across 10 cities, we test the relationship between age-graded measures of different types of voluntary organizations and neighborhood crime rates. We use fixed-effects negative binomial regression models that focus on change within neighborhoods of the relationship between voluntary organizations and neighborhood crime. Our results show that although each type of voluntary organization is found to exhibit crime-reducing behavior in neighborhoods, we find that many of them are consistent with what we refer to as the "delayed impact scenario"—there is a pronounced delay between the placement of a voluntary organization and a neighborhood subsequently experiencing a reduction in crime. With protective effects of organizations typically not demonstrated until several years after being in the neighborhood, these patterns suggest a need for long-term investment strategies when examining organizations.

Criminological theory and communities and crime research often suggest that voluntary organizations may provide important crime-control benefits to neighborhoods (Peterson, Krivo, and Harris, 2000; Sampson and Groves, 1989; Slocum et al., 2013; Triplett, Gainey, and Sun, 2003). Community voluntary organizations broadly refer to nonprofit organizations that provide services, activities, or events to the neighborhood. Voluntary organizations can contribute to neighborhood control through the provision of needed services or by creating favorable environments that facilitate the sharing of common values and goals among local residents. Thus, voluntary organizations are posited to

* Additional supporting information can be found in the listing for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2016.54.issue-2/issuetoc.

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 doi: 10.1111/1745-9125.12101

benefit neighborhoods through two possible mechanisms: 1) providing social services that help residents and therefore reduce the number of potential offenders; and 2) providing a forum for social interaction that increases the social capital in a neighborhood as well as the sense of cohesion.

A puzzle has emerged from the literature on voluntary organizations and neighborhood crime: Although there are many reasons to expect voluntary organizations will reduce the amount of crime in neighborhoods, the empirical evidence of their benefits is surprisingly weak. Some studies have not only failed to find evidence that certain types of voluntary organizations facilitate efficacious neighborhood control and social action, but also they have even found evidence to suggest that some types of voluntary organizations are associated with higher crime rates (Groff and Lockwood, 2014; Slocum et al., 2013; Wo, 2014). One commonality for these studies is that often they have only captured the *presence* of a voluntary organization in a neighborhood, and thus, one solution to this dilemma is that organizations might be more or less effective depending on how long they have been established in a neighborhood. These patterns suggest a need to understand the timing of when organizations are effective (if at all) at reducing crime.

In this article, we argue for an approach that considers the *dynamic* nature of the voluntary organization and crime process in neighborhoods. As we note here, there are at least four theoretical considerations: 1) if voluntary organizations cause crime rates to fall in neighborhoods, how long this process lasts; 2) whether the effectiveness of organizations changes or remains constant over time; 3) how other neighborhood processes change in response to the presence of a voluntary organization; and 4) the decision process for the location of organizations. Regarding the first point, even if the placement of a voluntary organization begins to reduce crime, the period in which crime is falling will be finite. This, along with the second point, implies that the impact of voluntary organizations on neighborhood crime will change over the life course of the voluntary organization: Thus, "newer" and "older" voluntary organizations will not equally impact neighborhood crime, but voluntary organizations' influence on crime (and the neighborhood in general) is dynamic rather than static given that organizational effectiveness can fluctuate over time (Kimberly and Miles, 1980; Quinn and Cameron, 1983; Whetten, 1987). Regarding the third point, if voluntary organizations attract potential constituents from the surrounding area, based on crime pattern theory, this can create more offending opportunities simply because there are more persons in the neighborhood (Brantingham and Brantingham, 1993, 1995), which can change the level of crime. In terms of the fourth point, voluntary organizations may be more likely to locate in neighborhoods with the most disorder and crime, which can have consequences for statistical models of their relationship to crime. All of this implies the need to consider how long an organization has been located in a neighborhood to understand more fully its relationship with neighborhood crime.

Although previous studies have considered the diversity of voluntary organizations in relation to crime (Slocum et al., 2013), we are aware of no study that has examined how organizational age underlies this process. We argue that studies should take organizational age into account because it captures potential changes that voluntary organizations undergo, as well as changes in the surrounding landscape, which in turn may have consequences for determining which voluntary organizations will be most effective in reducing crime. Accordingly, in this study, we do the following: 1) create age-graded measures of voluntary organizations, and classify them by seven different types, to test their relationship with changes in crime within census blocks; 2) use longitudinal negative binomial fixed-effects models that focus on change *within* neighborhoods rather than *across* neighborhoods; and 3) estimate these models on a sample of census blocks located across 10 U.S. cities, which provide us the statistical power to assess these relationships. The results demonstrate that voluntary organizations have differential effects on crime according to their age with some types of organizations even showing both criminogenic and crime reducing effects over the life course. In comparison, a measure that mimics the most common approach in the literature—the total number of voluntary organizations regardless of how long they have been in operation—conceals the observed differential effects, thereby overemphasizing the effects of certain age groupings.

VOLUNTARY ORGANIZATIONS AND NEIGHBORHOOD CRIME

The notion that voluntary organizations contribute to lower levels of neighborhood crime originates from social disorganization theory (Bursik and Grasmick, 1993; Sampson and Groves, 1989; Shaw and McKay, 1942). Social disorganization theory posits that factors such as poverty, family disruption, residential instability, and ethnic heterogeneity inhibit neighborhoods' ability to control informally the behavior of their residents—thereby increasing the likelihood of crime (Bursik and Grasmick, 1993; Kubrin and Weitzer, 2003; Sampson and Groves, 1989). Scholars have theorized that socially disorganized neighborhoods have a scarcity of voluntary organizations that facilitate the provision of important services and goods and the formulation of social ties that are required for informal social control, and this may suggest more crime (Peterson, Krivo, and Harris, 2000; Sampson and Groves, 1989; Wilson, 1987). Yet, Slocum et al. (2013: 175) pointed out that "the theoretical importance placed on organizations [in relation to crime rates] is not mirrored in the empirical literature." Thus, for communities and crime scholars, there is a growing need to determine how different types of voluntary organizations influence neighborhood crime.

Whereas social disorganization theory suggests that social capital and social ties benefit residents, crime pattern theory suggests that voluntary organizations might change the presence of targets, offenders, and guardians on the street (Brantingham and Brantingham, 1995). According to crime pattern theory, the consequences of voluntary organizations are unclear because they might imply more crime as a result of the increase of targets and offenders on the street, but they also might imply less crime as a result of the increase in reformed offenders. In this sense, voluntary organizations potentially represent what Brantingham and Brantingham (1995: 7) referred to as *crime generators*, "particular areas to which large numbers of people are attracted for reasons unrelated to any particular level of criminal motivation they might have or to any particular crime they might end up committing." Analogous to how a retail site not only provides positive services and economic benefits but also provides criminal opportunities by increasing the presence of both potential offenders and targets (Steenbeek et al., 2012), a voluntary organization has the ability to increase the number of potential offenders and targets in a neighborhood simply through the increased foot traffic that results.

WHY THE MIXED RESULTS FOR VOLUNTARY ORGANIZATIONS?

We are confronted with an empirical puzzle: On the one hand, numerous theories posit that the presence of voluntary organizations in a neighborhood will reduce the level of crime, and yet the empirical evidence for this proposition is weak (Slocum et al., 2013). What explains these mixed results? We propose four different *theoretical considerations* that could explain these mixed results and point to the importance of understanding the dynamic nature of voluntary organizations within neighborhoods.

