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Neighborhood Organizational Resources and  
Spatial Inequality in Urban and Suburban America

A dissertation submitted in partial satisfaction of  
the requirements for the degree Doctor of  
Philosophy in Sociology

by

Nicholas Vincent DiRago

2024

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## ABSTRACT OF THE DISSERTATION

### Neighborhood Organizational Resources and Spatial Inequality in Urban and Suburban America

by

Nicholas Vincent DiRago

Doctor of Philosophy in Sociology

University of California, Los Angeles, 2024

Professor Edward T. Walker, Chair

While it is widely recognized that urban organizations can influence neighborhood effects and spatial inequality in the United States, it often remains unclear how and how much organizations matter. This dissertation advances a flexible approach to analyzing organizational determinants of urban inequality. Applicable upstream and downstream, this approach can clarify how organizations broker goods, services, and social ties within communities and how organizations govern communities and allocate resources across places. The dissertation's foundation is a suite of metrics for neighborhood organizational resources (NORs) that reflects the porous nature of neighborhood boundaries, captures contact between residents and organizations, and distinguishes between organizational quantity and size. Seven novel measures are introduced, compared to conventional metrics, and applied empirically to organizational action at multiple levels. One set of analyses uses smartphone mobility data to capture how routine organizations facilitate micro-level interactions and transactions, including the case of grocery stores and disparities in food access. A second set of analyses turns to macro-level organizational action in the housing and community development sector, testing whether nonprofit housing developers influence the spatial distribution of new low-

income housing subsidized by the Low-Income Housing Tax Credit. Estimating spatial models on a novel dataset spanning 30 American metropolitan areas over 14 years, at most weak evidence emerges of a causal link between NORs and subsidy allocations. This dissertation brings organizational determinants of urban inequality into sharper focus through attention to spatial boundaries, the relationships that connect organizations to individuals, and dynamics of dependence among organizations.

The dissertation of Nicholas Vincent DiRago is approved.

Min Zhou

Jennie Elizabeth Brand

Ann Owens

Edward T. Walker, Committee Chair

University of California, Los Angeles

2024

## DEDICATION

For Lyolya, for tomorrow.

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# Vita

## Education

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| B.A. in Philosophy and Government (minor in Justice and Peace Studies)<br>Georgetown University | 2014 |

## Articles and Book Chapters

- Gaddis, S. Michael, and Nicholas V. DiRago. 2023. "Audit Studies of Housing Discrimination: Established, Emerging, and Future Research." Pp. 93–106 in *The Sociology of Housing: How Homes Shape Our Social Lives*, edited by B. J. McCabe and E. Rosen. Chicago, IL: University of Chicago Press.
- Gaddis, S. Michael, Colleen M. Carey, and Nicholas V. DiRago. 2023. "Changes over Time in COVID-19 Vaccination Inequalities in Eight Large US Cities." *Socius* 9.
- Zhou, Min, and Nicholas V. DiRago. 2023. "The Trajectory of the Colour Line in a US Immigrant Gateway: Hyperdiverse Spatialization in Los Angeles." *Ethnic and Racial Studies* 46(11):2474–2501.
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## Selected Other Publications

DiRago, Nicholas V. Forthcoming. *Balancing Act: Low-Cost Lodging and Affordable Housing along the California Coast*. Los Angeles, CA: Better Neighbors LA.

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DiRago, Nicholas V. 2024. “Neighborhood Organizational Resources and Spatial Inequality in Urban and Suburban America.” Presented at the UCLA Lewis Center for Regional Policy Analysis, May 24, Los Angeles, CA.

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|                                         |      |
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# Introduction

## Neighborhood Organizational Resourcecs

The central concern of this dissertation is the organizational determinants of neighborhood inequality—i.e., how neighborhood effects and disparities between hyperlocal, spatially bound communities are mediated by the activities of organizations or by access to organizations—in the United States (US). In urban sociology and related fields, research on these organizational determinants often foregrounds micro-level interactive mechanisms at the expense of more distal, structural mechanisms, or vice versa. I advance a flexible approach that is applicable both to downstream organizational action that brokers goods, services, and social ties within communities and to upstream organizational action that governs communities and allocates resources across them.

This intervention draws from the “institutional resources” model of neighborhood stratification, the growing body of organizational studies in urban sociology, and the social-structural tradition in organizational sociology. Empirically, the common point of departure is a straightforward but often under-theorized or unmeasured distinction among three attributes of organizations: the locations of their brick-and-mortar establishments, the boundaries of any formal jurisdictions or catchment areas, and the actual spatial distribution of their clientele or constituencies. These attributes usually have different geographical contours because they correspond to distinct relationships between organizations and individuals. Reflecting these

through research design and theoretically motivated measurement can help open up the black box of neighborhood effects.

Much of the heavy lifting for this intervention falls on the idea of *neighborhood organizational resources (NORs)*. Rather than to introduce a wholly new concept, the aim of using this terminology is to clarify existing concepts that have blurred over time as researchers have developed them in diverging or uneven ways. With any luck, “NORs” mitigates confusion or ambiguity that can arise when the same words are used to describe different things, especially across subfields of sociology. I discuss the *organizational* element of “NORs” in greater detail in the next section, picking up on many of the threads elsewhere in the dissertation and leaving others for future investigation. First, I briefly address the *resources* and *neighborhood* elements of NORs.

The *resources* element of NORs is the most open, deliberately. One of the primary goals of this project is portability across spatial scales and social contexts. As an orienting device, Giddens (1984:16) provides a helpful definition of resources as “media through which power is exercised, as a routine element of the instantiation of conduct in social reproduction”; people use resources to influence the behavior of other people or the allocation of material objects, most often in routine or ordinary social contexts. To refer to resources as organizational is to say that an organization is the social actor that exercises power, over which power is exercised, or which acts as an intermediary in distributing resources.

The *neighborhood* element of NORs is also flexible, with some guardrails. NORs are aspects of places or spatially bound groups at the population level, not individual inhabitants or community members. The line between a useful contextual variable and the ecological fallacy will vary from case to case. As I use the term in these pages, however, NORs measure characteristics of a place or a spatially bound population. As a neighborhood-level construct, the spatial scale of NORs is hyperlocal, usually below levels such as cities and municipalities, school districts, counties, metropolitan areas, etc. in the US. While the concept may scale readily to higher spatial levels in many contexts, the theoretical motivation for

NOR measurement that I develop in this dissertation stems from sociological research on the neighborhood as a social, ecological, or spatial unit with hyperlocal boundaries that is often relatively internally homogeneous compared to the wider society.

## **Organizations, Deinstitutionalization, and Urban Poverty**

Much of American urban sociologists' current interest in organizations traces to a literature that Sampson (2012) calls the poverty paradigm and its critics. Researchers generally agree that a key component of political and economic restructuring since the 1970s for poor urban communities in the US is deinstitutionalization: withdrawal or abandonment by formal organizations, including but not limited to the devolution and retrenchment of the welfare state (e.g., Harvey 1989b; O'Connor 1999; Sugrue [1996] 2005; Gilmore 2008; Smith [1984] 2008; Wacquant 2009; Biles 2011; Sharkey 2013; Brenner 2019). Drawing heavily from the ecological tradition in urban sociology—which measured neighborhoods' social organization in part by whether they had dense populations of formal community-based organizations, among other typical attributes of middle-class White communities in the 20th-century US (Shaw and McKay 1942; Breton 1964; Burgess [1925] 1984; McKenzie [1924] 1984; see Korver-Glenn, Dantzer, and Howell 2021)—the poverty paradigm offered a provocative and influential framing of deinstitutionalization.

Beginning in the late 1980s, academics, think tanks, philanthropists, and policymakers developed partially overlapping concerns about social disorganization in poor, predominantly Black urban neighborhoods, which were increasingly segregated from White and middle-class populations (Jencks and Mayer 1990; Jencks 1991; Peterson 1991; Massey and Denton 1993; Jargowsky 1997; Sampson, Raudenbush, and Earls 1997; Sampson, Morenoff, and Gannon-Rowley 2002; Wacquant 2008; Wilson [1987] 2012; see Wacquant 2022). Some researchers argued that formal organizations fled US inner-cities so extensively that an “underclass” emerged, detached from the institutions that once tethered it to mainstream society.

The assumption that the urban poor widely and consequentially lacked formal organizational resources was one of the poverty paradigm’s central contributions to academic and policy debates (Wilson 1996; Ludwig, Duncan, and Ladd 2003; Small 2007; Gay 2012). In response, organizational variables proliferated in urban poverty research (see Small and Stark 2005; McQuarrie and Marwell 2009; Sampson 2012; Sharkey and Faber 2014; Clifford 2018; Marwell and Morrissey 2020). Some researchers analyzed organizational density directly or exploited it to proxy social organization; others tested specific organizational mechanisms of neighborhood inequality.

Empirical research on organizational density has challenged the assumption that poor neighborhoods tend to be organizational deserts. Neither the concentration nor capacity of local organizations in the urban US is a simple linear function of neighborhood socioeconomic composition (Galaskiewicz 1985; Small 2004, 2007, 2008; Small and Stark 2005; Small and McDermott 2006; Guthrie and McQuarrie 2008; Murphy and Wallace 2010; Sampson 2012; Galaskiewicz, Mayorova, and Duckles 2013; Marquis et al. 2013; Marwell and Gullickson 2013; Garrow 2014, 2015; Lam and McDougale 2016; Freeman Anderson 2017). Poor neighborhoods’ organizational densities covary with their ethnoracial composition, whether they are in a central city or suburb, the demographic composition of the metropolitan area, the amount and distribution of philanthropic resources, and policies and political dynamics at the local and regional levels, among other variables. These studies cast doubt on the utility of organizational density as a unidimensional indicator of community well-being.

Other research in US urban sociology has analyzed how organizations co-produce—not merely reflect—neighborhood conditions (see McQuarrie and Marwell 2009). It has usually taken one of two directions, one concerned with social integration and another concerned with systemic integration (Marwell and McQuarrie 2013). Studies of social integration explain micro-level interactive processes through which urban organizations bridge social networks, build social capital, spread information, and shape how individuals and communities understand their spatial environments (e.g., Duneier 1992; McRoberts 2003; Pattillo 2007; Small, Jacobs,

and Massengill 2008; Small 2009; Curley 2010; Tran et al. 2013; Zhou and Lee 2013; Hunter et al. 2016; Bell 2020). Studies of systemic integration explain how organizations mediate among markets, the state, philanthropy, and local communities to mobilize residents and secure or distribute resources (e.g., Sampson et al. 2005; Marwell 2007; Zhou 2009; Levine 2013, 2016, 2021; Marwell and Gullickson 2013; Vargas 2016, 2019; Wo, Hipp, and Boessen 2016; Sharkey et al. 2017; Telep and Hibdon 2018; Hwang and Suárez 2019; Robinson 2021). Research on systemic integration has consistently found that, all else equal, poor neighborhoods with few or low-capacity organizations are at a disadvantage—although political and economic structures circumscribe even the most effective community organizations. From the social integration perspective, urban organizations matter primarily because they link people to other people; from the systemic integration perspective, urban organizations matter primarily because they link groups, often bound in space, to social structures.

Taken together, studies of organizational density and research on social and systemic integration refine oversimplified stories of deinstitutionalization. In US urban neighborhoods that firms and the state underserve, residents' well-being is particularly dependent on other organizations' interventions (Allard and Small 2013). It is more productive, however, to study deinstitutionalization as variation in the organizations serving poor urban neighborhoods than as uniformity in the organizations that are absent from them. Analyzing organizational heterogeneity as a dimension of complex processes helps explain spatial inequality without exoticizing, romanticizing, or moralizing about the urban poor (see Crenshaw 1989; Wacquant 2002; Small 2008, 2015; Rios 2011; Hunter and Robinson 2016). It jettisons a preoccupation with social disorganization that is often White-centered or exoticizing in favor of empirical sensitivity to how organizations shape interaction, production, distribution, and stratification.

## **Organizations, Institutionalization, and Urban Governance**

Affinity between urban sociology and the sociology of organizations is arguably greatest in studies that conceptualize organizations as social actors. According to the canonical

sociological definition, an organization is a formal social group with a hierarchical division of labor among a limited set of members that can reliably compel third parties to benefit some constituency (Weber [1968] 1978:48–53, 952–54). Stinchcombe ([1965] 2013:142) defines an organization as a “set of stable social relations deliberately created, with the explicit intention of continuously accomplishing some specific goals or purposes. These goals or purposes are generally functions performed for some larger structure.” Allard and Small (2013:9) offer urban sociologists a more relaxed definition of organizations: “formally recognized sets of people and practices whose activities are oriented toward an overarching purpose”. As all three definitions suggest, a foundational premise in the sociology of organizations is that treating organizations as goal-oriented social actors is sound. This premise is neither a metaphor nor a pragmatic tool for reducing dimensionality; for organizational theorists, it is an empirically adequate reflection of a defining, ubiquitous, and consequential type of actor in modern societies (Coleman 1990; Weber [1920] 2002; King, Felin, and Whetten 2010). More than the sums of their parts, organizations have lives of their own. They exhibit continuity and path-dependency over time despite turnover in their memberships.

Like individuals, organizations aggregate into populations that have vital indicators and other demographic attributes (Hannan and Freeman 1989; Hannan and Carroll 1992). Organizational ecologists typically measure populations at the level of organizational forms. Roughly analogous to species in natural ecology, organizational forms are archetypal combinations of goals, power relations, practices, and focus areas that are standard or appropriate in a given context (Romanelli 1991; Haveman and Rao 1997; Rao and Singh 1999; Greenwood and Suddaby 2006). The most common model of organizational populations is an inverted-U-shaped function of legitimation and competition. Where a form enjoys less legitimacy, fewer organizations of that form are founded, and more organizations fail. Legitimacy increases quickly as organizations of a form first emerge; it increases more slowly as more organizations are founded, fewer organizations fail, and competition increases. Eventually density reaches an upper bound known as the carrying capacity. Beyond this equilibrium, founding rates

fall, failure rates rise, and legitimacy wanes. An organizational form's carrying capacity may change over time because it can vary endogenously with legitimation and competition (Lomi, Larsen, and Freeman 2005). It may also differ across space due to endogenous dynamics between organizations and the geographic communities in which they are embedded (Freeman and Audia 2006; Marquis and Lounsbury 2007; Marquis et al. 2013). While cross-sectional measures of organizational density are sufficient in many empirical settings, organizational populations are dynamic life cycles that unfold over time and space.

Organizational interactions are institutionalized beyond the dynamics of emergence and survival. Like other social actors, organizations engage with one another and navigate social structures (Lounsbury and Ventresca 2002; Stinchcombe [1965] 2013). Institutions are durable social structures that constrain and enable organizational action through rules and regulations, normative standards, and cultural or cognitive systems of meaning (Zucker 1987; DiMaggio and Powell 1991; Clemens 1997; Scott [1995] 2014). Largely taken for granted in practice, institutions delineate what is permitted, morally justifiable, and expected or recognizable in a given context. On the one hand, institutionalization often leads to homogenization due to isomorphism among organizations; on the other hand, by narrowing down options, institutions provide organizations with repertoires of viable elements to recombine creatively in service of their goals.

Institutionalization happens at two fundamental levels: within communities and within organizational fields. At the community level, institutionalization is competitive, mostly endogenous, and occurs within spatially-bound, homogeneous populations of organizational forms; at the field level, institutionalization is hierarchical, mostly exogenous, and occurs across geographies, populations, and organizational forms (see Liu and Emirbayer 2016). At both levels, institutionalization is generally isomorphic.

Even in a globalized world, place and proximity remain salient to organizations, especially in metropolitan areas (Sassen [1991] 2001; Marquis and Battilana 2009). All else equal, organizations are typically more attuned to the activities of nearby organizations. Institutions

cohere within organizational populations in the same community, defined as a local spatial context (Lounsbury 2007; Marquis, Glynn, and Davis 2007; Marquis, Lounsbury, and Greenwood 2011). Community institutions are path-dependent: a community’s circumstances when an organization first emerges, such as available technologies, cast a long institutional shadow (Marquis 2003; Wry et al. 2010; Marquis and Tilcsik 2013). Isomorphism within local spatial contexts—known as community isomorphism—leads geographically proximate organizations to develop similar cultures, practices, norms, and logics.

At the same time, organizations take cues from beyond their immediate spatial environments. Some institutions cohere across geographies at the level of organizational fields—meso-level collectives of organizations that make up a recognizable domain, respond to or affect each other, and acknowledge shared purposes, hierarchies, and rules (DiMaggio and Powell 1983). Organizational fields are often sites of contestation over the power structure of the fields themselves (Bourdieu and Wacquant 1992; Martin 2003; Fligstein and McAdam 2015). They may correspond to sectors, industries, markets, networks, systems, and other conventional social orders, or they may combine or straddle them. Often comprised of nesting or overlapping subfields, organizational fields can be vast, encompassing the full range of actors that overlap with the social domain in question regardless of location or organizational form.

Ecological and institutional approaches to organizations are well-suited to analyzing urban governance, a common framework for recent political restructuring in the US and other industrialized urban areas (McQuarrie and Marwell 2009; Marwell and Morrissey 2020). In contrast with centralized and standardized resource distribution, urban governance refers to the “pursuit of collective goals through an inclusive strategy of resource mobilization” (Pierre 2005:449) in devolved and fragmented political systems. Austerity and interurban competition reward local governments that reduce expenditures and can act nimbly to attract investment (Harvey 1989a; Peck 2012, 2014; Theodore 2020). Public sector organizations have often responded by offloading policy, service delivery, economic development, and other

processes that organize urban life to networks of firms, nonprofits, civil associations, new agencies, and public-private partnerships (Smith and Lipsky 1993; Salamon 1995; Jessop 1998; Pierre 1999; Marwell 2004; Pacewicz 2016; McCann 2017; da Cruz, Rode, and McQuarrie 2019). These relatively horizontal, collaborative networks have varying levels of autonomy from the more vertical, partisan governing bodies that predominated US urban politics through the mid-20th century. In the process, “trial-and-error experimentation, more often than not under conditions of crisis” (Peck, Theodore, and Brenner 2009:52) yields novel political structures and organizational forms (Swyngedouw 2005; McQuarrie 2013). An urban governance framework refines the centralized and unitary conception of the state that predominated the poverty paradigm (Marwell 2016). Rather than diminishing state power, urban governance rescales the state—which is itself a set of organizations (Skocpol 1992)—over urban space (Swyngedouw 1996; Martin, McCann, and Purcell 2003; Brenner 2019). Urban governance intersects with three core concerns in the sociology of organizations discussed above: the emergence of organizational forms and their population sizes, meso-level organizational fields that mediate macro-level political structures, and the local dynamics that emerge among peers embedded in the same urban area.

Many social processes involve organizations without distinctively organizational dynamics. Heath and Sitkin (2001) differentiate among behavior that is relevant for organizations, behavior that happens within organizations, and behavior that is central to how organizations structure—i.e., organize—social action. They argue that distinctively organizational behavior lies in the third category, which includes institutionalization, legitimation, goal alignment, coordination, cooperation, and organizational adaptation or change. Clemens (1996:205) similarly argues that the “‘how’ of organization remains secondary to the ‘for what?’ and ‘for whom?’” in studies that focus on organizational density, treat organizations mainly as resources, or primarily measure the political orientation of an organization up against an *a priori* yardstick. Sociological studies of urban organizations would benefit making similar

distinctions. In other words, does it matter that an urban process occurs in an organizational context, or might it just as well have happened outside an organization?

## Comment on a Prominent Causal Model of Organizational Resources

Organizational research in urban sociology and the sociology of stratification has established that organizations play consequential roles in shaping neighborhood conditions and individual opportunities. The relative magnitude of their impact, however, is not as well understood. A promising avenue for advances in urban organizational research is to focus less on testing *whether organizations matter* and more on understanding *how much organizations matter*, especially alongside or compared to forces of markets and the state. Quantitative methods are well-suited to this question.

In quantitative and potential-outcomes approaches to causal inference, however, identifying organizations' causal effects on spatially bound communities is fraught. There is usually an endogenous relationship between organizational resources and social outcomes of interest. Organizations designed to address social problems often concentrate where those problems are more acute, while other organizations that are averse to disadvantaged areas will have less of a presence. As a result, it is typically difficult to isolate channels by which organizations affect neighborhood conditions from channels by which neighborhood conditions affect organizational populations or resources. In quantitative research, this feedback loop leaves conventional linear models and estimation techniques, including ordinary least squares (OLS), vulnerable to a bias known as simultaneity or reverse causality.

In recent years, prominent papers in sociology have dealt with the endogeneity between organizational resources and spatial disadvantage in a distinctive way (Sharkey et al. 2017; Messamore 2023). The model repurposes a strategy that Levitt (2002) deployed to overcome reverse causality in the relationship between policing and crime. While it has been applied at

the city level most prominently, the model could plausibly work at other spatial scales, and it is theoretically applicable across many organizational fields and forms. This portability makes the identification strategy a potential workhorse for a wide variety of research questions on organizational determinants of spatial inequality. In this comment, I evaluate how well the approach holds up, taking an organizational lens on this causal inference question.

## **“Community” Organizations and Crime**

Official crime rates fell precipitously in the 1990s and aughts across urban America. Sharkey et al. (2017) argue that “community” nonprofit organizations contributed substantially to this decline. Using longitudinal data on 264 cities from 1990 through 2014 and two-stage least squares (2SLS) estimation with an instrumental variable (IV), the authors attempt to identify the causal effect of the density of nonprofit organizations “whose activities focused on confronting violent crime and building stronger communities” (Sharkey et al. 2017:1227) on official rates of several serious crimes. The authors operationalize the explanatory variable, “community” organizations, as the per-capita density of legally recognized nonprofit organizations classified in one of five programmatic areas: crime prevention, substance abuse treatment, community development, workforce and job training, and youth programming. The outcomes are official per-capita rates of murder, violent crime, and property crime.

The authors estimate that, in typical cities, “community” organizations cut murder rates by nearly one-third, violent crime rates by nearly one-quarter, and property crime rates by about one-sixth. They find that the local average treatment effect (LATE) of an increase of one standard deviation in the density of “community” nonprofits was  $-29$  percent for murder,  $-24$  percent for violent crime, and  $-17$  percent for property crime over the 24-year period. Year over year, the estimated LATEs on the following year’s crime rates were  $-22$ ,  $-14$ , and  $-10$  percent, respectively. From these very large effect sizes, Sharkey et al. (2017:1236) conclude that “local organizations have tremendous capacity to play central roles in the fight against violence.” In addition to its contribution to the expansive academic debate on why

crime declined, this finding has major implications for policy, philanthropy, and the nonprofit sector.

