SEEING PAROCHIALITY AND ACTING LOCALLY: SOCIAL EXPOSURE, PROBLEM IDENTIFICATION AND SOCIAL ENTREPRENEURSHIP

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Abstract

Why some communities have greater rates of social entrepreneurship in similar domains is a question of importance to scholars and practitioners alike. Much of the literature in social entrepreneurship begins with a social problem that has been identified, and then analyzes the antecedents of the entrepreneurial process that lead to organizational solutions emerging for those problems. However, why some problems gain traction as being worthy of time and effort in solving, has garnered little attention. I argue that particular problems are more or less salient triggers of action by prospective social entrepreneurs based on the distribution of such problems in the local social environment, rather than aggregate levels of need. Yet, even problems widely experienced as shared, salient, and generally worthy of action might lack the emergence of solutions in fragmented communities, such as those with high levels of residential segregation by race and income. We study this in the context of founding of advocacy and support organizations in the domain of healthcare, and find support for our predictions. We also conducted additional tests to better characterize the findings and test robustness to alternative sources of influence, such as the local pool of potential social entrepreneurs, the role of local ecology, and geographic spillovers from neighboring areas.

Geographic communities face many shared challenges, such as improving quality of life, conserving the natural and built environment, taking care of the marginalized and the infirm, and revitalizing local economic activity. Although the government at various levels provides some of these goods, and corporations and individuals engage in philanthropic activity, many of these shared challenges necessitate local action. This can take the form of grassroots activity to demand these goods through activism and legislative channels. This can also take the form of local social entrepreneurship to create organizations that can help solve such problems in a reliable and reproducible manner. In this paper, we argue that a key overlooked driver of such local social entrepreneurship is the distribution of social problems in a community, which is further moderated by levels of local socio-economic segregation.

The existing research record speaks to the question of why some communities have greater rates of local social entrepreneurship from multiple perspectives, either directly or indirectly. Work in collective action and civic engagement suggests that the latent capacity for organizing inheres in communities with greater social capital (Putnam, 2000; Skocpol, 2003; Sampson, 2012; Greve and Rao, 2012), although not all forms of social capital are created equal (Fischer, 2005; Kwon, Heflin and Ruef, 2013; Ruef and Kwon, 2016). A different strain of work focuses on communities as an institutional order which provides both lenses for understanding the social environment and sites for mobilizing people and resources (Marquis and Battilana, 2009; Marquis, Lounsbury, and Greenwood, 2011; Jennings et al, 2013).² Work in social entrepreneurship has borrowed from both perspectives to argue for studying social

² Additionally work in population ecology has also implored scholars to consider the local environment as key drivers of ecological processes, such as through considering the local base of resources and competition (Lomi, 1995; Stuart and Sorenson, 2003) and local ties to the institutional environment (Baum and Oliver, 1996) rather than the population-wide environment alone. However, the domain of social entrepreneurship is often seen as a response to market failure, rather than as a response to attractiveness of market niches for entry (Austin, Stevenson, and Wei-Skillern, 2006)

entrepreneurship through an embeddedness perspective (e.g. Seelos et al, 2011), or as engines of formalized collective action for social change situated in local contexts (e.g. Steyaert and Hjorth, 2008; Corner and Ho, 2010).

However, much of the literature in social entrepreneurship begins with a social problem that has been identified, and then analyzes the antecedents of the entrepreneurial process that lead to organizational solutions emerging for those problems. Attention in this framework is often devoted to the characteristics and often-heroic stories of individuals that lead them to found organizations that solve social problems (e.g. Bornstein, 2007; see review in Dacin, Dacin, and Tracey, 2011). Similarly, work that focuses on assessing the value of entrepreneurial efforts for social change devotes attention to whether such organizations create social value and under what conditions (Seelos et al, 2010; Santos, 2012; Kroeger and Weber, 2014; Kaul and Luo, 2016). However, the question of why some problems are picked up by some groups as worthy of time and effort in solving, has garnered little attention. This study addresses this gap in two ways.

First, particular problems are more or less salient triggers of action by prospective social entrepreneurs based on their local social environment. Specifically, we argue that the geographic distribution of such problems in the social environment matters as much as if not more than the aggregate levels of the same in a community. An existing literature in entrepreneurship and social entrepreneurship has variously debated the influence of the external environment in entrepreneurial activity (Shane and Venkatraman, 2000; Sarasvathy, 2001; Austin et al, 2006; Alvarez and Barney, 2008; Alvarez, Barney and Young, 2010; Dacin, Dacin, and Matear, 2010; Seelos et al, 2011; Mitchell et al, 2011). Davidsson (2015) built on the interplay of the individual-opportunity nexus to argue that external enablers are aggregate-level circumstances that shape the creation of new organizations as distinct from bricolage opportunities and confidence in their

viability. Santos (2012) argued for a greater focus on positive externalities as distinct drivers of social entrepreneurship. Miller et al (2012) argued for a focus on drivers of compassion and prosocial behavior to understand why they sometimes lead to social entrepreneurship. However, external enablers might not always stimulate attention and effort, positive externalities might not always be apparent to the community, and compassion might get a short shrift when needs are confined to a few ‘problem’ neighborhoods. As Coleman (1971) presciently noted, even when faced with objectively shared or externality-inducing problems communities don’t often rise to the challenge of solving them, if those problems aren’t experienced as a shared fate requiring local action. One way in which problems are experienced as truly shared or widespread is through their salience across multiple parochial social worlds, rather than in concentrated pockets of need. The emergence of local social entrepreneurship—pooling voluntary resources (time and money) to organize to solve problems in a geographic community—is therefore influenced not just by cost-benefit calculations of aggregate need, but is also shaped by the particular spatial distribution of problems within a geographic community.

Second, even problems experienced as shared, salient, and generally worthy of action might lack the emergence of solutions in fragmented communities, such as those with high levels of residential segregation by race and income. Even if particular problems are experienced widely creating a common cause, resource mobilization might be lacking under conditions of greater inequality and segregation since socially distant others might be seen as less worthy beneficiaries of collective benefits local social entrepreneurs might seek to provide (e.g. Massey, 2007). Others have remarked how marginal members of the community might benefit less from community social capital when attempting entry into entrepreneurship (Kwon, Heflin, and Ruef, 2013). While community diversity has been brought to the forefront in several strains of work in social

movements and collective action (Putnam, 2007; Rao, Yue, and Ingram, 2010), little attention has been paid to the role of spatial segregation in communities as drivers of social entrepreneurship. Spatially segregated communities—by income or race—are not only settings where the community differs in economic and social characteristics, but also ones where these differences are starkly outlined in demarcations of neighborhoods as clusters of such characteristics. Segregated communities face the double bind of inequality in outcomes and greater social distance between those with the social capital to found collective-goods organizations and those who might benefit disproportionately from their founding.

These two issues—of lack of focus on the distribution rather than aggregate levels of problems in a community, and the distribution of resources and ascriptive characteristics as a constraint (or enabler) of resource mobilization—are key motivators for the study. Such distributional properties are often submerged under the averages that drive theorizing in the existing literatures on communities-and-organizations, as well as literatures in collective action and social entrepreneurship. These distributional drivers of why some communities have greater rates of social entrepreneurship when needs are unmet by the market or the state, are especially pertinent for goods that are at the margins of being seen as universally worthy of provision in any society, such as quasi-public goods, or private goods with large positive externalities. In this paper, we focus on one such good—healthcare—which has fueled not only public debate but also parochial variation in the United States in its perception as a worthy cause for prospective social entrepreneurs.

We find that it is the greater geographic dispersion of mortality in communities rather than its aggregate that spurs greater rates of local social entrepreneurship in healthcare. This effect is further moderated by the within-community segregation by race and income. Specifically even

greater dispersion of health outcomes spurs lower rates of founding under conditions of economic inequality and racial residential segregation between neighborhoods. In this manner, the study aims to provoke scholars and practitioners alike to think of the geographic distribution of outcomes and resources as key points of departure for understanding external enablers for social entrepreneurship, rather than community level averages.

We also conducted robustness checks, both to better characterize the findings and test its robustness to alternative sources of influence. Specifically we also explored the individual-opportunity nexus in social entrepreneurship, and emerged with findings that support the view of social entrepreneurship as driven by lack of commensurate support through formal and informal channels, rather than by supply side constraints alone. We find that the presence of people with the skills, knowledge, and professional ties in a focal problem area is a double-edged sword. On the one hand, they represent a larger pool of prospective social entrepreneurs. On the other hand, the presence of more of such individuals in a community also possibly presents alternative channels of informal helping, enhancing foundings at a lower rate in response to environmental stimuli. As Austin et al (2006) note, unlike commercial entrepreneurs who are drawn to growing and structurally attractive markets, social entrepreneurship emerges in domains with market or institutional failure. We also find some spatial spillovers between neighboring geographic communities, but these spillovers are alternative influencers of foundings rather than confounding our hypothesized relationship.