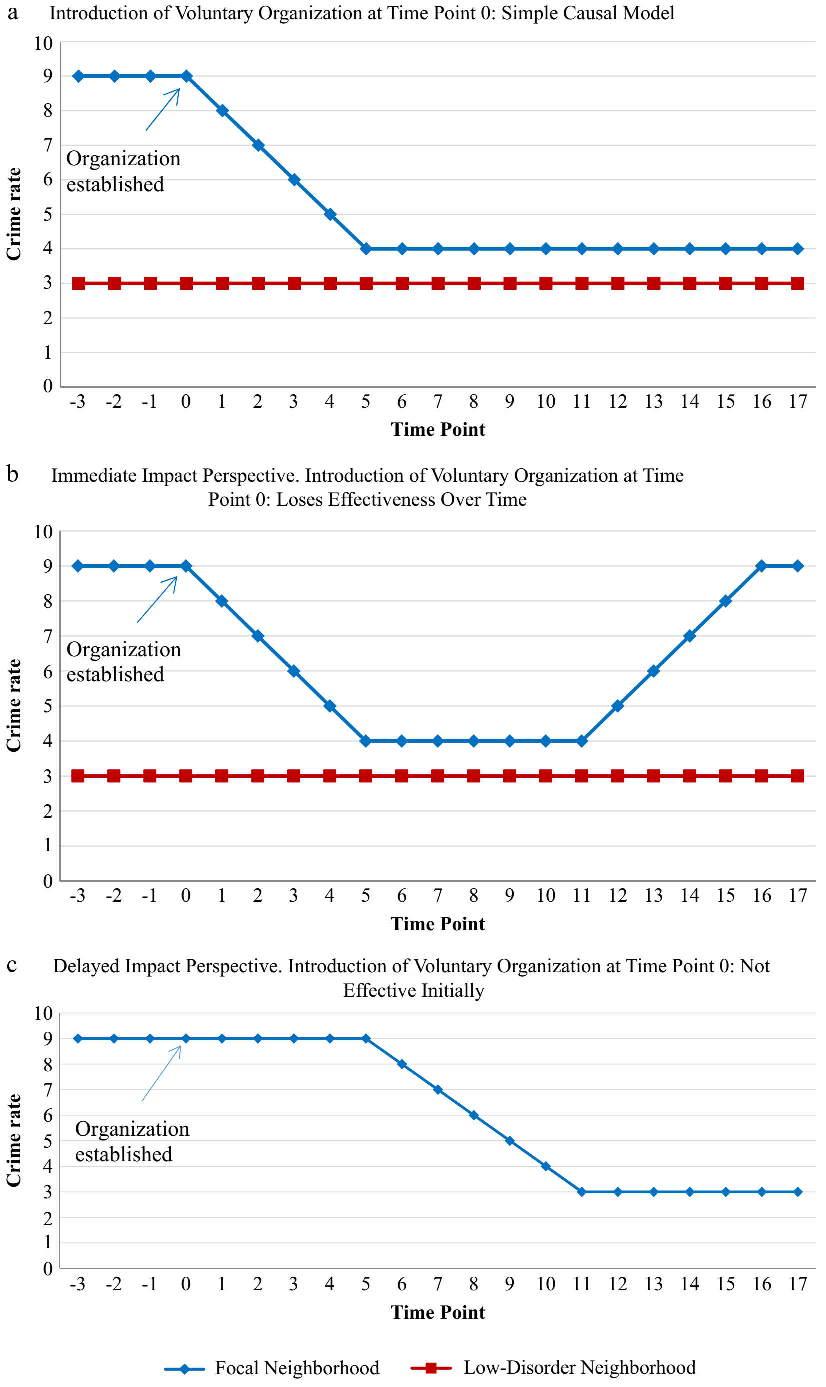
The first theoretical consideration regards the *temporality* of the posited causal model. One simplified version of the causal model is depicted in figure 1a, in which the crime rate is plotted on the *y*-axis and time is plotted on the *x*-axis. At the earliest time point observed, the neighborhood experiences a particular level of crime. Then at "time point" 0, a voluntary organization is established in the neighborhood. If this really helps the neighborhood, then we should see a decline in the crime rate as depicted here. Yet existing theories are not clear on how long, or how steep, this decline will be. Certainly it will not last forever and presumably would not drive crime rates all the way to zero. But after some period of time, we would expect crime to level off at a new, lower equilibrium level as depicted here beginning at time point 6.

There are some implications for this model. First, some scholars have attempted to detect the effect of voluntary organizations by time-lagging them and determining their effect on crime rates in subsequent years. Figure 1a makes clear that such a strategy will only work if the voluntary organization is relatively new; if we view the neighborhood between time points 0 and 5 (the top line), the presence of the voluntary organization will indeed be associated with lower crime rates the following year. However, if we were to view this neighborhood after time point 5, the presence of a voluntary organization would be associated with no change in crime. This is because the neighborhood has achieved a new equilibrium and crime is not changing any further. This poses a problem for studies that wish to look at the effect of voluntary organizations on changing neighborhood crime: Essentially, such studies would need to examine voluntary organizations that are *relatively new*. By "relatively new," we mean organizations that are still in the phase in which crime rates are falling and have not yet achieved the new, lower equilibrium.

On the other hand, figure 1a implies that a cross-sectional model should indeed detect a negative relationship between voluntary organizations and crime. That is, this neighborhood has now achieved a new, lower equilibrium crime level and if it were compared with another neighborhood similar on all characteristics (except the presence of a voluntary organization), it would have a lower level of crime, especially if the organization is more than 5 years old. Given that studies often do not document such a negative relationship in cross-sectional studies, this theoretical model likely does not capture the entire process.

The second theoretical consideration regards the possible varying effectiveness of organizations over time. This is based on the *organizational life-course* literature (Kimberly and Miles, 1980; Stevens, 2002; Whetten, 1987) and suggests that the dynamic nature of voluntary organizations might impact neighborhood crime over time in different ways. Research in sociology and management has suggested that organizations are dynamic entities that can exhibit characteristics associated with birth, maturation, innovation, decline, and death (Aldrich and Auster, 1986; Cameron and Whetten, 1981; Quinn and Cameron, 1983). This literature has revealed that organizations have a tendency to

Figure 1. Theoretical Models of Voluntary Organizations and Neighborhood Crime



transform over time with respect to financial capital, leadership, commitment, cooperation, and efficiency, thereby suggesting that recognition of these transformations is likely critical for understanding how voluntary organizations can affect neighborhood crime. Based on our reading of the organizational life-course literature, we propose two perspectives that may be particularly informative for understanding the time period in which organizations will be most effective for reducing crime: *immediate impact* and *delayed impact*.[1]

In the *immediate impact perspective*, the most effective organizations are those most recently established. In this view, recently placed voluntary organizations have a favorable and immediate impact on the neighborhood through the provision of services and the facilitation of common values and goals. These organizations have a sufficient stock of funding and committed volunteers willing to carry out the goals of the organization. As a result, they can provide resources to residents that help curtail crime for several years. However, over the course of time, these same organizations may lose their ability to address the needs and concerns of residents because of common challenges such as decreases in morale, lack of long-term planning, and reductions in financial capital (Cameron, Whetten, and Kim, 1987; Fichman and Levinthal, 1991), and they will therefore lose their crime-inhibiting effect. This implies that their negative effect on crime will be reversed over time, as shown in figure 1b (the top line).

Comparatively, in the *delayed impact perspective*, the newest organizations will not impact neighborhood crime because organizations are first faced with the challenge of establishing a strong foothold in the neighborhood. That is, they face challenges in building trust with neighborhood residents along with membership and participation, and they must grapple with funding issues (Freeman, Carroll, and Hannan, 1983; Hager, Galaskiewicz, and Larson, 2004; Stinchcombe, 1965). This implies that recently established voluntary organizations would not impact neighborhood crime; only after such organizations establish themselves would they impact crime. This implies a delay between the time of establishment of the organization and when it starts reducing neighborhood crime. This process is depicted in figure 1c. Despite the delay in organizational effectiveness, it would nonetheless eventually push the neighborhood to a new, lower equilibrium.

These considerations suggest that the impact of "newer" voluntary organizations on neighborhood crime rates will differ from that of "older" voluntary organizations. Consequently, we apply a dynamic organizational perspective—what we refer to as the *organizational life course*—that investigates whether the age of voluntary organizations underlies the relationship between such organizations and neighborhood crime.[2] If the organizational effectiveness of voluntary organizations is truly dynamic, previous studies

1. We are not aware of any specific authors or studies that have specifically used the terms "immediate impact" or "delayed impact"; however, several organizational scholars have broadly discussed how organizational effectiveness might be linked to organizational age (Whetten, 1987). In other words, we have adopted these terms to be consistent with the extant literature on organizational effectiveness and age.
2. Kimberly and Miles (1980) and Stevens (2002) advocated for theoretically similar perspectives, "The Organizational Life Cycle" and "Nonprofit Lifecycles," respectively. However, we choose not to adopt either of these terms because they place less emphasis on the temporal scaling (i.e., age) in which organizations are likely to change, nor do they apply how such change may impact the level of crime in neighborhoods.

that have used static organization measures—that is, constructing indices of organizations irrespective of the number of years organizations have been located in the focal neighborhood—may conflate various stages of the organizational life course. The limitation of this common approach is that it ignores the potential process in which an organization's resources, community support, membership, efficacy, effectiveness, or bureaucratic control changes over time.

The third theoretical consideration focuses on the possibility that the presence of a voluntary organization can bring about other changes in a neighborhood beyond impacting the level of crime. By building on the insights of routine activities theory and crime pattern theory (Brantingham and Brantingham, 1995; Felson and Boba, 2010), a voluntary organization will likely attract persons from outside the neighborhood to use its services. This influx of persons can increase the number of offenders and targets in a location, which can have consequences for crime. This suggests a more complicated causal process compared with figure 1a but similar to the immediate impact model in figure 1b. In this process, the introduction of the voluntary organization in a neighborhood initially has a negative effect on crime for a period of time (here it is from time points 0 to 5). Then, with the increasing influx of those using the services, the crime rate begins to reverse and increase from time points 11 to 16. How high it might rise is an empirical question: In this case, we show it returning to the initial equilibrium by time point 16. However, it is also possible that it may not return to such a high level or, alternatively, that it may reach an even higher level. Note that if the countervailing processes occur rapidly enough, one would not even observe a negative effect of organizations at all. This highlights the temporal uncertainty of this process as we cannot say definitively if it occurs over a period of weeks, months, or even years (Taylor, 2015). One implication of this model is that to capture the negative effect of voluntary organizations on crime requires measuring them in their early years in a neighborhood. A second implication is that a cross-sectional model of this process would find no effect of voluntary organizations on neighborhood crime if the countervailing process returns crime levels to the initial equilibrium point.

To estimate the model depicted in figure 1b requires either 1) precise temporal information on the placement of voluntary organizations or 2) measurements on both the impact of the services provided by an organization and the actual number of potential offenders and targets that are attracted to the neighborhood. Given that the latter would be extremely difficult to measure, we focus on an approach that applies precise temporal information to the placement of voluntary organizations.