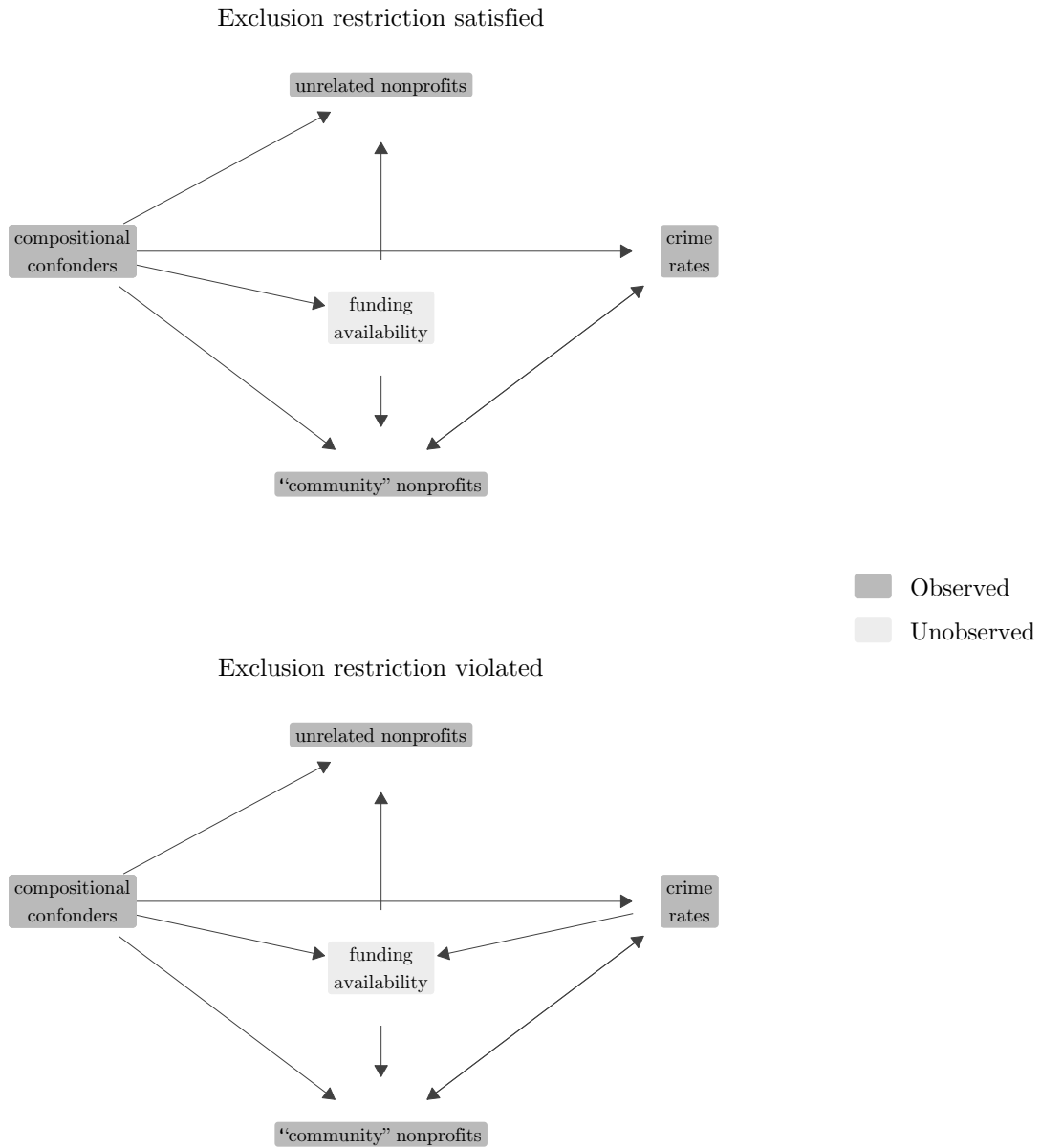
## **Unrelated Organizational Resources as a Surrogate Instrument**

Aside from omitted variables, which the authors address through covariate adjustment and fixed effects, the main threat to causal inference in the relationship between organizational resources and crime is simultaneity or reverse causality. An OLS estimate of a causal effect that is determined jointly with an outcome will be biased (correlated with the error term). If units with higher levels of an outcome are disproportionately exposed to higher values of the explanatory variable, then the OLS-estimated coefficient will be upwardly biased. In the context of the model in question, Sharkey et al. (2017) show that cities in their sample with higher crime rates tend to have more nonprofit organizations per capita. Simultaneity-biased models would be prone to underestimating “community” nonprofits’ crime-reducing effects or mischaracterizing them as crime-increasing.

To address simultaneity, the authors employ an IV design with time-lagged explanatory variables. The time lag partially mitigates reverse causality. The goal of the IV is to further purge endogeneity by exploiting an exogenous source of pseudo-randomization—the instrument—that isolates the causal association between the explanatory variable and outcome in at least a subset of the sampled cities (Angrist and Pischke 2009; Sovey and Green 2011). More precisely, the authors employ a surrogate instrument (or proxy instrument), a variable that does not cause the explanatory variable itself but correlates with it because both depend on the same unobserved variable, which is the underlying causal instrument (Morgan and Winship [2007] 2015; Felton and Stewart 2024).

The top panel of Figure 1 illustrates the authors’ conceptualization of their IV strategy as a directed acyclic graph (see Pearl [2000] 2009). The surrogate instrument is the density of nonprofits in the arts, health, and environmental sectors. The authors assume that organizations working in these domains “have nothing to do” with crime and violence

**Figure 1: Exclusion restrictions in two models of nonprofit organizational resources and crime with a surrogate instrumental variable**



(Sharkey et al. 2017:1225). These unrelated nonprofits are a good surrogate instrument, Sharkey et al. argue, because they are related to “community” nonprofits through common nonprofit sector funding structures, which are unobserved.

## **Exchangeability and the Exclusion Restriction**

There are two main reasons for concern about whether the model illustrated in the top panel of Figure 1 is sufficient to identify the causal effect of “community” nonprofit density on crime rates. The first issue, which Felton and Stewart (2024) also discuss in their didactic evaluation of Sharkey et al. (2017), is exchangeability: whether the model controls for all common causes of the causal instrument (nonprofit funding) and the outcome (crime). Assessing whether this relationship is confounded requires a reasonably clear picture of how the relevant nonprofit funding mechanisms work.

The authors provide little in the way of theory or empirical evidence about the link between the two kinds of nonprofits (the surrogate and causal instruments). They refer to “common mechanisms of funding availability,” the “broader funding landscape,” and how “cities adjust their rate of nonprofit formation” (Sharkey et al. 2017:1215, 1221, 1225, 1233). One potential interpretation is that the authors have in mind some version of resource dependence theory, a fuller version of which might focus on mechanisms such as funding stream diversification and inter-organizational competition (see Pfeffer and Salancik [1978] 2003; Hillman, Withers, and Collins 2009; Sacristán López de los Mozos, Rodríguez Duarte, and Rodríguez Ruiz 2016). Research on organizational emergence and nonprofit formation might also shed light on the factors that encourage the founding of new nonprofits and whether they are associated with crime (e.g., Katz and Gartner 1988; Brush, Manolova, and Edelman 2008; Andersson 2016). In the absence of a clear justification, however, it is hard to evaluate the exchangeability assumption.

The second issue—the exclusion restriction—is less ambiguous. The top panel of Figure 1 satisfies the exclusion restriction because the only causal pathway from the instrument to the

outcome is through the explanatory variable. Whether this is true is a theoretical question that cannot be tested empirically; it must be argued. The surrogate instrument setup means that the exclusion restriction must hold on two levels. First, the surrogate must satisfy the exclusion restriction: the density of arts, health, and environmental nonprofits must not be associated with the crime rate, directly or indirectly. Second, the underlying instrument must satisfy the exclusion restriction: the unobserved funding mechanisms that link the two types of organizations must be unrelated to crime rates.

If the alternative model in the bottom panel of Figure 1 is the correct one, then the exclusion restriction is violated. In this version, the arrow between the surrogate instrument and the outcome is bidirectional. If the crime rate affects nonprofit funding mechanisms directly, then a backdoor path opens from the explanatory variable to the underlying causal instrument: funding availability affects “community” nonprofits, community nonprofits affect crime rates, and crime rates affect funding availability. In this case, the IV strategy substitutes one endogenous loop for another rather than circumventing the endogeneity between “community” organizations and crime.

Organizational research provides support for the causal model in the bottom panel of Figure 1, showing that nonprofit funding availability frequently depends in part on crime rates. One example of compelling evidence that foundations and other funding gatekeepers respond directly to the crime rate when deciding how to allocate funding to community-based organizations comes from Sharkey (2018:39, 197):

In 2016 cities like Chicago and Las Vegas experienced a sharp rise in violence that provoked policy makers and heads of foundations to mobilize in response. . . . As an example, leaders of the largest foundations in Chicago convened an emergency meeting in mid-2016, inviting policy makers and researchers to develop ideas for how to respond to the surge in violence. They offered immediate resources to community groups who proposed the most innovative ideas to quell the violence.

In addition to increasing anti-violence funding when crime spikes, there is evidence that funders reallocate dollars away from violence-related issues when crime rates subside. For example, in the aftermath of the crime decline from 2011 to 2020, National Institutes of

Health (NIH) grants in the area of violence prevention decreased by 40 percent, more than any other area of grantmaking (Williams et al. 2022).

Causal paths from social conditions to nonprofit funding structures have appeared in other organizational fields and time periods. McAdam (1982) documents foundations' shifting preferences in support for civil rights organizations in response to the uprisings and riots of the 1960s in US cities. More recently, many foundations accelerated or initiated changes to their grantmaking practices to respond to changing needs during the COVID-19 pandemic or the increasing severity of climate issues (Lawrence 2022). According to a 2019 survey of family foundations, targeting the most pressing needs was the primary reason for current grantmaking priorities for one-third of foundations with a geographic focus and just under one-quarter of foundations with an issue-based focus (Born 2019).

## Implications

It is potentially possible that this general approach to identifying the causal effects of organizational resources would work under some very specific circumstances. But the burden of proof is high, and the default assumption should be that the exclusion restriction does not hold. In the case of crime, the model does not hold up to scrutiny. If what ties together the instrument and the surrogate instrument is the funding mechanisms of the nonprofit sector, there must be solid evidence that those funding mechanisms do not respond to the outcome variable. There certainly cannot be empirical reason to believe that the opposite is true. And if the reason that there is no backdoor path from the instrument to the treatment is that there are different funding mechanisms at play for the causal and surrogate instruments, then the theoretical link between the two instruments disappears. These issues point to the importance of attention to what is known empirically and theoretically about the organizational dynamics in the field under question. As wide as its applicability may seem, the appropriate cases for this approach to causal estimation are likely few.

## Outline of Empirical Chapters

The next three chapters are standalone empirical papers, tied together by a focus on organizational determinants of neighborhood inequality and a shared framework for NORs. The first paper, aimed at audiences interested in sociological methodology and spatial inequality, introduces the NORs framework conceptually with an illustrative empirical application that analyzes various routine organizations using smartphone mobility data. The same dataset is the basis of the second empirical paper. Prepared in the style of a general science journal, the paper explores NORs disparities by way of food access, focusing on grocery stores. In the third empirical paper, I shift from mainly descriptive to causal analysis and apply the NORs framework further upstream from routine organizations, analyzing NORs at the level of urban governance and economic development. I aim to identify community development corporations (CDCs)' causal effects on the spatial distribution of Low-Income Housing Tax Credit (LIHTC) allocations, targeting audiences across the sociological subfields of urban sociology, stratification, the sociology of housing, and organizational sociology.

In the first paper, I introduce a theoretically motivated framework for measuring NORs, a widely acknowledged mediator of neighborhood effects. The conventional measure of NORs, known as organizational density, often conflates residential neighborhoods with activity spaces, establishment locations with individual–organization relationships, and establishment quantity with size or capacity. To address these limitations, I develop measures of NORs that reflect that neighborhood boundaries are porous, capture contact between residents and organizations, and distinguish between quantity and size. In all, I introduce seven novel measures of NORs. I illustrate the framework by using smartphone mobility data to calculate the conventional and novel measures for 135,745 neighborhoods in the 100 largest American metropolitan areas. Across nine types of routine organizations, a single underlying dimension of NORs fails to emerge. The starkest divide is between the establishment- and contact-based measures. The measures that treat neighborhood boundaries as porous also differ considerably from

the measures that assume fixed boundaries. The magnitude and direction of the measures' covariance with neighborhood compositional variables often diverge widely, with major implications for model estimation. In contrast to the conventional unidimensional measure, NORs are multifaceted, and location only partially determines the routine organizations with which individuals interact. Choosing the right measure of NORs is a theoretical question about the nature of spatial boundaries, the relationships that link organizations to individuals, and dynamics of dependence among organizations. .

In the second paper, I further explore dimensions of neighborhood inequality that are differentiated by the metrics developed in the first paper, focusing on NORs in the form of grocery stores. I visually contextualize differences in the measures and explore ethnoracial and socioeconomic disparities in food access. .

In the third paper, I apply the framework for NORs farther upstream in the area of housing and community development. I test whether and how much the resources of CDCs affect the likelihood that neighborhoods receive an allocation from the LIHTC program. I assemble a novel dataset with 278,558 observations spanning 19,897 census tracts in 30 large metropolitan statistical areas (MSAs) from 2006 to 2019. To mitigate threats to causal inference, I combine elements of marginal structural models (MSMs), spatial lag of  $X$  (SLX) modeling, and lagged-outcome IVs to address time-varying confounding, spatial spillovers, and reverse causality. Effect sizes are substantial across the models, but in the most comprehensive models, the effect is statistically indistinguishable from zero. At the national level over the recent history of LIHTC, at most weak evidence emerges for a causal link between NORs from CDCs and LIHTC allocations. .

# Neighborhood Organizational Resources: Measuring Boundaries, Relationships, and Dependence

## Theorizing Neighborhood Organizational Resources

### Establishments, Organizations, and Neighborhoods

Research on spatial inequality has largely reached consensus on the basic premise of institutional resources theory (IRT), which holds that neighborhood organizational resources (NORs) mediate concentrated disadvantage (Sampson 2012; Clifford 2018; Marwell and Morrissey 2020). In addition to the well-known association between neighborhood composition and individual life chances, IRT assumes a link between neighborhood composition and NORs; in turn, NORs also directly influence life chances. If IRT is correct that neighborhood disadvantage runs partly through organizations, understanding NORs is a promising way to open up the black box of neighborhood effects by specifying inequality-generating mechanisms (Wacquant 2008; Allard and Small 2013; Sharkey and Faber 2014). In this way, IRT grounds a more relational approach to neighborhood inequality.

Understood relationally, stratification results from concrete relationships among actors with unequal structural positions; people, organizations, and the state actively stratify social groups (Wright 1997; Desmond 2014; Ray 2019; Tomaskovic-Devey and Avent-Holt 2019).

Relational theories of stratification motivate much of the growing organizational literature in urban sociology (McQuarrie and Marwell 2009; Marwell and McQuarrie 2013; Levine 2017) and the social-structural tradition in organizational sociology (Stern and Barley 1996; Lounsbury and Ventresca 2003; Stinchcombe [1965] 2013). By emphasizing relationships between individuals and organizations, IRT can bridge stratification research with these relational approaches. Compared to qualitative studies of how organizations reproduce and mitigate inequality, quantitative applications of IRT will tend to yield less robustly relational explanations because they distill relationships into variables within causal models (see Abbott 1997; Emirbayer 1997). Still, by integrating NORs into frameworks that are often relatively mechanical otherwise, IRT markedly increases insight into the underlying social relationships that stratify groups over space.

In practice, most studies of NORs are studies of *establishments*, the brick-and-mortar locations through which organizations operate. The standard conceptualization of an organizational resource, borrowing from Small and McDermott (2006:1698), is “any establishment that has a physical location and offers services or sells goods basic to day-to-day living.” From this perspective, the resources in question are establishments themselves, as opposed to the organizations they represent or the goods and services that organizations channel through them. The concept of NORs scales organizational resources to the neighborhood level, representing an aggregate property of establishments as a community attribute. This aggregation is relatively straightforward in the narrow sense of what Koschinsky, Marwell, and Mansour (2022) call the “container approach:” counting the number of physical establishments (or summing another establishment-level variable) within areal boundaries.

Mapping organizational resources to neighborhoods via establishments is less clean-cut from a relational perspective. *Organizations*—not establishments—are social actors that enter into relationships. Irreducible to their staff or members, organizations are goal-oriented agents that interact with individuals and other organizations, including organizations of the state (Coleman 1990; King et al. 2010; Scott [1995] 2014). Establishments enable organizational

action and social interaction, but they are sites or venues rather than actors. By the same token, while neighborhoods and communities are distinct social formations that decisively influence relationships, they lack the standalone agency that sets apart individual and organizational actors. From a relational perspective, an establishment-based measure of NORs passes sociological muster only if it captures relevant aspects of the relationships among organizations and residents that shape individual outcomes.

## Dimensions of Neighborhood Organizational Resources

Research in the IRT tradition can better reflect that organizations are social actors by attending to three dimensions of NORs: the nature of spatial *boundaries*, the structure of *relationships* between individuals and organizations, and the dynamics of *dependence* among organizations in a given field or industry. Each dimension concerns dynamics of organizations, as opposed to establishments. How well establishments' attributes capture or proxy these dimensions is a domain-specific question.

Relationships between organizations and individuals may strictly follow or freely cross areal *boundaries*, such as the borders between neighborhoods. While individuals' immediate residential environments shape their day-to-day activities, researchers increasingly recognize the difference between residential neighborhoods and activity spaces: where people live is distinct from where they spend time (Jones and Pebley 2014; Sharp, Denney, and Kimbro 2015; Levy, Phillips, and Sampson 2020; Browning et al. 2021). Most people routinely venture outside their home neighborhoods. By the same token, while some organizations—especially community-based organizations—target their activities and establishments in one neighborhood, many other organizations have establishments in multiple neighborhoods, wider or multiple service areas, or non-overlapping establishment locations and service areas (Galaskiewicz 1997; Levine 2013; Marwell and Gullickson 2013). Many studies, however, conflate establishments' brick-and-mortar locations with the geographical extents of their communities, constituencies, or catchment areas (Joassart-Marcelli and Wolch 2003; McDougale 2015). The

first key question for measuring NORs is whether it is safe to assume correspondence between establishment locations and residential neighborhoods.

Organizations shape individual outcomes through *relationships* at two causal levels: proximate causes within social networks and distal causes within institutional environments (Nee 2005; Marwell and McQuarrie 2013). The proximate causes, known as social integration, comprise interactive processes through which NORs create social ties, build social capital, spread information, and influence how people understand their communities (Oldenburg [1989] 1999; Small 2009; Zhou and Lee 2013; Hunter et al. 2016; e.g., Bell 2020). The distal causes, known as systemic integration, comprise how organizations navigate markets, the state, philanthropy, and local politics to mobilize residents and secure or distribute resources (Sampson et al. 2005; Marwell 2007; Vargas 2016; Marwell, Marantz, and Baldassarri 2020; e.g., Levine 2021). From the social integration perspective, organizations matter for spatial inequality primarily because they link people to other people; from the systemic integration perspective, organizations matter primarily because they link groups, often bound in space, to social structures. Neither social nor systemic integration necessarily occur in establishments, but proximate forms of brokerage typically depend more on gatherings in brick-and-mortar locations than more distal organizational functions.

Finally, NORs are subject to *dependence* among organizations. Like other social actors, organizations form populations (Hannan and Freeman 1989; Hannan and Carroll 1992) within which they compete for scarce resources (Galaskiewicz 1997; Marwell 2007; Vargas 2019; Levine 2021). According to the most common model of organizational populations, where a kind of organization enjoys less legitimacy, fewer organizations are founded and more organizations fail. Legitimacy increases as more organizations emerge and failure rates decline. The organizational population eventually reaches an upper bound known as the carrying capacity, which varies across space due to endogenous dynamics between organizations and their geographic contexts (Marquis and Lounsbury 2007; Marquis et al. 2013). In addition to the number of organizations in the population, carrying capacity may covary

**Table 1: Dimensions of neighborhood organizational resources (NORs) and corresponding measurement approaches**

| Dimension     | Key question                                                                                 | Measurement |                   |
|---------------|----------------------------------------------------------------------------------------------|-------------|-------------------|
| Boundaries    | Does movement across areal boundaries characterize access to organizations?                  | No          | Areal (A)         |
|               |                                                                                              | Yes         | Spatial (S)       |
| Relationships | Do establishments' locations accurately reflect residents' relationships with organizations? | No          | Contact (C)       |
|               |                                                                                              | Yes         | Establishment (E) |
| Dependence    | Do levels of organizational resources depend on organizations' sizes?                        | No          | Density (D)       |
|               |                                                                                              | Yes         | Mass (M)          |

with organizations' sizes, especially if larger organizations are more competitive (Haveman 1994; Ruef 2000; Barnett and McKendrick 2004). A population that grows regardless of organizations' sizes is known as density-dependent; if size is consequential, carrying capacity is mass-dependent. Research on NORs should consider whether the number of organizations matters more for securing and distributing resources than organizations' sizes or capacities. Domain knowledge of industries or organizational fields, including their maturity and perceived legitimacy, can help determine the structure of inter-organizational dependence.

## Aligning Measurement to Theory

### Measuring the Dimensions of Neighborhood Organizational Resources

The three dimensions of NORs—boundaries, relationships, and dependence—should be measured differently based on the organizational mechanisms under study. Table 1 distills each dimension into a binary question and identifies a measurement approach that corresponds to each option. According to this framework, the two variants of each of the three dimensions form eight basic measures of NORs. Table 2 summarizes the combinations. Consistent with the concept of NORs within the basic IRT model, the measures are attributes of communities

**Table 2: Measures of neighborhood organizational resources (NORs)**

| Measure                             | Description                                                                                                                 |
|-------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|
| Areal Establishment Density (AED)   | Number of establishments within areal unit                                                                                  |
| Areal Establishment Mass (AEM)      | Number of establishments within areal unit, weighted by establishments' sizes                                               |
| Spatial Establishment Density (SED) | Number of establishments within and around areal unit, weighted by distance from unit                                       |
| Spatial Establishment Mass (SEM)    | Number of establishments within and around areal unit, weighted by distance from unit and establishment sizes               |
| Areal Contact Density (ACD)         | Amount of organizational contact by residents of areal unit, regardless of travel distance                                  |
| Areal Contact Mass (ACM)            | Amount of organizational contact by residents of areal unit, regardless of travel distance, weighted by organizational size |
| Spatial Contact Density (SCD)       | Amount of organizational contact by residents of areal unit, weighted by distance from unit                                 |
| Spatial Contact Mass (SCM)          | Amount of organizational contact by residents of areal unit, weighted by distance from unit and organizational size         |

bound within neighborhood or other areal units. Depending on the nature of the areal units, the measures may require normalization by population.

Researchers can represent the *boundaries* of NORs through areal (A) or spatial (S) measures. The differentiating factor is whether understanding individual–organization relationships depends on knowing how people move across areal boundaries to access organizations. If so, it is necessary to use a spatial (S) measure, treating areal boundaries as porous or adjusting for the distance individuals travel to access organizations. If not, it is appropriate to use an areal (A) measure, which is limited to interactions within a given areal unit or unadjusted for travel distance. Researchers should opt for spatial (S) measures if they are concerned about ease of accessing organizations or suspect that spatial boundaries poorly reflect organizational service areas. Areal (A) measures may be appropriate if travel distance is less relevant or if a study's areal units are relatively self-contained with respect to a given organizational field.

Researchers can measure the *relationships* that underlie NORs in terms of establishments (Es) or contact (C). The differentiating factor is whether establishments’ locations can accurately reflect the relationships between individuals and organizations that shape neighborhood inequality. If so, establishment (E) locations alone may suffice. If not, researchers must find alternative measures that capture the relevant forms of individual contact (C) with organizations. No universal metric exists for contact (C) because the nature of individual–organization relationships varies across organizations and outcome variables. Establishment (E)-based measures are appropriate if accessibility is more important than how much residents actually access organizations. It is obviously also well-suited to organizational functions that tend to take place face-to-face within brick-and-mortar locations. Contact (C)-based measures are appropriate when establishment locations poorly predict concrete relationships or organizational functions depend less on in-person interaction.

The *dependence* between organizations can take the form of density (D) dependence or mass (M) dependence. The differentiating factor is whether levels of organizational resources depend on the sizes of the organizations that provide them. If so, measures based on mass (M), which are weighted by organizational size or capacity, are preferable. If not, density (D), a raw count, is sufficient. Researchers should use mass (M)-based measures for industries in which larger organizations enjoy a competitive advantage or can deliver resources more effectively than smaller organizations. Density (D) are appropriate where the reverse is true or if organizational sizes vary little.

The conventional measure of NORs in existing research is areal establishment density (AED), known as organizational density or the “container approach” (Marwell and Morrissey 2020). Table 3 shows how recent studies of NORs have measured the construct, using the framework I develop in this paper and the abbreviations listed in Table 2. As the rightmost column shows, AED is by far the most common metric. Yet without addressing the questions summarized in Table 1, defaulting to AED to measure NORs runs the risk of conflating organizational quantity with size or capacity, organizational location with community contact

**Table 3: Aspects of research design and measurement in selected quantitative studies of organizational resources with areal units of analysis**

| Study                                        | Areal Unit   | Industry        | Measure(s) |
|----------------------------------------------|--------------|-----------------|------------|
| Bielefeld, Murdoch, and Waddell (1997)       | Neighborhood | Nonprofits      | SED        |
| Allard, Rosen, and Tolman (2003)             | Neighborhood | Health care     | SED        |
| Allard, Tolman, and Rosen (2003)             | Neighborhood | Health care     | SCD        |
| Joassart-Marcelli and Wolch (2003)           | Municipality | Social services | AED/ACD    |
| Sampson et al. (2005)                        | Neighborhood | Various         | AED        |
| Small and Stark (2005)                       | Neighborhood | Child care      | AED        |
| Small and McDermott (2006)                   | Postal code  | Various         | AED        |
| Small (2007)                                 | Postal code  | Various         | AED        |
| Peck (2008)                                  | Neighborhood | Social services | SED        |
| Murphy and Wallace (2010)                    | Postal code  | Nonprofits      | AED        |
| Marquis, Davis, and Glynn (2013)             | MSA          | Nonprofits      | AED        |
| Marwell and Gullickson (2013)                | Neighborhood | Nonprofits      | ACM        |
| Garrow (2014)                                | Neighborhood | Social services | AEM/ACM    |
| Yan, Guo, and Paarlberg (2014)               | Neighborhood | Social services | AED        |
| Bauer, Monuteaux, and Fleegler (2015)        | Neighborhood | Social services | AED        |
| Garrow (2015)                                | Neighborhood | Social services | AED        |
| Lam and McDougale (2016)                     | Postal code  | Social services | AEM        |
| Freeman Anderson (2017)                      | Postal code  | Nonprofits      | AED        |
| Sharkey, Torrats-Espinosa, and Takyar (2017) | Municipality | Nonprofits      | AED        |
| Clifford (2018)                              | Neighborhood | Nonprofits      | AED        |
| Wo (2018)                                    | Neighborhood | Nonprofits      | AED        |
| Messamore (2023)                             | Municipality | Nonprofits      | AED        |

or spatial reach, and residential neighborhoods with activity spaces. Compared to using the standard measure, AED, in isolation, this approach provides a more versatile and holistic framework for measuring NORs. It distinguishes location from contact by including areal and spatial measures. The contact-based measures directly capture the spatial extent of organizations' reach by integrating visitors' spatial origins; the spatial measures model organizations' reach as a function of proximity. It also distinguishes quantity from quality by separately calculating organizational density and mass. And it distinguishes residence from activity spaces by including contact- alongside establishment-based measures, making it possible to disentangle levels of contact from physical proximity.