SOCIAL ENTREPRENEURSHIP IN HEALTHCARE

Healthcare is a complicated good. It is technically not a public good but not entirely private either. On the one hand its benefits are enjoyed inextricably by individuals themselves, higher levels of it can be restricted to paying customers, and it is almost always ‘rivalrous’, in that there’s

not enough to go around without affecting others' quality of care. On the other hand, it has significant positive externalities. Healthy people are often better employees, better neighbors, and more able to participate fully in community life. Having healthy coworkers and acquaintances also improves community members' chances of staying healthy themselves—either by reducing chances of contracting a contagious disease, or by providing mutual support for healthy lifestyles. So in some ways healthcare approaches the notion of a public more than a private good alone, which benefits everyone in the community to some degree over and above any individual benefits it confers. From the point of view of externalities (Santos, 2012), social entrepreneurship in healthcare, such as the founding of local organizations engaged in health advocacy and support, can greatly improve the overall community's productivity and quality of life. However, even if its benefits accrue to the collective, its costs are substantial and when socialized often paid by people with already better health outcomes.³ Why do some communities then see more social-entrepreneurial activity in this domain, while others appear relatively uncaring?

Seeing parochially and acting locally

An example. Amador County in inland California was the former site of the gold rush in California, and to this day calls itself the “The Heart of the Mother Lode.” While the gold rush was long gone, Amador, like many other inland counties along the Sierra Nevada Mountains

³ Political beliefs have typically been credited with variations in support for the collective provision of care for those unable to afford it (e.g. Jacobs and Skocpol, 2015), and little can be done to bridge those schisms per se. Others have credited historical processes of contention between alternative views of care and legitimacy in health-organizational fields (Starr, 1982; Scott, 2000; Ruef and Scott, 1998; Ruef, Mendel, and Scott, 1998; Ruef, 1999; Scott, Ruef, Mendel, and Caronna, 2000) as determinants of quality of care across communities. The design of organizational and market structures similarly is seen as an economic answer for the right way to solve the problem (Arrow, 1967; Flood and Scott, 1987; Donabedian, 1992; Eldenburg et al, 2004; Horwitz, 2005; Bloom et al, 2015). These debates however ignore the confluence of community characteristics and the emergence of community healthcare organizations whose founding can help shore up gaps in care and support by the market and the state.

found itself the center of health crises due to the intermixture of demographics, addiction, poor living conditions, and outmigration to the coasts. The widespread experience of mortality to cancer among friends and family was central to the founding of Amador STARS, a local healthcare advocacy and support organization targeted towards solving local needs of cancer patients, survivors, and caregivers.⁴ Founded in 2004 by local cancer survivors and activists who had lost relatives and friends to cancer, Amador STARS “has a local office with a caring staff to answer questions about local and regional services available to cancer patients and survivors—from where to find a wig when they are going through chemotherapy, to what support is available locally for patients and survivors. STARS also oversees cancer patient transportation providing FREE rides to radiation and chemotherapy treatments.” The local community was crucial not only during founding, but also in its continuing support in the form of volunteer time and effort, and financial contributions. It is from the local community that current board members and officers are drawn to retain local ties, even as the organization has grown larger and employed full time staff to ensure continuity and professional management. Yet at the very core of the organization lies the founding story of a shared cause that was widely experienced and seen as a motivator for services and support that were not available from either the market or the local government.

Coleman (1971) suggested that the extent to which communities will contribute to solving collective problems might depend upon how ‘shared’ problems truly are, and whether there is awareness of such interdependence or externalities. Whether geographic communities collectively contribute towards healthcare for other nonpaying members (in the present or future) depends on the extent to which they believe the positive externalities from having a healthy

⁴ <http://www.amadorstars.org/about.html>

community outweighs the costs of providing care to people who are unable to afford it. However, for many private-like goods with positive externalities such interdependence and shared interest is not always apparent, for several reasons.

First, people can create exclusive access to private goods if the availability of a similar collective good is not to their liking. E.g., Access to local private schools can decouple parents' concern for local public education from their private concern for their child's education. The presence of exclusive gated communities with in-house security details might similarly reduce the extent to which local persistent crime rates are seen as a shared problem. Second, people with greater efficacy, means, and social capital can move to places where the level of particular services and conditions are to their liking (Bandura, 1997; Coleman, 1988). Examples include white-collar flight to suburbs with better schools and lower crime. Neighborhoods with a high crime rate often continue to have a high crime rate if those with human and social capital leave for lower-crime areas. Over time, such neighborhoods become inextricably associated with its manifest symptoms such as poor schools, higher crime rates, and poor health outcomes. The larger surrounding community begins to associate all its ills with the place and not with the absence of social entrepreneurial efforts to improve it. Finally, even without funding private substitutes of collective goods or moving too far, people with social and economic capital can still isolate themselves into smaller neighborhoods within geographic communities such that through all their daily interactions they might almost never encounter any adverse effects of the missing collective goods. As a result, even if people were to have the latent capacity to organize to improve local conditions, they might never do so if the need for them is never felt widely.

Founding of Healthcare Advocacy and Support Organizations

Tocqueville (1899) famously remarked how Americans of all stripes associated with each

other in creating formal organizations to provide services and exert influence on their local community outcomes, distinct from the market and the state. While some scholars have lamented the decline in such organizations (Putnam, 2000; Skocpol, 2003), others have described how such forms of organization have become more formal and goal-directed over time (Wuthnow, 1998; Sampson et al., 2005; Walker, McCarthy, and Baumgartner, 2011). Nonprofit and voluntary organizations are key conduits for channeling community needs into organizational ends, such as those providing information, advocacy, and support. Wuthnow (2012) for example argued that the value of such organizations lay in their ability to provide a macrostructure for helping, such as providing clearly defined roles, institutionalizing them so they become reliable, routinized, and a source of narrative self-understanding (Wuthnow, 2012:196-197).

What processes determine the foundings of community advocacy & support organizations as a form of social entrepreneurship is therefore a question of importance to scholars of both communities and organizations alike. To the former they present an organizational form unfettered by profit-making in solving problems, and a set of (at least somewhat) formalized goals and procedures to achieve those objectives in a reliable and reproducible manner (Sampson et al., 2005; Wuthnow, 2012). To the latter the ability of geographic communities to spawn such organizations represent a key form of latent organizing capacity (Greve and Rao, 2012; Marquis, Davis and Glynn, 2013). Even community members, who belong to professions more suited than the average person to understand and attempt to solve a problem, often associate with others in purpose-driven formal organizations rather than leveraging their knowledge and personal ties in personal crusades against such problems. An example is the Sepsis Alliance, founded in Sacramento, CA (later moving to San Diego, CA). Its founding story also illustrates perhaps a more extreme version of the role of parochial concerns in driving foundings.

On April 30, 2002, Carl Flatley's life changed. It was the day his 23-year old daughter Erin died from septic shock, something Dr. Flatley, a retired endodontist, had never heard of. After Erin's death, Dr. Flatley learned everything he could about sepsis and he was astounded at what he – and millions of other Americans – did not know about the condition. He was shocked to learn that sepsis killed well over 200,000 people in the U.S. every year and affected so many more survivors. In 2004, Dr. Flatley founded the American Sepsis Alliance, which in 2007, became Sepsis Alliance. He made it his mission that sepsis would become as well-known as cancer, diabetes, and other illnesses, and that as few people as possible would get sepsis, let alone die from it.⁵

Towards that end, the Sepsis alliance engages in outreach to a wide range of stakeholders and audiences. Activities of the Sepsis Alliance range from informational resources for patients and medical professionals, to portals that connects prospective funders, volunteers, survivors, and medical professionals.⁶ Similarly, Small and Simonsohn's (2008) study of motivations underlying volunteering in healthcare services finds people on average are more likely to contribute their volunteer time and effort towards medical causes based on the number of victims of similar causes they knew through their family and social circles. Other reports such as of Bekkers (2010) and Breeze (2013) similarly find that even those who perceive themselves as driven by objective needs of a community are instead influenced by their parochial concerns in their support for solving the community's problems. When poor health outcomes are dispersed rather than concentrated geographically in a few neighborhoods, it is more likely that the community will widely experience the shared nature of the problem and its externalities. Health-related issues in such communities are therefore more likely to be seen as salient and a worthy destination for social-entrepreneurial efforts. In this manner, what matters is not just the aggregate need in the community but its spatial dispersion. Additionally, when social distance—such as disparities in income and racial characteristics—overlaps with separation in space and

⁵ <https://www.sepsis.org/about/board/carl-flatley/>

⁶ The link <https://web.archive.org/web/20161029005905/http://www.sepsisalliance.org/> provides an illustration of the activities of the Sepsis Alliance (archived link provided in case websites move or change domains. The organization continues to be active at the time of writing)

social worlds, it makes it easier for communities to dismiss high mortality to medical conditions as a feature of such ‘bad neighborhoods’ and their associated bundles of risk factors and demographics, rather than a problem of the larger community.