The fourth theoretical consideration emphasizes the decision process through which voluntary organizations choose a location. It is likely that organizations that provide services choose to locate in neighborhoods nearer to more persons in need of such services (Peck, 2008; Small and McDermott, 2006; Small and Stark, 2005). For example, neighborhood crime watch organizations might be more likely to form in a neighborhood that experiences a spike in crime compared with neighborhoods with low levels of crime. It is less clear where social capital organizations might form. It may be that they are more likely to form in neighborhoods that are not in the worst shape. They may even form in neighborhoods with the *highest* levels of informal social capital, which might be useful when establishing such organizations.

There are important implications of this nonrandom selection process in which voluntary organizations choose where to locate. One implication is that we would expect service organizations to locate in the most disordered neighborhoods in need of such services. To the extent that such organizations are effective, they would achieve their largest target audience by locating in such needy neighborhoods. However, this has consequences for models estimating the relationship between voluntary organizations and crime. Most notably, if the statistical model does not measure the extent to which such neighborhoods are disordered, but leaves it latent, neighborhoods with such organizations will seem to have more crime simply because the presence of the organization is serving as a proxy of the extent to which it is a disordered neighborhood. This implies a causal model such as that shown in figure 1a where we now take into account the fact that the neighborhood begins with more crime than an otherwise similar neighborhood (the "low-disorder neighborhood" line) because of this latent characteristic, crime falls over time with the introduction of the organization, and then crime levels off at a new equilibrium, although still higher than the "low disorder neighborhood." If crime eventually begins to rise over time as a result of the consequences of organizational life-course or crime pattern theories, then the crime rate might rise back to its initially higher level in the neighborhood as shown in figure 1b.

An implication of this theoretical model is that a cross-sectional model that cannot account for the extent to which the neighborhood is disordered would conclude that a neighborhood with such an organization has more crime. This is an omitted variable problem, and it needs to be modeled. Another way to address this is to focus on the short-term effects during which crime is falling in response to the placement of the organization.

Overall, these dynamic considerations highlight the challenges inherent in estimating the possible effect of voluntary organizations on neighborhood crime rates. In the next section, we consider the diversity of organizations, as well as their possible impact on crime.

THE DIVERSITY OF VOLUNTARY ORGANIZATIONS

We suggest that different types of organizations may have different temporalities in their effect on crime as some may be more effective in their early age, whereas others may take several years to become effective. Although there are numerous possible classification schemes, we focus on seven different types of organizations that we broadly classify under three categories: social service organizations, bonding social capital organizations, and bridging social capital organizations—as we expect these classifications to reflect similar temporal trajectories in their mechanisms.

The provision of need-based *social services* is one mechanism in which voluntary organizations may impact neighborhood crime rates. When social service organizations are effective in improving the social circumstances of residents, these residents may be less inclined to resort to criminal behavior. Yet, it is possible, according to crime pattern theory, that social service organizations over time will attract more individuals to the neighborhood who are more likely to be offenders or targets, which might counteract the short-term benefits of such organizations. Criminological research has shown some evidence that social service organizations help to lower criminal dispositions and neighborhood crime, including youth development organizations (Gardner and Brooks-Gunn, 2009; Zimmerman, Welsh, and Posick, 2014), vocational organizations (Hipp, Petersilia, and Turner, 2010; Hipp and Yates, 2009), and mental health organizations (Wallace and Papachristos 2014). However, the literature also includes studies that have offered little-to-no evidence for the salutary effects of social service organizations on crime (Groff and

Lockwood, 2014; Morenoff, Sampson, and Raudenbush, 2001; Slocum et al., 2013). Given that social service organizations provide need-based services that might quickly affect the distribution of potential offenders and level of informal social control in neighborhoods, it is plausible that the placement of these organizations will follow the *immediate impact* scenario.

Another mechanism of voluntary organizations is that they might provide residents with a sense of *bonding social capital* (Beyerlein and Hipp, 2005; Putnam, 2000) and parochial social control (Hunter, 1985). According to social disorganization theory, voluntary organizations provide opportunities for local residents to participate in activities and events that encourage mutual trust and cohesion, develop generalized norms of reciprocity, and expand networks of effective social action (Rosenfeld, Messner, and Baumer, 2001; Sampson et al., 2005; Sampson and Groves, 1989), and we suggest this may occur in organizations with crime prevention programs and those that do recreational activities. One study found evidence of a protective effect of bonding social capital organizations while employing cross-sectional analysis (Peterson, Krivo, and Harris, 2000), whereas other studies did not find consistent evidence that they affected crime rates (Moore and Recker, 2013; Slocum et al., 2013; Wo, 2014). A few studies have highlighted the theory and policy behind crime prevention organizations (Garofalo and McLeod, 1989; Rosenbaum, 1987; Skogan, 1988), but a dearth of research remains on whether such organizations (e.g., Neighborhood Watch) actually influence neighborhood crime. Given that the formulation of cohesion and social ties can be a lengthy process, it may take an even longer amount of time before such ties operate as avenues of informal control (Taylor, 2015). Accordingly, the placement of voluntary organizations that foster bonding social capital may follow the *delayed impact* scenario.

Whereas bonding social capital refers to voluntary organizations that primarily facilitate intraneighborhood cohesion and social ties, a third mechanism of voluntary organizations suggests that *bridging social capital* works to build interneighborhood cohesion and social ties (Beyerlein and Hipp, 2005; Putnam, 2000). Bridging social capital organizations refer to community associations (Putnam, 2000) and philanthropy and civil advocacy organizations (Slocum et al., 2013). These organizations may help to strengthen the local area's institutions and provide public social control (Hunter, 1985). Similar to voluntary organizations that facilitate bonding social capital, organizations that induce bridging social capital would likely follow the *delayed impact* scenario. In fact, it might take longer for the protective effects of bridging social capital organizations to manifest (compared with bonding social capital organizations) given that bridging social capital relies on the formation of social ties and cohesion that span the focal neighborhood.

CURRENT STUDY OVERVIEW

The empirical consideration of organizational age is crucial because it captures potential changes that voluntary organizations undergo, as well as changes in the surrounding landscape, which in turn may have consequences for determining which voluntary organizations will be most effective in reducing neighborhood crime rates. It is therefore important to consider how different types of voluntary organizations might have different temporalities in their effect on crime. Accordingly, in this study, we test the relationship between age-graded measures of different types of voluntary organizations and crime rates on census blocks across 10 U.S. cities. We adopt a fixed-effects modeling strategy, which allows us to test changes *within* a particular neighborhood rather than *across* neighborhoods.

DATA AND METHODS

DATA

This study uses data from the National Center of Charitable Statistics (NCCS), the U.S. Census Bureau, and official crime data reported by police departments. The analyses use census blocks (N = 87,641) located across 10 U.S. cities from 2000 to 2010. These cities are a convenience sample of cities with at least 7 years of available crime data in the study period.[3] Therefore, the findings of our study do not generalize to the population of U.S. cities. Census blocks are the units of analysis because they have been shown to be an effective proxy for "neighborhoods" in community studies (Bernasco and Block, 2011; Hipp, 2007; Smith, Frazee, and Davison, 2000). All data are normalized to 2000 census block boundaries by using population-weighted interpolation when necessary.

DEPENDENT VARIABLES

The dependent variables are based on crime reports officially coded and reported by police departments (table 1). We geocoded these crime events by using a geographic information system (ArcGIS) and aggregated them to their corresponding census block year. This process produced for all cities a match rate greater than 90 percent, which exceeded Ratcliffe's (2004) proposed minimum reliable match rate of 85 percent. Therefore, the estimated models use the number of *robberies, aggravated assaults, burglaries, larcenies,* and *motor vehicle thefts* as outcome measures.[4]

ORGANIZATIONAL MEASURES

The NCCS is a longitudinal data source that contains information on tax-exempt nonprofit organizations, as determined by the Internal Revenue Service (IRS) and derived from its Business Master File. The NCCS data include information on an organization's address, activities/operations, and the date in which it received its recognition of exemption from the IRS (ruling date). We had data for each of the 11 years of the study, and if an organization were listed in a later year (e.g., 2010) but not in some of the earlier years (e.g., 2009)—but showed a ruling and listing date prior to the earlier years (e.g., 2008)—we considered it present in all of the intervening years.[5] We used ArcGIS to geocode all

3. The cities included in the study (with number of census blocks in parentheses) are Atlanta, GA (3,876); Chicago, IL (17,439); Cleveland, OH (4,501); Columbus, OH, (7,231); Dallas, TX (10,602); Fort Worth, TX (7,267); Los Angeles, CA (23,713); San Francisco, CA (4,502); St. Paul, MN (3,394), and Tucson, AZ (5,116). The cities have an average of 9.8 years of data, and each city contains a minimum of 7 years of data.
4. We do not use homicides as an outcome given that their rareness makes them difficult to model statistically in these longitudinal models with small geographic units. And we do not use rapes as an outcome given the known reporting issues with this type of crime. Chicago does not provide data on aggravated assault throughout the study period; therefore, models estimating aggravated assault use a smaller sample of census blocks (N = 70,202).
5. Although this is a rare feature of the NCCS data, we perform this interpolation method because there are instances in which a voluntary organization fails to report to the IRS in certain years.

