A Geographic Perspective on Place-Based Policies

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ABSTRACT

To evaluate a policy intervention, we must be able to reliably observe and estimate the outcomes of that intervention. However, most public policy is implemented at a large scale, covering diverse communities and populations, which can lead to locally differentiated outcomes. Accordingly, there is growing recognition that understanding spatial variations in policy outcomes and the place-based contextual factors that cause them is key to successfully scaling promising interventions. Nevertheless, many of the placed-based policies we design have yet to adequately incorporate our current understanding of the relationships that exist between places, or rigorously consider the influence of potential misalignments between the scale of the policy and the places in which they are implemented. With the recent regulatory shift toward evidence-based policymaking, there is an urgent need to critically examine the spatial assumptions embedded within the research designs used for policy evaluation and evidence creation.

We argue that integrating a geographic perspective on place in the design, implementation, and evaluation of place-based policies will enhance the reliability of the evidence generated and increase our chances of scaling successful interventions. To demonstrate the downstream consequences of adopting this perspective, we review commonly used methods for quantitative policy analysis focusing on how place and spatially varying contextual factors are incorporated into these approaches. Conventional methods typically rely on strong assumptions about the homogeneity and independence of locations to estimate average treatment effects of policy interventions. These methodological assumptions fail to incorporate what we know about the interdependencies of places and the role that geography can play in confounding policy interventions. Incorrectly specified, the effect estimates these models produce are likely to be biased and the evidence they create may lead to inappropriate inferences regarding the underlying processes of interest.

I. Introduction

At a time when economic and social disparities across communities in the U.S. are deepening and regional mobility remains low, where someone grows up has substantial impact on their life chances and overall well-being (Chetty et al. 2016; Austin et al. 2018; Neumark and Simpson 2015; Connor and Storper 2020). Acknowledging the inequality-producing effects that entrenched disparities between communities can create, federal agencies have introduced a series of place-based policies designed to revitalize distressed communities. While early place-based policies offered economic incentives to spur local job creation, recent initiatives more broadly aim to improve community capacity and support the local coordination of services. These newer place-based policies point to a growing awareness that neighborhoods are part of a complex 'open system' requiring mutually reinforcing and nested public policies that link to broader regional geographies (Ferris and Hopkins 2015). At the same time, policy scholars have come to conceptualize communities as systems in which intra- and inter-community interactions produce agglomeration and network effects that operate at multiple scales that complicate policy design and evaluation.

In theory and in practice, place has become a deep-set feature of the policy landscape. While much of the literature has focused on establishing theoretical justifications for implementing these policies, and, more recently, on methods for evaluating their impacts (Neumark and Simpson 2015; Bifulco et al. 2019; Hulsey et al. 2015; Marcin 2020; Chen et al. 2019; Olfert et al. 2014), the available evidence suggests that many place-based policies, as currently designed and implemented, often do not achieve their intended outcomes (Lynch and Zax 2011; Elvery 2009; Reynolds and Rohlin 2014; Bozick et al. 2015). We argue that a closer examination of how the location-specific features of places impact the effectiveness of these investments will lead to improvements in policy implementation, evaluation, and scalability.

This paper is divided into two parts. In the first section, we demonstrate how the success of place-based policies may be threatened by a lack of consideration of how the processes they seek to change vary across locations and spatial scales. In the second section, we briefly introduce a geographic conception of place before shifting to an examination on how elements of place, such as spatial dependencies, heterogeneity, and scale, can impede traditional techniques for (1) exploring associations, (2) evaluating the impacts of a specific intervention, and (3) establishing evidence for which interventions work. Throughout this section, we provide a review of geographic approaches that account for the ways in which places may mediate, moderate, or confound the processes we seek to analyze and change. We conclude with reflections on how place-based policies can benefit from increased cross-disciplinary engagement between geography and public policy.