## Empirical Application

I illustrate this approach to measuring NORs by applying it to *routine organizations*. Per Small and Gose (2020:90), routine organizations are “organizations such as workplaces, churches, childcare centers, schools, soup kitchens, gyms, bars, neighborhood restaurants, community centers, and other establishments . . . [that] are arguably the primary means through which low-income—and other—populations form ties outside the family” Bell (2020:918) develops the similar concept of located or place-situated institutions, which include organizations such as “schools, churches, retailers, . . . certain industries, and . . . the police [that] operate as lenses through which people understand geographic communities.” Through the proximate mechanisms that routine organizations facilitate, poor and marginalized people form ties with their neighbors and make sense of their communities. Routine organizations also broker public or philanthropic resources that residents of more affluent communities can more easily acquire on the private market or from the state, sometimes by providing a venue for informal interaction through which neighbors learn about opportunities. In the context of a retrenched and devolved welfare state, routine organizations are vital nodes of social life for the urban poor.

Routine organizations provide tractable cases from which to build on the establishment-based approach to measuring NORs that predominates in existing studies. Because routine organizations work mainly by facilitating proximate brokerage, the main mechanisms of contact (C) between organizations and individuals are relatively clear and well-measured by in-person traffic to establishments.

I distinguish between two overarching categories of routine organizations: resource providers and third places. These categories entail different mechanisms of contact between individuals and organizations, which could be a source of heterogeneity in the dynamics of NORs. Resource providers are establishments to which people go primarily to buy or receive a good or service. Interaction occurs but as a means to an end in the relevant aspects of the organization–individual relationship for neighborhood inequality. Third places, by contrast, matter for stratification precisely because they facilitate everyday interaction (Oldenburg [1989] 1999).

To test for heterogeneity between and within the categories, I compute the NORs measures for organizational establishments in nine industries. I study resource providers in three industries: food providers, financial institutions, and non-hospital medical providers. Within food providers and financial institutions, I separately analyze two sub-industries that past research suggests may correlate with the demographic composition of neighborhoods. Within food providers, I compare grocery stores and convenience stores, a common point of comparison in research on food deserts. Within financial institutions, I compare banks and credit unions to alternative, often predatory financial institutions such as payday lenders and check cashing establishments. I analyze four industries that serve as third places: religious establishments, personal care (e.g., hair and nail care), bars, and cafes.

I address three research questions with respect to routine organizations:

1. Do the measures summarized in Table 2 converge on one underlying factor, suggesting NORs is a unidimensional construct? Or do they capture distinct factors, suggesting NORs are multidimensional?

2. If NORs are multidimensional, which dimensions summarized in Table 1 distinguish between aspects of NORs?
3. Do the measures covary differently with typical neighborhood compositional variables?

## Data and Methods

### Data

I constructed the dataset by combining smartphone-based mobility data, areal demographic estimates, and geospatial vector data. The analytic sample consisted of 135,745 census block groups (CBGs) with at least 100 estimated inhabitants across the 100 most populous metropolitan statistical areas (MSAs) in the United States of America (USA), reflecting a 53-week period spanning the year 2019.

I collected smartphone-based mobility data from SafeGraph (Hoffman 2018; Yu 2018; SafeGraph 2020b, 2020a). Aggregated from a sample of anonymized device-level location records acquired from wireless carriers, the SafeGraph data covered approximately 10 percent of USA-based smartphones, tracking traffic to more than 12 million formal establishments. SafeGraph used machine-learning procedures to match device locations to establishments; to assign establishments to industries according to the 2017 North American Industry Classification System (NAICS); and to identify devices’ “home” CBGs based on their nighttime locations over the preceding six weeks. SafeGraph provided weekly sample sizes by CBG and overall, enabling normalization across the panel. The panel ran from 2018 through 2022; by limiting the analysis to 2019, I avoided the distorting effects of any inconsistencies that surfaced in the panel’s earliest iterations and disruptions to mobility during the COVID-19 pandemic.

The smartphone-based data presented two major advantages. Unlike many commonly-used data sources in research on NORs, they provided insight into concrete contact with

establishments. By tracking both origins and destinations at a very local scale, the data allowed me to measure spatial dynamics more precisely than studies that only measure establishments’ physical locations. Additionally, the data encompassed a wide range of industries and organizational domains, extending well beyond the nonprofit organizations and social service providers that predominate existing research (see Table 3).

The smartphone data had several limitations (see Coston et al. 2021; Couture et al. 2022). SafeGraph sampled populations across CBGs proportionally to the US population (Squire 2019). The data, however, were not drawn from a random sample of individuals; they were drawn from a random sample of devices. For the smartphone data to represent the population, the distribution of smartphones within neighborhoods must be random. This assumption is tenuous. Measurement error was also likely. SafeGraph bottom-coded the number of unique visitors to each establishment per CBG on privacy grounds. The data processing methods—in addition to being proprietary and largely opaque to researchers—were necessarily approximate where device coordinates could correspond to multiple establishments or organizations, such as multi-story buildings or multi-organization establishments. These limitations are nontrivial. For the purposes of this analysis, however, the fundamental advantage of the smartphone data—concrete evidence of organizational contact via establishment visits—outweighs them.

I supplemented the smartphone data with demographic and geospatial data from the US Census Bureau’s 2015–2019 American Community Survey Five-Year Estimates and 2019 TIGER/LINE files.

## Measures

I calculated the NORs measures by CBG and industry, i.e. for CBG  $g$  and industry  $i$ , where  $j$  indexed establishments within industries;  $t$  indexed weeks;  $q_g$  was the estimated population of CBG  $g$ ;  $v_{gijt}$  was the total number of visits recorded to establishment  $ij$  in CBG  $h$  during week  $t$ , such that  $b_{gijt}$  indicated whether establishment  $gij$  received any recorded visits during week  $t$ ;  $u_{ghijt}$  was the count of unique sampled devices from home CBG  $g$  that

visited establishment  $ij$  in CBG  $h$  during week  $t$ ;  $r_{gt}$  was the number of devices in the sample for CBG  $g$  during week  $t$ .

AED measured the number of establishments in each industry that were located within each CBG. I calculated it as the average number of establishments that received at least one recorded visit over each of the 53 weeks in the sample:

$$AED_{gi} = f\left(\frac{1}{q_g T} \sum_{t=1}^T \sum_{j=1}^{J_{gi}} b_{gijt}\right) \quad (1)$$

Areal establishment mass (AEM) measured the number of establishments in each industry that were located within each CBG, weighted by establishments' sizes. I calculated it as the average number of visits to establishments that received at least one recorded visit over each of the 53 weeks in the sample:

$$AEM_{gi} = f\left(\frac{1}{q_g T} \sum_{t=1}^T \sum_{j=1}^{J_{gi}} v_{gijt}\right) \quad (2)$$

Spatial establishment density (SED) measured the number of establishments in each industry that were located within and around each CBG. It was a weighted version of AED, with farther establishments weighted higher and closer establishments weighted lower.

$$SED_{gi} = f\left(\frac{1}{T} \sum_{h=1}^n w_{gh} \sum_{t=1}^T \sum_{j=1}^{J_{gi}} b_{hijt}\right) \quad (3)$$

Spatial establishment mass (SEM) measured the number of establishments in each industry that were located within and around each CBG. It was a weighted version of AED, with farther establishments weighted lower and closer establishments weighted lower.

$$SEM_{gi} = f\left(\frac{1}{T} \sum_{h=1}^n w_{gh} \sum_{t=1}^T \sum_{j=1}^{J_{gi}} v_{hijt}\right) \quad (4)$$

Areal contact density (ACD) measured the amount of contact with organizations in each industry by residents of each CBG, regardless of travel distance. It was comparable

to AED but replaced the total number of establishments with the total number of visits to establishments.

$$ACD_{gi} = f \left( \frac{1}{T} \sum_{t=1}^T \sum_{\ell(g)} \sum_{j=1}^{J_{hi}} \frac{u_{ghijt}}{r_{gt}} \right) \quad (5)$$

Areal contact mass (ACM) measured the amount of contact with organizations in each industry by residents of each unit regardless of travel distance, weighted by organizational size. It was a weighted version of ACD, with larger establishments (those receiving more visitors) weighted higher.

$$ACM_{gi} = f \left( \frac{1}{T} \sum_{t=1}^T \sum_{\ell(g)} \sum_{j=1}^{J_{hi}} \frac{u_{ghijt} v_{gijt}}{r_{gt}} \right) \quad (6)$$

Spatial contact density (SCD) measured the amount of contact by residents of each CBG with establishments in each industry, weighted by distance. It was a weighted version of AED, with farther establishments weighted lower and closer establishments weighted lower.

$$SCD_{gi} = f \left( \frac{1}{T} \sum_{t=1}^T \sum_{\ell(g)} \sum_{j=1}^{J_{hi}} \frac{u_{ghijt}}{k_{gh}^2 r_{gt}} \right) \quad (7)$$

Spatial contact mass (SCM) measured the amount of contact by residents of each CBG with establishments in each industry, weighted by distance and establishment size. It was a weighted version of ACD, with larger establishments (those receiving more visitors) weighted higher.

$$SCM_{gi} = f \left( \frac{1}{T} \sum_{t=1}^T \sum_{\ell(g)} \sum_{j=1}^{J_{hi}} \frac{u_{ghijt} v_{gijt}}{k_{gh}^2 r_{gt}} \right) \quad (8)$$

The function  $\ell(g)$  returned the set of CBGs that were in the same MSA as CBG  $g$  or in an adjacent county to the MSA; and  $k_{gh}$  was the number of kilometers between CBGs  $g$  and  $h$ , such that  $w_{gh}$  represented the share of influence on unit  $g$  attributable to unit  $h$  and  $W$  was a row-standardized inverse-squared distance spatial weights matrix.

$$b_{gijt} = \begin{cases} 1 & v_{gijt} > 0 \\ 0 & v_{gijt} = 0 \end{cases} \quad (9)$$

$$w_{gh} = \frac{k_{gh}^{-2}}{\sum_{\ell(g)} k_{gh}^{-2}} \quad (10)$$

The function  $f$  was a three-step transformation. First, it standardized the measure within each MSA, setting its mean to zero and its variance to one. This standardization played a crucial role in enhancing the comparability of measures between MSAs because it helped mitigate the distorting effects of inter-MSA heterogeneity in metropolitan layouts. (For instance, a kilometer in one MSA might not carry the same functional significance as a kilometer in another MSA, potentially leading to misleading results in the absence of standardization). Second, the function  $f$  rescaled the standardized measures from  $e^0$  to  $e^{10}$ . Third, it took the natural logarithm of the rescaled, standardized measures. As a result, the range of each measure was  $[0, 10]$ . The underlying measures exhibited significant positive skew but were roughly log-normal. The transformed measures were more interpretable and better-suited to analyzing correlations and to regression settings.

The spatial weighting scheme used in developing the measures is an extension of conventional spatial weighting methods used in spatial regression modeling and related methods (Dubin 2009; LeSage and Pace 2009). The standard practice in spatial weighting is for the diagonal of the matrix to have zero values, meaning that an observation does not influence itself. In the case of the spatial (S) measures, however, the objective was to capture conditions in *and* around a neighborhood. Neighborhoods should influence themselves. In line with this, I populated the diagonal (self-weights) with the average distance among 1,000 randomly drawn points within the neighborhood. In most cases, this self-weight was the largest weight of the neighborhood's influences. In some cases, however, the neighborhood was subject to more influence from a nearby neighborhood than its self-influence. This is a

theoretically plausible outcome, especially in cases where most of the geographic territory of a census tract is unpopulated or sparsely populated.

The map demonstrates the structure of the spatial weights used in generating the spatial (S) NORs measures. The weights are shown for an example neighborhood located at the center of the darkest-shaded part of the map. As the map shows, the example neighborhood is at the edge of one MSA, which borders another MSA and several non-metro counties. Every neighborhood shown in the extent of the map contributes at least a very small amount, proportionate to its distance-decay spatial weight, to the NOR value for the example neighborhood. The weights cross MSA and county lines, avoiding edge effects and reflecting that people may freely cross such boundaries in the course of their day-to-day contact with establishments of routine organizations.

## Methods

To address the first two research questions, I first analyzed bivariate correlations and performed exploratory factor analysis (EFA). These analyses test whether my measurement framework captures different elements of NORs and, if so, along what axes the measures vary. The bivariate analyses compared correlations between measures of NORs that differ by one of the three dimensions—i.e., areal (A) vs. spatial (S) measures, establishment (E) vs. contact (C) measures, and density (D)- vs. mass (M)-dependent measures. Higher correlations would indicate that the dimensions fail to differentiate aspects of NORs or track the same aspect; lower correlations would indicate that the dimensions are a consequential axis of heterogeneity in NORs. The EFA sought underlying latent factors that explained the patterns of relationships among the eight measures of NORs. While the EFA yielded specific factors, I focused less on the factors themselves than on the more basic question of whether there was a single underlying dimension of NORs.

To address the third research question, I estimated population-weighted linear models of each of the nine measures of NORs by weighted least squares (WLS). In addition to a control

for the population density of the CBG, the predictor variables were standard compositional measures in studies of neighborhood inequality: the share of the population that was under age 16, age 65 or older, Hispanic or Latinx, Black, Asian, a limited speaker of English, without a high school diploma, and in a household that was at or below 150 percent of the federal poverty level (FPL). To net out unobserved heterogeneity, I included county-level fixed-effects. I accounted for spatial clustering by clustering the standard errors by MSA and census tract.

## Results

### Bivariate Analysis

Table 4 summarizes the correlations between measures of NORs that differ by one of the three dimensions—i.e., areal (A) vs. spatial (S) measures, establishment (E) vs. contact (C) measures, and density (D)- vs. mass (M)-dependent measures.

The weakest correlations are between the establishment (E)-based and contact (C)-based measures. Across industries, the correlations between AED and ACD and between AEM and ACM are low; the correlations between SED and SCD and between SEM and SCM are moderate and exceed 0.6 in only one instance. The establishment (E)-based and contact (C)-based measures appear to capture relatively different aspects of NORs, though the differences are smaller for the spatial (S) than for the areal (A) measures. For the routine organizations under study, this suggests that establishments’ physical locations and residents’ day-to-day contact with establishments are distinct dimensions of organizational *relationships* with individuals, though the differences are relatively less stark for measures that take spatial boundaries into account.

The strongest correlations are between the density (D) and mass (M) measures. With one notable set of exceptions, all correlations are quite high, exceeding 0.8. The correlations between ACD and ACM, however, are moderate, ranging from 0.353 for grocery stores to

0.690 for banks and credit unions. These findings suggest that, for the routine organizations under study, inter-organizational *dependence* distinguish between distinct aspects of NORs only for areal (A), contact (C)-based measures. If the relevant aspect of NORs is the amount of contact individuals have with establishments in a given industry regardless of how far they travel to contact them, dependence is worth considering; otherwise, it may be reasonable to ignore size differences among establishments for routine organizations.

In the middle are the correlations between the areal (A) and spatial (S) measures. Overall, the measures are low to moderate, and they are consistently lower for the establishment (E)-based measures than for the contact (C)-based measures. This suggests that, across types of routine organizations, the nature of the *boundaries* between neighborhoods is a consequential axis of distinction for NORs—strongly so for establishment (E)-based measures and moderately so for contact (C)-based measures. Insofar as routine organizations, it is likely necessary to make note of the nature of boundaries to understand NORs, but the stakes of correctly capturing these boundaries may be lower if the measures also capture contact between individuals and organizations.

The comparative strength of the correlations between routine organizations acting as resource providers and those serving as third places suggest that the distinction between these two categories is not particularly consequential. This observation indicates a certain consistency in the dynamics of NORs across various types of routine organizations. Researchers may have greater confidence in the generalizability of their findings from one sub-type of routine organization to another. While some evidence does indicate variations in NORs dynamics in sub-industries within food providers and financial institutions, the modest differences in correlations in these sectors provide little evidence of fundamentally distinct patterns for NORs.

**Table 4: Correlations between neighborhood organizational resources (NORs) measures by industry and dimension**

|                                    |    | A vs. S |    | E vs. C |    | D vs. M |  |
|------------------------------------|----|---------|----|---------|----|---------|--|
| Resource Providers                 |    |         |    |         |    |         |  |
| Grocery Stores                     | ED | 0.306   | AD | 0.098   | AE | 0.948   |  |
|                                    | EM | 0.289   | AM | 0.087   | SE | 0.856   |  |
|                                    | CD | 0.394   | SD | 0.349   | AC | 0.353   |  |
|                                    | CM | 0.468   | SM | 0.418   | SC | 0.872   |  |
| Convenience Stores                 | ED | 0.371   | AD | 0.200   | AE | 0.974   |  |
|                                    | EM | 0.325   | AM | 0.218   | SE | 0.820   |  |
|                                    | CD | 0.600   | SD | 0.655   | AC | 0.564   |  |
|                                    | CM | 0.624   | SM | 0.545   | SC | 0.933   |  |
| Banks and Credit Unions            | ED | 0.364   | AD | 0.164   | AE | 0.955   |  |
|                                    | EM | 0.330   | AM | 0.116   | SE | 0.849   |  |
|                                    | CD | 0.675   | SD | 0.602   | AC | 0.690   |  |
|                                    | CM | 0.636   | SM | 0.547   | SC | 0.927   |  |
| Alternative Financial Institutions | ED | 0.206   | AD | 0.053   | AE | 0.960   |  |
|                                    | EM | 0.173   | AM | 0.048   | SE | 0.663   |  |
|                                    | CD | 0.659   | SD | 0.443   | AC | 0.981   |  |
|                                    | CM | 0.642   | SM | 0.417   | SC | 0.961   |  |
| Medical Providers                  | ED | 0.407   | AD | 0.191   | AE | 0.945   |  |
|                                    | EM | 0.380   | AM | 0.150   | SE | 0.915   |  |
|                                    | CD | 0.546   | SD | 0.529   | AC | 0.441   |  |
|                                    | CM | 0.458   | SM | 0.449   | SC | 0.902   |  |
| Third Places                       |    |         |    |         |    |         |  |
| Religious Organizations            | ED | 0.459   | AD | 0.218   | AE | 0.963   |  |
|                                    | EM | 0.426   | AM | 0.294   | SE | 0.805   |  |
|                                    | CD | 0.532   | SD | 0.551   | AC | 0.474   |  |
|                                    | CM | 0.620   | SM | 0.541   | SC | 0.913   |  |
| Personal Care                      | ED | 0.370   | AD | 0.200   | AE | 0.941   |  |
|                                    | EM | 0.379   | AM | 0.214   | SE | 0.808   |  |
|                                    | CD | 0.552   | SD | 0.416   | AC | 0.538   |  |
|                                    | CM | 0.599   | SM | 0.482   | SC | 0.897   |  |
| Bars                               | ED | 0.345   | AD | 0.203   | AE | 0.970   |  |
|                                    | EM | 0.321   | AM | 0.232   | SE | 0.940   |  |
|                                    | CD | 0.578   | SD | 0.536   | AC | 0.534   |  |
|                                    | CM | 0.575   | SM | 0.432   | SC | 0.917   |  |
| Cafes                              | ED | 0.352   | AD | 0.157   | AE | 0.962   |  |
|                                    | EM | 0.333   | AM | 0.087   | SE | 0.892   |  |
|                                    | CD | 0.600   | SD | 0.534   | AC | 0.383   |  |
|                                    | CM | 0.568   | SM | 0.401   | SC | 0.837   |  |