Table 1. Descriptive Statistics

	Sample Statistics	
Predictors	**Mean**	**SD**
Crime (count)		
Robberies	.46	1.34
Aggravated assaults	.42	1.31
Burglaries	1.20	2.56
Larcenies	2.60	6.58
Motor vehicle thefts	.83	1.84
Voluntary Organizations (not age-graded)		
Youth development	2.85	5.77
Vocational	.91	3.06
Mental health	2.41	34.66
Recreational	2.38	6.06
Crime prevention	.40	1.75
Philanthropy and civil advocacy	22.27	132.86
Community associations	3.14	6.39
Block Characteristics		
Concentrated disadvantage	–.71	2.47
Residential stability	.02	.14
Percent White	41.89	4.30
Percent Black	22.98	3.39
Percent Latino	26.85	4.26
Percent Asian	6.01	2.09
Percent other race	2.28	1.41
Population count	125.72	30.97
Block Group Characteristics		
Concentrated disadvantage	–1.29	2.02
Residential stability	.07	.13
Percent White	41.03	4.30
Percent Black	23.22	3.30
Percent Latino	27.55	4.18
Percent Asian	6.01	2.02
Percent other race	2.19	1.33
Population density[a]	108.76	11.44

NOTES: Descriptive statistics are for all cities and years combined. The mean and standard deviation of the different types of voluntary organizations are in their original form (i.e., prior to group mean centering). The mean of the block and block group characteristics are in their original form, whereas the standard deviation refers to their mean-centered version. Number of blocks (except aggravated assault) = 87,641. Number of blocks (aggravated assault) = 70,202. The descriptive statistics for the mean-centered organizational predictors are presented in the online supporting information (table S.1).
ABBREVIATION: SD = standard deviation.
[a]Population density is measured in hundreds per square mile.

nonprofit organizations that were present sometime during 2000 to 2010;[6] therefore, we could calculate the number of such organizations with considerable geographic accuracy.

We created three sets of organizational measures. The first measure is an index of the total number of voluntary organizations that have been theorized to have a meaningful impact on neighborhood crime—an approach that mimics the most common approach

6. Percentage matched of those voluntary organizations with addresses for 2000 to 2010 = 95 percent. Approximately 20 percent of the voluntary organizations that are represented by the data for 2000 to 2010 provide zip code information only. As a result, we have evenly apportioned such organizations to those blocks that comprise the focal zip code.

in the literature (this measure and the next only include the organizations in the seven categories described shortly). The second set of measures capture the total number of voluntary organizations that have been in operation based on two-year age groupings up until 20 years, and then a single group of those 20 years or more.[7] The last set of measures captures specific categories of voluntary organizations in the same two-year age groupings. We used NCCS information on an organization's activities/operations to create three social service categories: 1) *youth development,* 2) *vocational,* and 3) *mental health;* two bonding social capital categories: 1) *recreational* and 2) *crime prevention;* and two bridging social capital categories: 1) *philanthropy and civil advocacy* and 2) *community associations* (for examples of the organization types that constitute these measures, see table A.1).[8]

Given that organizations not only impact the block on which they are located, but also are likely to have a broader spatial impact (with a distance decay), we created the organizational measures by using ArcGIS and Stata (StataCorp, College Station, TX) as the number of voluntary organizations within a ½-mile radius of the focal block based on an inverse distance decay function.[9]

NEIGHBORHOOD CHARACTERISTIC MEASURES

We control for other important neighborhood characteristics with measures of the local block from the U.S. Census for 2000 and 2010 and of the block group from the Census (2000) and the 2009 American Community Survey 5-year estimates (ACS).[10] Given that the census data are only available at the beginning and end time points, we used linear interpolation for the intervening years (Crowder, Pais, and South, 2012; Sampson and Sharkey, 2008; Wo, 2014). We constructed measures of *concentrated disadvantage* (aggregated to both blocks and block groups) based on factor analyses on the following variables: the percentage at or below 125 percent of the poverty level, the average household income, the percentage with at least a bachelor's degree, and the percentage of single-parent households.[11] For both blocks and block groups, principal components factor analyses identified one factor (with an eigenvalue above one) with all factor loadings

7. This largest bin (20 years or more) captures older organizations as we do not theorize organizational life-course differences beyond this point.
8. These categories are created based on the National Taxonomy of Exempt Entities (NTEE) codes—a classification system used by the NCCS that delineates different types of nonprofit organizations according to the activities and operations of organizations. Each voluntary organization is assigned a single NTEE code. For more details, see the following website: http://nccs.urban.org/classification/NTEE.cfm.
9. Although the radius distance is inherently arbitrary, some evidence suggests that a ½-mile radius effectively captures the broader spatial impact of various neighborhood factors on crime and is consistent with the journey to crime literature (Boessen and Hipp, 2015; Hipp and Boessen, 2013; Rengert, Piquero, and Jones, 1999).
10. The ACS 5-year estimates are for 2005–2009, which we use for 2007. Observations from years 2008–2010 are given this same value. We do not use more recent waves of the ACS given that they are in 2010 boundaries; apportioning from 2010 to 2000 boundaries arguably creates more error than using the 2005–2009 ACS data.
11. For the block-level version of the concentrated disadvantage measure, only the percentage of single-parent households variable is available. We therefore used an ecological inference technique that comprises ancillary data (McCue, 2011). See Boessen and Hipp (2015) for a more complete description of this approach. The variables used in the imputation model were as follows: percent owners, racial composition, percent divorced households, percent households with children,

greater than an absolute value of .7. We also constructed *residential stability* measures (aggregated to both blocks and block groups) by standardizing and summing two variables: percentage in same house 5 years previously and percentage of homeowners. We constructed measures of *percent Black, percent Latino, percent Asian,* and *percent other race* (with *percent White* as the reference category) in the block and block group. Lastly, we created a measure of *population* (in blocks) and another measure of *population density* (in block groups).

ANALYTIC STRATEGY

We adopted an analytic strategy that captures *within-neighborhood* change over time in the voluntary organizations and neighborhood crime relationship. This approach matches most of our theoretical considerations in that comparisons occur within a particular neighborhood rather than across neighborhoods. A fixed-effects model avoids the strong assumption of the random effects model that time-invariant unobserved variables are uncorrelated with the explanatory variables in the model (Allison, 2005, 2009). Whereas a common approach for estimating fixed-effects models is to include dummy variables for all subjects/units (excluding one), our large sample size ($N = 87{,}641$) makes this computationally infeasible. We therefore adopt a "hybrid approach" proposed by Allison (2009: 65–9) for count models in which we compute group mean variables for the time-varying measures and leave the outcome variables unchanged given that they are counts. Thus, we first computed a mean score for each neighborhood over the entire period, and then we subtracted this from the observed value at each time point.

Crime might affect where planners and entrepreneurs choose to locate voluntary organizations. The methodological implication is that the presence of a voluntary organization may vary in response to crime, inducing a potential reciprocal relationship, which in turn, jeopardizes the ability to determine accurately the unidirectional influences of voluntary organizations on crime. Accordingly, we time lag each of the mean deviation predictors by 1 year for organizations, block neighborhood characteristics, and block group neighborhood characteristics.

Given that the dependent variables of crime counts show overdispersion, we estimate fixed-effects models by using longitudinal negative binomial regression—a variant of Poisson regression that effectively deals with overdispersion (Osgood, 2000).[12] We include fixed effects for years and cities. The longitudinal models that we estimate can be expressed as follows:

$$y_t = \alpha + B_1\mathbf{X}_{t-1} + B_2\mathbf{Z}_{t-1} + B_3\mathbf{I}_{t-1} + B_4\mathbf{J}_t + B_5\mathbf{K}_t$$

where y is the number of crime events in year t, α is an intercept, $\mathbf{X}$ is a matrix of the organizational (mean deviation) predictors of the previous year, $\mathbf{Z}$ is a matrix of the block neighborhood characteristic (mean deviation) predictors of the previous year, $\mathbf{I}$ is a matrix of the block group neighborhood characteristic (mean deviation) predictors of the previous year, $\mathbf{J}$ is a matrix of the dummy variables for cities, and $\mathbf{K}$ is a matrix of the

percent vacant units, population density, and age structure (percent aged: 0–4, 5–14, 20–24, 25–29, 30–44, 45–64, 65 and older).

12. We estimate longitudinal negative binomial regression models with random effects that allow the dispersion parameter to vary across blocks (the Stata command: `xtnbreg`).

dummy variables for years. For all models, we included the population within the block as an exposure variable, and this estimates the outcome as a crime rate.

We found little evidence of spatial autocorrelation in our main models that explicitly account for block and block group characteristics (tables S.2 and S.3 in the online supporting information[13]). Specifically, we computed Moran's I values in ArcGIS for the types of crime and their corresponding residuals for the most recent year of each city. Whereas there is some spatial clustering of crime as the average Moran's I statistic (across cities) is .12 for robbery, .09 for aggravated assault, .13 for burglary, .08 for larceny, and .11 for motor vehicle theft, there is little spatial clustering of the residuals, with the average Moran's I statistics between .02 and .04. These small values provide evidence that the models have adequately accounted for most of the spatial autocorrelation. Additionally, we assessed and found no evidence of collinearity problems or influential cases.