II. Considerations of Place in Place-Based Policymaking

Despite the growing prominence of place-based policies within the U.S., what constitutes a 'place' remains ill-defined both within the literature and within the policies themselves. Although a number of scholars suggest that 'place-based' refers to policies in which eligibility and implementation are targeted to a locally, bounded geography (Parker et al. 2022; Kline and Moretti 2014; Neumark and Simpson 2015; Olfert et al. 2014), others have used this term to more generally refer to regional economic and development policies aimed at spurring competition amongst jurisdictions within labor markets in multi-county or multi-state regions (Bartik 2022). These definitional differences in part reflect an evolution in place-based policies over the past half century from single, one-off investments to comprehensive, multi-site initiatives aimed at tackling concentrated poverty at both the micro- and macro-scales (Hopkins and Ferris, 2015). Championed by the Obama Administration, place-based policies became a centerpiece of the U.S. domestic agenda beginning in 2010. Presented as an efficient and effective mechanism for influencing the prosperity, equity, sustainability, and livability of communities, federal agencies were encouraged to design and implement place-based policies in an effort to streamline otherwise redundant and disconnected federal programs (White House 2009). In the decade since, federal investments in place-based policies continue to grow and are experiencing renewed interest in the wake of the COVID-19 pandemic.

Ranging from places as small as individual Census tracts and neighborhoods to entire counties and regional economic zones (Parker et al. 2022; Hadden Loh 2022), federal place-based policies vary considerably with respect to the scale of their investments both across and within specific policy initiatives. Although some variation is expected, given differences in policy objectives, the lack of a unified conception of place within individual policies is concerning, as it speaks to an under-theorization of how the scale of the policy intervention aligns to the scale of the places in which these interventions are implemented. For instance, Promise Neighborhoods, a place-based initiative developed by the Department of Education in 2011, is rooted in the theory that knitting together high-quality early learning programs, schools, and comprehensive community supports through coordinated community development will foster a college-going culture to create a cradle-to-career pipeline in distressed communities (U.S. Department of Education 2010; Smith 2011). Since its inception, 28 Promise Neighborhoods have been established, ranging in size from a few square blocks in Los Angeles, California to as large as a 386 square mile region of central Appalachia. Despite the stark differences in geographic scale, urbanicity, and populations served across Promise Neighborhoods, each receives equal implementation funding to achieve its goals. Taken together, these facts point to a lack of consideration for how the scale of these policy investments conforms to the scale of the problems they are intended to solve within these heterogeneous places. Successful policy interventions rely on clear theories of change regarding how a given intervention is expected to lead to a defined change in a specific context. When the scale of a policy intervention does not align with the scale of the place in which it will be implemented, the policy's impact may be weakened and its chances for success reduced.

Despite an increasing awareness that places are open systems interlinked with other locations, existing place-based policies often do not adequately account for these interdependencies within their theories of change. For example, the Healthy Food Financing Initiative (HFFI), a place-based program administered by the Department of Agriculture, has provided more than $500 million in one-time grants to increase access to grocery stores and healthy food retailers by providing the funding necessary to open new supermarkets in food deserts across the country. A recent impact analysis of an HFFI intervention in the Hill District neighborhood of Pittsburgh, PA, however, showed that this particular investment failed to significantly improve the availability of healthy food or reduce the distance traveled by residents to their regular place of food shopping three years later (Ghosh-Dastidar et al. 2017). As Ghosh-Dastidar and colleagues hypothesize, a couple of reasons may account for why this HFFI grant failed to achieve its intended outcomes. First, while the HFFI-funded supermarket offered a wide variety of healthy foods, following its opening, smaller food retailers in the surrounding areas reduced the number and variety of healthy foods they offered, thus offsetting the impact of opening the new supermarket. Second, because the neighborhood had been without a supermarket for more than 30 years, a majority of residents already shopped outside of the neighborhood for groceries, and few changed their behavior in response to the supermarket's opening. These findings point to a need to understand and account for the complex interactions between people and their environments, which may undermine policy initiatives if ignored.