EMPIRICAL CONTEXT AND HYPOTHESES

The Community Structure of Health and Mortality

A long tradition of work in sociology has documented how health outcomes are often strongly tied to place (e.g. Goldberger et al, 1920; Shaw and McKay, 1942; Sampson, 2003) even when controlling for certain individual characteristics and lifestyle choices (Robert 1998, 1999). A range of socioeconomic factors that typically coincide in neighborhoods or blocks (e.g. Kawachi and Berkman, 2003) often drives these effects. These include conditions such as poverty, unemployment, un-insuredness, lack of residential stability, poor quality housing, low economic opportunity, lack of nutritional foods being sold in corner stores, prevalence of dealers of contraband, lack of informal social control of the same, and so on, that not only co-occur but often each fuel the dysfunctions imposed by the other. For example, poorer communities have access to fewer nutritional foods locally, which increases susceptibility to health-related medical conditions, which in turn affects productivity, which in turn affects the ability to get good health insurance necessitated by poor health outcomes, which might further impede people’s ability to travel further away to purchase nutritional foods such as from suburban grocery stores.

Sampson (2003) notes how these social characteristics, which tend to vary systematically across neighborhoods and persist within neighborhoods, are also related to the strong spatial clustering of mortality and health (also see Garcia and Lochner, 2003; Fang et al, 1998)⁷.

⁷ Fang et al (1998) also report some contradictory results for the elderly, probably driven by survivorship-effects.

Neighborhoods can become ‘hot spots’ for poor health outcomes through a confluence of circumstances and choices. For example, people without means might end up both living in high-poverty neighborhoods and not purchasing health insurance, or live in sub-standard housing and also engage in high-risk behaviors such as alcoholism and substance abuse. The National Research Council (1993) referred to such concentration of poverty, poor health, and high-risk behaviors as akin to a “synergism of plagues” that is hard to escape. Conversely, the exceptions—poorer individuals with relatively greater self-efficacy, human capital, or social capital—move to better neighborhoods where they encounter better health outcomes and social support systems (or informal social control) that reinforce positive behaviors. Other evidence has pointed to the emergent properties of place being an institutional legacy of policies stretching as far back as the New Deal (Logan and Molotch, 1987; Massey, 2007; Massey, Rothwell, and Domina, 2009); and its effects possibly independent of self-selection into neighborhoods (Katz, Kling, and Liebman, 2001; Sampson, Morenoff, and Earls, 1999). Regardless of the mechanism by which certain neighborhoods come to have clusters of poor health and “comorbidity”, the strong correlation itself is a harbinger of why residents of other neighborhoods might discount public health crises as long as they are socially distant and limited to particular neighborhoods.

Mortality and its Dispersion

Claude Fischer (2010: 29) in his wide-ranging social history of the United States notes that:

Americans in the colonial era had to face what one historian called “the sheer normality of death.” Perhaps in the modern context, the occasional experience of a loved ones’ dying or debility became all that much scarier and more painful for being so much rarer.

From the standpoint of eliciting sentiment about the state of healthcare—mortality is seen as an absolute bad, and almost no extenuating circumstances help ameliorate concerns raised by it. For example, Baron and Ubel’s (2002) results show that people on average perceive death as

an infinitely bad outcome. In their study they find that that respondents view death as equally worse than normal health, blindness, or paralysis of arms and legs—suggesting that mortality elicits an absolute response that is incomparable to any (even starkly different) gradations of health. It's quite possible that death reports are infinitely more salient because people have default beliefs about the curability (or non-mortality) of most conditions owing to modern medicine, so death comes as a shock that is incomparable to any condition (good or bad) of living.

Second, mortality to health conditions such as disease and organ malfunction is a prominent event, and especially so in low-mortality neighborhoods. Media attention and public opinion is often biased towards dramatic or unusual instances of mortality, and against the usual patterns and rates of the same (e.g. Best, Dennis, and Draper, 1977; Budd and McCron, 1981, Williamson et al, 2011). People can overestimate fewer proximal instances of death, while underestimating larger numbers if they are distant (e.g. Lichtenstein et al, 1978). Even those who report perceiving themselves as driven by the objective needs of a community are found to be influenced by their proximal experiences with particular diseases and causes when deciding what health issues are important and how much to contribute (Bekkers, 2010; Breeze, 2013).

When mortality due to medical conditions is dispersed widely in geographic communities, it is more likely that a larger proportion of the community will find common cause, and the need for community organizations in healthcare can appear to be more salient. When aggregated geographically this suggests one reason why some geographic communities have higher rates of social entrepreneurship in healthcare domains than others, *ceteris paribus*.

Hypothesis 1: The number of foundings of local healthcare advocacy and support organizations in a community is greater when past mortality due to medical conditions is more distributed across neighborhoods.

Residential segregation between neighborhoods

Several scholars have shown how entrepreneurial action owes its genesis to the social group, such as the community, family, neighbors, and friends (Timmons, 1975; Ruef, Aldrich, and Carter, 2003; Ruef, 2010). The local geographic community is relevant for entrepreneurship not merely as a setting within which people are situated and go about their business, but also act a consideration set of information, resources, and organizational models, which determine what combinations are possible and feasible (Stinchcombe, 1968: ch. 4; Zahra et al., 2009; Ruef, 2010; Marquis, Davis, and Glynn, 2013). Founding a local civic organization, that is sustained by the local community, requires some agreement on the cause of the problem, the awareness that said problem can be solved by conjoint action, the ability to arrive at some consensus over how the problem ought to be addressed, and a process of evangelizing the local community over why the chosen set of problems and solutions deserves attention and resources (e.g. Coleman, 1971). Much attention has been paid to aggregate measures of diversity in communities as fonts/impediments to organizing (Costa and Kahn, 2003; Putnam, 2007; Rao, Yue and Ingram, 2010). However, little attention has been paid to how the separation of geographic communities into enclaves separated by race or income are central in influencing the emergence of organizational action in solving a community's problems. As Massey (2007) eloquently noted:

Americans have come to inhabit a postmodern political economy characterized by fragmented markets, segregated geography, segmented social organization, and a differentiated culture..., yielding a mosaic of distinct societal inches whose inhabitants are similar to one another but different from those around them (Massey, 2007: 191-192).

Residential segregation by race. A review of the literature by Cutler and Glaeser (1997) found that racial segregation can have mixed effects based on whose outcomes are being compared; they however find that within a racial group, living in more segregated metro areas is associated with lower educational and economic outcomes. Greater residential segregation by

race might further increase the social distance between neighborhoods, impeding the effects of mortality dispersion on spurring founding rates of organizations engaged in healthcare advocacy and support. For example, Cikara, Bruneau, and Saxe (2011) find that people's motivation to alleviate others' suffering is somewhat fragile when the target of helping is an out-group, such as of a different race. The greater social distance engendered by racial differences makes it less likely that donors would directly relate their personal experience of grief and shared fate to that of different others. In parallel, Fong (2007) suggests that even those who perceive their altruism to be unconditional tend to give based on their beliefs about others' worthiness, such as based on perceptions of how those with poor health might be responsible for their health outcomes and high-risk behaviors (e.g. Crawford, 1977).

Therefore, we argue that in communities with greater residential segregation by race or ethnicity, a wider spatial dispersion of mortality might provide less of an impetus to solve such problems through social entrepreneurship, even as the need for such local civic organizations engaged in advocacy, education, and basic preventative services might be greater.

Hypothesis 2: The number of foundings of local healthcare advocacy and support organizations driven by greater spatial dispersion of mortality is lower when there is higher residential segregation by race or ethnicity.

Income disparity between neighborhoods. Inequality in income has come to the fore as a key driver of social conflict that threatens to upend modern societies. Georg Simmel, writing with a dichotomous economic class divide in mind (lower vs. upper) noted:

[O]n account of the social distance, the former appear to the latter not as individuals but only as a unified mass, and that this very distance creates the appearance that the two classes are in principle connected with each other only in the one respect that together they constitute a 'society' (*Gesellschaft*) (Simmel, 1909:290).

Communities where people are segregated across place by income, are more likely to

experience greater social distance that intersects both place and economic class. This further reduces the chances of even a widespread cause being seen as worthy of action. Parts of the community with the knowhow and social capital to found formal organizations might find little impetus to help create health advocacy and support organizations if the majority of beneficiaries will be socially distant via an intersection of separation in neighborhoods and income. As a result, we hypothesize that greater income disparity between neighborhoods would impede the effects of spatial dispersion of mortality on foundings.

Hypothesis 3: The number of foundings of local healthcare advocacy and support organizations driven by greater spatial dispersion of mortality is lower when there is greater variation in income between different parts of the geographic community.

DATA AND METHODS

The data for the paper were gathered from several sources, including the National Center for Charitable Statistics, the Census Bureau (including American Community Surveys, and the SAHIE estimates), the California Department of Finance, the California Secretary of State, the Office of Statewide Health Planning and Development of the State of California, the California Department of Public Health, and Centers for Medicare and Medicaid Services. Below we describe the data and the related variables. Also discussed are methods used for constructing the variables, and for the hypothesis tests.