We estimate three sets of models for each crime outcome that allow for different types and temporalities of voluntary organizations: 1) aggregated to the total number of voluntary organizations regardless of age of organization, 2) total organizations aggregated into two-year age groupings, and 3) organizations aggregated into two-year age groups based on the different types of voluntary organizations.

RESULTS

TOTAL VOLUNTARY ORGANIZATIONS

The first series of models assesses the relationship between crime and the total number of voluntary organizations, irrespective of age (table 2). We find that a block with more voluntary organizations in the surrounding ½ mile has lower crime rates (except for robbery) the following year with all else being equal. The aggravated assault model in table 2 suggests that voluntary organizations can provide crime-control benefits to neighborhoods that are substantively meaningful. Specifically, a 1 standard deviation (SD) increase in the total number of voluntary organizations reduces the aggravated assault rate 4.97 percent the following year ($\exp(\beta \times \mathrm{SD}) - 1$). Such organizations are also associated with lower burglary, larceny, and motor vehicle rates, although just 1 percent lower (at most) for a 1 standard deviation increase. Thus, there is modest evidence that voluntary organizations have a salutary influence on neighborhood crime. These weak results parallel much of prior research.

AGE-GRADED MEASURES OF TOTAL VOLUNTARY ORGANIZATIONS

The second series of models test whether the relationship between voluntary organizations and neighborhood crime differs based on stage of the organizational life course. Table 2 presents the coefficient estimates along with the results that test for equality of the two-year coefficients as a joint test (i.e., Wald test). For each crime model, we find that the coefficients are not all equal to each other, which implies temporal differences in the effects. Figure 2 visually presents these results as moving averages of each two-year coefficient with the coefficient for subsequent period (with 20 years or more as its own point). This approach smooths the results and allows for more interpretable general trends.

13. Additional supporting information can be found in the listing for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2016.54.issue-2/issuetoc.

Table 2. Longitudinal Negative Binomial Regression: Estimating Crime Rates Featuring Total Voluntary Organizations

Predictors	Robbery b (SE)	Robbery[a] b (SE)	Agg. Assault b (SE)	Agg. Assault[a] b (SE)	Burglary b (SE)	Burglary[a] b (SE)	Larceny b (SE)	Larceny[a] b (SE)	Motor Vehicle b (SE)	Motor Vehicle[a] b (SE)
Total Voluntary Organizations										
Not age-graded	.0001		–.0024**		–.0003**		–.0001*		–.0002**	
	(.0001)		(.0004)		(.0001)		(.0000)		(.0001)	
0–1 years		.0001		–.0025**		.0000		–.0001**		–.0000
		(.0001)		(.0007)		(.0001)		(.0000)		(.0001)
2–3 years		.0002†		–.0011		–.0001		–.0000		.0001
		(.0001)		(.0007)		(.0001)		(.0000)		(.0001)
4–5 years		.0000		–.0041**		–.0001		–.0001*		.0001
		(.0001)		(.0007)		(.0001)		(.0000)		(.0001)
6–7 years		.0002		–.0019**		–.0003		.0003		–.0005
		(.0004)		(.0007)		(.0003)		(.0002)		(.0003)
8–9 years		.0001		.0012†		–.0011**		.0004*		–.0019**
		(.0005)		(.0007)		(.0003)		(.0002)		(.0004)
10–11 years		–.0006		–.0017*		–.0020**		–.0000		.0026**
		(.0005)		(.0008)		(.0004)		(.0002)		(.0004)
12–13 years		–.0005		–.0018*		–.0022**		–.0005*		–.0024**
		(.0006)		(.0009)		(.0004)		(.0003)		(.0005)
14–15 years		–.0017*		–.0055**		–.0056**		–.0014**		–.0056**
		(.0007)		(.0010)		(.0005)		(.0003)		(.0006)
16–17 years		–.0031**		–.0086**		–.0035**		–.0020**		–.0028**
		(.0007)		(.0011)		(.0005)		(.0003)		(.0006)
18–19 years		–.0033**		–.0068**		–.0042**		–.0016**		–.0027**
		(.0007)		(.0012)		(.0005)		(.0003)		(.0006)
≥20 years		–.0006		–.0036**		–.0059**		–.0009**		–.0065**
		(.0004)		(.0009)		(.0004)		(.0002)		(.0004)

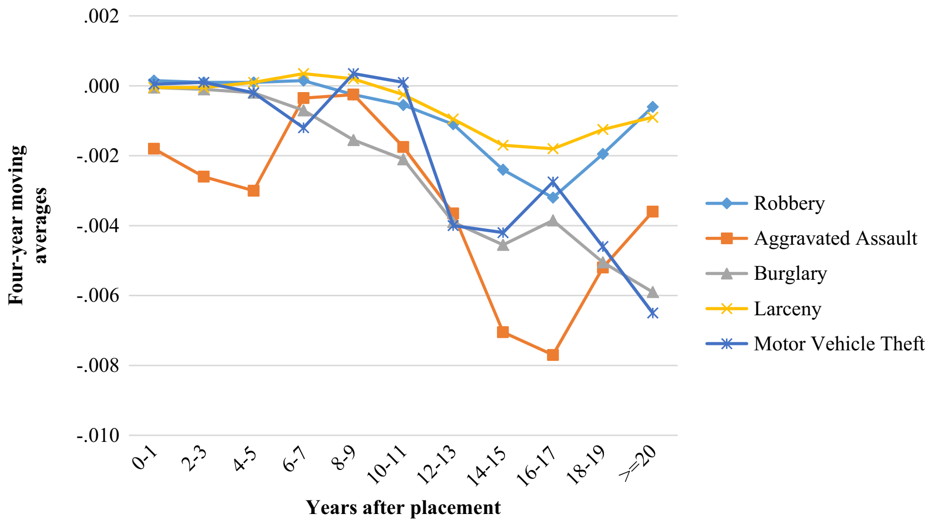
(*Continued*)

Table 2. Continued

Predictors	Robbery b (SE)	Robbery[a] b (SE)	Agg. Assault b (SE)	Agg. Assault[a] b (SE)	Burglary b (SE)	Burglary[a] b (SE)	Larceny b (SE)	Larceny[a] b (SE)	Motor Vehicle b (SE)	Motor Vehicle[a] b (SE)
Wald chi-square value		39.17**		102.91**		367.58**		74.07**		435.61**
Random Effects (logged)	1.9043	1.9051	1.6755	1.6765	2.0834	2.085	1.6716	1.672	2.4000	2.4066
	(.0137)	(.0137)	(.0126)	(.0126)	(.0083)	(.0083)	(.0065)	(.0065)	(.0111)	(.0111)
Dispersion (logged)	–.6534	–.6534	–.2470	–.2467	.7159	.7146	.5386	.5383	.4445	.4430
	(.0073)	(.0073)	(.0093)	(.0093)	(.0068)	(.0068)	(.0058)	(.0058)	(.0074)	(.0074)
N (Blocks)	87,641	87,641	70,202	70,202	87,641	87,641	87,641	87,641	87,641	87,641
N (Block-years)	782,055	782,055	625,104	625,104	782,055	782,055	782,055	782,055	782,055	782,055

NOTES: Models include fixed effects for cities and years. Coefficients and standard errors are rounded to four decimal places. This table only shows the results for the organizational predictors.
ABBREVIATIONS: Agg. = aggravated; b = unstandardized coefficient; SE = standard error.
[a]Corresponding results for block and block group characteristics are presented in table 3.
$^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$.

Figure 2. Marginal Effect of Total Organizations by Years After Placement on Five Crime Types



Except for aggravated assault, there appears to be a delay between the placement of a voluntary organization and lower rates of crime. For example, we observe little impact on burglary rates shortly after placement of a voluntary organization, but then after 8 years, there are lower burglary rates. A 1 standard deviation increase in the total number of voluntary organizations aged 12 or more years reduces the burglary rate between .61 percent and 2.20 percent the following year. In comparison, the delay between placement of a voluntary organization and lower crime rates involves a longer period of time for robbery, larceny, and motor vehicle theft. For larceny and motor vehicle theft, consistently lower rates are attributed to those organizations aged 12 or more years, whereas lower rates for robbery are indicated by those organizations aged 14–19 years. Aggravated assault rates are consistently lower over the organizational life course.

AGE-GRADED MEASURES OF DIFFERENT TYPES OF VOLUNTARY ORGANIZATIONS

The final series of models evaluates how seven types of voluntary organizations influence neighborhood crime at stages of the organizational life course. The regression coefficients are presented in the online supporting information (table S.2). We typically find that the coefficients for each type of voluntary organization are not all equal to each other, which implies temporal differences in their effects on crime. Figures 3a–3g plot the coefficient results as four-year moving averages for each type of voluntary organization. In addition to discussing organizational life-course patterns, we also provide the coefficient interpretations for selected organizational effects on crime. We argue that the coefficients are substantively significant given that each coefficient pertains to a single type of voluntary organization for just one stage of the organizational life course, as well as across a ½-mile area. Moreover, we will later demonstrate that several sociodemographic measures have similarly sized coefficients. We begin our discussion with organizations focused on providing social services.