While many argue that improved neighborhood-level data allows for better alignment between policies and places (Hopkins and Ferris 2015), the selection of Promise Neighborhoods, and more recently, Opportunity Zones, suggest that federal initiatives still rely on aggregated metrics to identify possible places for intervention. For example, the eligibility criteria established under the 2017 Tax Cuts and Jobs Acts to identify low-income communities that may benefit from the Opportunity Zones initiative, which provides tax incentives to spur job creation and encourage economic development, were based primarily on poverty rates and median incomes of Census tracts. While poverty is one element of disadvantage, not all communities with high poverty are equally well-positioned to benefit from this type of intervention. By relying on simple indicators of disadvantage, such as poverty rates or median incomes, important contextual factors that may impact the quality of implementation or threaten the intervention's success may be missed. Improving the chances that place-based policies will be successful in achieving their goals requires better targeting of these policies to areas most likely to benefit from them (Gelfond and Looney 2018; Hadden Loh 2022), which in turn requires a deeper understanding of how local contextual factors relevant to the intervention may vary across places.

III. Embedding a geographic perspective on place in policy analysis

Although many federal initiatives are now firmly tied to places, the theories of change that underpin these policies continue to largely ignore space as a critical axis of conceptualization and investigation. In prioritizing the socioeconomic dimensions of the processes they seek to change, place-based policymakers and analysts have yet to rigorously incorporate how these processes may vary across and between places and geographic scales. In many policy frameworks places continue to be treated as containers in which socioeconomic relations unfold.

A geographic conception of place, however, recognizes places as not simply the setting of a bounded set of social relations but as part of a larger network of social relationships and social processes operating at spatial and temporal scales that extend beyond a particular location or a particular moment (Agnew 2011; Giddens 1979; Martin 2001; Massey 2001; Porter 2011). The key ideas that differentiate this geographic perspective from those embodied by the theories of change enacted in current place-based policies are that (1) the spatial scale of social processes and (2) the interconnections between places are fundamental to understanding what works in a community. From this perspective, places, and the success of policies that are implemented within them, are not only the product of their internal social processes but of how those processes interact with local characteristics and histories and may be influenced by the broader network of surrounding communities. We argue it is by identifying this spatial interconnectedness (MacEachren 2017) and incorporating it into theories of change, policy designs, and analytical frameworks that policymakers and researchers can better determine which places are appropriate settings for targeted investment and improve the likelihood of success of these policies.

The spatial dimensions of places can influence whether policymakers and researchers are able to identify the relationships that interventions are built around, evaluate the efficacy of those interventions, and effectively scale promising interventions to new places. Traditional methods for approaching these questions have embedded assumptions regarding the distributional characteristics of the features examined. In particular, statistical models often rely on a 'Gaussian way of thinking' (Jiang 2015) in which the independence of features is assumed and the relationships we seek to measure are presumed to be well-represented by mean associations and average treatment effects. However, the central arguments of both placed-based policy and a geographic perspective on place imply that this conception is incorrect. Places exhibit strong interdependencies that contribute to heterogeneous outcomes that may not be adequately captured using conventional statistical techniques. Although these interdependencies raise concerns related to model misspecification and inference-making, when these structures are properly accounted for, statistical models can provide estimates on the impact neighboring locations may have in mediating the associations we seek to measure; the identification of which could support new hypotheses regarding possible causal mechanisms and provide additional insights for developing and refining theories of change.

For instance, the family of global spatial regressions models, such as spatial lag models, spatial lag of X models, and spatial error models, provide flexible methods for examining different pathways through which spatial dependencies may arise (Fig. 1). While detailed reviews of these methods are available elsewhere (Anselin 2010; Cliff and Ord 1975; Drolc et al. 2021; Anselin and Arribas-Bel 2011; Rutternauer 2022), key to this discussion is how spatial regression models can be used to formally define hypothesized spatial spillovers, quantify the magnitude of these spillovers, and test for their statistical significance (LeSage 2014).