**Figure 2: Demonstration of spatial weights used for neighborhood organizational resources (NORs) measures**

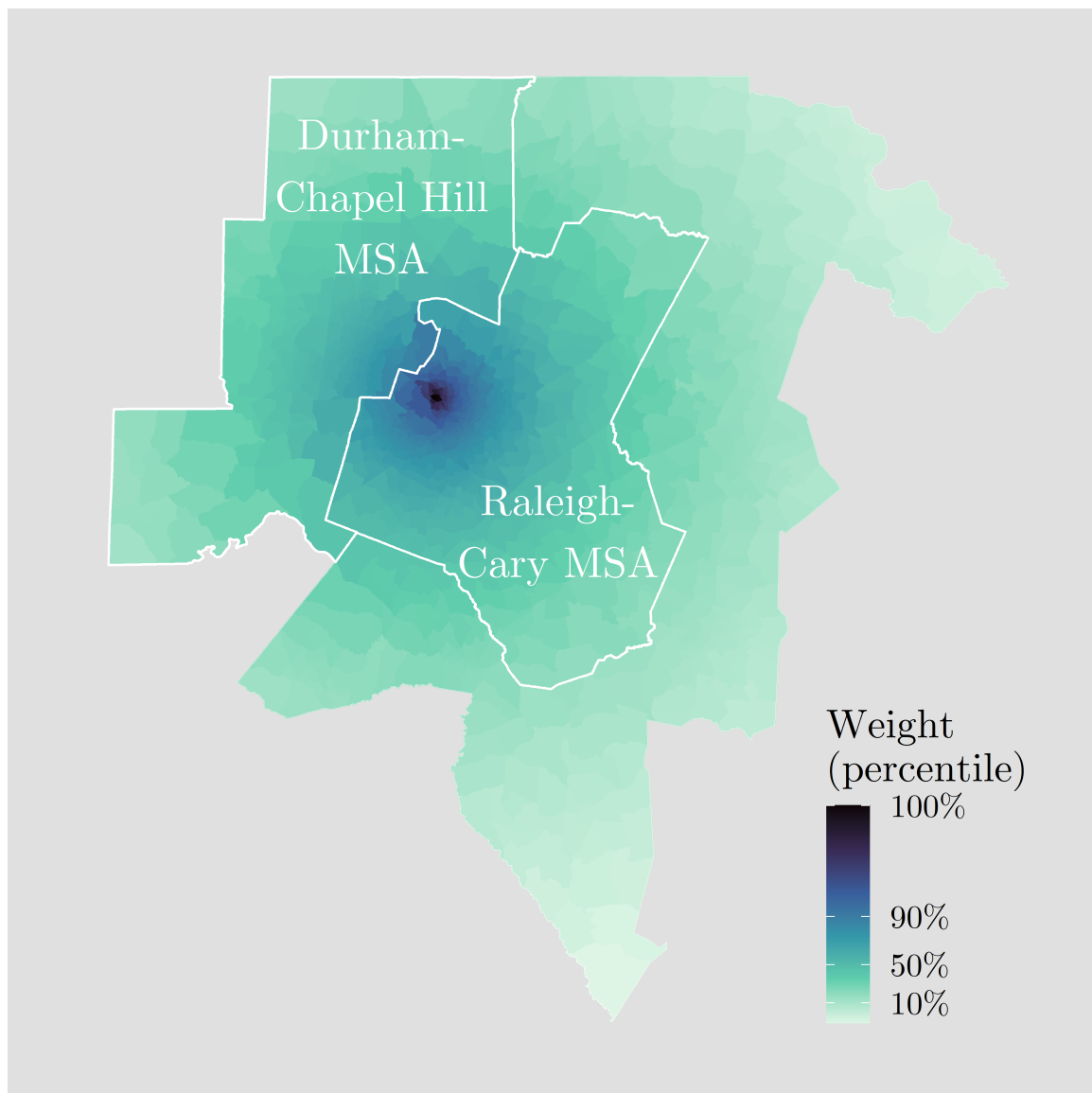
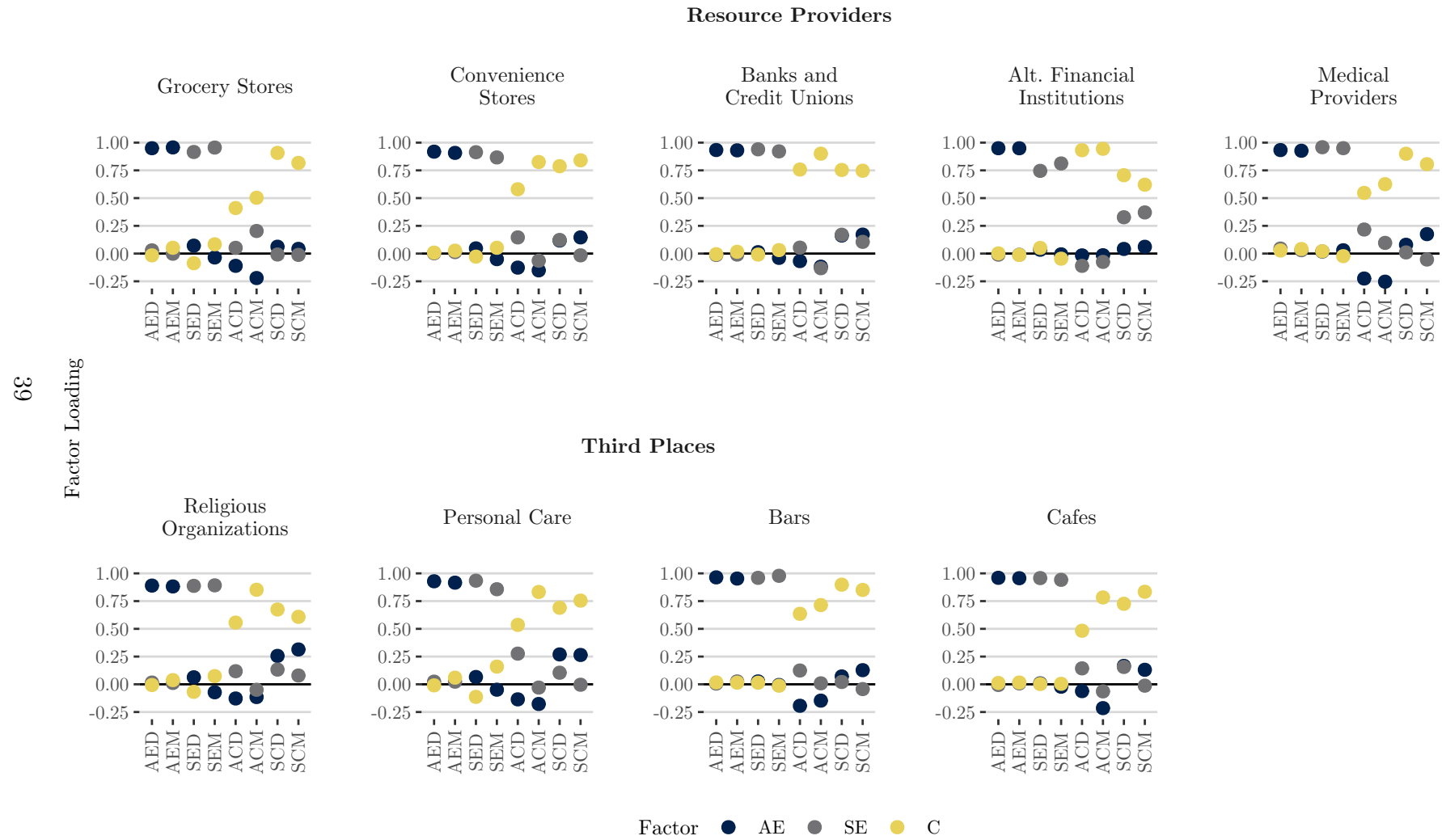


Figure 3: Factor analysis for neighborhood organizational resources (NORs) measures

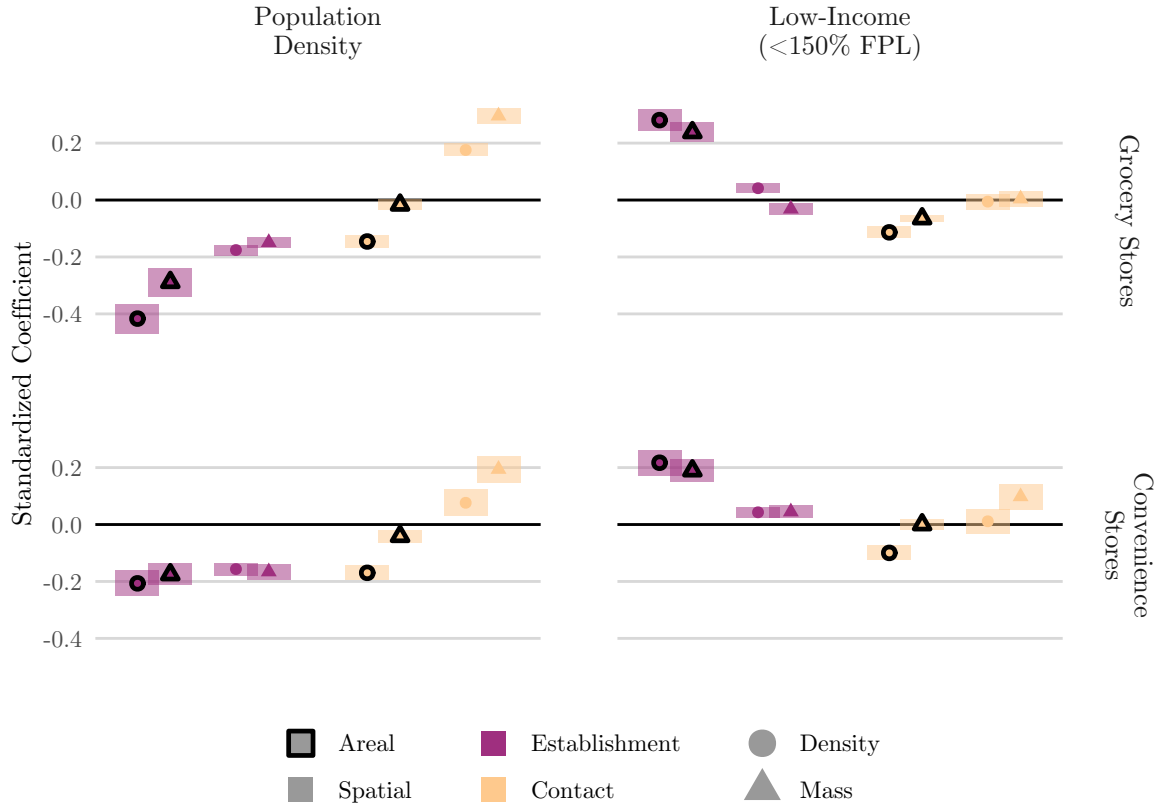


## Factor Analysis

Figure 3 illustrates the factor loadings produced by the EFAs by category of routine organization and industry. The results are highly consistent across the nine categories. In each case, three factors emerge. The first factor, denoted AE, exhibits high factor loadings for the areal (A), establishment (E)-based measures and near-zero or negative loadings for the other measures. The second factor, denoted SE, exhibits high loadings for the spatial (S), establishment (E)-based measures and low or negative loadings otherwise. The third factor, denoted C, exhibits moderate to high loadings with the four contact (C)-based measures. Notably, unlike the establishment (E)-based measures, the contact (C)-based measures are summarized by a single factor regardless of whether they are spatial (S) or areal (A). This finding reinforces the importance of clarity about the nature of spatial boundaries when reliable measures of contact are unavailable and suggests that the stakes of correctly identifying the nature of areal boundaries is somewhat lower if measures of contact are integrated into an analysis.

The findings of the EFA have two main implications, with respect to routine organizations. NORs are clearly multidimensional. The eight measures fail to converge on a single underlying factor that can summarize the construct. One measure of NORs cannot reliably stand in for another or represent the overall level of organizational resources in a neighborhood because those resources break down into several distinct aspects. Furthermore, there appear to be three distinct and consistent factors of NORs for routine organizations. The first factor, AE, corresponds to the conventional “container” measure known as organizational density: it represents the concentration of establishments within an areal boundary. The second factor, SE, expands the spatial boundaries of the first factor: it represents the concentration of establishments within and around an areal boundary, weighted by distance to establishments. The third factor, C, represents the level of contact that residents of an areal unit have with establishments of a given type.

**Figure 4: Selected estimates from models of neighborhood organizational resources (NORs) measures for food providers**



## Regression Analysis

Figures 4 and 5 summarize the point estimates and 95-percent confidence intervals for selected coefficients from the WLS models of the eight measures of NORs. Fuller numerical summaries of the estimated models are in the appendix.

Figure 4 compares the coefficient estimates for population density and the proportion of the population that is low-income for the two sub-types of food providers: grocery stores and convenience stores. The magnitudes and directions of the estimates vary widely by the NORs measures. For example, for grocery stores, the coefficient estimate for population density is  $-0.417$  for AED, compared to only  $-0.176$  for SED and  $-0.146$  for ACD, which differ from AED by only one dimension each. The differences among the same three measures are less stark and significant for convenience stores, by contrast. Similarly, for grocery stores,

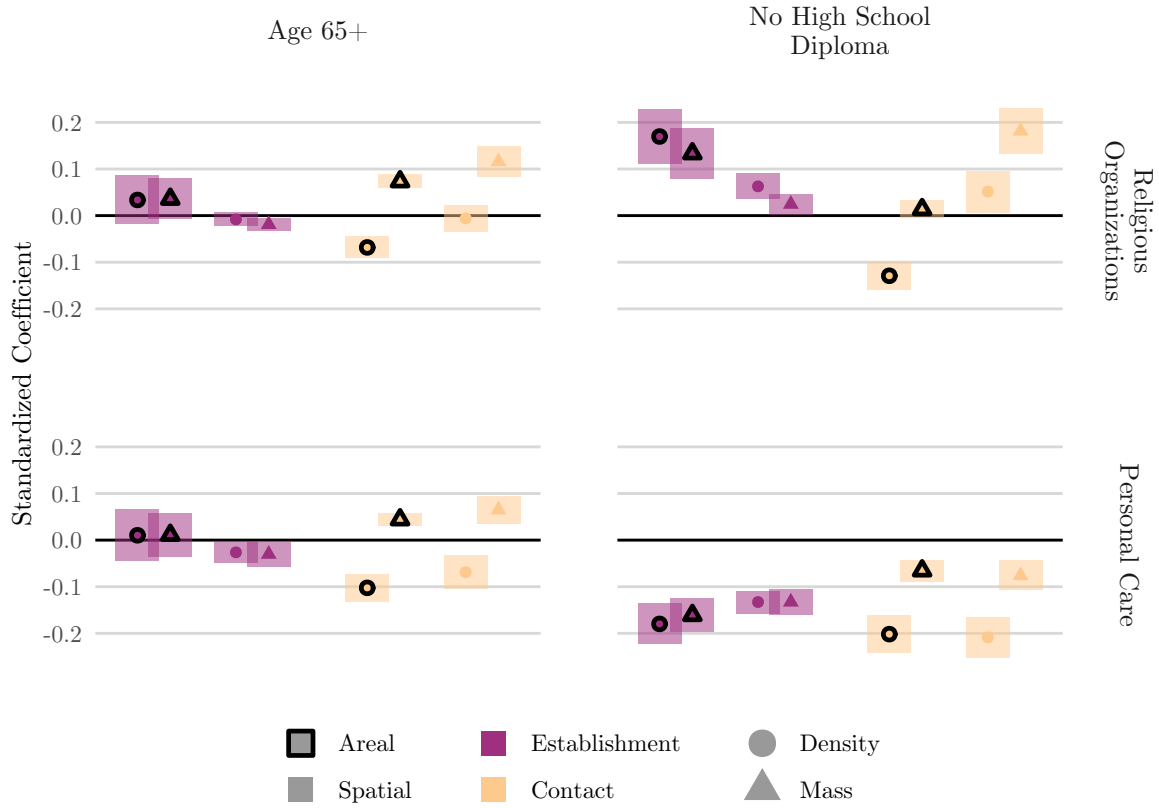
**Figure 5: Selected estimates from models of neighborhood organizational resources (NORs) measures for financial institutions**



the estimates for low-income for SCD and SCM are indistinguishable from zero, while they exceed 0.2 for AED and AEM.

Figure 5 compares the coefficient estimates for the proportions of the population that are Black and low-income for the two sub-types of financial institutions, mainstream banks and credit unions and alternative financial institutions. The magnitudes and directions of the estimates again vary by the NORs measures. For example, for banks and credit unions, the coefficient estimate for the Black population share is  $-0.130$  for AED, compared to  $0.054$  for ACD and  $-0.074$  for AEM, which differ from AED by only one dimension each. The differences between AED and AEM are less stark and significant for alternative financial institutions, by contrast, but they are more stark between AED and ACD. The coefficient estimates for the percent of the population that is low-income also vary widely for banks and

**Figure 6: Selected estimates from models of neighborhood organizational resources (NORs) measures for third places**



credit unions, but the differences are notably less significant and dramatic for alternative financial institutions.

Figure 6 compares the coefficient estimates for the proportions of the population that are over age 65 and without a high school diploma for two types of third places, religious organizations and personal care. The coefficients for the population over age 65 are relatively consistent between the two industries for all measures except SCD, where they are indistinguishable from zero for religious organizations but slightly negative for personal care. The divergence between the industries is more pronounced for the educational variable. The coefficients for the establishment (E)-based measures are all significant and positive for religious organizations and all significant and negative for personal care. Within the contact (C)-based measures, density (D) vs. mass (M) proves to be a consequential distinction for

both variables. The overall variation is somewhat smaller for these third places than the preceding examples of resource providers.

The choice of the NORs measurement can significantly alter parameter estimates. The structure of covariance between NORs and the common compositional variables varies significantly among the eight measures. Some initial evidence suggests that the covariance is more similar across the measures for third places compared to research providers, although this observation is provisional at most. Similarly, drawing precise conclusions about specific variables from these basic models is challenging. However, the key remains and carries substantial implications for the interpretation of model estimates, which can exhibit substantial variations in both magnitude and direction depending on the chosen NORs measure.

## **Discussion and Conclusion**

### **Key Findings**

One of the clearest takeaways from this analysis is that location only partially determines contact with routine organizations. The starkest distinction is between the establishment- and contact- based measures. Also consequential is whether neighborhood boundaries are assumed to be porous, i.e., areal vs. spatial measures.

There appear to be three basic aspects of NORs insofar as routine organizations: the establishments located in a neighborhood, the establishments located in and around a neighborhood, and residents' actual contact with establishments. Which one is the relevant dimension will vary with research questions. Yet especially in the case of organizations that matter for social outcomes because people physically go there to interact with other people or buy something, it is crucial to make a case for which one of these three aspects of NORs is relevant to a given research question and assess the best way to measure it given available data. In many cases, it is the actual contact with organizations that researchers are likely

to care about, even for research questions that have usually been addressed with areal, establishment-based densities. As researchers' access to human mobility data continue to improve, richer measures of NORs should develop as well.

NORs are multifaceted. Choosing the right measure is a theoretical question about the nature of spatial boundaries, the relationships that link organizations to individuals, and dependence among organizations. Aligning measurement to theory requires researchers to attend to each element. The choice of NOR measure has real empirical consequences in the context of regression analysis. The structure of the measures' covariance with common neighborhood compositional variables diverges considerably.