Community Healthcare Nonprofit Organizations

Data on community healthcare nonprofit organizations was gathered from the Core Files of the National Center for Charitable Statistics (2015). This includes foundings of health advocacy groups, health education nonprofits, charities that help particular disadvantaged populations get health care, small nonprofit clinical support, counseling groups to help cope with

trauma and grief, public health organizations, organizations that espouse underfunded research into rare conditions, advocacy for expanding healthcare options and safety nets, and so on. These organizations are identified using the National Taxonomy of Exempt Entities (NTEE) codes.

The category codes used to enumerate such organizations include E (Health Care), F (Mental Health), G (Voluntary Health Associations & Medical Disciplines) and H (Medical Research). From these larger category codes we excluded nonprofit hospitals and other professional organizations that require certified medical professionals such as physicians and nurses.⁸ These organizations such as hospitals are excluded because their foundings require more than just civic effort and are driven by not only need or exposure but also an extended process of mobilization of resources such as land, real estate, medical professionals and certification requirements.

Thus, the focal organizations whose foundings we study are best described as healthcare nonprofit organizations driven by civic effort that focus on healthcare advisory and support services in the community. They are often supported by local donations and rely on a large pool of volunteers, but also have full time staff to ensure administrative continuity and reliability in the nature of services provided. While often small on paper, such organizations end up having impacts much larger than their formal size and structure would indicate (Powell and Steinberg, 2006). As key vectors of knowledge and skills unique to serving the community, and carriers of institutionalized roles where exceptional individuals can volunteer their time, such organizations

⁸ The excluded subcategories include P7A (Residential Intellectual and Developmental Disability Facilities, such as group homes, intermediate care facilities & hospitals), P74 (Hospices, which provide long term nursing care), F31 (Psychiatric Hospitals), E92 (Home Health Care, by certified nursing professionals), E91 (Nursing Facilities), E62 (Emergency Medical Services & Transport, such as standalone emergency care centers and ambulances), E31 (Group Health Practices, which are typically physicians' collectives), E30 (Ambulatory & Primary Health Care), E24 (Specialty Hospitals), E22 (General Hospitals), E21 (Community Health Systems, which include rural health systems, as well as broad-based hospital systems), and E20 (Hospitals, unclassified in other categories), and so on, which require professional certification and a longer founding process that is hard to tie to local community need alone.

become central to community wellbeing. For brevity's sake, for the rest of the paper we will refer to these organizations as 'healthcare nonprofit organizations' or 'healthcare nonprofits', with the understanding that the kinds of organizations outlined in the previous paragraph (such as hospitals, medical research labs, and nursing homes⁹) are excluded from the set.

Data on these organizations were gathered from annual 990 filings aggregated in the annual NCCS core files for the period (National Center for Charitable Statistics, 2015). The core files were merged and cleaned such as by removing duplicates, correcting errors in reported location, and text overflows in the scanned data that generated unusable entries. The organizations enumerated are typically classified as 501(c)(3) charities (IRS, 2017). The 501(c)(3) public charity status however has relatively high burdens of reporting and a higher legal bar for establishing the proposed 'community benefit' and beneficiary or serviced population at the time of incorporation (Hopkins, 2006, 2011; IRS, 2017). As a result several organizations often incorporate under other 501(c) rulings at the time of founding, and then change status to 501(c)(3) as they grow or become viable. These include classifications such as social clubs (501(c)7), fraternal benefit society (501(c)8), social welfare organization such as service clubs and local associations (501(c)4), and so on. At the time of founding therefore, we classify organizations as the aforementioned healthcare nonprofits based on the 3-digit National Taxonomy of Exempt Entity Classification codes rather than their legal 501(c) classification based on their type of IRS tax-exemption ruling at the time of founding (the NCCS data only includes nonprofits however, so commercial ventures are excluded).

Enumerating foundings. Unique organizations are identified using their EIN (Employer

⁹ Adding these organizations into the founding counts, while inappropriate theoretically, doesn't significantly change the results because they are rarely founded spontaneously in response to stimuli in the civic sphere.

Identification Number). Since the IRS has typically allowed for three years of failure to file returns before revoking an organization's nonprofit status (IRS, 2017), enumerating foundings requires looking back a few years to make sure an earlier filing doesn't exist for the organization. Less than half a percent of organizations in the sample re-emerge after a period of more than three years (often these rare cases are organizations that petitioned for exceptional circumstances underlying failure to file returns beyond three years). For the purposes of the study we added two years to the IRS' 3-year rule for a conservative 5-year stretch of missing observations for the organization to be considered as newly founded. In other words, a newly founded healthcare nonprofit is enumerated when the organization's EIN hasn't occurred in the 990 filing data for the previous five years (changing the window to the default 3 year rule doesn't change the results since less than 0.5% of organizations ever re-emerge after going missing for three years in the sample).

The number of foundings are aggregated for annual periods for each of the 58 counties in California (we discuss the use of counties as the units of aggregation after we describe the mortality data). The dependent variable is measured for the period 1996-2014, while the independent and control variables are measured for the 1-year lagged period, i.e. 1995-2013. Figure 1 below illustrates the average annual foundings of healthcare nonprofits during the period 1996-2014. The figure also shows the annual standard deviation of foundings across counties, pointing to the need for accounting for overdispersion in counts of foundings when we get to a discussion of modeling choices later in the paper.

<Insert Figure 1 here>

Mortality

Mortality data were gathered for medically-related deaths, such as due to disease or general medical conditions for 5-digit zip codes within the counties. Mortality is recorded by location of

last residence of the deceased rather than the hospital in which death occurred¹⁰. Figure 3 shows a sample of the 1989 version of the certificate of death from the CDC. The zip code of residence of a deceased person is recorded in field 13f in the 1989 version of death certificates.¹¹

<Insert Figure 2 here>

Conditions. The primary causes of mortality are also recorded in certificates of death, and comprise several categories. For the period 1989-1998 deaths were coded with the Ninth Revision of the International Classification of Diseases (ICD-9), and for the period 1999 and after the coding is done using the next revision of the classification system (ICD-10). These are aggregated into high-level categories of general conditions such as Chronic Obstructive Pulmonary Diseases (COPD, *ICD-10 classes* J40-J47), Diabetes Mellitus (DIA, *ICD-10 classes* E10-E14), Chronic Liver Disease and Cirrhosis (LIV, *idem.* K70, K73, K74), Pneumonia and Influenza (PNF, *idem.* J09-J18), Acquired Immune Deficiency Syndrome (AID, *idem.* B20-24), and so on. The counts and neighborhood dispersion of mortality excludes deaths due to non-medical causes such as homicide, accidental injury, and suicide.

Why mortality instead of morbidity (illness): Apart from the previously discussed theoretical reasons (perceived as an incomparably bad outcome, people overestimating fewer proximal instances, prominence), studying mortality as the focal shock also provides methodological benefits. Unlike morbidity (illness), which are reported by clinic or hospital location, mortality data are based on death certificates which record location of residence, and a lot easier to tie to the neighborhoods they would have happened in. Second, morbidity data vary widely in the level of affliction and certainty of diagnosis that is reported; mortality is a certain

¹⁰ unlike illness which is recorded by hospital location

¹¹ The 2003 version of the death certificate (not shown below, available on request) similarly shows the zip code of last permanent residence (not place of death) in field 7f.

outcome that is terminal. Third, perceptions of morbidity are often intertwined with beliefs about how lifestyle choices, habits, and morality can help overcome it, which might attenuate the perception of need; mortality on the other hand can't be overcome and "people are dying" is an unmistakable call to do something if in one's social world.

Finally, mortality carries with it a great deal of (short run) temporal exogeneity: Park et al (1990) found that for CHF (Coronary Heart Failure) and AMI (Acute Myocardial Infraction, i.e. cardiac arrest), more than half of the excess mortality unexplained by condition, hospital quality/access, or process of medical care could be tied to random variation from a complex confluence of time and circumstance. As such, mortality, as Baron and Ubel's (2002) results show is not only perceived as an infinitely bad outcome incomparable to any (even starkly different) gradations of health—but also its occurrence itself is relatively exogenous in time even among those with existing conditions (Park et al, 1990).

Aggregation: Counties and Zip-codes within Counties

Counties are used as the boundary for enumerating findings, but we use zip codes to enumerate the dispersion of mortality (the independent variable). First, counties are default administrative units for healthcare planning, decisions about budget appropriations for 'County Indigents', and government programs to cover the uninsured, particularly in California. Therefore, the institutional environment for healthcare nonprofits such as clinics, advocacy groups, and financial assistance programs, comprise county level forces and conditions is inextricably tied to the county as an administrative and planning unit. Second, aggregating at too-fine-grained a level makes it difficult to enumerate organizations founded through a confluence of trans-local patterns of demand and supply in the domain of nonprofit founding. For example, neighborhoods that are 'service areas' (such as those with the greatest need) are often not the

places where registered offices of the aforementioned nonprofits or their founders are located. Finally, counties apart from aggregating the distribution of need vs supply of entrepreneurs, are also methodologically valuable as geographical units that present stable boundaries over long periods. Boundaries of cities and suburbs often change due to demographic change. For example the relatively high population growth in California has led to new “places” emerging in census reports. As a result, not only do the boundaries of cities and suburbs change to accommodate new population centers, but also existing organizations tend to find themselves in newly demarcated cities and towns during the period of study, without actually relocating. For example as suburbs of San Francisco have incorporated themselves into new places, some existing organizations report change in their city without any corresponding change in their addresses. Counties on the other hand have had static boundaries in California since 1957 and are unaffected by the ebb and flow of boundaries of its subunit).