Figure 3. Marginal Effect of Each Organization Type by Years After Placement on Five Crime Types

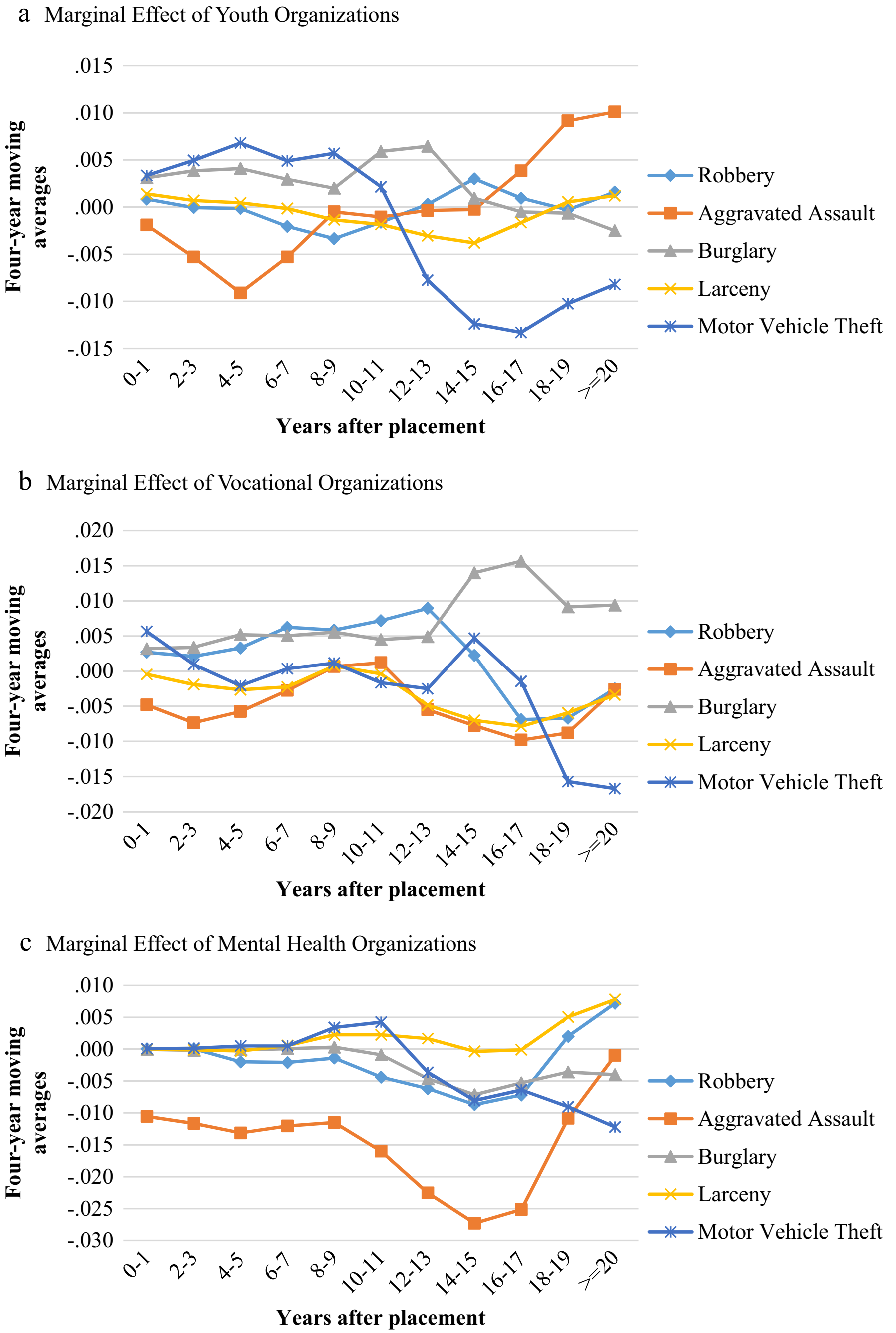
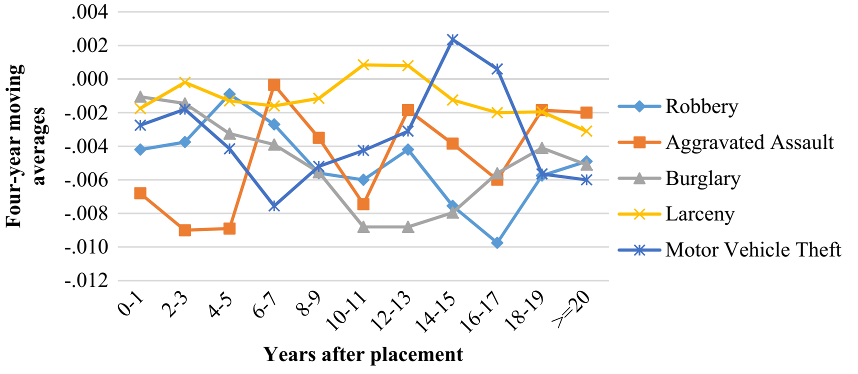
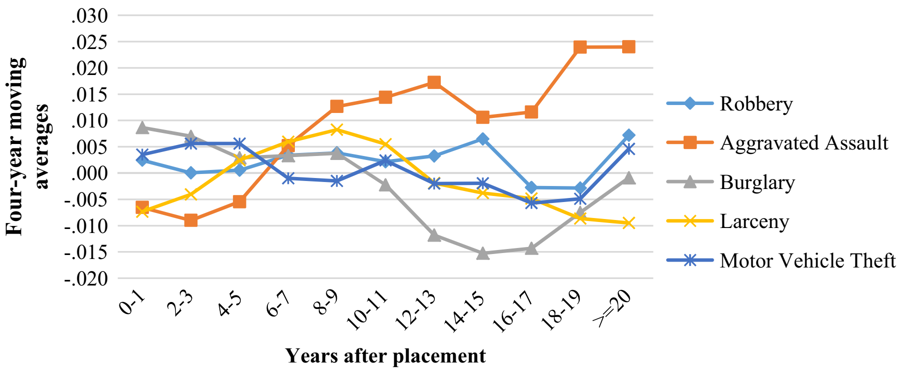


Figure 3. Continued

d Marginal Effect of Recreational Organizations



e Marginal Effect of Crime Prevention Organizations



f Marginal Effect of Philanthropy and Civil Advocacy Organizations

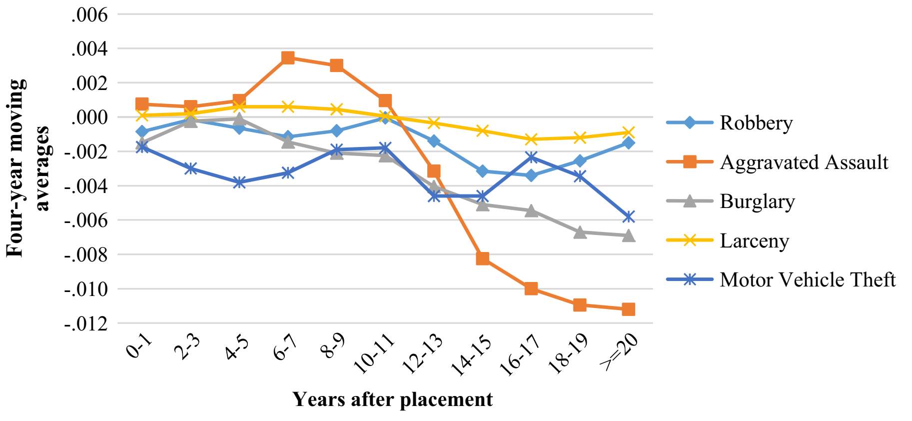
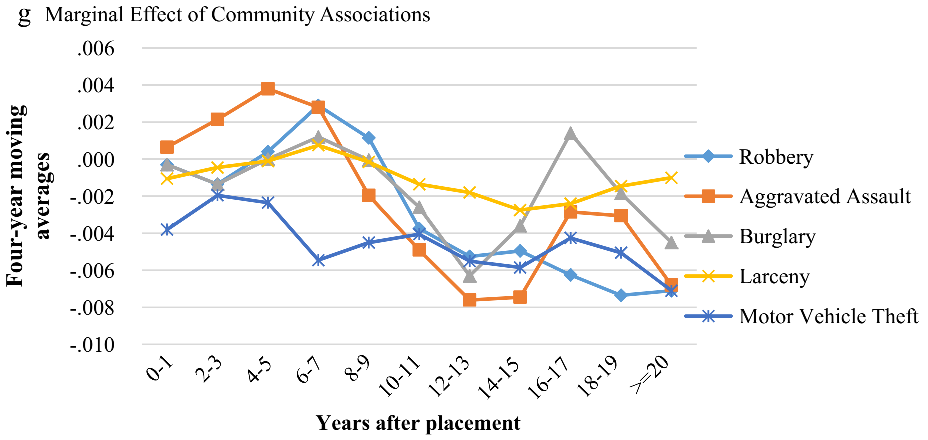


Figure 3. Continued



Social Service Organizations

The service organizations exhibit different patterns on crime across the organizational life course. For youth development organizations (figure 3a), the pattern is an immediate impact for aggravated assaults as a 1 standard deviation increase in these organizations in the first 7 years reduces the aggravated assault rate between .47 percent and 1.33 percent the following year; however, older youth development organizations are associated with higher aggravated assault rates beyond about 17 years in the neighborhood (between .44 percent and .84 percent higher for a 1 standard deviation increase). Youth development organizations demonstrate a delayed impact scenario for motor vehicle theft as they are associated with higher crime rates for the first 10 years or so but with lower crime rates after 12 years (between .4 and .93 percent lower for a 1 standard deviation increase). There is also a delayed impact of youth development organizations on larcenies as they are lower approximately 10–17 years after founding. There is no evidence that youth development organizations reduce burglary rates as burglary rates are higher near these organizations for the first 15 years before returning to normal. Furthermore, these organizations do not show a consistent pattern with robberies.