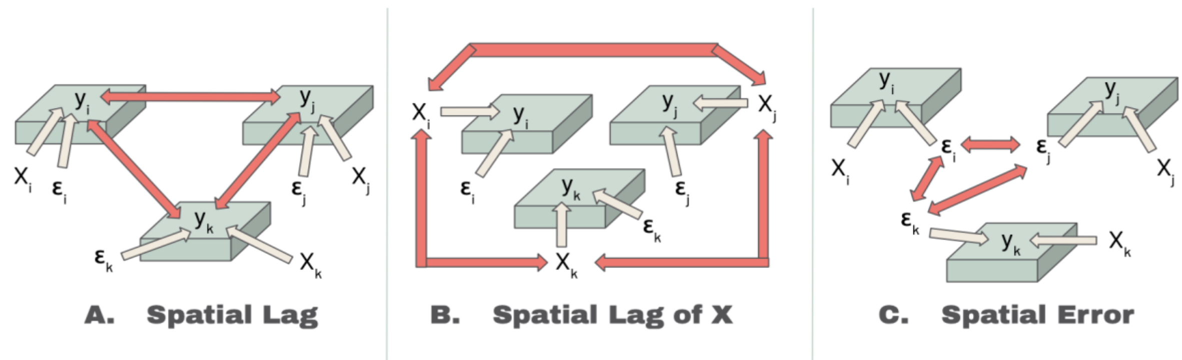

Fig.1. Stylization of global spatial regression model assumptions. Red arrows depict hypothesized spatial dependencies between dependent variables (A), independent variables (B), and error terms (C). Adapted from Akbari et al. (2021).

For instance, a spatial lag of X model can be used to explore spillover effects driven by exogenous covariates, such as in the case of student achievement, where we might expect average test scores in a school district to be be influenced not only by the characteristics of students and schools within the district but also by the educational environment in neighboring districts. These models have been shown to not only provide accurate estimates of direct impacts but also indirect spillover effects even in the presence of highly complex dependency structures (Rutternauer 2022).

In addition to global spatial regression models, local statistical models provide another mechanism for explicitly controlling for spatial dependencies while also allowing for an examination into whether the strength of relationships vary across places. While spatial fixed effects models, in which the model's intercept is allowed to vary between subgroups, are commonly used within the social sciences to control for unobservable variation among well-delineated groups (Anselin and Arribas-Bel 2011; Kuminoff et al. 2010; Ciccone 2002), newer techniques, such as multiscale geographically weighted regression (MGWR), offer opportunities to explore not only the variability in relationships across places but also how these relationships might vary across geographic scales.

Unlike global regression models, MGWR does not assume that processes are constant over space, and as a result, provides estimates of the relationship between each covariate and the outcome for every location in the study region. These location-specific parameter estimates can then be visualized for a more detailed understanding of how a process varies across space. As a result, these models may offer insights into where, and at what scale, interventions are likely to be successful. To obtain these location-specific parameter estimates, MGWR performs a series of local regressions by borrowing data from nearby locations and weighting them according to how far they are from the regression location; data from locations nearby are weighted more than data from locations farther away (Fig. 2). The spatial extent over which data are borrowed varies by covariate and is controlled by a bandwidth parameter, which provides an indicator of the scale over which the process varies. For more information, see Li and Fotheringham 2020, Li et al. 2020, Yu et al. 2018, Wolf et al. 2018, and Oshan et al. 2019.