Zip-code level data. Mortality data were gathered annually at the 5-digit Zipcode level (based on CDC data) from the California Department of Public Health (2016). The zip code of residence of a deceased person is recorded in field 13f in the 1989 version of death certificates (see Figure 3), and in field 7f in the 2003 revision of the standard death certificate (not displayed but available on request)¹². Several past studies have used zipcodes as proxies for neighborhoods, which is a relatively acceptable (although not perfect) way to delineate neighborhoods. In California for example zipcodes signify starkly different economic and sociodemographic characteristics. These come to be ingrained in local popular perception as not only social distance but also different spatial settings from the point of view of health, such of disease, high-risk behaviors, perceptions of sexual promiscuity and substance abuse, and collective memory of

¹² http://www.cdc.gov/nchs/nvss/mortality_methods.htm

local historical events that reinforce these persistent perceptions.

For example, looking east of the 90210 zip code (Beverly hills) home to the rich and famous of Hollywood, one encounters the relatively more modest zip codes of 90069 (Norma Triangle/Sunset Strip), and 90046 (Laurel Canyon/West Hollywood). Crossing from the former to the latter two, housing values drop remarkably (by almost 50%)—just by crossing east of the 90210 boundary. Also varying is the sociodemographic profile. Moving from 90210 to 90069 one gradually encounters fewer sleepy but pretty blocks, and more entertainment, shopping, and tourist traps. Moving further east and north to 90046 mainstream glamour gives way to counterculture such as of rock music in the sixties and substance abuse and experimentation in general. Additionally, while 90210 holds glamour and superficiality as its badge of honor, the neighborhoods to the east have been known for the history of LGBT activism, the resident gay male population, and more recently being the vanguard in marijuana legalization. Similarly, the Mission neighborhood in San Francisco (94110 zip code) represents a mostly Hispanic population, residential buildings, family-owned stores, and a lower-priced bar scene frequented by purportedly penniless artists and musicians. In contrast the 94103 zip code (SoMA and Folsom) with its office buildings, alternative movie studios, and a larger homeless population is perceived as milling with financial analysts during the day and a more gritty (occasionally dangerous) crowd at night. As such, zip codes, by their characteristics of being easily remembered markers of place and its social attributes, come close to collective perceptions of neighborhoods.¹³

Aggregation. 5-digit Zipcodes were matched to counties with data from the Census Data

¹³ A map of zip codes in San Francisco (from <http://www.healthysf.org/bdi/outcomes/zipmap.htm>) illustrates not only the social divides represented by the zip codes, but also the subsequent links on the above page illustrate the patterns of mortality and general health conditions that vary by zip codes. An archived link for the same can be accessed at <https://web.archive.org/web/20190524032236/http://www.healthysf.org/bdi/outcomes/zipmap.htm>

Center (MABLE, 2016). The matching was done separately for different decades based on the census data (and occasionally shorter periods if inter-censal mappings were available) to account for any drift in zip code boundaries. In a few cases when a zip-code fell between multiple counties, it was allocated to the county with the larger proportion of the zip code population. The spatial dispersion of mortality (Shannon index) was calculated within these boundaries.

Spatial Dispersion of Mortality. The dispersion of mortality across zipcodes is parameterized in the models using the Shannon index of diversity (Shannon and Weaver, 1949). The Shannon index of mortality across zipcodes in a county can be calculated as:

$$S_{County} = - \sum_{\left(\begin{smallmatrix} \text{Over: All} \\ \text{Zipcodes} \\ \text{in County} \end{smallmatrix} \right)} \left(\frac{D_{Zipcode}}{D_{County}} \times \ln \left(\frac{D_{Zipcode}}{D_{County}} \right) \right)$$

$$S_{County} = - \sum_{\left(\begin{smallmatrix} \text{Over: All} \\ \text{Zipcodes} \\ \text{in County} \end{smallmatrix} \right)} \left(R_{Zip5} \times \ln(R_{Zip5}) \right)$$

Where $\ln(.)$ is the natural logarithm, $D_{zipcode}$ is the number of deaths in a zipcode due to medical conditions, and D_{County} is the number at the county level, so their ratio R_{Zip5} is the proportion of medically-caused mortality in the county concentrated in a 5-digit zipcode area. $\sum$ is the summation sign indicating a sum over all zipcodes in the county. The negative sign in front of the summation makes the expression positive since the natural log of proportion is always negative or zero. Note that the Shannon Index is bounded on the lower end (zero) but doesn't have an absolute upper bound apart from the features of the setting.

The Shannon index produces a measure of variety or dispersion which can be qualitatively compared across communities through its standardized exponential form (Jost, 2006). For

example, a community where mortality across neighborhoods is distributed with a Shannon index of 1.61 has a distribution equivalent to a community where mortality is dispersed perfectly evenly across 5 neighborhoods. The “5” number is the exponential of the index value (i.e. $\exp(1.61)=5$) (e.g. see Jost, 2006). This provides the Shannon index with a qualitative interpretation that can be used for comparative purposes other than being part of a regression. For greater detail on the properties of Shannon diversity and its applications see Jost (2006; also see White, 1986: 199–201; McDonald and Dimmick, 2003; Page, 2011: ch. 2). A scatterplot of spatial dispersion of medical-cause mortality by year (pooled z-score values) for San Francisco County is shown in Figure 3.

<Insert Figures 3 and 4 here >

In contrast with an urban, coastal, densely populated, diverse, and high income county such as San Francisco, Butte County is rural, inland, sparsely populated (220k population), has middling to low diversity, and middling to low income. The mortality dispersion for Butte county is shown in Figure 4. These figures largely illustrate that patterns of spatial dispersion of mortality don’t follow a simple time trend. Instead, as mortality carries with it a great deal of (short run) temporal exogeneity, at least part of the shifts in dispersion can be attributed to temporal chance. For example Park et al (1990) found that for CHF (Coronary Heart Failure) and AMI (Acute Myocardial Infraction, i.e. cardiac arrest), more than half of the excess mortality unexplained by condition, local hospital quality, access to care, or process of medical care, could be tied to random variation from a complex confluence of time and circumstance.

Controls and Interacting Variables

Community sociodemographic characteristics. We control for sociodemographic characteristics of the county using several variables. This includes population density, measures

as thousands of people per square mile, calculated annually based on intercensal population estimates. Intercensal population estimates are were gathered from data released by the California Department of Finance (2014) which combines Decennial Census population data with migration statistics, and CDC data on births and deaths to create annual estimates of population between the censuses. We control for racial diversity using population data for different combinations of race and ethnicity. The categories used include enumerations of Hispanic and non-Hispanic counts of White, Black American Indian, Eskimo, or Aleut, Asian or Pacific Islander, and Other race (descriptive labels are those used in the 1990 census; the labels change to more sensitive ones in later years).

Racial residential segregation was measured using zip code populations by race and ethnicity provided by the Census Bureau's zip code (ZCTA) statistics series (Census Bureau, 2014). Since there are multiple categories of individuals than are allocated across multiple pockets of space within a larger area, it has too many degrees of freedom to be measurable by the usual diversity indices. Measures of residential segregation by race therefore use probabilistic measures of exposure, which is either measured as an interaction index or an isolation index (Massey and Denton, 1988:287-288). Using a base category of race or ethnicity, such indices measure the extent to which interaction patterns are statistically more or less likely based on residential location. Rather than measuring evenness across places, this index attempts to more vividly capture the interaction of place and categorical differences (such as of race) of people in a geographic community. We used the Isolation index of residential segregation. The key reason for using the isolation index was that it offers a conceptual analog to the processes underlying the hypothesized interaction effects—viz. the degree to which racial groups might be isolated in distinct neighborhoods and have lower exposure to others who are similarly isolated in other

neighborhoods. Specifically, the isolation index measures the extent to which the focal category members are exposed only to one another, rather than the alternative category (others), and is dependent on proportion distributed across geographic sub units rather than relative size alone (Massey and Denton, 1988: 287-289). The isolation index is calculated as:

$$P_{x,x}^* = \sum_{i=1}^n \left(\frac{x_i}{X} \right) \left(\frac{x_i}{t_i} \right)$$

where P^* is the isolation index, the subscript i indicates the i^{th} zip code, $\sum_{i=1}^n$ represents the sum over all zip codes in the county, x_i is the population of the focal racial category in a zip code, X is the population of the focal racial category in the county, and t_i is the total population of the i^{th} zip code. Thus it's a sum over the product of (a) the proportion of the focal race in the zip code relative to their numbers in the county, and (b) the proportion of the focal race in the zip code relative to the total population of the zip code. The key reason for using the isolation index was that it offers a conceptual analog to the processes underlying the hypothesized interaction effects—viz. the existence of distinct social worlds at the intersection of space and race. For California counties we use Non-Hispanic-White as the base or comparison category. Similar results are obtained using other base categories, such as of race or ethnicity, or a combination of the two. We discuss this more when describing the results and hypothesis tests.