Vocational organizations demonstrate an immediate impact on aggravated assault rates, which are lower in the first 5 years or so after placement (approximately .5 percent lower for a 1 standard deviation increase), but then they generally return to normal over the life course (figure 3b). Such organizations also tend to have a negative relationship with larceny rates, regardless of the age of the organization. Whereas neighborhoods with vocational organizations have higher motor vehicle theft rates immediately after placement, these rates do turn negative after 18 years. There is no evidence that vocational organizations reduce burglaries; in fact, neighborhoods with such organizations almost always have higher burglary rates, particularly as the organizations age. Likewise, robbery rates near vocational organizations typically do not differ except that they are higher in the middle range of their existence of about 6–15 years.

Mental health organizations have the most pronounced negative relationship with aggravated assault rates. Neighborhoods with mental health organizations within less than 20 years of placement have consistently lower aggravated assault rates (figure 3c). In comparison, these organizations demonstrate a delayed impact scenario with robberies, burglaries, and motor vehicle thefts; the relationship with robbery drifts increasingly negative after 5 years, but then it becomes positive after 20 years. Burglaries are lower near such organizations after approximately 13 years. Motor vehicle theft rates remain normal or slightly higher for the first 13 years after placement, and then they are noticeably lower after that. There is no clear pattern for larcenies.

Social Capital Organizations

The predominant effects for the *bonding social capital organizations* are crime specific with some organizational life-course effects. For example, recreational organizations (bonding social capital) typically have a negative relationship with crime rates (figure 3d). Larceny rates are lower in the first year of such organizations, and aggravated assault rates are lower for the first 5 years or so. On the other hand, the relationship with burglaries is delayed: After 5 years, burglary rates are almost always lower (approximately .5 percent lower for a 1 standard deviation increase). Furthermore, motor vehicle theft rates and robbery rates are almost always lower regardless of the age of the organization.

Crime-prevention organizations show distinctly different relationships across crime types. On the one hand, such organizations have a delayed impact on burglaries: Whereas there are more burglaries in the first 3 years after the placement of a crime prevention organization, from 12 to 19 years after placement, there are lower burglary rates near such organizations of approximately .4 percent for a 1 standard deviation increase (figure 3e). On the other hand, whereas neighborhoods near crime prevention organizations seemingly have lower aggravated assault rates in the early years after placement, aggravated assault rates are higher near such organizations as they age (greater than 10 years). In the earliest stages of the organizational life course—the first 3 years—there are lower larceny rates near crime prevention organizations, and then again after 14 years. There is no pattern with robberies or motor vehicle theft.

Turning to the *bridging social capital organizations*, the philanthropy and civil advocacy category predominantly shows delayed impact crime-inhibiting effects (figure 3f). The violent crimes demonstrate the delayed impact scenario: Although aggravated assault rates are somewhat higher from 6 to 10 years after placement, approximately 13 years after placement, the relationships for aggravated assaults and robberies turn negative near these organizations. Whereas larceny rates are higher from 4 to 9 years after placement, they turn negative after 16 years, again reflecting a delayed impact. Motor vehicle theft rates and burglary rates are typically lower near philanthropy and civil advocacy organizations regardless of age (burglaries are 2.2 percent lower for a 1 standard deviation increase after 20 years).

The other bridging social capital organizations—community associations—also demonstrate a delayed impact scenario (figure 3g). For violent crimes, both robbery and aggravated assault rates are lower 12 years or so after placement (whereas aggravated assaults are actually somewhat higher in the earlier years after placement). Burglaries generally demonstrate a pattern of lower rates after 12 years or so, whereas larcenies are lower from approximately 10 to 20 years after placement. And motor vehicle theft rates are almost always lower regardless of age of the organization. The model for motor vehicle theft suggests that a 1 standard deviation increase in community associations reduces the motor vehicle rate between .32 percent and .62 percent the following year.

Table 3. Longitudinal Negative Binomial Regression: Estimating Crime Rates Featuring Block and Block-Group Characteristics

Predictors	Robbery[a] b (SE)	Agg. Assault[a] b (SE)	Burglary[a] b (SE)	Larceny[a] b (SE)	Motor Vehicle[a] b (SE)
Block Characteristics					
Concentrated disadvantage	.0018†	.0019	.0003	.0026**	.0001
	(.0011)	(.0013)	(.0007)	(.0005)	(.0009)
Residential stability	–.2040**	–.3178**	–.2242**	–.1173**	–.0427**
	(.0141)	(.0174)	(.0083)	(.0065)	(.0110)
Percent Black	.0029**	.0175**	.0017**	–.0022**	.0025**
	(.0009)	(.0010)	(.0005)	(.0004)	(.0007)
Percent Latino	.0047**	.0106**	–.0006	–.0040**	.0037**
	(.0008)	(.0009)	(.0004)	(.0003)	(.0006)
Percent Asian	–.0001	–.0021	–.0085**	–.0062**	–.0043**
	(.0013)	(.0015)	(.0008)	(.0006)	(.0009)
Percent other race	.0023	.0158**	.0032*	–.0009	.0025
	(.0021)	(.0025)	(.0013)	(.0010)	(.0015)
Population count	–.0008**	–.0007**	–.0006**	–.0006**	–.0007**
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
Block Group Characteristics					
Concentrated disadvantage	.0104**	.0256**	.0111**	.0008	.0043**
	(.0013)	(.0016)	(.0008)	(.0006)	(.0010)
Residential stability	–.0592**	–.0644**	–.0677**	–.0347**	–.0565**
	(.0158)	(.0200)	(.0101)	(.0078)	(.0124)
Percent Black	.0029**	.0029**	–.0001	–.0000	.0009
	(.0008)	(.0009)	(.0005)	(.0004)	(.0006)
Percent Latino	.0032**	.0058**	.0017**	.0005	.0013**
	(.0007)	(.0008)	(.0004)	(.0003)	(.0005)
Percent Asian	.0002	–.0026*	–.0014*	.0002	–.0010
	(.0012)	(.0013)	(.0007)	(.0005)	(.0008)
Percent other race	.0038*	.0151**	.0080**	.0006	.0083**
	(.0017)	(.0020)	(.0010)	(.0008)	(.0012)
Population density[b]	–.0000	–.0009**	–.0009**	–.0004**	–.0004**
	(.0001)	(.0002)	(.0001)	(.0001)	(.0001)
Random Effects (logged)	1.9051	1.6765	2.085	1.672	2.4066
	(.0137)	(.0126)	(.0083)	(.0065)	(.0111)
Dispersion (logged)	–.6534	–.2467	.7146	.5383	.4430
	(.0073)	(.0093)	(.0068)	(.0058)	(.0074)
N (Blocks)	87,641	70,202	87,641	87,641	87,641
N (Block-years)	782,055	625,104	782,055	782,055	782,055

NOTES: Models include fixed effects for cities and years. Coefficients and standard errors are rounded to four decimal places. Although table 2 presented organizational results for total voluntary organizations (not age-graded and age-graded), the corresponding results for block and block group characteristics are essentially the same. Hence, in this table, only the results using age-graded measures of total voluntary organizations are shown.

ABBREVIATIONS: Agg. = aggravated; b = unstandardized coefficient; SE = standard error.

[a]Models using age-graded measures of total voluntary organizations.

[b]Population density is measured in hundreds per square mile.

†$p < .10$; *$p < .05$; **$p < .01$.

NEIGHBORHOOD CHARACTERISTICS

We briefly consider the effects of the neighborhood demographic measures, which are generally consistent across all the crime models. The coefficients for these measures in the models with age-graded measures of total voluntary organizations are shown in table 3, and those from the models using age-graded measures of different types of voluntary organizations are shown in table S.3 in the online supporting information.

We find that block population and block group population density are almost always negatively related to all crime types. Although concentrated disadvantage generally has negligible effects on crime at the block level, more concentrated disadvantage at the block group level is mainly associated with higher crime rates. Conversely, more residential stability at both the block and block group levels translates to lower rates of all crime types. For the racial composition, whereas the percent Black, percent Latino, and percent other race in the block and block group are generally positively related to most crime types, the percent Asian is generally negative.

Finally, to give a sense of the magnitude of the organizational effects we described earlier, we interpret the size of a few of the neighborhood characteristics (from table 3). For example, we find that a 1 standard deviation increase in concentrated disadvantage at the block level increases the larceny rate .64 percent the following year. As another example, a 1 standard deviation increase in residential stability at the block level reduces the motor vehicle theft rate .60 percent. In terms of the racial composition, a 1 standard deviation increase in the percent Black at the block level increases the burglary rate .58 percent. Thus, historically robust predictors of neighborhood crime (i.e., concentrated disadvantage, residential stability, and the percent Black) can have substantive effects that are of a similar magnitude to those of the organizational predictors.