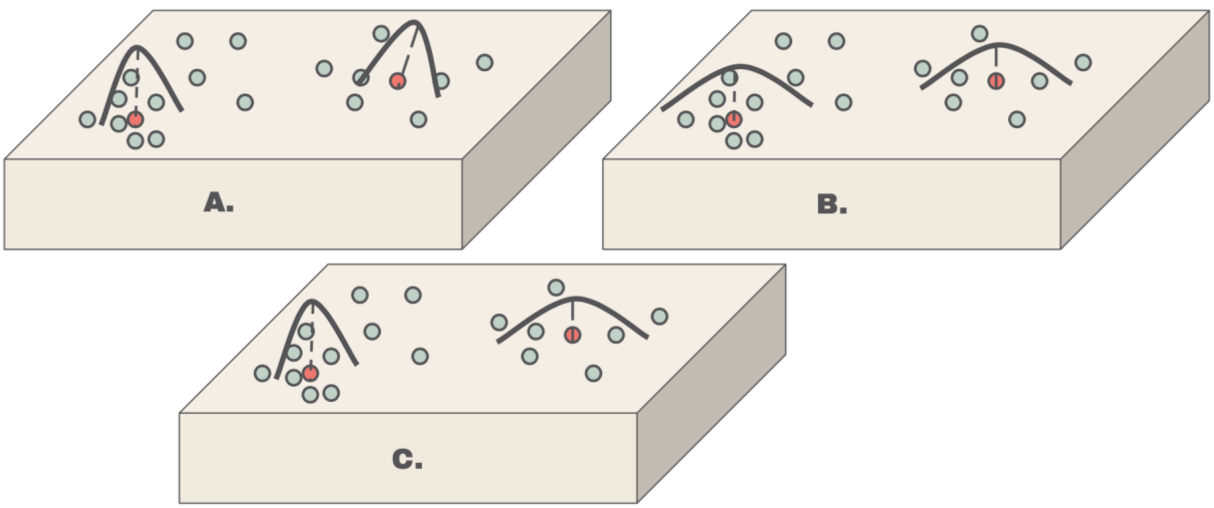

Fig.2. Stylization of MGWR information borrowing procedure. Panels A, B, and C represent separate model covariates, each with a unique bandwidth parameter controlling the number and location of places from which information is borrowed to fit the local regressions for a given focal place (depicted in red). Adapted from Fotheringham et al. (2003).

While spatial statistical models can help explore potential spatial dependencies and heterogeneities to support the development of geographically explicit theories of change, issues related to the geographic dimensions of places pose particular challenges when estimating the impact of specific place-based interventions. Because multiple place-based investments, often operating at different scales, are frequently present within a single community, spatial confounding is a major impediment to determining the effects of an individual place-based policy. In California, for example, the Los Angeles Promise Neighborhood comprises two small areas within a broader Promise Zone neighborhood–a separate place-based program funded through the Department of Housing and Urban Development that provides tax incentives, preference for competitive federal grant programs, and technical assistance and capacity building to support community revitalization (HUD 2013). To measure the impact of the Promise Neighborhood investments, it is necessary to separate out the impact from the broader Promise Zone. Several techniques ranging from case-control matching, spatial smoothing, and propensity-score matching have been used in empirical work to mitigate the bias introduced through spatial confounding. See Reich et al. (2021) for a detailed review and comparison of these methods.

In addition to spatial confounding, spatial spillovers from place-based investments to surrounding communities can create spatial interference, which produce violations of stable unit treatment value assumption that underlies unbiased estimation of causal effects using conventional econometric and statistical approaches. As was the case in the HFFI example presented in the previous section, when place-based investments induce changes in surrounding areas, such as nearby retailers changing their provision of foods in response to the opening of a supermarket, we can no longer assume that the differences we observe in these surrounding areas are independent of the policy intervention. This interference complicates our ability to identify high quality control groups with which to make comparisons. Although there has been widespread examination into the ways in which spatial interference impedes efforts to identify unbiased causal impacts (Neumark and Simpson 2015; Kolak and Anselin 2020; Pollmannn 2020; Hong 2017; VanderWeele 2015; Gibbon and Overman 2012; Giffin et al. 2022), solutions to this problem are limited. Most solutions rest on the assumption that spatial spillovers are confined to nearby geographic areas (Neumark and Simpson 2015; Pollmann 2020). As such, a common approach to mitigating the impact of spatial spillovers is to identify a control group that is sufficiently far but otherwise indistinguishable from the treated place. Several techniques for identifying these types of control groups have been explored, ranging from using distance-based buffering (Neumark and Kolko 2010), propensity score matching (Elvery 2009) and advanced machine learning algorithms (Pollmann 2020). However, more research is needed to determine what constitutes “sufficiently far,” and how this definition may vary by policy and place-specific considerations.

Beyond exploring associations and estimating impacts of place-based interventions, a key concern for both policymakers and researchers is establishing robust evidence for which place-based interventions reliably and credibly achieve their intended outcomes, in other words, which interventions ‘worked.’ Knowing which interventions worked is the first step in scaling promising solutions to other places in need. However, given the pronounced heterogeneity within and across places, knowing that an intervention has produced desirable outcomes in one place is a necessary but insufficient criterion for determining whether the same intervention will work elsewhere (Cartwright and Hardie 2012). Rather, we argue that to scale promising interventions, we need to know not only what works but what works where.