We control for (household) income segregation across zip codes within a county and median household income for the county, using income data from the decennial Censuses and the American Community Survey (for later years). Income measures for missing inter-censal years are calculated by simple linear interpolation (more complex, higher-order measures of interpolation often create unnecessary curves in the data leading to unrealistic values for some years, so linear interpolation seemed most sensible for intercensal years of income). By the

income segregation measure, we wanted to capture in a single measure how different neighborhoods might have clusters of affluence or poverty (e.g. see the previously discussed example of the 90210 zip code vs others). One such measure, used in the models is the standard deviation of zip code median incomes in a county (in thousands of dollars). Higher values indicate wide disparities in income between neighborhoods within counties, and vice versa for lower values. Other range-based measures were also calculated, such as difference in median income between the most affluent and least affluent zip codes; these don't change the results of hypothesis tests, and are discussed in the results section.

We also control for political diversity, measured as the diversity of party affiliations in voter registration records. Voter registration numbers were gathered from data reported (by mandate) by the California Secretary of State (2014). These include numbers registered to vote across party affiliations such as Republican, Democrat, Green, Libertarian, Reform, and American Independent parties, as well as residual categories of independents, and "other" declared affiliations. Diversity of political affiliation was calculated using the Shannon Index. We used diversity of voter registration instead of votes cast in general and local elections because election voting numbers can be driven by candidate effects, while voter registration is a better representation of broad ideological orientation of constituents.

We also controlled for mortality-related variables that might confound the effect of spatial dispersion of mortality across neighborhoods in a county. Continuing the data discussion from pages 20-21 under the subsection on "Conditions", this included the aggregate mortality in a year in a county, and the (space-free) Shannon diversity of medical conditions of mortality in a county. The latter was calculated as a Shannon index measure along the following set of categories of proximal medical causes as noted in the CoD: Immune Deficiency Syndrome (AIDS/HIVD),

Alzheimer's Disease, Malignant Neoplasms (Cancers), Chronic Lower Respiratory Disease (CLRD), Chronic Obstructive Pulmonary Disease (COPD), Diabetes Mellitus, (Other) Diseases of the Heart, Essential Hypertension and Hypertensive Renal Disease, Chronic Liver Disease and Cirrhosis, Pneumonia and Influenza, Cerebrovascular Disease (Stroke), and Other Medical Causes not classifiable under the aforementioned causes, but excluding non-medical causes such as Homicide, Unintentional Injuries (from accidents), Suicide (incl. self-harm). Also, see earlier discussion under the subheading “Mortality” for more detail on classification systems and the location of mortality to places of residence rather than to place of death.

Lack of Insurance Coverage (“un-insuredness”). We control for variations in the lack of insurance coverage in the county, as a key third variable that can confound the link between dispersion of mortality and healthcare nonprofit foundings. We use four control variables to measure the extent of insured-ness. These include percentage of children (under 18 years of age) without insurance and percentage of adults without insurance; these are disaggregated because of differing responsiveness to public health crises concerning children’s health (greater) compared to adults. Annual insurance uptake data for counties split by age group we gathered from the Small Area Health Insurance Estimates of the Census Bureau (SAHIE, 2014). We also control for percentage of county residents enrolled in Medicare (any plan, including parts A and B), and percentage enrolled in Medicare Advantage plans (which are Medicare plans administered by private insurers, and often include prescription drug coverage and other benefits along with coverage from Medicare part A & B). Medicare enrollment data by county were gathered from data provided by the Centers for Medicare and Medicaid Services (CMS, 2015a; 2015b).

Healthcare sector capacity. We control for the capacity of the local healthcare sector,

including hospitals and nonprofits. Data on the number of hospitals and their bed capacity were gathered from the reports of the Office of Statewide Health Planning and Development (2016) of the State of California. We calculated the total capacity of hospitals in a county by aggregating the total number of staffed beds across all hospitals in the county for each year. “Staffed beds” represent beds “that are licensed and physically available for which staff is on hand to attend to the patient who occupies the bed.”¹⁴ Often hospitals are licensed to have more beds than they do actually have, and sometimes hospitals lack staff to attend on existing beds. As a result, we use the total number of staffed beds in the county to establish the actual hospital capacity in the county (measured in thousands of beds). We also control for the total number of hospitals (of any kind) in the county in the previous year, gathered from the OSHPD data, to measure the density of the professional healthcare organizations in the county.

We control for the lagged density (in thousands) of healthcare nonprofits in the county to control for base effects in foundings, and pre-existing need that is already serviced. These counts are gathered from the National Center for Charitable Statistics data that was discussed earlier in the Data section. We also added the square of the density term to control for underlying ecological forces that drive or impede foundings, as has been popularized by the literature on density dependence in organizational ecology (Carroll and Hannan, 1989). We also added a time trend to measure any time varying unobservable factors that are not accounted for by the sociodemographic, insuredness, and healthcare sector variables. Summary statistics and pairwise correlations between variables are reported in Table 1.

<Insert Table 1 Here>

¹⁴ <https://archive.ahrq.gov/research/havbed/definitions.htm>

Models

Organizational foundings can be characterized as count data, which are modeled by some version of the Poisson model. The Poisson specification however assumes that the mean is equal to the variance, which is rarely true for organizational foundings (Cameron and Trivedi, 1998). For example, Figure 2 (previously shown) illustrates the high standard deviation (square root of variance) relative to the mean for this set of foundings. As a result a negative binomial specification is used. The negative binomial is a two-parameter model, which includes a mean parameter which provides the scale of the baseline distribution, and an overdispersion parameter which characterizes the extent to which variance deviates from the mean per unit of the mean (Cameron and Trivedi, 1998; Hilbe, 2011). When estimating the (pooled or population averaged) negative binomial the overdispersion parameter is computed first and then held constant as a baseline for the corrected Poisson model. However studying foundings in geographic units requires not only accounting for overdispersion but also heterogeneity in overdispersion across geographic units. This posed a significant problem in estimation owing to the existence of two parameters in a nonlinear functional form, which requires conditional estimation instead of just linear adjustments for different units. Hausman, Hall, and Griliches (1984) proposed a functional form that conditions out the heterogeneity in overdispersion by using a reduced-form estimation procedure where the intercepts (such as random effects) are conditioned out in the final specification. We use the random effects version of this negative binomial model to predict foundings in counties over annual periods. Specifically, we use the following specification in predicting foundings:

$$(F_{it}|\delta_i) = \exp \left[\left(\sum_{k=1}^n x_{itk} \beta_k \right) + \varepsilon_{it} \right]$$

where F_{it} represents the number of organizations founded in period t in the i^{th} geographic

unit, δ_i is the overdispersion parameter for the i^{th} group, x_{itk} represents the right-hand-side covariates across time and space, n is the number of covariates, β_k represents estimated coefficients, and ε_{it} is the random error. The random effects represent draws from a two-parameter beta distribution based on the distribution of group means in the data. The random effects aren't directly estimated but instead are partialled out in the reduced-form Quasi-Maximum Likelihood Estimation procedure (Hausman, Hall, and Griliches, 1984).

Later in the paper, we also test the results under alternative modeling choices, such as of other specifications, dependent variable construction, and time windows for calculating the independent variable. Further, in the robustness checks section we discuss extensions to the hypotheses that help elaborate how social entrepreneurship might be similar yet different from entrepreneurship in general by focusing on the individual-opportunity nexus, and spillovers of geography and existing organizations in the same domain.

RESULTS

Tables 2 and 3 report the results of the hypothesis tests. Also included are tests for robustness to alternative specifications, alternate formulations of the dependent variable, and the use of alternative lagged windows for understanding the relationship between the dependent and independent variables. The headers in the tables indicate the type of model used, and the dependent variable for each model. Discussed below are the models in their numerical sequence.

<Insert Table 2 here>

Control model

Model 1 in Table 2 is the control model, which includes variables such as community social and economic characteristics, insured-ness across different segments, and the local healthcare sector capacity. Net of other factors, the time trend, population density and racial diversity are

all non-significant in predicting foundings of healthcare nonprofit organizations, such as those engaged in advocacy and support in the county. The coefficient for residential segregation—which is calculated as an isolation index of non-hispanic white residents compared to others—is also not significant net of other factors.¹⁵ Income segregation, median household income, and political diversity are all non-significant in predicting founding rates.

The next set of four variables measure insurance uptake (“insuredness”) across various demographic and serviced populations. The percentage un-insured among both children and adults don’t significantly predict number of foundings. The percent of the eligible population enrolled in Medicare is negative but also not statistically significant. The proportion enrolled in Medicare Advantage plans has a positive coefficient, but is not a significant predictor of founding rates in the control model, although the coefficient becomes significant in some other models, particularly the pooled model (discussed later).