# Appendix

**Table 6: Estimated models of neighborhood organizational resources (NORs) measures for grocery stores**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                 | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|---------------------|----------------------|
| Population density       | -0.417***<br>(0.026) | -0.289***<br>(0.025) | -0.176***<br>(0.009) | -0.149***<br>(0.009) | -0.146***<br>(0.011) | -0.017<br>(0.009)    | 0.176***<br>(0.011) | 0.296***<br>(0.014)  |
| Under age 16             | -0.118***<br>(0.014) | -0.078***<br>(0.016) | -0.031***<br>(0.006) | 0.015<br>(0.008)     | 0.142***<br>(0.014)  | 0.108***<br>(0.006)  | 0.116***<br>(0.014) | 0.124***<br>(0.010)  |
| Age 65+                  | -0.082***<br>(0.020) | -0.053**<br>(0.019)  | -0.034***<br>(0.007) | -0.024***<br>(0.005) | -0.075***<br>(0.011) | 0.060***<br>(0.005)  | -0.016<br>(0.013)   | 0.089***<br>(0.011)  |
| Hispanic/Latinx          | 0.102***<br>(0.028)  | 0.127***<br>(0.029)  | 0.074***<br>(0.016)  | 0.069***<br>(0.016)  | 0.116***<br>(0.021)  | 0.028**<br>(0.010)   | 0.084*<br>(0.033)   | 0.002<br>(0.027)     |
| Black                    | -0.018<br>(0.016)    | 0.007<br>(0.020)     | -0.005<br>(0.010)    | -0.045*<br>(0.018)   | 0.042<br>(0.026)     | -0.006<br>(0.013)    | -0.052<br>(0.033)   | -0.108***<br>(0.026) |
| Asian                    | 0.074**<br>(0.025)   | 0.096***<br>(0.026)  | 0.043***<br>(0.010)  | 0.052***<br>(0.014)  | 0.089***<br>(0.017)  | -0.014**<br>(0.005)  | 0.020<br>(0.018)    | -0.062***<br>(0.012) |
| Limited English speaking | 0.106***<br>(0.019)  | 0.096***<br>(0.018)  | 0.056***<br>(0.011)  | 0.053***<br>(0.009)  | 0.060***<br>(0.007)  | 0.017***<br>(0.004)  | 0.094***<br>(0.010) | 0.060***<br>(0.012)  |
| No high school diploma   | 0.051**<br>(0.018)   | 0.0003<br>(0.015)    | 0.057***<br>(0.013)  | -0.007<br>(0.018)    | -0.115***<br>(0.016) | 0.016<br>(0.008)     | -0.017<br>(0.016)   | 0.057***<br>(0.015)  |
| Low-income (<150% FPL)   | 0.281***<br>(0.019)  | 0.238***<br>(0.017)  | 0.042***<br>(0.008)  | -0.031**<br>(0.010)  | -0.114***<br>(0.010) | -0.065***<br>(0.006) | -0.006<br>(0.014)   | 0.004<br>(0.013)     |
| Mean of NORs measure     | 1.57                 | 1.38                 | 6.65                 | 6.58                 | 8.12                 | 8.82                 | 6.91                | 6.26                 |
| Adjusted R <sup>2</sup>  | 0.073                | 0.060                | 0.786                | 0.726                | 0.362                | 0.367                | 0.219               | 0.192                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 7: Estimated models of neighborhood organizational resources (NORs) measures for convenience stores**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | -0.207***<br>(0.023) | -0.175***<br>(0.019) | -0.156***<br>(0.011) | -0.166***<br>(0.014) | -0.170***<br>(0.013) | -0.041***<br>(0.011) | 0.076**<br>(0.023)   | 0.194***<br>(0.023)  |
| Under age 16             | -0.160***<br>(0.014) | -0.142***<br>(0.012) | -0.057***<br>(0.009) | -0.066***<br>(0.009) | 0.120***<br>(0.021)  | 0.042***<br>(0.008)  | 0.027<br>(0.025)     | -0.036*<br>(0.017)   |
| Age 65+                  | -0.159***<br>(0.014) | -0.148***<br>(0.012) | -0.083***<br>(0.007) | -0.099***<br>(0.007) | -0.169***<br>(0.012) | -0.048***<br>(0.007) | -0.224***<br>(0.015) | -0.124***<br>(0.014) |
| Hispanic/Latinx          | 0.084*<br>(0.039)    | 0.085*<br>(0.035)    | 0.021<br>(0.034)     | 0.032<br>(0.030)     | 0.118***<br>(0.030)  | 0.045**<br>(0.017)   | 0.156*<br>(0.063)    | 0.096<br>(0.055)     |
| Black                    | -0.030<br>(0.024)    | -0.019<br>(0.022)    | -0.036<br>(0.020)    | -0.025<br>(0.021)    | 0.046<br>(0.029)     | 0.031*<br>(0.012)    | -0.028<br>(0.048)    | -0.044<br>(0.038)    |
| Asian                    | 0.037*<br>(0.015)    | 0.044**<br>(0.014)   | 0.017<br>(0.010)     | 0.028*<br>(0.012)    | 0.090***<br>(0.016)  | -0.008<br>(0.006)    | 0.058**<br>(0.020)   | -0.032<br>(0.021)    |
| Limited English speaking | 0.040*<br>(0.016)    | 0.036**<br>(0.012)   | 0.008<br>(0.009)     | 0.008<br>(0.010)     | 0.048***<br>(0.011)  | 0.004<br>(0.007)     | 0.060**<br>(0.021)   | 0.022<br>(0.018)     |
| No high school diploma   | -0.035<br>(0.030)    | -0.037<br>(0.024)    | 0.002<br>(0.020)     | -0.028*<br>(0.014)   | -0.119***<br>(0.012) | 0.025*<br>(0.012)    | -0.042<br>(0.030)    | 0.077*<br>(0.036)    |
| Low-income (<150% FPL)   | 0.217***<br>(0.022)  | 0.190***<br>(0.020)  | 0.043***<br>(0.009)  | 0.045***<br>(0.011)  | -0.100***<br>(0.013) | 0.0001<br>(0.009)    | 0.011<br>(0.021)     | 0.098***<br>(0.022)  |
| Mean of NORs measure     | 1.18                 | 1.01                 | 6.85                 | 6.51                 | 7.74                 | 8.18                 | 5.72                 | 5.02                 |
| Adjusted R <sup>2</sup>  | 0.049                | 0.052                | 0.579                | 0.597                | 0.360                | 0.471                | 0.302                | 0.312                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 8: Estimated models of neighborhood organizational resources (NORs) measures for banks and credit unions**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | -0.016<br>(0.029)    | -0.042<br>(0.025)    | -0.129***<br>(0.013) | -0.175***<br>(0.017) | -0.198***<br>(0.016) | -0.061***<br>(0.013) | -0.020<br>(0.029)    | 0.113***<br>(0.026)  |
| Under age 16             | -0.117***<br>(0.016) | -0.107***<br>(0.014) | -0.009<br>(0.010)    | -0.022<br>(0.011)    | 0.175***<br>(0.022)  | 0.098***<br>(0.012)  | 0.204***<br>(0.027)  | 0.123***<br>(0.020)  |
| Age 65+                  | 0.056*<br>(0.022)    | 0.033<br>(0.019)     | 0.004<br>(0.009)     | -0.024*<br>(0.011)   | -0.086***<br>(0.013) | 0.060***<br>(0.007)  | 0.010<br>(0.020)     | 0.143***<br>(0.016)  |
| Hispanic/Latinx          | 0.020<br>(0.024)     | 0.044*<br>(0.022)    | -0.085***<br>(0.022) | -0.043<br>(0.030)    | 0.127***<br>(0.029)  | 0.070***<br>(0.020)  | 0.043<br>(0.043)     | -0.010<br>(0.036)    |
| Black                    | -0.130***<br>(0.019) | -0.074***<br>(0.014) | -0.164***<br>(0.015) | -0.092***<br>(0.015) | 0.054*<br>(0.026)    | 0.045***<br>(0.013)  | -0.102**<br>(0.034)  | -0.109***<br>(0.024) |
| Asian                    | 0.143***<br>(0.033)  | 0.131***<br>(0.029)  | 0.055***<br>(0.015)  | 0.089***<br>(0.020)  | 0.162***<br>(0.018)  | 0.069***<br>(0.007)  | 0.196***<br>(0.023)  | 0.103***<br>(0.013)  |
| Limited English speaking | 0.046**<br>(0.017)   | 0.036*<br>(0.015)    | 0.039**<br>(0.013)   | 0.031<br>(0.018)     | 0.062***<br>(0.016)  | 0.017<br>(0.009)     | 0.109***<br>(0.028)  | 0.062**<br>(0.021)   |
| No high school diploma   | -0.238***<br>(0.025) | -0.196***<br>(0.021) | -0.136***<br>(0.013) | -0.116***<br>(0.016) | -0.200***<br>(0.014) | -0.066***<br>(0.011) | -0.281***<br>(0.023) | -0.150***<br>(0.022) |
| Low-income (<150% FPL)   | 0.135***<br>(0.018)  | 0.116***<br>(0.015)  | -0.033**<br>(0.012)  | -0.023*<br>(0.011)   | -0.210***<br>(0.015) | -0.111***<br>(0.009) | -0.215***<br>(0.024) | -0.114***<br>(0.019) |
| Mean of NORs measure     | 1.04                 | 0.795                | 6.54                 | 6.22                 | 7.20                 | 7.95                 | 4.87                 | 4.49                 |
| Adjusted R <sup>2</sup>  | 0.056                | 0.055                | 0.604                | 0.584                | 0.436                | 0.447                | 0.397                | 0.408                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 9: Estimated models of neighborhood organizational resources (NORs) measures for alternative financial institutions**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | -0.007<br>(0.006)    | -0.007<br>(0.004)    | -0.318***<br>(0.019) | -0.401***<br>(0.023) | -0.209***<br>(0.030) | -0.103***<br>(0.023) | -0.068***<br>(0.013) | -0.005<br>(0.012)    |
| Under age 16             | -0.034***<br>(0.005) | -0.022***<br>(0.004) | -0.052***<br>(0.011) | -0.017<br>(0.012)    | 0.155***<br>(0.032)  | 0.085***<br>(0.020)  | 0.055***<br>(0.015)  | 0.014<br>(0.011)     |
| Age 65+                  | -0.018***<br>(0.005) | -0.009**<br>(0.003)  | -0.047***<br>(0.011) | -0.059***<br>(0.013) | -0.308***<br>(0.029) | -0.192***<br>(0.021) | -0.085***<br>(0.012) | -0.028***<br>(0.008) |
| Hispanic/Latinx          | 0.009<br>(0.006)     | 0.007<br>(0.005)     | 0.066*<br>(0.026)    | 0.022<br>(0.039)     | 0.228**<br>(0.075)   | 0.178**<br>(0.065)   | 0.072<br>(0.042)     | 0.042<br>(0.033)     |
| Black                    | 0.011<br>(0.005)     | 0.010*<br>(0.004)    | 0.094***<br>(0.025)  | 0.042<br>(0.030)     | 0.321***<br>(0.055)  | 0.269***<br>(0.055)  | 0.115***<br>(0.029)  | 0.080**<br>(0.027)   |
| Asian                    | -0.0007<br>(0.004)   | 0.001<br>(0.003)     | 0.022<br>(0.022)     | 0.030<br>(0.024)     | 0.196***<br>(0.050)  | 0.118**<br>(0.036)   | 0.049*<br>(0.021)    | 0.007<br>(0.012)     |
| Limited English speaking | 0.019*<br>(0.008)    | 0.014*<br>(0.006)    | 0.046<br>(0.024)     | 0.042<br>(0.023)     | 0.119**<br>(0.044)   | 0.086*<br>(0.038)    | 0.068*<br>(0.028)    | 0.045<br>(0.024)     |
| No high school diploma   | -0.008<br>(0.005)    | -0.006<br>(0.004)    | -0.015<br>(0.015)    | -0.027<br>(0.024)    | -0.229***<br>(0.046) | -0.121***<br>(0.033) | -0.039<br>(0.024)    | 0.010<br>(0.015)     |
| Low-income (<150% FPL)   | 0.048***<br>(0.005)  | 0.035***<br>(0.004)  | 0.041**<br>(0.015)   | 0.007<br>(0.018)     | -0.094**<br>(0.034)  | -0.023<br>(0.025)    | 0.007<br>(0.018)     | 0.045**<br>(0.014)   |
| Mean of NORs measure     | 0.173                | 0.139                | 5.43                 | 4.16                 | 2.61                 | 2.25                 | 0.699                | 0.544                |
| Adjusted R <sup>2</sup>  | 0.438                | 0.580                | 0.453                | 0.703                | 0.233                | 0.215                | 0.230                | 0.197                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 10: Estimated models of neighborhood organizational resources (NORs) measures for medical providers**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | 0.078*<br>(0.030)    | 0.043<br>(0.024)     | -0.126***<br>(0.011) | -0.147***<br>(0.012) | -0.123***<br>(0.012) | 0.026**<br>(0.008)   | 0.256***<br>(0.020)  | 0.404***<br>(0.019)  |
| Under age 16             | -0.140***<br>(0.015) | -0.133***<br>(0.014) | -0.032***<br>(0.009) | -0.044***<br>(0.010) | 0.178***<br>(0.018)  | 0.104***<br>(0.007)  | 0.108***<br>(0.016)  | 0.024<br>(0.013)     |
| Age 65+                  | 0.109***<br>(0.029)  | 0.086***<br>(0.024)  | -0.004<br>(0.011)    | -0.017<br>(0.012)    | -0.075***<br>(0.016) | 0.078***<br>(0.007)  | -0.020<br>(0.025)    | 0.115***<br>(0.019)  |
| Hispanic/Latinx          | -0.097***<br>(0.027) | -0.050*<br>(0.021)   | -0.156***<br>(0.025) | -0.126***<br>(0.025) | 0.023<br>(0.025)     | -0.052***<br>(0.015) | -0.192***<br>(0.034) | -0.265***<br>(0.029) |
| Black                    | -0.198***<br>(0.017) | -0.123***<br>(0.011) | -0.198***<br>(0.020) | -0.152***<br>(0.018) | -0.027<br>(0.024)    | -0.045***<br>(0.009) | -0.265***<br>(0.025) | -0.284***<br>(0.020) |
| Asian                    | 0.066*<br>(0.032)    | 0.076**<br>(0.028)   | 0.036<br>(0.032)     | 0.054<br>(0.030)     | 0.097***<br>(0.022)  | -0.003<br>(0.008)    | 0.037<br>(0.037)     | -0.060*<br>(0.026)   |
| Limited English speaking | 0.047***<br>(0.011)  | 0.043***<br>(0.008)  | 0.038***<br>(0.010)  | 0.035**<br>(0.012)   | 0.060***<br>(0.014)  | 0.012<br>(0.009)     | 0.136***<br>(0.028)  | 0.093***<br>(0.023)  |
| No high school diploma   | -0.218***<br>(0.024) | -0.190***<br>(0.017) | -0.181***<br>(0.019) | -0.163***<br>(0.020) | -0.207***<br>(0.018) | -0.061***<br>(0.006) | -0.297***<br>(0.023) | -0.164***<br>(0.015) |
| Low-income (<150% FPL)   | 0.159***<br>(0.019)  | 0.154***<br>(0.017)  | -0.006<br>(0.012)    | 0.018<br>(0.013)     | -0.176***<br>(0.014) | -0.081***<br>(0.006) | -0.029<br>(0.025)    | 0.076**<br>(0.023)   |
| Mean of NORs measure     | 1.23                 | 0.923                | 6.16                 | 5.95                 | 7.40                 | 8.68                 | 5.67                 | 5.33                 |
| Adjusted R <sup>2</sup>  | 0.080                | 0.061                | 0.540                | 0.480                | 0.471                | 0.377                | 0.253                | 0.246                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 11: Estimated models of neighborhood organizational resources (NORs) measures for religious organizations**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                 | SCM                 |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|---------------------|---------------------|
| Population density       | -0.500***<br>(0.044) | -0.355***<br>(0.042) | -0.184***<br>(0.013) | -0.150***<br>(0.012) | -0.146***<br>(0.014) | -0.006<br>(0.010)    | 0.115***<br>(0.022) | 0.250***<br>(0.019) |
| Under age 16             | -0.061***<br>(0.015) | -0.026<br>(0.016)    | -0.015<br>(0.007)    | 0.006<br>(0.008)     | 0.192***<br>(0.019)  | 0.129***<br>(0.008)  | 0.200***<br>(0.016) | 0.139***<br>(0.010) |
| Age 65+                  | 0.034<br>(0.026)     | 0.036<br>(0.022)     | -0.008<br>(0.007)    | -0.019**<br>(0.007)  | -0.068***<br>(0.012) | 0.073***<br>(0.007)  | -0.006<br>(0.015)   | 0.116***<br>(0.016) |
| Hispanic/Latinx          | -0.016<br>(0.040)    | -0.007<br>(0.037)    | -0.009<br>(0.019)    | 0.013<br>(0.016)     | 0.111***<br>(0.022)  | 0.036*<br>(0.015)    | 0.020<br>(0.043)    | -0.058<br>(0.038)   |
| Black                    | 0.250***<br>(0.025)  | 0.242***<br>(0.028)  | 0.133***<br>(0.013)  | 0.118***<br>(0.023)  | 0.164***<br>(0.030)  | 0.147***<br>(0.019)  | 0.142**<br>(0.048)  | 0.122**<br>(0.037)  |
| Asian                    | -0.023<br>(0.031)    | 0.004<br>(0.028)     | -0.002<br>(0.016)    | 0.032*<br>(0.012)    | 0.136***<br>(0.017)  | 0.041**<br>(0.013)   | 0.012<br>(0.028)    | -0.078*<br>(0.033)  |
| Limited English speaking | -0.064*<br>(0.032)   | -0.061*<br>(0.029)   | -0.032**<br>(0.012)  | -0.028<br>(0.014)    | 0.026*<br>(0.012)    | -0.024**<br>(0.008)  | -0.020<br>(0.029)   | -0.065*<br>(0.026)  |
| No high school diploma   | 0.170***<br>(0.029)  | 0.133***<br>(0.027)  | 0.063***<br>(0.014)  | 0.025*<br>(0.011)    | -0.129***<br>(0.015) | 0.014<br>(0.009)     | 0.052*<br>(0.023)   | 0.182***<br>(0.025) |
| Low-income (<150% FPL)   | 0.283***<br>(0.024)  | 0.246***<br>(0.024)  | 0.082***<br>(0.008)  | 0.052***<br>(0.010)  | -0.150***<br>(0.014) | -0.056***<br>(0.007) | 0.004<br>(0.019)    | 0.094***<br>(0.018) |
| Mean of NORs measure     | 2.70                 | 2.39                 | 7.33                 | 7.16                 | 7.65                 | 8.25                 | 6.07                | 5.47                |
| Adjusted R <sup>2</sup>  | 0.102                | 0.094                | 0.442                | 0.436                | 0.354                | 0.347                | 0.221               | 0.229               |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 12: Estimated models of neighborhood organizational resources (NORs) measures for personal care**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | 0.224***<br>(0.034)  | 0.191***<br>(0.031)  | -0.046***<br>(0.010) | -0.064***<br>(0.012) | -0.081***<br>(0.014) | 0.066***<br>(0.009)  | 0.325***<br>(0.020)  | 0.463***<br>(0.016)  |
| Under age 16             | -0.182***<br>(0.016) | -0.148***<br>(0.014) | -0.045***<br>(0.009) | -0.038***<br>(0.010) | 0.143***<br>(0.020)  | 0.069***<br>(0.009)  | 0.096***<br>(0.024)  | 0.019<br>(0.015)     |
| Age 65+                  | 0.010<br>(0.028)     | 0.011<br>(0.024)     | -0.026*<br>(0.012)   | -0.030*<br>(0.013)   | -0.102***<br>(0.015) | 0.044***<br>(0.007)  | -0.069***<br>(0.018) | 0.065***<br>(0.015)  |
| Hispanic/Latinx          | -0.061**<br>(0.022)  | -0.037<br>(0.020)    | -0.126***<br>(0.030) | -0.103**<br>(0.036)  | 0.060<br>(0.034)     | -0.007<br>(0.022)    | -0.036<br>(0.045)    | -0.100**<br>(0.033)  |
| Black                    | -0.123***<br>(0.014) | -0.067***<br>(0.014) | -0.105***<br>(0.017) | -0.066**<br>(0.022)  | 0.059*<br>(0.026)    | 0.043**<br>(0.015)   | -0.004<br>(0.034)    | -0.017<br>(0.024)    |
| Asian                    | 0.031<br>(0.024)     | 0.043<br>(0.022)     | -0.016<br>(0.021)    | 0.014<br>(0.026)     | 0.103***<br>(0.023)  | 0.007<br>(0.009)     | 0.033<br>(0.027)     | -0.058***<br>(0.015) |
| Limited English speaking | 0.051***<br>(0.015)  | 0.042***<br>(0.012)  | 0.059***<br>(0.012)  | 0.068***<br>(0.014)  | 0.077***<br>(0.013)  | 0.031***<br>(0.008)  | 0.126***<br>(0.019)  | 0.081***<br>(0.014)  |
| No high school diploma   | -0.180***<br>(0.022) | -0.161***<br>(0.018) | -0.133***<br>(0.012) | -0.133***<br>(0.014) | -0.202***<br>(0.020) | -0.065***<br>(0.012) | -0.209***<br>(0.022) | -0.076***<br>(0.016) |
| Low-income (<150% FPL)   | 0.169***<br>(0.023)  | 0.153***<br>(0.019)  | -0.024*<br>(0.012)   | -0.022<br>(0.012)    | -0.161***<br>(0.014) | -0.060***<br>(0.006) | -0.090***<br>(0.020) | 0.010<br>(0.019)     |
| Mean of NORs measure     | 1.71                 | 1.36                 | 6.76                 | 6.39                 | 7.53                 | 8.07                 | 5.47                 | 4.68                 |
| Adjusted R <sup>2</sup>  | 0.057                | 0.056                | 0.559                | 0.570                | 0.337                | 0.382                | 0.168                | 0.239                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 13: Estimated models of neighborhood organizational resources (NORs) measures for bars**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | -0.005<br>(0.017)    | 0.008<br>(0.016)     | -0.131***<br>(0.024) | -0.160***<br>(0.027) | -0.034*<br>(0.014)   | 0.111***<br>(0.010)  | 0.244***<br>(0.026)  | 0.378***<br>(0.026)  |
| Under age 16             | -0.302***<br>(0.015) | -0.286***<br>(0.013) | -0.216***<br>(0.010) | -0.214***<br>(0.011) | 0.039<br>(0.021)     | -0.048***<br>(0.008) | -0.186***<br>(0.034) | -0.265***<br>(0.024) |
| Age 65+                  | -0.191***<br>(0.023) | -0.182***<br>(0.018) | -0.152***<br>(0.010) | -0.160***<br>(0.011) | -0.189***<br>(0.013) | -0.054***<br>(0.006) | -0.289***<br>(0.019) | -0.168***<br>(0.019) |
| Hispanic/Latinx          | -0.087***<br>(0.019) | -0.079***<br>(0.018) | -0.119***<br>(0.029) | -0.115***<br>(0.034) | -0.034<br>(0.037)    | -0.111***<br>(0.024) | -0.196**<br>(0.066)  | -0.267***<br>(0.059) |
| Black                    | -0.232***<br>(0.020) | -0.204***<br>(0.016) | -0.164***<br>(0.023) | -0.146***<br>(0.023) | -0.127***<br>(0.024) | -0.150***<br>(0.010) | -0.479***<br>(0.032) | -0.505***<br>(0.025) |
| Asian                    | -0.031**<br>(0.011)  | -0.020<br>(0.011)    | -0.051**<br>(0.016)  | -0.034<br>(0.018)    | 0.065**<br>(0.024)   | -0.035**<br>(0.011)  | -0.082**<br>(0.029)  | -0.176***<br>(0.022) |
| Limited English speaking | 0.003<br>(0.017)     | 0.005<br>(0.014)     | 0.013<br>(0.021)     | 0.017<br>(0.022)     | 0.058***<br>(0.013)  | 0.010<br>(0.009)     | 0.086**<br>(0.030)   | 0.041<br>(0.026)     |
| No high school diploma   | -0.102***<br>(0.013) | -0.101***<br>(0.011) | -0.054***<br>(0.015) | -0.059***<br>(0.015) | -0.267***<br>(0.022) | -0.130***<br>(0.010) | -0.310***<br>(0.023) | -0.186***<br>(0.022) |
| Low-income (<150% FPL)   | 0.243***<br>(0.014)  | 0.224***<br>(0.014)  | 0.178***<br>(0.011)  | 0.172***<br>(0.012)  | -0.111***<br>(0.014) | -0.009<br>(0.007)    | 0.146***<br>(0.025)  | 0.246***<br>(0.024)  |
| Mean of NORs measure     | 0.701                | 0.591                | 5.43                 | 5.21                 | 7.27                 | 8.22                 | 4.83                 | 4.58                 |
| Adjusted R <sup>2</sup>  | 0.067                | 0.070                | 0.552                | 0.568                | 0.418                | 0.453                | 0.261                | 0.299                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**Table 14: Estimated models of neighborhood organizational resources (NORs) measures for cafes**

| NORs measure             | AED                  | AEM                  | SED                  | SEM                  | ACD                  | ACM                  | SCD                  | SCM                  |
|--------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Population density       | -0.035<br>(0.028)    | -0.029<br>(0.027)    | -0.074***<br>(0.011) | -0.099***<br>(0.013) | -0.090***<br>(0.012) | 0.056***<br>(0.005)  | 0.284***<br>(0.014)  | 0.421***<br>(0.013)  |
| Under age 16             | -0.324***<br>(0.019) | -0.318***<br>(0.020) | -0.131***<br>(0.009) | -0.140***<br>(0.009) | 0.110***<br>(0.019)  | 0.018**<br>(0.006)   | -0.018<br>(0.024)    | -0.096***<br>(0.014) |
| Age 65+                  | -0.194***<br>(0.016) | -0.189***<br>(0.016) | -0.115***<br>(0.007) | -0.129***<br>(0.009) | -0.156***<br>(0.013) | -0.042***<br>(0.008) | -0.200***<br>(0.013) | -0.113***<br>(0.011) |
| Hispanic/Latinx          | -0.039<br>(0.021)    | -0.036*<br>(0.017)   | -0.097***<br>(0.015) | -0.092***<br>(0.016) | 0.017<br>(0.023)     | -0.067***<br>(0.011) | -0.076**<br>(0.026)  | -0.163***<br>(0.020) |
| Black                    | -0.278***<br>(0.020) | -0.239***<br>(0.020) | -0.218***<br>(0.014) | -0.198***<br>(0.016) | -0.138***<br>(0.031) | -0.179***<br>(0.015) | -0.466***<br>(0.043) | -0.510***<br>(0.028) |
| Asian                    | 0.123***<br>(0.034)  | 0.129***<br>(0.030)  | 0.058***<br>(0.015)  | 0.075***<br>(0.019)  | 0.123***<br>(0.020)  | 0.027***<br>(0.006)  | 0.072**<br>(0.026)   | -0.013<br>(0.016)    |
| Limited English speaking | 0.056**<br>(0.020)   | 0.059**<br>(0.019)   | 0.027**<br>(0.010)   | 0.028*<br>(0.012)    | 0.058***<br>(0.011)  | 0.010<br>(0.006)     | 0.096***<br>(0.019)  | 0.056***<br>(0.015)  |
| No high school diploma   | -0.276***<br>(0.029) | -0.272***<br>(0.026) | -0.135***<br>(0.018) | -0.154***<br>(0.020) | -0.258***<br>(0.026) | -0.134***<br>(0.014) | -0.338***<br>(0.034) | -0.239***<br>(0.025) |
| Low-income (<150% FPL)   | 0.261***<br>(0.023)  | 0.253***<br>(0.021)  | 0.068***<br>(0.011)  | 0.075***<br>(0.013)  | -0.180***<br>(0.015) | -0.088***<br>(0.008) | -0.083***<br>(0.018) | 0.008<br>(0.015)     |
| Mean of NORs measure     | 1.27                 | 1.06                 | 6.43                 | 6.04                 | 7.47                 | 8.24                 | 6.31                 | 5.52                 |
| Adjusted R <sup>2</sup>  | 0.066                | 0.071                | 0.565                | 0.639                | 0.464                | 0.610                | 0.339                | 0.413                |

*Notes:* Linear models estimated by WLS.  $N = 135,745$  CBGs with at least 100 estimated inhabitants across the 100 most populous MSAs. All models include population weights, county fixed-effects, and standardized predictors ( $M = 0$ ;  $SD = 1$ ). See Table 2 for definitions of outcome variables. Population density is the natural logarithm of the estimated number of inhabitants per square kilometer; other predictors are proportions. “FPL” is the federal poverty line. Parentheses contain standard errors clustered by MSA and census tract. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

# Neighborhood Organizational Resources and Food Access: Disparities in Proximity and Visits to Grocery Stores

## Introduction

One the clearest and most widely known areas of consensus in the social sciences today is neighborhood effects: in the United States (US), levels of opportunity vary across geographies, especially at the neighborhood level (Jencks and Mayer 1990; Sampson 2012; see Chyn and Katz 2021). Well into the maturity of the neighborhoods effects literature, however, the underlying mechanisms that link neighborhoods to individual outcomes were often poorly understood, ultimately leaving neighborhoods as something of a “black box” (Sampson 2008; Sharkey and Faber 2014; Galster and Sharkey 2017). To better understand why geography is so consequential for life chances, researchers are taking increasingly finer-grained approaches to what happens within neighborhoods.

One such development in neighborhood effects research is increased attention to *neighborhood organizational resources (NORs)*, often associated with institutional resources theory (IRT). From this perspective, the link between neighborhood conditions and individual outcomes is mediated by resources that organizations distribute or in the form of organizations themselves (McQuarrie and Marwell 2009; Allard and Small 2013; Clifford 2018).

Another development in neighborhood effects research is the distinction between residential neighborhoods and *activity spaces*. This distinction reflects that where people live may be different than where they spend time and money. An activity space comprises the places a person visits as part of routine activities (Browning and Soller 2014; Cagney et al. 2020). Movement across neighborhoods is key to the concept of an activity space because most people’s day-to-day lives take them to places that include but extend beyond the neighborhoods in which they live (Jones and Pebley 2014; Browning et al. 2021). Activity spaces exhibit social, economic, and ethnoracial disparities and segregation that resemble but do not directly mirror inequalities in US residential patterns overall (Phillips et al. 2021; Zhang et al. 2023; Cai, Browning, and Cagney 2024).

These two developments—IRT’s focus on NORs and increased consideration of activity spaces—intersect instructively with the case of food access. This issue is sometimes referred to in academic and policy circles as the problem of “food deserts.” This issue was commonly studied with data from surveys, self-reports, and establishment-based measures of density (see Walker, Keane, and Burke 2010). More recently, some researchers have begun taking concrete travel behavior into account in household-level indices (Abel et al. 2022).

I take up the issue of food access in this chapter as a worked example and extension of the metrics developed in the preceding chapter. See Table 2 for a breakdown of the measures.

## Results

### Illustrative Comparison of Measures

The two maps in this section zoom in on the example neighborhood whose weights are summarized in the previous map. All grocery stores within a ten-mile radius are displayed on each map. The first map visualizes the spatial weights; the second map visualizes the number of visitors to grocery stores in each census block group from the example neighborhood on a

weekly basis, averaged over the 53-week analysis period. The highlighted neighborhood is an instructive case of the differences among the measures.