Traditional methods for generating evidence of what works across locations rely on systematic reviews of program evaluations that are then meta-analyzed to determine the likelihood that the evaluated interventions work given all available evidence (Hillocks 1984; Harris et al 2009; Sneyers and De Witte 2018; Deke et al. 2022). Importantly, meta-analyses can only provide credible and reliable information regarding an intervention's effectiveness for the population from which the evidence base was generated (Deke et al. 2022). Because where an intervention has been implemented may meaningfully influence the impacts observed, prior reviews may have in fact measured effects from several heterogeneous populations but treated those effects as if they were drawn from a single homogeneous population. If this is the case, the average effect estimate produced may in fact mask important variation across places. While existing meta-analytic models do not typically account for where interventions have been implemented and evaluated, it is possible to incorporate place-based parameters into existing techniques to assess whether intervention effects vary by these factors. If intervention effects are found to be sensitive to these types of place-based factors, then policymakers will have deeper insights into the types of places where impacts are strongest, and weakest, and the degree to which impacts are expected to vary.

Limited research has explored how we might determine where interventions are likely to work (Cartwright and Hardie 2012; List 2022; Al-Ubaydli et al. 2019). Cartwright and Hardie (2012) offer a conceptual framework for establishing the causal contextual support factors, including location-based factors, that are necessary for the successful scaling of interventions across places. As Cartwright and Hardie explain, knowing that an intervention has worked somewhere is a necessary but insufficient condition for determining whether the same intervention will work elsewhere. However, a deep conceptual understanding of the causal mechanism and support factors, what they refer to as the "causal cake," of a successful intervention can shed light on the conditions that need to be present in other places for the intervention to scale. In a similar vein, Al-Ubaydli and colleagues (2019) suggest using backwards induction to develop a sequence of experiments that block on core situational features of an intervention's implementation to determine the sensitivity of the intervention to changes in the spatiotemporal contexts in which it may be implemented. In the same way that experimental research designs block on key characteristics of populations to assess differential treatment effects by age, race, and gender, Al-Ubaydli and colleagues suggest we must take a similar approach for assessing the potential differential treatment effects by environmental conditions under which the intervention may be implemented.

IV. Conclusion

Place-based policies have the potential to revitalize distressed communities and level geographic disparities in outcomes, but in order for them to realize this potential, the policies must align with the places in which they will be implemented. Determining where to target place-based investments, how to establish the efficacy of these investments, and ultimately scale successful solutions to other places requires a deep understanding of the characteristics of, and connections between, places. In this paper, we have suggested that existing approaches to place-based policies have under-conceptualized the spatial dimensions of place within their theories of change. We argue that adopting a geographic conception of place, which accounts for how socio-spatial processes may vary by location and scale, has the potential to improve the design and evaluation of place-based policies.

Our argument centers on two points. The first point is methodological. If the processes place-based policies seek to change do in fact create spatially structured observations, then failing to account for that spatial structure in the statistical models used to analyze and evaluate those policies will produce misspecification errors and omitted variable biases that will affect our measurements. Many spatial statistical techniques exist within the geographic and spatial statistical literature to combat these errors. These methods should be incorporated into policy analysis and evaluation. Our second point is practical. To be effective in targeted communities, and to have a chance at scaling across communities, the theories of change that define the processes and mechanisms that place-based policies are built around need to account for the factors and relationships that might alter those processes in the real world. Communities do not exist in isolation and the processes that affect them operate at many spatial scales. Considering how those realities may affect a planned policy intervention is likely to lead to improved policy designs and outcomes.

The cross-disciplinary nature of this work speaks to a need for greater engagement between geography and public policy scholars to move this work forward. While geographers have much to offer with respect to how places, and the spatial processes that produce them, can complicate efforts to intervene in reliable ways, it is collaborations with policymakers, subject matter experts, and other social scientists that will generate the value of these imports. The first step, however, is recognizing the spatial dimensions of the policy problems before us.

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