CONCLUSION

Although many theories posit that voluntary organizations have crime-reducing effects in neighborhoods, the empirical evidence for this proposition is mixed. We presented four theoretical considerations that could explain this mismatch between theory and data, and we emphasized the importance of understanding the dynamic nature of voluntary organizations within neighborhoods. Similar to how researchers of the life-course criminology tradition examine offending over some period of time (Laub and Sampson, 2003; Sampson and Laub, 1993)—recognizing that individuals and the environments in which they are situated can both experience changes—we argue that voluntary organizations and the neighborhoods in which they are located can experience changes that not only have consequences for statistical modeling but also, more importantly, determine the timing of when organizations are effective at reducing crime. The current study contributes to the extant literature by examining how organizational age reveals voluntary organizations' differential capacity to control crime in neighborhoods. We highlight four key findings.

The first key finding was that when we disaggregated the total number of voluntary organizations by age, we saw a relatively consistent delayed impact of voluntary organizations on crime over time. Given that there was often a delay between the placement of a voluntary organization and the focal neighborhood experiencing a reduction in crime, this suggests that voluntary organizations may need to mature over time along a host of dimensions (e.g., resources/funding, community support, membership, efficacy/effectiveness, and leadership) before they can meaningfully impact the distribution of offenders or the level of social capital in the neighborhood. These results when disaggregating voluntary organizations by age contrasted with the mixed results we found when adopting the traditional approach to studying voluntary organizations and not accounting for the age of the voluntary organization.

Our second key finding was that when disaggregating voluntary organizations by type, *bridging social capital organizations* most consistently exhibited the delayed impact effect. These organizations often exhibited a pronounced delay of approximately 10 years between the placement of an organization and when crime subsequently decreased in the neighborhood. These patterns suggest that bridging social capital voluntary organizations can help to address problems in the community but that they may require several years to become effective. Future research might extend these findings by examining the coordination efforts among different types of voluntary organizations to provide a triage of services over time, the network of key members (Sampson, 2012), and the links between voluntary organizations with other institutional resources (Ramey and Shrider, 2014), including schools and churches.

These results suggest distinguishing between intraneighborhood and interneighborhood processes of social control when considering organizational life-course effects. We posit that bridging social capital organizations generally followed the delayed impact scenario because it is inherently difficult for such organizations to combat challenges of being "new" and facilitating social ties and cohesion that span the focal neighborhood. This pattern suggests a process rooted in social disorganization theory as it focuses on longer term patterns of relationships in neighborhoods (Bursik and Grasmick, 1993). It follows that if bridging social capital organizations are to be effective in precipitating social organization, they may need to mature gradually along a host of dimensions so that they can adequately address geographic distance and a lack of familiarity among individuals, between organizations and individuals, and among organizations. Comparatively, such challenges may not inhibit bonding social capital organizations to the same degree, which may explain why in some instances recreational organizations were able to reduce crime in their early years and throughout subsequent stages of the life course.

Our third key finding was that several of the organization types exhibited a delayed impact effect on the three major acquisitive types of crime: robbery, burglary, and motor vehicle theft. For the social service organizations, there is likely a delay between an individual receiving need-based services and that person being able to make personal changes that reduce his or her likelihood of being an offender. To the extent that services help the recipient function economically, this may particularly impact offending for acquisitive crimes. For organizations generally, the organizational life-course literature has suggested that newly established organizations face inherent challenges coordinating tasks and roles, recruiting personnel with specialized skills, establishing a culture of initiative, and developing strong ties with individuals and other organizations (Freeman, Carroll, and Hannan, 1983; Hager, Galaskiewicz, and Larson, 2004; Stinchcombe, 1965), which may inhibit their ability to help residents.

The fourth key finding was that aggravated assault was the one crime type that consistently showed an immediate impact scenario (with the exception of the bridging social capital organizations). This was particularly the case for social service organizations: Whereas we theorized that the need-based services of these organizations might reduce the number of potential offenders and therefore exhibit an immediate impact scenario to reduce crime in neighborhoods, this was only the case for the expressive violent crime of aggravated assault. For both vocational and youth development organizations, aggravated assaults were lower in the earlier years of existence of these organizations. And mental health organizations showed an immediate impact that resulted in lower aggravated assault rates—the difference was that aggravated assault rates remained lower throughout the first 20 years of existence of mental health organizations. It was also the case that crime prevention organizations demonstrated the immediate impact scenario for aggravated assaults. It seems that there is something fundamentally different about this nonacquisitive type of crime that allows several of the organization types to have an immediate impact on them. Nonetheless, the effectiveness of several of the organization types for reducing aggravated assaults wanes over time. Future research might make more theoretical strides in how different types of organizations might be better suited for addressing certain types of crime. Organizations that focus on a specific crime type might be able to address problems more quickly and efficiently in their area similar to problem-oriented policing approaches (Braga and Clarke, 2014), rather than adopting an approach to curb all crime.

Although this study has provided important new insights for understanding the relationship between the presence of voluntary organizations and crime, we acknowledge certain limitations. First, although our findings illuminate the differential effects of voluntary organizations by their age, pinpointing the internal changes that occur within these organizational settings are beyond the scope of this study. Future research will want to measure organizational change in terms of membership/clientele, assets, employees, and general level of community support. Moreover, qualitative research may help to contextualize the immediate and delayed impact scenarios associated with organizational life-course theory. Second, we acknowledge that it is challenging to classify organizations based on their types of activities. Indeed, organizations that we classify into the same category may engage in different types of activities. Nonetheless, we believe that some of the differences over the organizational life course that we detected across these broad categories suggest that exploring organizations by using more fine-grained categorization schemes based on more detailed information may be a useful future direction. Third, given the sparseness of the organizational data when disaggregating to year of establishment, we required multiple cities to test the models and therefore lacked the statistical power to assess empirically the consistency of our findings across the individual cities by using simple meta-analyses. We have no reason to suspect city differences in organizational life-course effects and, therefore, combined blocks from the 10 cities; however, our results depend on our assumption. Therefore, future research will want to test organizational life-course effects on other cities with a large number of voluntary organizations in combination with a radius distance that exceeds the one used for the present study (1/2 mile). Fourth, this study assessed the influence of voluntary organizations on crime rates with longitudinal data by using yearly lags. An obvious extension is for future studies to assess how crime affects the placement of new voluntary organizations. An open question is whether nonprofit voluntary organizations tend to develop in neighborhoods that need them most. Finally, we acknowledge that official crime data are not void of measurement error given that not all crimes are reported and not all are recorded (Lynch and Addington, 2007; Mosher, Miethe, and Phillips, 2002). Nevertheless, we have no reason to suspect that these data are any less valid than other official crime data sources, and Baumer (2002) provided evidence that underreporting of Part 1 crimes is not systematically related to neighborhood disadvantage.

Our findings suggest that policies and evaluations of neighborhood programs may need to be considerably longer (i.e., for at least several years). Whereas some research has highlighted that many neighborhood problems might be quickly addressed through focused deterrence (Braga and Clarke, 2014), many neighborhood problems are much more long standing and durable (Sharkey, 2013). Making matters even more complicated, many policy makers frequently want immediate solutions, and funding streams are often only for a few years. Our findings suggest that voluntary organizations can be protective for neighborhoods, but they sometimes take considerably more time with a delay in reaping benefits from them. The mixed findings in the existing literature for voluntary organizations may simply be a result of not examining and evaluating them over a long enough time span. Even if we use the most rigorous evidence-based techniques, our findings remind us that this is not enough as we need to consider the temporal dynamics associated with the process of interest. Voluntary organizations may help to reduce crime, but they are not short-term fixes; rather, they are often a part of long-standing challenges in communities that need considerable time to mature and cultivate relationships with the local community.

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APPENDIX A.

Table A.1. Examples of Organizational Measures

Youth Development	Crime Prevention
Youth Centers	Citizen Patrol
Adult, Child Matching Programs	Delinquency Intervention
Scouting Organizations	Drunk Driving Related
Youth Community Service Clubs	
	Philanthropy and Civil Advocacy
Vocational	Public Foundations
Employment Procurement Assistance	Charities
Vocational Training	Minority Rights
Vocational Counseling, Guidance and Testing	Disabled Persons' Rights
	Women's Rights
Mental Health	LGBT Rights
Counseling and Support Groups	Civil Liberties
Mental Health Disorders	
Substance/Alcohol Treatment	Community Associations
Rape Victim Services	Community/Neighborhood Development
	Community Coalitions
Recreational	Neighborhood/Block Associations
Physical Fitness and Recreational Facilities	
Community Recreational Centers	
Recreational, Pleasure, or Social Club	
Sporting Camps	

ABBREVIATION: LGBT = lesbian, gay, bisexual, and transgender.

SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Table S.1. Descriptive Statistics for Mean-Centered Organizational Predictors
Table S.2. Negative Binomial Regression: Estimating Crime Rates Featuring Age-Graded Measures of Different Types of Voluntary Organizations
Table S.3. Negative Binomial Regression: Estimating Crime Rates Featuring Block and Block Group Characteristics