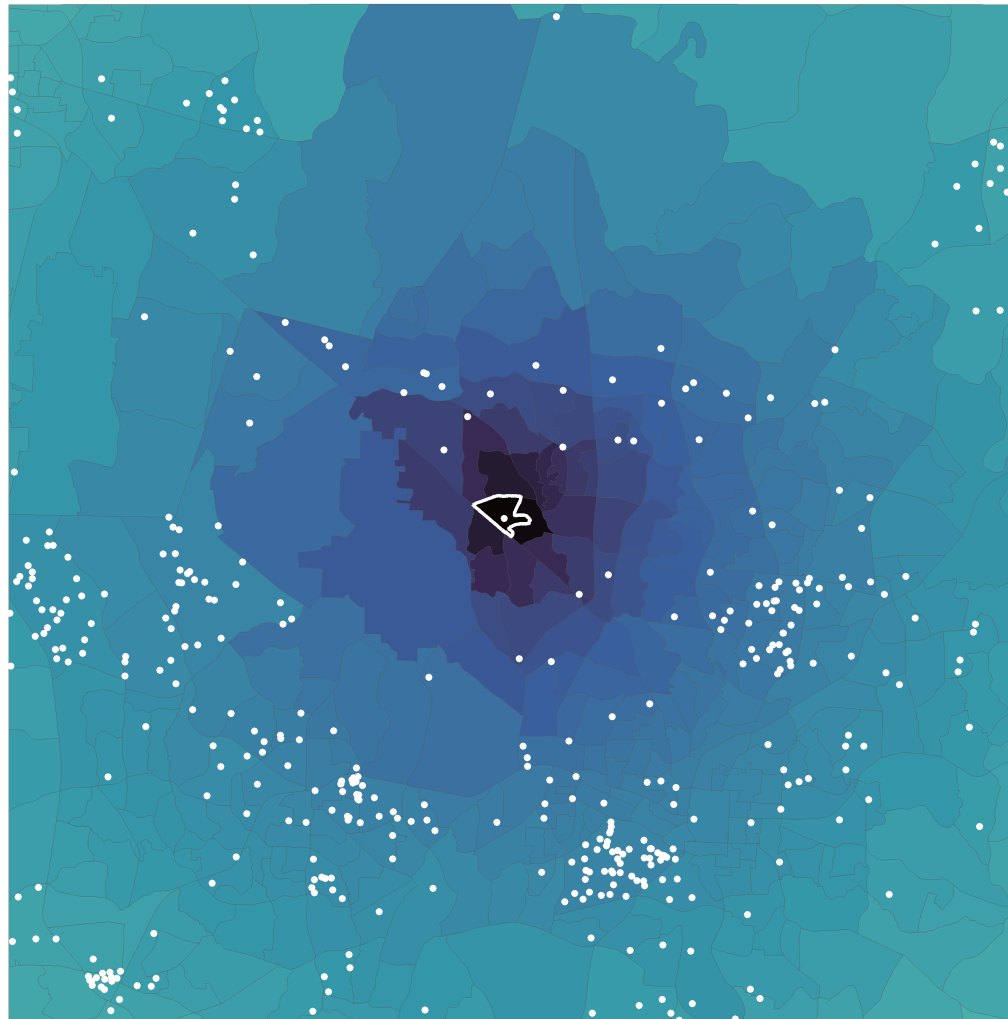
The example neighborhood demonstrates how a neighborhood can diverge on the boundaries dimension of NORs. Ranked within its metropolitan statistical area (MSA), the example neighborhood is in the 88th percentile for areal establishment density (AED). There is one grocery store within the example neighborhood; most neighborhoods in the MSA do not have a grocery store within their boundaries. Measured as the within-neighborhood density of grocery stores, the example neighborhood is ranked relatively highly. Taking into account not only what is in the neighborhood but what is around it, however, the example neighborhood is ranked in the 10th percentile for spatial establishment density (SED). This stems from the fact that there are relatively few neighborhoods in the area immediately surrounding the block group, where the weights are highest.

As the second map shows, however, residents of the example neighborhood make their way to grocery stores outside the highest-weighted neighborhoods at a relatively high rate. Moving from SED to spatial contact density (SCD), which measures visits to grocery stores weighted by distance, the example neighborhood is in the 70th percentile within the MSA. So while there are not a particularly high number of grocery stores in the area immediately surrounding the example neighborhood, the residents of the neighborhood visit grocery stores at a relatively high rate.

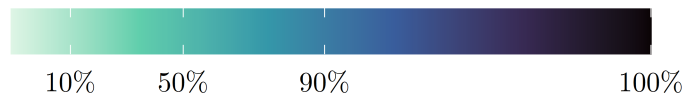
## **Illustrative Example of Disparities**

Figure 9 shows average marginal predictions based on the models summarized in the preceding section. The predictions are representative values averaged across the neighborhoods in a given category. It compares the NORs measures for grocery stores across neighborhoods with low, medium and high poverty rates and Black population shares. The low, medium, and high levels are  $k$ -means clusters.

Figure 7: Spatial weights and grocery stores near example neighborhood

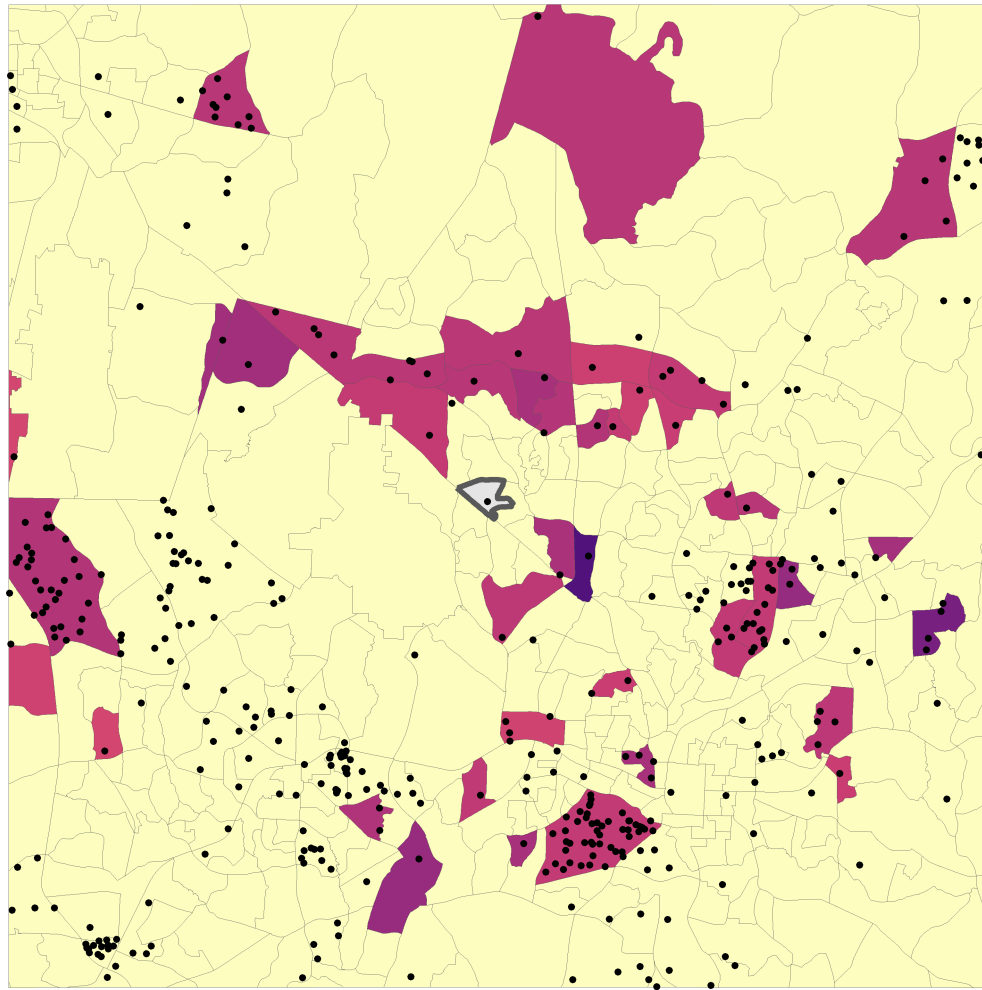


Weight (percentile)



Points are grocery stores. Polygons are census block groups.  
Example neighborhood outlined in white.

Figure 8: Visits to grocery stores near example neighborhood

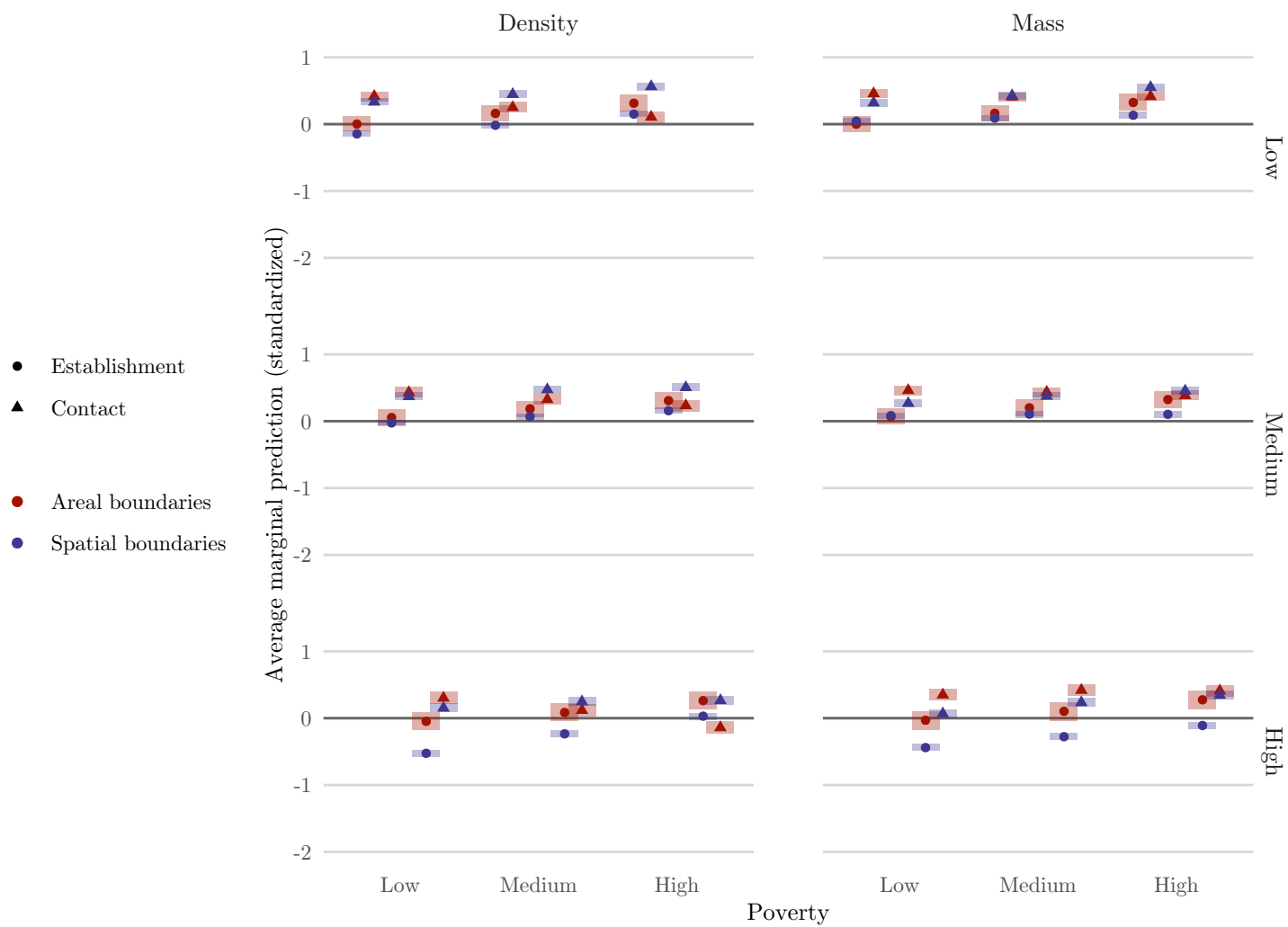


Unique visitors per week  
(example neighborhood residents)



Points are grocery stores. Polygons are census block groups.  
Example neighborhood outlined in dark gray

Figure 9: Neighborhood organizational resources (NORs), grocery stores, by Black population share and poverty level



One trend that holds across the board is that neighborhoods' contact-based NORs are higher on average than their establishment-based NORs, in the case of grocery stores. On average, overall contact with grocery stores is relatively higher than the concentration of grocery stores in residential neighborhoods. The more important distinctions in this setting are between the demographic categories.

Some illustrative disparities emerge in the bottom-left panel, which compares the density-based measures in neighborhoods with high Black population shares and various socioeconomic compositions. Both AED and SED increase with poverty: there are more grocery stores in and around high-poverty, predominantly Black neighborhoods than in and around low- to medium-poverty, predominantly Black neighborhoods. The gradient is significantly steeper, however, for the spatial measures than the areal measures. Comparing these results to those in neighborhoods with low and medium Black populations, the differences between the spatial and areal measures is not as stark.



# Neighborhood Organizational Resources and Subsidized Housing: Community Development Corporations' Effects on Low-Income Housing Tax Credit Allocations

## Motivation and Background

### The Low-Income Housing Tax Credit

Today, housing subsidies for low-income people in the United States (US) break down into three main categories (Schwartz [2006] 2021). The first is project-based public housing, comprised mainly of large multifamily complexes owned and operated by public entities. Once the primary means of subsidizing low-income housing, the US federal government decisively moved away from this model in the late 20th century. New project-based housing is no longer built and many units have been demolished, but local authorities still manage nontrivial portfolios of remaining project-based public housing. The second category is Housing Choice Vouchers, also known as “Section 8,” tenant- or unit-based assistance for rent in privately owned housing (Rosen 2020).

The third category of subsidized housing is the Low-Income Housing Tax Credit (LIHTC), which defrays housing developers' costs in exchange for long-term affordability

guarantees (Scally, Gold, and DuBois 2018; Heightley 2023). It is currently the only large-scale public affordable housing subsidy on the supply side—i.e., for building new low-income housing units. A complex and decentralized program, LIHTC credits are allotted to public agencies in each state, which award them on a competitive basis to projects proposed by for-profit and nonprofit housing developers. LIHTC award recipients sell the tax credits to third-party investors. The proceeds effectively compensate for losses that organizations would otherwise incur from charging rents that satisfy LIHTC affordability rules, which set rents below market rates, usually for 30 years. While nonprofit developers are responsible for around one in five LIHTC projects, the program was designed to increase the role of private capital in creating affordable housing, one of many turns towards the private sector and market competition in US housing policy over the last half-century (Guthrie and McQuarrie 2005; Bratt and Lew 2016).

The points systems by which state agencies evaluate applications and distribute LIHTC awards are called Qualified Allocation Plans (QAPs). States' QAPs vary widely and change from year to year, within some common parameters established by the federal government (Khadduri 2013; Scally et al. 2018; Aurand et al. 2022). All QAPs must reward applications for projects located in areas designated as Qualified Census Tracts (QCTs) or Difficult Development Areas (DDAs), federal definitions for low-income neighborhoods and places with high construction and land costs, respectively (Lang 2012; Eriksen 2017). In addition, states must reserve at least 10 percent of their credits each year for nonprofit-led developments. To the federal requirements, state QAPs add a variety of other incentives and priorities, which may act at cross purposes with each other or federal rules (Gustafson and Walker 2002; Ellen et al. 2015; Ellen and Horn 2018). Examples of state-level QAP priorities include serving particular populations (e.g., the elderly, veterans, and people with disabilities), tie-ins to social services and other supports, proximity to public transit, location in “high-opportunity” neighborhoods and other community-level compositional characteristics, and receiving buy-in from local authorities.

How states should structure QAPs and distribute LIHTC developments geographically is the subject of considerable debate. Over the life of the program, LIHTC-assisted projects have been sited disproportionately in communities of color and lower-income, densely populated neighborhoods that score poorly on conventional measures of “opportunity,” especially in education and the labor market (Oakley 2008; Williamson, Smith, and Strambi-Kramer 2009; Dawkins 2013; Ellen, Horn, and Kuai 2018). There is ample evidence that LIHTC is an effective channel of investment into disadvantaged neighborhoods, which often struggle to attract private capital (Baum-Snow and Marion 2009; Lang 2012; Dillman, Horn, and Verrilli 2017; Diamond and McQuade 2019; Voith et al. 2022; Won 2022; An et al. 2023). By the same token, however, concern has arisen that LIHTC fails to promote mobility into more advantaged communities for low-income renter households, potentially reinforcing segregation or compounding neighborhood effects (Newman and Schnare 1997; Ellen et al. 2018; Kuai 2024b). Over the past decade, spurred by a US Supreme Court ruling in 2015, most states have restructured their QAPs to incentivize LIHTC development in variously defined “high-opportunity” neighborhoods. These efforts have generally been successful, increasing the share of LIHTC developments that are located in more advantaged areas (Ellen et al. 2015; McClure and Johnson 2015; Ellen and Horn 2018; Walter, Wang, and Jones 2018; Kuai 2024a; Owens and Smith 2024).

## **Community Development Corporations**

Community development corporations (CDCs) are nonprofit organizations that specialize in housing and economic development, often including job creation, in disadvantaged neighborhoods. CDCs create over 100,000 new housing units each year (Bratt 2008). CDCs are community-based organizations; they focus on a relatively local geographic area, often (but not always) a neighborhood. The kinds of projects that CDCs take on and the dynamics of CDCs’ relationships within and outside their communities vary greatly (Stoecker 1997; Johnson 2004; Kirkpatrick 2007). Often growing out of (or coopting) social movement or-

ganizations and less formal community-level organizing, CDCs emerged during the War on Poverty years as a channel for new federal funding streams into neighborhoods.

The introduction of LIHTC was a turning point for the organizational field of CDCs. The playing field for CDCs changed dramatically in the 1970s and 1980s as federal support for community economic development—especially dollars for US Department of Housing and Urban Development (HUD)—was downsized and restructured. Although LIHTC was designed mainly to incentivize private investment in low-income housing, it became an important source of funding for CDCs. They have grown increasingly professionalized over time (Frisch and Servon 2006), partly in response to LIHTC. Today, as many as a third of CDCs benefit from LIHTC funds in any given year (Sally et al. 2023). Robinson (2020) argues that LIHTC has affected CDCs so strongly that there are effectively two cohorts of CDCs: pre- and post-LIHTC.

CDCs are a particularly useful case for studying neighborhood organizational resources (NORs) because their activities are usually limited to a tight geographic area. Unlike for many kinds of establishments and organizations, it is reasonable to assume for most CDCs that the location of their headquarters conveys something meaningful about the spatial reach of its organizational activities.

## **Research Questions and Theoretical Estimand**

The empirical question in this paper is how much CDCs influence the spatial distribution of LIHTC projects. I approach the effect of CDCs on LIHTC allocations as an aggregate, causal, neighborhood-level theoretical estimand (Lundberg, Johnson, and Stewart 2021), comparing communities’ average potential outcomes as NORs vary across the population of metropolitan neighborhoods. I estimate the average change in the likelihood that a LIHTC award that would be allocated in a given neighborhood and year if, all else held equal, levels of CDC resources were increased. Various likely sources of effect heterogeneity are outside the scope of this analysis; the estimand is the average effect of NORs from CDCs

on the probability that a neighborhood receives a LIHTC award, aggregated over a wide geographic extent and multiple rounds of LIHTC allocations. The analysis cuts across policy environments and housing markets over a wide swath of the program’s history, aiming for an overall picture of NORs’ effects on LIHTC.

The role of CDCs in the geographic allocation of LIHTCs awards is one of many empirical cases of a wider set of relationships in US urban governance. The broader aim of this paper is to better understand the magnitude of local organizations’ impacts on the spatial distribution of scarce public resources that influence neighborhood inequality. When state actors have discretion over where to allocate attention and investments across unequal places, how much do a community’s relevant NORs affect its outcome? Distinct from NORs that facilitate social interaction and day-to-day individual transactions, this question analyzes how NORs contribute to governance and resource allocation across places and social groups (Marwell and McQuarrie 2013; Stinchcombe [1965] 2013). Many studies have shown that local organizations often play such a role in community economic development. Rather than taking up *whether* CDCs shape LIHTC’s spatial distribution, the contribution of this paper is to clarify *how much* of an impact NORs have in this area.

## Data and Measures

### Unit of Analysis and Sample

I limited the analysis to metropolitan statistical areas (MSAs), cities and suburbs that are tied into the same regional economy and housing market around a major population center (Sunstein 2010). MSAs account for most CDC and LIHTC activity. In addition, QAPs and developers often approach rural areas much differently than urban and suburban communities (Scally, Dabir, and Lipsetz 2017; Schwartz and McClure 2023; Owens and Smith

2024). Focusing on MSAs allowed for an expansive view of a comparable set of CDC and LIHTC dynamics.

The units of analysis were census tracts, the most common areal unit for US neighborhood-level research. Averaging around 4,000 inhabitants, census tracts are stable, nationally consistent local units with relatively homogeneous populations, facilitating statistical comparison (Aultman et al. 1994). I used the tract boundaries defined for the 2010 US census (Murdock 2008). Where necessary, I harmonized the areal units of other datasets with the 2010 tract boundaries using correlation lists from the Missouri Census Data Center’s geographic correspondence engine and the Longitudinal Tract Database (LTDB) crosswalk files (Logan, Xu, and Stults 2014).

The analytic sample contained 1) variation between states within years and 2) variation within states between years. This sampling approach accounted for states’ evolving QAPs and the ebb and flow of various state-level funding sources for low-income housing or nonprofit developers, which have proliferated unevenly over the past several decades (Bratt 2008; Ellen and Horn 2018; Schwartz [2006] 2021). While attributes of these policy environments and programs were not measured directly, the sample’s breadth made it possible to net them out of the estimates through fixed effects, as discussed on page 73.

The time-series cross-sectional (TSCS) analytic sample that I analyzed contained annual observations of 19,897 census tracts for 14 years from 2006 through 2019, a total of 278,558 observations. This sample was a subset of a larger original dataset that spans from 2001 through 2019 and comprises every census tract in the 100 most populous MSAs in the continental US according to the American Community Survey (ACS) 2019 five-year estimates. For a TSCS dataset of this size, the computational costs of the analytic approach described beginning on page 75 were prohibitive. I narrowed the analytic sample to 30 of the 100 MSAs in the full dataset by dividing the MSAs into population quintiles and randomly selecting six MSAs from each. Table 15 lists the randomly selected MSAs. This sampling strategy

balanced computational feasibility with the spatio-temporal variation and relatively large sample necessary for the paper’s analytic approach.

## Outcome

The outcome of interest was a neighborhood’s likelihood of receiving a LIHTC allocation. This variable was unobserved. Operationally, the outcome was a binary indicator that took a value of one in tract-year units in which at least one LIHTC project was awarded tax credits and zero otherwise. I constructed this variable using the recorded years and locations of every project in the national LIHTC database, maintained by the HUD. These data comprised 52,007 projects from LIHTC’s first projects in 1987 through the 2021 allocation round.

Because few tracts are sites of LIHTC allocations in a given year (see Table 17), I took steps to minimize information loss by addressing missing data in the outcome. Three sources of missingness impacted this analysis. As summarized in Table 16, some records in HUD’s database had empty values for the project’s locations, allocation years, or both. And while HUD has reduced the number of omissions in its public LIHTC records over time, a small number of allocated projects remain absent from the dataset (Ellen et al. 2018). It was infeasible to integrate the unknown number of LIHTC projects that were excluded from the raw data altogether, and imputing coordinates for the 2,319 records without recorded locations was more likely to compound distortion. However, I salvaged 3,120 projects with observed locations but unobserved allocation years using the imputation strategy described beginning on page 75. As a result, just under 4.5 percent of the observations in the HUD database were dropped from the analysis. Combined with the projects that were missing altogether, the total share of unmeasured LIHTC projects from 1987 through 2021 was probably in the single digits.

**Table 15: Randomly selected metropolitan statistical areas (MSAs) in analytic sample for models of Low-Income Housing Tax Credit (LIHTC) allocations**

| MSA                                         | Population (2015–19) | Rank |
|---------------------------------------------|----------------------|------|
| New York-Newark-Jersey City, NY-NJ-PA       | 19,294,236           | 1    |
| Los Angeles-Long Beach-Anaheim, CA          | 13,249,614           | 2    |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 6,079,130            | 8    |
| Atlanta-Sandy Springs-Alpharetta, GA        | 5,862,424            | 9    |
| Boston-Cambridge-Newton, MA-NH              | 4,832,346            | 10   |
| San Francisco-Oakland-Berkeley, CA          | 4,701,332            | 12   |
| Detroit-Warren-Dearborn, MI                 | 4,317,848            | 14   |
| Minneapolis-St. Paul-Bloomington, MN-WI     | 3,573,609            | 16   |
| Charlotte-Concord-Gastonia, NC-SC           | 2,545,560            | 22   |
| Orlando-Kissimmee-Sanford, FL               | 2,508,970            | 23   |
| San Antonio-New Braunfels, TX               | 2,468,193            | 24   |
| Portland-Vancouver-Hillsboro, OR-WA         | 2,445,761            | 25   |
| Pittsburgh, PA                              | 2,331,447            | 26   |
| Indianapolis-Carmel-Anderson, IN            | 2,029,472            | 34   |
| Providence-Warwick, RI-MA                   | 1,618,268            | 38   |
| Jacksonville, FL                            | 1,503,574            | 40   |
| Louisville/Jefferson County, KY-IN          | 1,257,088            | 46   |
| Tucson, AZ                                  | 1,027,207            | 53   |
| Greenville-Anderson, SC                     | 895,942              | 60   |
| Albany-Schenectady-Troy, NY                 | 880,736              | 62   |
| El Paso, TX                                 | 840,477              | 68   |
| Cape Coral-Fort Myers, FL                   | 737,468              | 76   |
| Colorado Springs, CO                        | 723,498              | 78   |
| Des Moines-West Des Moines, IA              | 680,439              | 83   |
| Syracuse, NY                                | 652,416              | 88   |
| Deltona-Daytona Beach-Ormond Beach, FL      | 646,288              | 89   |
| Toledo, OH                                  | 644,137              | 90   |
| Durham-Chapel Hill, NC                      | 626,695              | 92   |
| Provo-Orem, UT                              | 616,791              | 93   |
| Jackson, MS                                 | 597,727              | 95   |

**Table 16: Missingness and imputation in Low-Income Housing Tax Credit (LIHTC) project data**

|                   | Year recorded | Year imputed | Total  |
|-------------------|---------------|--------------|--------|
| Location recorded | 46,568        | 3,120        | 49,688 |
| Location missing  | 2,084         | 235          | 2,319  |
| Total             | 48,652        | 3,355        | 52,007 |

## Explanatory Variable

I drew from three data sources to construct the explanatory variable, a measure of NORs by way of CDCs. The most comprehensive census of community-based nonprofit housing developers was compiled recently by researchers at the Urban Institute (Lo, Lecy, and Scally 2022), who reconciled a variety of data sources to delimit the population of organizations more precisely than was possible using other common data sources for the nonprofit sector, especially on a longitudinal basis. The census enumerates community-based nonprofit housing development organizations that were active from 2001 through 2019. While the data include some organizations that operated at a wider geographic scale than would fall under most definitions of CDCs (Scally et al. 2023), this census provided the best available estimate of the population of the CDC organizational field over time. I linked the Urban Institute’s organizational census to the Business Master Files and Core Files prepared by the National Center for Charitable Statistics (NCCS), which provided location and financial variables on an annual basis (Urban Institute 2013). From 2001 to 2019, 6,807 unique CDCs were active in the US according to the Urban Institute’s census. Of these, I was able to match all but 315 (4.63%) to census tracts using the locations recorded in the NCCS data, which usually correspond to a headquarters or similar organizational establishment.