The control variables for health care sector size—number of active hospital beds in county, and the total number of hospitals in the county—are non-significant predictors of founding rates. The coefficient on density of existing healthcare nonprofits is positive and significant, and the coefficient on the square of density is negative and significant. This indicates a local inverted-U shaped density dependence on founding rates of healthcare nonprofits: at low densities, rising density encourages foundings by institutionalizing the local healthcare nonprofit scene, but at high densities, competition for resources and attention takes over, lowering founding rates. The control variable for total mortality rate in county is not a significant predictor of founding rates. As we show below, what matters instead is how mortality is distributed across zip codes and

¹⁵ Similar results are obtained when this variable is replaced by isolation index based on other categories such as of ethnicity, e.g. Hispanic-Non-Hispanic segregation (models available on request).

conditions.

Main model

Model 2 is the main model, where variables representing the distribution of mortality are added to the control model. Model statistics indicate an improvement over the control model. The coefficient for spatial dispersion of mortality is positive and significant at the $p < .001$ level. Thus, Hypothesis 1 is supported: greater dispersion of mortality across zip codes increases founding rates of healthcare nonprofits. In magnitude terms, a 1 standard deviation increase in spatial dispersion (SD for this variable is 1.052), increases founding by about 3 more organizations on average. Model 2 also includes the variable for medical-cause diversity of mortality, added as a control. The coefficient on this variable is positive and significant at the $p < .001$ level, and is therefore an alternative pathway rather than a confound to the hypothesized effects of the spatial dispersion of mortality.

Robustness to alternative modeling choices

Focusing only on local community-driven foundings: One might argue that since the proposed hypotheses are about variations in the distribution of the stimulus in the local environment, it should only affect the founding of locally-driven organizations, to the exclusion of foundings of affiliates and branches of regional or nationally federated nonprofits. This problem while analytically legitimate is however not a major one in practical terms because branches of large federated nonprofits already exist in most counties and new ones are rarely founded. Figure 5 below shows a comparison of the number of overall annual foundings of healthcare nonprofits, with foundings excluding new branches of multi-unit organizations, illustrating the above.

<Insert Figure 5 here>

We nonetheless ran a separate model (Model 3) where the same specification as Model 2 is used, but the predicted foundings exclude founding of branches of other organizations (typically regional or nationally federated nonprofits). The results are largely unchanged in magnitude and significance, supporting H1 as in Model 2.

Alternative specifications: We also considered alternative specifications. In Model 4 we used a pooled negative binomial specification with standard errors clustered on county, instead of the Random Effects model. In the pooled model, the control for population density is a significant predictor of foundings; this effect appears in the absence of RE on county possibly because of significantly greater founding rates in urban counties. Enrollment in the more comprehensive Medicare Advantage plans has a positive effect on foundings, and is significant at the $p < .01$ level of significance. These plans are extensions of Medicare A/B coverage which includes typically higher levels of coverage such as of prescription drugs, and are administered by private insurers such as UnitedHealthcare and Humana. It's hard to predict why this control variable is significant, but one possibility is that the proportion of Medicare Advantage enrollments might indicate to some degree the proportion of affluent retirees, who are typically the most active in the civic sphere. Density dependence continues to be inverted u-shaped and significant. H1 is supported as before; the coefficients on spatial dispersion of mortality continues to be positive and significant, although the coefficient is lower in the pooled negative binomial model. In unreported models (available on request), we also ran the models using a Poisson specification (both pooled and random effects) with similar support for the impact of spatial dispersion of mortality on foundings.

Alternative windows for spatial dispersion of mortality: It is possible that the widespreadness of need across neighborhoods might be somewhat cumulative and not entirely driven by

recency. Therefore in Model 5, we replicated Model 2 except for the use of 5-year cumulative rolling widows in calculating the lagged mortality variables (total rate, spatial dispersion, and diversity of medical causes of mortality). Results from Model 5 indicate that the effect of spatial dispersion is similar in size and significance, even with a 5-year rolling window for calculating spatial dispersion of mortality. The coefficient on the control for medical cause diversity however becomes lower and not significant in predicting foundings when one considers a 5-year window, indicating that local responses to diversity of medical causes of mortality are driven by recency instead of cumulative exposure, even though the spatial dispersion of mortality has similar effects when consider recent or cumulative measures of the stimulus.

Interaction models

Models 6 through 9 in Table 3 report the results of the hypothesis tests that involve interaction effects.

<Insert Table 3 here>

Segregation by race. Model 6 is an interaction model testing the effect of an interaction between residential segregation by race and spatial dispersion of mortality. The coefficient is negative but not significant, indicating lack of support for Hypothesis 2. This suggests that net of factors such as income disparity and racial diversity, residential segregation by race in itself does appear to impede the main effects of mortality dispersion on foundings. The measure used in this model was the Isolation Index of segregation, with non-hispanic-white as the base category. Similar (non-significant) results are obtained for other measures of residential segregation such as the exposure index and dissimilarity index, and for other bases of segregation such as hispanic/latino ethnicity as the base category (models available on request).

However, residential segregation by race (such as measured by the Isolation Index) often

goes hand in hand with (space-free) measures of racial diversity, especially in the United States. As a result, we decided to find out if it's not residential segregation per se, but supernormal levels of residential segregation (unexplained by levels of racial diversity) that might impede normal patterns of social exposure. Therefore, we next predicted the Isolation Index of residential segregation in a linear OLS model with racial diversity as the only independent variable; we calculated the residuals from this model (i.e. actual minus predicted segregation). The residuals from the above OLS prediction have a range of -0.38 to 0.096 (mean=0, sd=0.063).

In Model 7, the residential segregation variable was replaced with this residual (representing supernormal levels of race-based residential segregation), and an interaction term was added between the residual and spatial dispersion of mortality. Results from Model 10 indicate that the interaction term is negative and significant: increasing supernormal residential segregation decreases the effect of spatial dispersion of mortality on foundings. Conversely, having lower residential segregation than what is predicted by the aggregate racial diversity in the county, increases the effect of spatial dispersion of mortality on foundings. The interaction effect is plotted below in Figure 6. This indicates conditional support for Hypothesis 2. Residential segregation moderates the main effect in the hypothesized manner, but only for supernormal levels of such segregation, i.e. when abstracted away from 'normal' patterns of residential segregation that are predicted by increasing racial diversity alone.

<Insert Figure 6 here>

Income disparity across neighborhoods. In Model 8 we included an interaction term to test Hypothesis 3, that when there is greater income disparity between neighborhoods, the effects of spatial dispersion of mortality on foundings is impeded. The effect of the added interaction term is negative and significant at the $p < .005$ level. Figure 7 below is a graph of the interaction effect. Even when mortality is widely dispersed across neighborhoods, increases in income

dispersion across zip codes drastically decreases the number of foundings (the reverse effect for low mortality dispersion is much lower in magnitude). The income dispersion variable has a mean of around 16 (in thousands of dollars) and a standard deviation of around 7. At high spatial dispersion of mortality, when income dispersion is low (mean – 1*sd) there are about 8 more organizations founded compared to when income dispersion is high (mean + 1*sd). Thus, Hypothesis 3 is supported.

<Insert Figure 7 here>

Similar results are obtained when using simpler range-based measures of income disparities across place, such as the difference in income between the most affluent vs least affluent neighborhoods (models available on request). Additionally, in Model 9 we ran a robustness check: instead of the income dispersion interaction we added an interaction term between the overall median household income in the county and spatial dispersion of mortality. The interaction coefficient in this model is also negative but not significant. Thus, the impending effects of income disparity across neighborhoods aren't being driven by places at the lower end or higher end of incomes alone.

EXTENSIONS AND ROBUSTNESS CHECKS

The individual-opportunity nexus in social entrepreneurship

While the paper emphasizes the spatial dispersion of problems and its intersection with income and racial segregation as key structural features influencing greater rates of social entrepreneurship, such an account is possibly incomplete without a window into the individual-opportunity nexus that has been central in the study of entrepreneurship in general (Shane and Venkatraman, 2000; Shane, 2003). Davidsson (2015) extended this line of work by arguing that apart from external enablers of new venture creation, what also matters is the set of

recombinations that comprise new venture ideas, the means of bringing these ideas into fruition, and the confidence in the subjective assessment of the above as a basis for entrepreneurial effort. In this framework therefore, individuals play a crucial role, particularly in their efforts at leveraging their human and social capital to bring together ideas, resources, and organizational routines to create new ventures.

The individual-opportunity nexus in social entrepreneurship however needs to be understood in light of the fact that starting such ventures to solve local problems is also a response to the absence of such solutions (or a sufficient quantity of the same) from formal channels, and informal channels. Formal channels include organizations such as firms, healthcare institutions and government agencies, and informal channels include advice and help from people with relevant skills and resources in the neighborhood. The stock of people with the right skills and knowledge who might be potential social entrepreneurs in a particular domain might not always lead to greater foundings of formal organizations aimed at solving local problems, if those very same people are also embedded in institutions and organizations that constitute formal channels of action, apart from being informal channels of relevant advice and knowledge in their neighborhoods.