The foundation of the measure of CDCs’ resources was the total expenditures reported in their annual tax filings. Consistent with the framework introduced on pages 23 to 27, determining how to operationalize NORs via CDCs involved assumptions about the *boundaries* of CDCs’ activities, the relevant *relationships* between CDCs and communities, and the inter-organizational dynamics of *dependence* within the CDC field. The true spatial extents of CDCs’ activities or investments over time were unobserved at the field level. The best available spatial basis for their boundaries and contact with communities was their recorded locations in the NCCS data. Rather than focusing on the density or number of establishments, however, a contact-based measure that captured the flows of resources that CDCs funneled into neighborhoods was a better gauge of organization-community relationships. Similarly, a

mass-based measure of CDC resources was preferable to a density-based measure. Larger CDCs have a well-documented advantage over their smaller counterparts in attracting resources and are typically more stable over time (Bratt 2008; Scally et al. 2023).

CDCs’ annual expenditures were a good proxy metric for the organizational size of CDCs and the amount of investment they channel into their communities. I summed the total expenditures of CDCs with recorded locations in each census tract and took the cubic root of the totals to address a long right tail that emerged in the nonzero tract-level sums. (Other common transformations for this purpose, such as logarithmic transformations, were unusable in this case because there was a small number of organizations with negative expenditures in each year). The spatial weighting strategy described beginning on page 80 approximated the boundaries of each CDC’s contact with communities, which in most cases were not limited to the census tract in which their official address is located.

## Controls and Fixed Effects

To execute the analytic approach described beginning on page 75, the covariate adjustment strategy had to reconcile several partially competing priorities. To estimate a causal effect, the control variables and fixed effects had to adjust for pre-treatment confounders, or common causes of the outcome (LIHTC allocations) and explanatory variable (CDC resources). It was also optimal to adjust for known causes of LIHTC allocations, even if they were unrelated to CDC resources, to shore up the lagged-outcome approach to reverse causality. At the same time, because the theoretical estimand was the total effect of NORs, it was inappropriate to control for variables that may mediate the link between CDCs and LIHTC allocations (Elwert and Winship 2014; Cinelli, Forney, and Pearl 2022). On a practical level, parsimony was expedient. Because of the structure of the weights and spatial lags included in the models, each additional parameter significantly increased the computational costs of estimation. To address these issues simultaneously, I included in the covariate adjustment set variables that had a plausible causal relationship with CDC resources or LIHTC

allocations (or both), measuring unobserved confounders with appropriate proxies where necessary (VanderWeele 2019; Brand et al. 2021).

The models included fixed effects for municipalities by year and for counties. The municipality-by-year fixed effects controlled for unobserved heterogeneity within individual localities in each year. Because municipalities are nested within states, it also controlled for shared effects of states' QAPs in a given year, among other unobserved state-level factors. The county fixed effect, which was time-invariant, netted out the effects of unobserved factors in each county—and, due to nesting, each MSA—that were consistent across years and tracts. While most municipalities do not cross county lines, municipalities are not perfectly nested within counties.

I controlled for tracts' QCT and DDA status, which bolstered the covariate adjustment strategy in several ways. By law, both designations, established annually by HUD, increase a LIHTC application's likelihood of securing funding. In addition, they both functioned as proxies for neighborhood-level constructs that were otherwise difficult to measure in a parsimonious way. QCTs are tracts in which the majority of households' incomes are at or below 60 percent of the area median or at least one-quarter of the population is below the poverty line, with some rare exceptions. QCT status functioned as an effective proxy for neighborhood disadvantage. DDAs are communities that are likely to struggle to attract private capital for low-income housing development, which could plausibly affect CDC capacity and developers' interest in LIHTC projects in the area. I also included an interaction term between QCT and DDA status, allowing for the possibility that these designations are non-additive or compounding, which would constitute a kind of double-penalty for disadvantaged neighborhoods in expensive housing and labor markets. Both designations are published on an annual basis by HUD, usually in a non-machine-readable format for most of the years in the analytic sample. In these cases, I used standard text-scraping tools and regular expressions to wrangle the information into columnar data.

Using interpolated counts from decennial censuses and ACS estimates gathered from the LTDB, I constructed controls for several relevant compositional variables: population density (log-transformed), the Black and Hispanic/Latino population shares, the share of housing that was owner-occupied (as opposed to rented), and median household income. I measured the latter as a within-MSA percentile to avoid the contaminating effects of inter-MSA differences in housing and labor markets. I used linear interpolation to calculate tracts' values for years between censuses or ACSs. Missing values were imputed, as described beginning on page 75.

In addition to neighborhood composition in a given year, a neighborhood's socioeconomic trajectory was a likely confounder and predictor of the outcome. I controlled for several dimensions of neighborhood change: the share of residents that had lived in their unit for less than 10 years, change in the tract's within-MSA median income percentile, change in the White population share, and a log-transformed index of housing appreciation. The year 1990 (1989 for the appreciation index) was the comparison year for the neighborhood change measures because the gradients in urban neighborhoods' population compositions steepened in the 1990s, making the beginning of the decade an appropriate baseline (Ellen and O'Regan 2008; Owens 2012; Hwang and Lin 2016). To reflect that how far a neighborhood could descend or ascend its MSA's socioeconomic ladder depended on its starting point in 1990 (see, e.g., Hwang and Sampson 2014; Finio 2022), I also adjusted for the interaction between tracts' current and 1990 MSA income percentiles. The housing appreciation measure, a repeat-sales index developed by Contat and Larson (2024), was a tract-level extension of the well-known Housing Price Index published by the US Federal Housing Finance Agency.

# Methods

## Multiple Imputation

I addressed missingness in the linearly-imputed demographic data and project-level LIHTC data using multiple imputation, which allowed me to maintain a balanced panel and reduce bias compared to listwise deletion and more rudimentary imputation methods (Rubin 1987; Allison 2001). On average over the analysis period, less than 1.5 percent of census tracts in the 30 analyzed MSAs received a LIHTC allocation. Given such a rare event, every observation with a value of one in the outcome was valuable (King and Zeng 2001), making imputation a particularly useful strategy in this analysis.

I created eight multiply imputed versions of both incomplete datasets via expectation-maximization with bootstrapping, an algorithm that is well-suited to TSCS data (Honaker and King 2010). To increase the quality of the imputation results, I implemented the algorithm using the full LIHTC project dataset and demographic data from 1990 through 2020, even though some of these years are outside the analytic sample. After aggregating each of the eight imputed LIHTC datasets to the census tract level, I merged every combination of them with the other data sources, creating a total of 64 multiply imputed analysis datasets.

I estimated the models described below on each of the 64 imputed datasets. Estimates stabilized using eight imputations each of the two datasets with missing observations; more imputations would have only negligibly reduced bias further. I pooled descriptive statistics, coefficient estimates, standard errors, and model diagnostics using the conventional “Rubin’s rules” and their extensions (Rubin 1987; Grund, Lüdtke, and Robitzsch 2016).

## Modeling Strategy

Estimating CDCs’ causal effects on the likelihood of LIHTC allocations entailed four main modeling choices: how to model a rare event in a TSCS setting, how to deal with

reverse causality, how to manage time-varying confounding, and how to satisfy the stable unit treatment value assumption (SUTVA) with spatially interdependent areal units of analysis. I implemented a modeling strategy that harnessed benefits of the linear probability model (LPM) with group fixed effects, lagged-outcome instrumental variables (IVs), marginal structural models (MSMs), and spatial lag of  $X$  (SLX) models.

The basic structure of the model was a LPM. It included group-level—i.e., not unit-level—fixed effects, as discussed on page 73. For rare binary event outcomes, many researchers turn to a logistic regression or other generalized linear model (GLM), often with an intercept adjustment or other form of bias correction (Firth 1993; King and Zeng 2001). Timoneda (2021), however, shows that in TSCS analyses of various sizes, LPMs with group-level fixed effects outperform logit models for rare-event outcomes, in part because the ordinary least squares (OLS)-estimated LPM can accommodate groups without variation in the outcome. By comparison, in maximum likelihood (ML) estimation for GLMs, researchers face the tradeoff between losing the information provided by units with all-zero outcomes or changing the fixed-effects structure, which can reintroduce unwanted heterogeneity. Estimating a LPM made it possible to include municipality-by-year fixed effects even though only a small number of municipalities received LIHTC allocations in any given year. To address the heteroskedasticity inherent to the LPM and account for potential autocorrelation among observations of the same tract between years (which was not controlled by the fixed effects), I report robust standard errors clustered by census tract.

One threat to a causal interpretation was reverse causality. There are potential sources of simultaneity in the relationship between LIHTC allocations and NORs, especially when measured via CDC expenditures. When LIHTC tax credits are awarded to CDCs, the funds are likely to be reflected on the organizations’ balance sheets not long after. Developers must place LIHTC-supported projects “in service” in the same year or the year after they win the allocation (Heightley 2023). For most CDC-led projects, expenditure records would reflect the LIHTC allocation relatively quickly because CDCs are particularly dependent on selling

the credits to investors so that they can spend the proceeds on the development project right away (Bratt and Lew 2016).<sup>1</sup> In many cases, the tax filings would reflect the LIHTC funding in the same year a CDC receives the allocation. Even though most LIHTC awards are made to for-profit developers and some are made to non-CDC nonprofits, there is a plausible bidirectional path between CDC resources and LIHTC allocations.

I addressed potential reverse causality in two ways. First, I lagged the explanatory variable, controls, and fixed effects one year behind the outcome. The temporal lag ensured that the allocation (made in year  $t$ ) could not be reflected in the CDC resources measure (based on organizational expenditures in year  $t - 1$ ). It also had desirable theoretical properties: organizations typically begin planning for a LIHTC application well before they apply for a round of tax credits. Resources from a prior period are a reliable proxy for the NORs that would need to be in place to initiate a LIHTC application.

There was a good chance, however, that temporally lagging the right hand side fell short of completely purging endogeneity (Reed 2015; Bellemare, Masaki, and Pepinsky 2017); reverse causality also had to be addressed through the structure of the model. For reasons discussed beginning on page 10, I opted against one existing solution to this issue: using NORs in other organizational fields as a surrogate instrument. Dynamic panel models, cross-lagged panel models, and related structural-equations approaches are other popular remedies for reverse causality (Bollen and Brand 2010; Allison, Williams, and Moral-Benito 2017; Leszczensky and Wolbring 2022), but they were ill-suited or intractable in this case because ML estimators could not accommodate the separation in the data or because they would entail tract-level effects rather than a municipality-by-year setup.

To further mitigate reverse causality, I used a lagged-outcome IV approach (Holm, Hjorth-Trolle, and Andersen 2023). To the explanatory and control variables above, I added a right-hand-side binary variable for whether the tract received a LIHTC allocation in year  $t - 1$ ;

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<sup>1</sup>Selling the credits to investors is the most common course of action in LIHTC projects regardless of whether the developer is a for-profit or nonprofit entity. Yet developers may exercise the option to hold onto the tax credits and claim them in equal installments over a ten-year period. This is likely only to be an option for larger, better-capitalized organizations.

I estimated the model by two-stage least squares (2SLS), using the outcome variable in year  $t - 3$  as an instrument. The usual assumptions of IV regression applied (Angrist and Pischke 2009; Sovey and Green 2011). The monotonicity assumption was relatively trivial in this case, as there is little reason to suspect that a neighborhood would receive a LIHTC allocation only in the absence of a LIHTC allocation in the past. The relevance condition was directly testable. The exchangeability assumption raised the stakes of the covariate adjustment and fixed-effects strategy, namely whether it controlled for all relevant predictors of the outcome, even if they did not confound the effects of the explanatory variable. If the outcome (LIHTC allocations in year  $t$ ) and instrument (LIHTC allocations in year  $t - 3$ ) shared unmeasured common causes, the exchangeability assumption would be jeopardized.

The sufficiency of the control variables was also important for the exclusion restriction, which assumed that LIHTC allocations in year  $t - 1$  were conditionally independent of LIHTC allocations in year  $t - 3$ . The grounds for this assumption come partly from the nature of states' QAPs, which are reflected in the municipality-by-year fixed effects and indirectly in the neighborhood characteristics in the adjustment set. LIHTC developments are known to cluster in space (Oakley 2008; Dawkins 2013; Voith et al. 2022; Won 2022). There is little evidence, however, that this clustering is because states favor placing LIHTC projects near other LIHTC projects. It is more plausible that the spatial clustering of allocations is a reflection of the spatial clustering of the underlying neighborhood conditions, which shape the number of points each application receives according to the respective state's QAP. The lagged-outcome IV approach is viable under such an assumption of conditional independence over time (Holm et al. 2023). The choice of a three-year lag instrument (using the outcome in year  $t - 3$  as an instrument for the outcome in year  $t - 1$ ) reflects the fact that LIHTC allocations will typically hit organizations' balance sheets within two years of the allocation. The three-year lag rules out this source of temporal cross-contamination.

In addition to the feedback loop between the explanatory variable and outcome, there may have been a feedback loop between the explanatory variable and the controls. Standard

covariate adjustment and estimation techniques are vulnerable to bias when time-varying confounders respond to past treatment. As organizations that often prioritize housing for lower-income populations that make direct investments in neighborhoods’ housing stock and commercial real estate, CDCs’ investments have a direct effect on the neighborhood conditions and neighborhood change.

MSMs are the standard modeling tool for addressing time-varying confounding (Robins, Hernán, and Brumback 2000; Shinozaki and Suzuki 2020). MSMs accommodate links between past exposures and subsequent confounding variables by reweighting the sample such that treatment is orthogonal to the controls. In addition to LPMs incorporating the lagged-outcome IV and MSMs, I estimated approaches that combined the two (Tan 2010; Michael et al. 2023). I estimated the weights for the MSM using residual balancing weight (RBW) (Zhou and Wodtke 2020). This method essentially generalizes entropy balancing, a common weighting scheme for MSMs with continuous treatments, to panel settings. RBW had the advantage of computational efficiency, which made it feasible—but still very computationally intensive—to estimate MSM weights with a large, multiply imputed dataset. For each of the 64 imputed iterations of the dataset, estimating the RBWs lasted about one hour on a high-performance supercomputer with 24 cores (12–16 gigabytes of memory per core). I included all of the control variables and fixed effects (except the lagged-outcome IV) in the predictor set for the weights, ensuring that the explanatory variable was balanced across levels of all other right-hand-side variables. In addition to addressing time-varying confounding, the MSM approach was appropriate for the population-level average estimand that I sought to estimate. The RBWs were estimated based on weighted values of the control variables over the past five years, with the previous year’s observation counting five times more than the observation from five years prior. (The first five years in the sample from 2001 through 2005 are excluded from the analysis because they were used to estimate the  $\text{ac}\{\text{rbw}\}$ ).

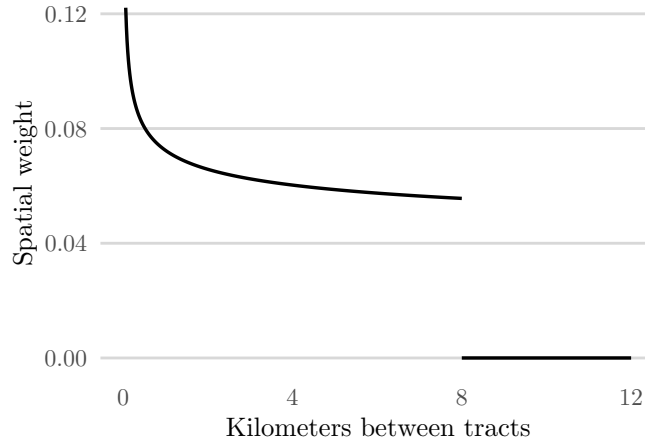
## Spatial Lags and Weights

The last component of the model was the SLX setup. Violations of the SUTVA are common in analyses of areal units, which are unlikely to be truly independent of one another. This problem is particularly severe in the cases of units such as census tracts that, even though they are designed to be numerically comparable, are unlikely to correspond theoretically to the optimal spatial boundaries for a given research question (Logan 2012). As a result, spatial spillovers (or spatial dependence) between units is very likely in neighborhood-level models (Anselin 1988). What happens in one neighborhood often depends closely on what happens nearby.

This issue was particularly important to address given the structure of the explanatory variable, CDC resources operationalized as expenditures. CDCs' activities are unlikely to be limited to the census tract in which their locations are recorded in public tax data, even if they serve a relatively small geographical area. Without addressing the spillovers inherent to the explanatory variable, the modeling strategy was bound to underestimate the level of CDC resources in census tracts that benefited from CDC investment even though no CDC was headquartered formally within them. The difficulties of establishment-based measures, discussed earlier in this dissertation in the context of routine organizations, manifest similarly when analyzing the effects of organizations that work farther upstream or are not sites of day-to-day social interaction.

The idea of the SLX model is to separately estimate effects *within* and *around* a unit of analysis; these are known as the *direct* and *indirect* effects (LeSage and Pace 2009; Vega and Elhorst 2015; Rüttenauer 2022). For each explanatory and control variable, the model contains one term for the census tract itself and one term for a spatially-weighted average of the variable in its neighbors. Which units are neighbors to another unit and how strongly they are weighted depends on the spatial-weights matrix chosen (Dubin 2009). This model has several benefits. First, it mitigates the problem of spillovers, isolating dynamics within single observations from nearby dynamics and allowing both to influence the outcome. Because

**Figure 10: Spatial weights in models of Low-Income Housing Tax Credit (LIHTC) allocations**



the SLX model parameterizes the spatial effects, it does not require a separate estimation technique than the corresponding non-spatial model. And it is still possible to measure the overall effect of a variable in a parsimonious way by summing the direct and effects, known as the *total effect* (Golgher and Voss 2016).

The spatial weights used in the model are summarized in Figure 10. I assumed that dynamics within a tract depended on all tracts within an eight-kilometer radius on a distance-decay basis. The eight-kilometer kernel comes from Baum-Snow and Marion (2009), who find that neighborhood-level clustering in the effects of LIHTC programs subsides at a distance of eight kilometers. Within the eight-mile radius, each tract's influence is the inverse squared logarithm of the distance from the reference tract's population center to that of the neighbor tract. In this way, closer tracts were weighted more strongly than tracts that were farther away; the nonlinear function weighted the farthest tracts about half as strongly as the closest tracts. To facilitate interpretability and simplify the calculation of the total effects, I normalized the spatial weights matrix by row. This normalization meant that each cell in the matrix represented the portion of the spatial influence it had on the reference tract. The spatial weights matrix, by convention, had values of zero along the diagonal; each tract's spatially weighted value was not affected by its own value.

# Results

## Descriptive Statistics

Table 17 presents descriptive statistics for the explanatory and control variables within and around (spatially weighted) each census tract. The values are stratified across four levels of the NORs measure of CDC expenditures, according on a measure that combines the within- and around-tract values. The “none” category measures tracts with no CDCs within an eight-kilometer radius. The “low”, “medium”, and “high” levels are measured among tracts with nonzero values, representing CDC expenditures that are below, within, and above one standard deviation, respectively, from the mean.

LIHTC allocations are more common within and around census tracts that had more CDC resources. In a given year from 2006 to 2019, nearly 5.7 out of every 100 tracts with the highest levels of CDC expenditures were the sites of LIHTC allocations in the following year ( $M = 0.057, SD = 0.231$ ), compared to 3.2 per 100 tracts with low levels of CDC resources ( $M = 0.032, SD = 0.175$ ) and 1.5 out of every 100 tracts without CDC resources ( $M = 0.015, SD = 0.122$ ). Without controlling for any of the covariates or fixed effects, there is a positive relationship between CDC expenditures and the probability of LIHTC allocations to tracts.

As expected, CDCs expenditures trend higher in and around disadvantaged neighborhoods. Nearly one-third of neighborhoods with the most CDC resources were QCTs over the course of the sample ( $M = 0.316, SD = 0.465$ ) compared to just over one-tenth of neighborhoods without CDC resources ( $M = 0.112, SD = 0.315$ ). Similarly, CDC expenditures were higher in tracts with lower median incomes. They also spent more in neighborhoods with higher proportions of Black residents, though the highest-spending CDC tracts had lower Black population shares ( $M = 0.207, SD = 0.233$ ) than the medium-spending CDC tracts ( $M = 0.249, SD = 0.283$ ). CDCs also spent considerably more in and around tracts where renters were more represented compared to owner occupants.

**Table 17: Low-Income Housing Tax Credit (LIHTC) allocations, demographics, housing stock, and neighborhood change by community development corporation (CDC) expenditure levels within and around census tracts in 30 metropolitan statistical areas (MSAs), 2006–2019**

|                                       |        |  | CDC expenditures |                |                |                |
|---------------------------------------|--------|--|------------------|----------------|----------------|----------------|
|                                       |        |  | None             | Low            | Medium         | High           |
| <b>Outcome</b>                        |        |  |                  |                |                |                |
| LIHTC allocation                      | Within |  | 0.015 (0.122)    | 0.032 (0.175)  | 0.044 (0.204)  | 0.057 (0.231)  |
|                                       | Around |  | 0.013 (0.113)    | 0.011 (0.104)  | 0.021 (0.142)  | 0.027 (0.161)  |
| <b>Demographics and housing stock</b> |        |  |                  |                |                |                |
| Qualified Census Tract (QCT)          | Within |  | 0.112 (0.315)    | 0.202 (0.401)  | 0.306 (0.460)  | 0.316 (0.465)  |
|                                       | Around |  | 0.042 (0.200)    | 0.105 (0.307)  | 0.199 (0.399)  | 0.218 (0.412)  |
| Difficult Development Area (DDA)      | Within |  | 0.347 (0.474)    | 0.276 (0.446)  | 0.293 (0.453)  | 0.355 (0.476)  |
|                                       | Around |  | 0.237 (0.422)    | 0.453 (0.496)  | 0.446 (0.495)  | 0.326 (0.467)  |
| Hispanic/Latino share                 | Within |  | 0.185 (0.231)    | 0.170 (0.223)  | 0.217 (0.247)  | 0.212 (0.235)  |
|                                       | Around |  | 0.133 (0.187)    | 0.207 (0.245)  | 0.243 (0.259)  | 0.183 (0.228)  |
| Black share                           | Within |  | 0.148 (0.231)    | 0.229 (0.290)  | 0.249 (0.283)  | 0.207 (0.233)  |
|                                       | Around |  | 0.097 (0.163)    | 0.159 (0.252)  | 0.212 (0.278)  | 0.181 (0.250)  |
| Owner-occupied housing share          | Within |  | 0.602 (0.256)    | 0.542 (0.244)  | 0.450 (0.250)  | 0.392 (0.261)  |
|                                       | Around |  | 0.709 (0.207)    | 0.590 (0.245)  | 0.487 (0.259)  | 0.477 (0.246)  |
| MSA income percentile                 | Within |  | 0.510 (0.298)    | 0.435 (0.305)  | 0.354 (0.300)  | 0.361 (0.310)  |
|                                       | Around |  | 0.593 (0.274)    | 0.503 (0.288)  | 0.415 (0.298)  | 0.417 (0.309)  |
| Population density                    | Within |  | 1.924 (0.170)    | 1.936 (0.154)  | 1.969 (0.145)  | 1.987 (0.125)  |
|                                       | Around |  | 1.831 (0.177)    | 1.976 (0.106)  | 2.009 (0.113)  | 2.002 (0.122)  |
| <b>Neighborhood change</b>            |        |  |                  |                |                |                |
| In residence less than 10 years       | Within |  | 0.577 (0.153)    | 0.590 (0.144)  | 0.627 (0.147)  | 0.649 (0.167)  |
|                                       | Around |  | 0.573 (0.157)    | 0.553 (0.157)  | 0.587 (0.148)  | 0.618 (0.149)  |
| Housing appreciation index            | Within |  | 5.287 (0.339)    | 5.252 (0.346)  | 5.324 (0.396)  | 5.397 (0.392)  |
|                                       | Around |  | 5.240 (0.294)    | 5.248 (0.328)  | 5.337 (0.374)  | 5.373 (0.386)  |
| Income percentile change since 1990   | Within |  | -0.002 (0.200)   | 0.014 (0.189)  | 0.037 (0.204)  | 0.063 (0.233)  |
|                                       | Around |  | -0.004 (0.205)   | -0.034 (0.193) | 0.004 (0.194)  | 0.045 (0.212)  |
| White share change since 1990         | Within |  | -0.137 (0.152)   | -0.108 (0.137) | -0.105 (0.164) | -0.086 (0.163) |
|                                       | Around |  | -0.135 (0.140)   | -0.165 (0.147) | -0.133 (0.164) | -0.117 (0.166) |

Means shown; standard deviations in parentheses. Within- and around-tract statistics are for each tract and its spatial lag, respectively. Low, medium, and high CDC expenditures are below, within, and above one standard deviation, respectively, from the mean among tracts with nonzero values of a combined within- and around-tract measure.

Neighborhoods with more CDC resources tend to have more pronounced upward socioeconomic trajectories and a somewhat larger presence of new residents. Compared to 1990 levels, incomes relative to the rest of the MSA as well as housing prices rose most in high-CDC resource neighborhoods. There were slightly more residents who had lived in their residence for less than a decade in the tracts where CDCs spent the most.

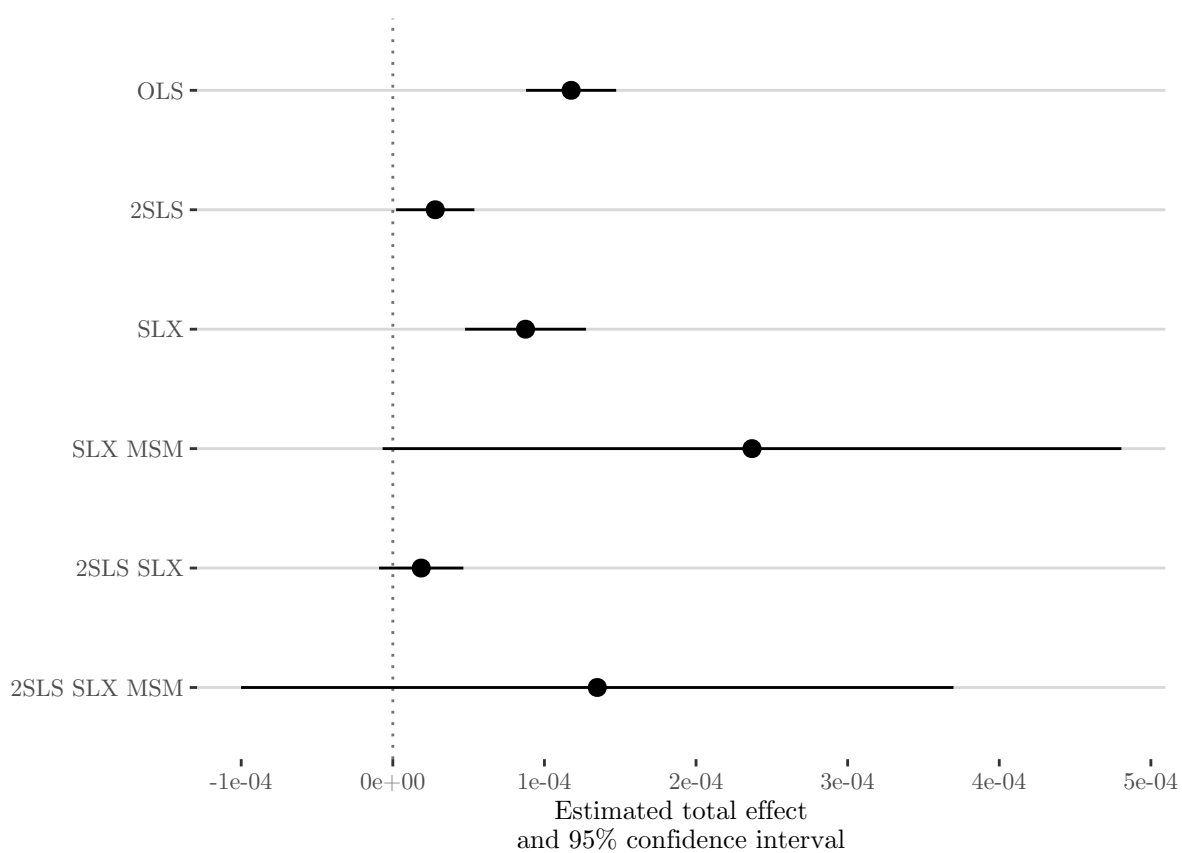
## Model Estimates

Table 18 summarizes the results of the estimated models of the probability that census tracts in 30 MSAs from 2006 to 2019 received a LIHTC allocation in the following year. For all models, the total effects (TEs) are shown; for the SLX models, the direct effects (DEs) and indirect effect (IE) are shown. The standard errors for the TEs were calculated by the delta method. For interpretation, I focus on the TEs of the explanatory variable only.

The bottom two rows of Table 18 display the results of the first-stage  $F$  test for the IV models and the effective sample size, which is reduced by the RBWs in the MSMs. For all of the IV models, the  $F$ -statistic for the first-stage models are far above the conventional threshold of 10 for both the DE and IE. This suggests that the relevance assumption for IV is satisfied comfortably.

The effective sample size shows the difficulty of managing time-varying confounding in this setting. The reduction in the effective size of the sample—from 178,558 observations in the dataset to 12,496 effective observations in the MSMs with weights—is very large, but it is generally in line with expectations for a rare event in highly unequal neighborhoods across which the explanatory variable is far from randomly assigned. The RBWs effectively created a sample size than five percent of the overall analytic sample in order to render CDC resources independent of the time-varying confounders. The reductions in bias from the MSMs clearly come at the cost of efficiency; the analytic strategy pursued in this paper requires a very large sample to estimate the aggregate effect of CDCs on LIHTC allocations.

**Figure 11: Estimated total effects of community development corporations (CDCs) on Low-Income Housing Tax Credit (LIHTC) by linear probability model (LPM) specification**



**Table 18: Linear probability models (LPMs) of the effects of community development corporations (CDCs) on neighborhood Low-Income Housing Tax Credit (LIHTC) allocations, 2006–2019**

|                                       | OLS                    | 2SLS                  | SLX                    |                        |                        | SLX MSM             |                     |                     | 2SLS SLX              |                     |                       | 2SLS SLX MSM        |                      |                      |
|---------------------------------------|------------------------|-----------------------|------------------------|------------------------|------------------------|---------------------|---------------------|---------------------|-----------------------|---------------------|-----------------------|---------------------|----------------------|----------------------|
|                                       | TE                     | TE                    | DE                     | IE                     | TE                     | DE                  | IE                  | TE                  | DE                    | IE                  | TE                    | DE                  | IE                   | TE                   |
| <b>Lagged outcome</b>                 |                        |                       |                        |                        |                        |                     |                     |                     |                       |                     |                       |                     |                      |                      |
| LIHTC allocation                      |                        | 0.7184***<br>(0.0860) |                        |                        |                        |                     |                     |                     | 0.7157***<br>(0.0867) | 0.1036<br>(0.1694)  | 0.8194***<br>(0.1887) | -0.1666<br>(0.1775) | -0.3049<br>(0.6575)  | -0.4715<br>(0.7431)  |
| <b>Explanatory variable</b>           |                        |                       |                        |                        |                        |                     |                     |                     |                       |                     |                       |                     |                      |                      |
| CDC expenditures                      | 0.0001***<br>(0.0000)  | 0.0000*<br>(0.0000)   | 0.0001***<br>(0.0000)  | -0.0000*<br>(0.0000)   | 0.0001***<br>(0.0000)  | 0.0002*<br>(0.0001) | 0.0000<br>(0.0001)  | 0.0002<br>(0.0001)  | 0.0000*<br>(0.0000)   | -0.0000<br>(0.0000) | 0.0000<br>(0.0000)    | 0.0002<br>(0.0001)  | -0.0000<br>(0.0001)  | 0.0001<br>(0.0001)   |
| <b>Demographics and housing stock</b> |                        |                       |                        |                        |                        |                     |                     |                     |                       |                     |                       |                     |                      |                      |
| Qualified Census Tract (QCT)          | 0.0080***<br>(0.0018)  | 0.0022<br>(0.0014)    | 0.0084***<br>(0.0019)  | -0.0017<br>(0.0043)    | 0.0067<br>(0.0043)     | -0.0037<br>(0.0076) | 0.0045<br>(0.0280)  | 0.0008<br>(0.0284)  | 0.0021<br>(0.0015)    | -0.0014<br>(0.0034) | 0.0007<br>(0.0036)    | 0.0145<br>(0.0110)  | 0.0243<br>(0.0228)   | 0.0388<br>(0.0229)   |
| Difficult Development Area (DDA)      | 0.0020<br>(0.0015)     | 0.0014<br>(0.0011)    | 0.0024<br>(0.0016)     | -0.0029<br>(0.0022)    | -0.0005<br>(0.0023)    | 0.0030<br>(0.0097)  | -0.0021<br>(0.0164) | 0.0009<br>(0.0154)  | 0.0017<br>(0.0012)    | -0.0009<br>(0.0015) | 0.0008<br>(0.0015)    | -0.0066<br>(0.0066) | 0.0006<br>(0.0106)   | -0.0061<br>(0.0105)  |
| QCT × DDA                             | 0.0130***<br>(0.0034)  | 0.0014<br>(0.0025)    | 0.0118***<br>(0.0035)  | 0.0108<br>(0.0078)     | 0.0226**<br>(0.0077)   | 0.0077<br>(0.0151)  | 0.0458<br>(0.0423)  | 0.0535<br>(0.0400)  | 0.0017<br>(0.0024)    | -0.0056<br>(0.0068) | -0.0039<br>(0.0070)   | 0.0059<br>(0.0169)  | 0.0080<br>(0.0370)   | 0.0139<br>(0.0409)   |
| Hispanic/Latino share                 | 0.0103***<br>(0.0029)  | 0.0023<br>(0.0015)    | 0.0084*<br>(0.0035)    | 0.0033<br>(0.0053)     | 0.0117*<br>(0.0046)    | 0.0065<br>(0.0180)  | 0.0039<br>(0.0286)  | 0.0104<br>(0.0261)  | 0.0023<br>(0.0016)    | -0.0007<br>(0.0025) | 0.0017<br>(0.0026)    | 0.0211<br>(0.0186)  | 0.0325<br>(0.0356)   | 0.0536<br>(0.0299)   |
| Black share                           | 0.0273***<br>(0.0025)  | 0.0058*<br>(0.0027)   | 0.0327***<br>(0.0029)  | -0.0217***<br>(0.0045) | 0.0110**<br>(0.0039)   | 0.0466<br>(0.0239)  | -0.0006<br>(0.0380) | 0.0460<br>(0.0287)  | 0.0069*<br>(0.0033)   | -0.0055<br>(0.0036) | 0.0014<br>(0.0032)    | 0.0198<br>(0.0147)  | 0.0145<br>(0.0205)   | 0.0342<br>(0.0202)   |
| Owner-occupied housing share          | -0.0150***<br>(0.0025) | -0.0039<br>(0.0023)   | -0.0142***<br>(0.0026) | -0.0147**<br>(0.0057)  | -0.0289***<br>(0.0058) | -0.0106<br>(0.0154) | 0.0189<br>(0.0339)  | 0.0083<br>(0.0362)  | -0.0039<br>(0.0023)   | -0.0021<br>(0.0046) | -0.0059<br>(0.0051)   | 0.0073<br>(0.0146)  | -0.0199<br>(0.0328)  | -0.0126<br>(0.0319)  |
| MSA income percentile                 | -0.0167***<br>(0.0020) | -0.0042*<br>(0.0020)  | -0.0180***<br>(0.0022) | 0.0049<br>(0.0047)     | -0.0131**<br>(0.0045)  | -0.0091<br>(0.0117) | 0.0009<br>(0.0245)  | -0.0082<br>(0.0246) | -0.0045*<br>(0.0021)  | 0.0013<br>(0.0027)  | -0.0032<br>(0.0029)   | -0.0266<br>(0.0149) | 0.0241<br>(0.0238)   | -0.0025<br>(0.0237)  |
| Population density                    | -0.0072**<br>(0.0028)  | -0.0029*<br>(0.0013)  | -0.0040<br>(0.0030)    | -0.0168**<br>(0.0053)  | -0.0208***<br>(0.0055) | -0.0048<br>(0.0158) | -0.0600<br>(0.0391) | -0.0649<br>(0.0412) | -0.0016<br>(0.0015)   | -0.0042<br>(0.0028) | -0.0057<br>(0.0033)   | 0.0059<br>(0.0174)  | -0.1002*<br>(0.0392) | -0.0943*<br>(0.0374) |
| <b>Neighborhood change</b>            |                        |                       |                        |                        |                        |                     |                     |                     |                       |                     |                       |                     |                      |                      |
| In residence less than 10 years       | 0.0155***<br>(0.0032)  | 0.0031<br>(0.0028)    | 0.0154***<br>(0.0032)  | -0.0103<br>(0.0066)    | 0.0051<br>(0.0071)     | 0.0150<br>(0.0194)  | 0.0179<br>(0.0343)  | 0.0330<br>(0.0395)  | 0.0030<br>(0.0028)    | -0.0030<br>(0.0054) | -0.0000<br>(0.0052)   | 0.0424*<br>(0.0199) | 0.0061<br>(0.0432)   | 0.0486<br>(0.0482)   |
| Housing appreciation index            | 0.0079***<br>(0.0021)  | 0.0010<br>(0.0013)    | 0.0069**<br>(0.0022)   | 0.0084***<br>(0.0020)  | 0.0153***<br>(0.0027)  | 0.0158<br>(0.0129)  | 0.0161<br>(0.0149)  | 0.0319<br>(0.0172)  | 0.0009<br>(0.0013)    | 0.0017<br>(0.0015)  | 0.0026<br>(0.0021)    | 0.0042<br>(0.0102)  | 0.0326*<br>(0.0139)  | 0.0368*<br>(0.0171)  |
| Income percentile change since 1990   | 0.0223***<br>(0.0035)  | 0.0053<br>(0.0035)    | 0.0231***<br>(0.0036)  | 0.0150<br>(0.0082)     | 0.0381***<br>(0.0089)  | 0.0205<br>(0.0188)  | 0.0598<br>(0.0423)  | 0.0803<br>(0.0465)  | 0.0056<br>(0.0035)    | 0.0024<br>(0.0074)  | 0.0080<br>(0.0084)    | 0.0330<br>(0.0236)  | -0.0104<br>(0.0641)  | 0.0226<br>(0.0667)   |
| Income percentile × change            | -0.0149**<br>(0.0053)  | -0.0035<br>(0.0058)   | -0.0146**<br>(0.0053)  | -0.0320*<br>(0.0131)   | -0.0467**<br>(0.0146)  | -0.0263<br>(0.0284) | -0.0966<br>(0.0758) | -0.1230<br>(0.0830) | -0.0037<br>(0.0057)   | -0.0086<br>(0.0113) | -0.0123<br>(0.0128)   | -0.0327<br>(0.0281) | -0.0173<br>(0.0976)  | -0.0500<br>(0.1003)  |
| White share change since 1990         | 0.0135***<br>(0.0028)  | 0.0033*<br>(0.0016)   | 0.0139***<br>(0.0030)  | -0.0115*<br>(0.0058)   | 0.0024<br>(0.0057)     | 0.0249<br>(0.0179)  | -0.0312<br>(0.0386) | -0.0063<br>(0.0393) | 0.0036*<br>(0.0017)   | -0.0042<br>(0.0029) | -0.0006<br>(0.0029)   | 0.0410*<br>(0.0195) | -0.0418<br>(0.0368)  | -0.0008<br>(0.0303)  |
| First-stage <i>F</i> -test            |                        | 855.2***              |                        |                        |                        |                     |                     |                     | 420.7***              | 763.9***            |                       | 1566.0***           | 1377.9*              |                      |
| Effective sample size                 | 278,558                | 278,558               | 278,558                |                        |                        | 12,496              |                     |                     | 278,558               |                     |                       | 12,496              |                      |                      |

Pooled estimates from multiply imputed panel ( $n = 278,558$ ) of annual observations of 19,897 census tracts in random selection of 30 of 100 most populous MSAs.

Models include municipality-by-year and county fixed-effects. Robust standard errors clustered by tract in parentheses. Instrumental variable in 2SLS models: year-lagged outcome.

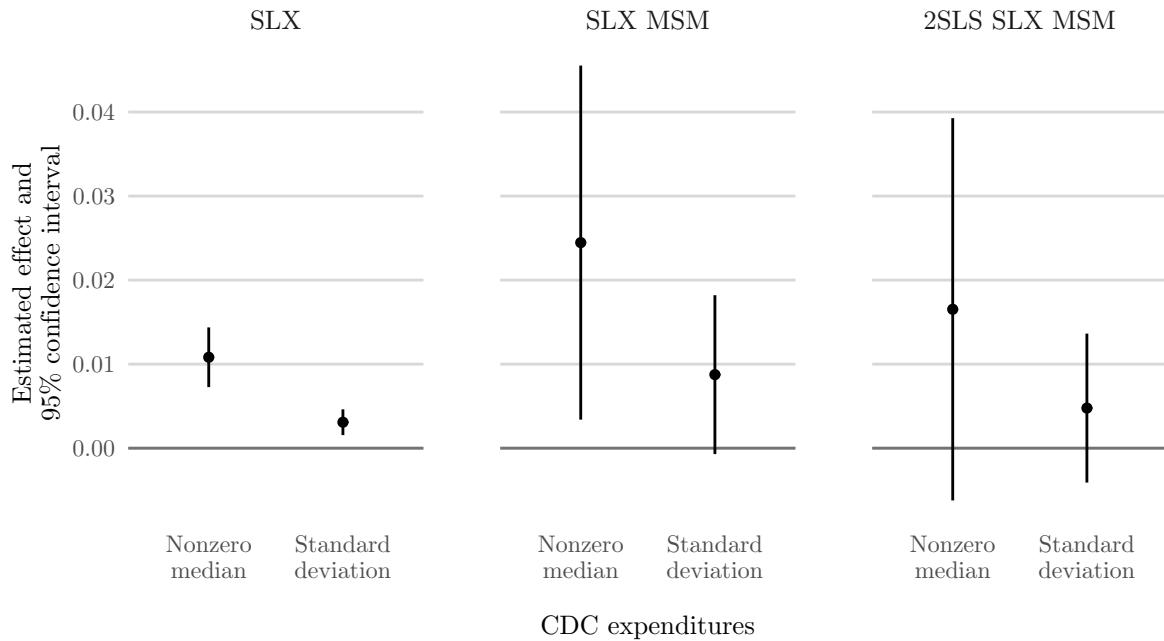
DE: direct effect. IE: indirect effect (spatial lag). TE: total effect.

Models designed to account for spatial spillovers and reverse causality, compared to their OLS counterparts, reduce the estimated total effect of CDC resources. Figure 11 illustrates the coefficient estimates and confidence intervals for the explanatory variable for each of the six estimated models. Compared to the naive OLS case, the 2SLS and SLX specifications reduce the estimated total effect of CDC resources, though the changes induced by the latter are not statistically significant at the 95-percent level. Both the 2SLS and SLX estimates, however, return a significant, positive total effect. Combining the features of these two specifications in the 2SLS SLX model, however, yields a smaller positive estimate that is not distinguishable from zero.

The MSMs, however, which address time-varying confounding, yield higher effect estimates than their counterparts, with considerably more uncertainty. The largest effect estimate is the SLX MSM. Integrating the IV into this model to mitigate reverse causality nearly halves the coefficient. Neither effect is statistically significant, though the former very closely approaches significance. The increased uncertainty is to be expected given the drastic decrease in the effective sample size in the MSMs. That the MSMs generally yield higher estimates than their counterparts, however, suggests that these models are correcting for distortion in the corresponding SLX and 2SLS models stemming from the uneven distribution of CDC resources across levels of the control variables (which measure neighborhood composition, neighborhood change, and unobserved heterogeneity at the county and municipal levels). Ultimately, however, the estimates fall short of showing a statistically significant difference between the estimated total effects of NORs from CDCs in the RBW-weighted MSMs models.

Figure 12 contextualizes the model estimates by showing the magnitude of the predicted effects at representative values of CDC resources for three of the models. The figure shows the increased predicted probability that a tract will receive a LIHTC allocation given an increase in CDC expenditures of one standard deviation and at the median level of spending among tracts with nonzero levels of CDC resources. Consistent with the relative instability in

**Figure 12: Estimated effects of community development corporations (CDCs) on Low-Income Housing Tax Credit (LIHTC) allocations at representative values by linear probability model (LPM) specification**



the coefficient estimates, the prediction intervals for the MSMs are considerably wider than for the non-weighted SLX model.

The absolute magnitude of these effect sizes is small in percentage-point terms, but they are nontrivial given that the outcome is a rare event. Over the period covered in the analytic sample, less than 1.5 percent of census tracts received allocations in a given year. All predicted increases illustrated in Figure 12 are below 2.5 percentage points (probability scale). All predicted increases for an increase in CDC resources of one standard deviation are below one percent, with the prediction intervals not passing above two percent. For an average neighborhood, then, typical levels of CDC spending could increase the likelihood of receiving a LIHTC allocation by more than half; by some of the model estimates, it could more than double them. Only for very large increases in CDC spending in some of the models, however, do the models show with confidence that the effects are significant. Hewing to the model that accounts simultaneously for reverse causality, spatial spillovers, and time-varying

confounding, the effects of CDC resources are positive and approaching significance, but there is considerable uncertainty in the estimates in this population-wide analysis.

## Discussion and Conclusion

Whether and how much CDCs affect the spatial allocation of LIHTC projects remains somewhat unclear. At the aggregate level across a 14-year stretch from 2006 to 2019, the most comprehensive models suggest that CDCs' effects are substantial and positive but only approaching statistical significance. To some extent, the uncertainty may decrease with a larger sample. The potential need for even more information than provided in such a large sample demonstrates the difficulty of addressing three simultaneous threats to causal inference: reverse causality, time-variant confounding, and spatial spillovers. Models that account for all three of these issues generate the largest effect sizes, but also the least precise effects.

One of the puzzles of LIHTC in the current housing policy climate in the US is that, regardless of the direction and magnitude of CDCs' effects on allocations, the policy implications are ambiguous. Advocates of desegregation and access to "high-opportunity" neighborhoods may be skeptical of CDCs' impact if their effect is to draw more housing into low-income areas. Advocates for those communities and place-based investment may see LIHTC as a crucial lifeline for investment that is otherwise difficult to attract. Others still may be skeptical of the benefits of that investment, especially if it contributes to neighborhood change and displacement.

In this way, LIHTC and CDCs complicate the basic institutional resources theory (IRT) model of NORs somewhat. From the conventional IRT perspective, NORs are a positive attribute for communities because they intervene in the inequality-generating processes that lock in neighborhood effects. Yet many other factors are at play. For one, perhaps the biggest beneficiaries of LIHTCs are the CDCs as organizations. More broadly, however, some NORs are investments and interventions in places, while others are investments in people or

interventions in individual circumstances. LIHTC is a place-based investment. How it links to individual outcomes is an important frontier for urban inequality research. Regardless, as much as NORs act as mediators between neighborhood conditions and individual outcomes, they are also determinants of neighborhood conditions. This highlights the importance of understanding the variety of organizational mechanisms at play in urban and suburban neighborhoods.

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