To test this we gathered annual data on the number of medical professionals by county from the facility-level records of the California Office of Statewide Health Planning and Development (OSHPD, 2016). This included the number of nurses, physicians and surgeons working in any health facility in a county (i.e. hospitals, clinics, ambulatory units, hospices, substance abuse treatment centers, mental health institutions, sports medicine centers, clinical research labs, and so on). The modal number of such professionals in a county is 1,001. We added the number of nurses and doctors (physicians and surgeons) to calculate the total number of

medical professionals in the county in thousands. Such professionals might have greater knowledge and connections in the medical community than the average person, and so greater number of them represents a possibly larger pool of potential healthcare social entrepreneurs in a geographic community.

<Insert Table 4 here>

In Model 10 of Table 4 we added this variable (scaled to thousands) to the main model. The coefficient indicates a small negative main effect but it is not statistically significant. The effect of spatial dispersion of mortality on foundings continues to be positive, significant, and similar in magnitude even with the inclusion of this variable. In Model 11, we added an interaction term between the spatial dispersion of mortality and the number of medical professionals (in thousands) in a county in the previous year. The interaction coefficient is negative and significant at the $p < .01$ level, although accounting for the interaction makes the main effect of medical professionals positive. In magnitude terms, once the interaction is accounted for, having more medical professionals in a county generally increases the founding rate, but their marginal impact is lower when there is high spatial dispersion of mortality.

Thus, the positive impact of the presence of higher number of medical professionals is negatively moderated by spatial dispersion of mortality. When the focal stimulus (spatial dispersion of mortality) is stronger, such prospective entrepreneurs might be less vital to foundings. Conversely, such professionals are relatively more important in spurring foundings when mortality is spatially concentrated in a few neighborhoods and the community at large is less likely to see healthcare as a worthy cause for social entrepreneurship. Instead of conventional wisdom that more potential social entrepreneurs who have the knowhow to understand the community's problems will spur more foundings in response to external stimuli, we find that the

individual—opportunity nexus in social entrepreneurship is in fact more complicated. Our results suggest that social entrepreneurs might be best seen as a blend of Wuthnow's (2012) rugged individualists seeking self-actualization through community problem-solving, and Oliver's (1984) pessimistic activists who act because they believe no one else will.

Interaction with existing stock of organizations

As noted previously the control variables for ecological forces affecting foundings indicate an inverted u-shaped relationship, as would be anticipated by typical ecological processes (legitimation benefits increase founding rates with density, but competition for resources kicks in at very high densities and depresses founding rates). However, apart from such baseline processes, stimuli that drive social entrepreneurship are more potent when there is a lack of solutions from other quarters such as the government, institutions, or informal civic behavior in communities. That might be one key distinction between social and commercial entrepreneurship—the former is about people and groups creating organizations to “solve problems when no one else will”, while many entries into commercial entrepreneurship are driven by herding behavior into new domains, where early movers have already established viability of the opportunity space.

Consistent with the above, we sought to explore whether similar dynamics would be substantiated through other interaction effects. For example, one would expect that when there are already many healthcare advocacy and support organizations in a community, even emergent stimuli might have a weaker impact on foundings. In Model 12 of Table 4, we added an interaction model with an interaction term between density of aforementioned existing organizations, and the spatial dispersion of mortality. The interaction coefficient is negative and significant at the $p < .01$ level indicating support for the view that the stimuli such as widespread

rather than concentrated mortality, is a weaker stimuli for social entrepreneurial effort when there are already large numbers of existing organizations focusing on healthcare advocacy and support in the community.

Geographic spillovers in foundings

We also ran additional tests to check if the results are robust to accounting for geographic spillovers from neighboring communities. While geographic neighbors are geographically static and unchanged over time, so the focal county effects are also implicitly absorbing some consistent features of the static neighbors, there is a possibility that stimulus-response dynamics in the neighboring area will affect the same in the focal county. To test this we gathered adjacency between counties from the Census County Adjacency File¹⁶ (we excluded the focal county as its own neighbor, and included those connected by land or bridges). We calculated three variables that can drive focal community foundings based on spillovers from the previous year on the dependent and independent variables: number of foundings in neighboring counties, density in neighboring counties, and spatial dispersion of mortality in neighboring counties.

These variables are added as additional covariates in Model 13 in Table 4. The effect of neighboring foundings is negative, but not significant. Neighboring density doesn't affect focal county foundings either in these models. The spatial dispersion of mortality in neighboring counties is positive but not significant. Most importantly, the model suggests that the hypothesized effects of spatial dispersion of mortality on foundings are not significantly confounded by goings on in neighboring counties.

In Model 14 we ran a similar specification but with the goal of testing whether there are certain components of the foundings that have spillover influences but others don't. For this

¹⁶ <https://www.census.gov/geo/reference/county-adjacency.html>

model, we first predicted neighboring county foundings in the previous year on the spatial dispersion of mortality in neighboring counties in the previous-to-previous year using a simple univariate regression (unreported, available on request). From this regression we calculated two components. The first was the $\hat{y}$, which represents the prediction of neighboring counties' foundings on neighboring counties' spatial dispersion of mortality. The second was the residual, which represents the portion of neighboring foundings unexplained by neighboring spatial dispersion of mortality. These two variables are added in Model 14 in place of the neighboring-county foundings variable. The coefficient on neighboring county foundings predicted by neighboring counties' spatial dispersion of mortality is negative and significant at the $p < .05$ level. Foundings driven by responses to spatial dispersion of mortality in neighboring counties slightly depress focal-county foundings. This possibly suggests that the emergence of similar organizations driven by similar stimuli in neighboring places might instead crowd out focal county foundings by offering alternative (albeit more distant) sources of formalized health advocacy and support. The coefficient on the residual is also negative but not significant. Most importantly, the effect of spatial dispersion of mortality in the focal county continues to be positive and significant in predicting foundings and of a similar magnitude, even when controlling for more disentangled sources of geographic spillovers.

DISCUSSION

Motivated by understanding why problems are picked up as worthy of social entrepreneurial effort in some places and times than others, this paper offers a key implication for understanding the nexus of need and emergence of solutions, for scholars and policymakers alike. As long as problems are concentrated in neighborhoods rather than widely dispersed across the community, they end up drawing little collective effort. Instead of aggregate levels of need

in a geographic community, what matters instead is how such need is distributed across neighborhoods in the community. When poor health is confined in a few ‘hot spots’ (e.g. National Research Council, 1993; Katz, Kling, and Liebman, 2001; Sampson, Morenoff, and Earls, 1999), the larger community can ignore the problem simply by being spatially distant from such places. On the other hand, when the same stimuli are widespread they spur the collectives and individuals into action. In this manner, our study speaks to the existing work on external enablers of entrepreneurship (Shane and Venkatraman, 2000; Davidsson, 2015), ported to the social entrepreneurial domain, while also possibly suggesting that opportunity confidence and external enablers might be quite closely intertwined in the domain of social entrepreneurship. In parallel, the study also offers extensions to thinking about social entrepreneurship as driven by the search for organizational solutions to problems with externalities for community and society (Santos, 2012). We argue that while positive externalities are a fundamental basis of social entrepreneurship, entrepreneurial efforts might not emerge if the potential externalities of social entrepreneurship are not apparent to the majority of the geographic community, such as when poor health outcomes are concentrated in small pockets of space.

A burgeoning literature in organizational theory and economic sociology has shed light on how collective action influences organizations and markets (e.g. see reviews in Strang and Soule, 1998; Davis et al, 2008; Diani and McAdam, 2003; King and Pearce, 2010; Briscoe and Gupta, 2016). Much of this work either focuses on the scaling of goods and ideas that are already deemed worthy of prosocial collective action. We step back to ask—why are particular goods or ideas seen as worth contributing to? This question is especially important in domains where the benefits accrue not only to the local community but society as a whole. Further, these benefits are not merely external, but can improve the experience of the private good at the individual level as

well. For example, a well-educated citizenry not only leads to a better workforce and a conscientious electorate, but also directly affects the extent to which a private individual can gain value from their own education (such as by having knowledgeable peers in the classroom, knowledgeable neighbors, and so on). Thus, from the standpoint of social welfare, these nominally ‘private goods with externalities’ matter not just for their aggregate benefits but their provision also directly feeds back into improving individuals’ private experience of such goods. Finding why such private goods with positive externalities draw greater resources and organizing efforts in some communities than others is therefore valuable beyond the measured number of foundings alone.

In doing so, this paper also draws attention to some oft-overlooked aspects in management and entrepreneurship. First, the impact of income inequality and residential segregation often escapes attention in these research domains because studies explaining community outcomes look at place based average conditions rather than the unique patterns in which the same level of average income and racial diversity can be distributed. Although several scholars have drawn attention to various aspects of community as fields of social entrepreneurial activity (Marquis, Davis, and Glynn, 2006; Marquis and Battilana, 2009; Dacin et al, 2011; Seelos et al, 2011), we extend this line of work by focusing on communities as aggregates of spatial sub-units that overlaps with clusters of socioeconomic characteristics. In doing so, we draw attention to the unexplored role of community structure in macro-level studies of social entrepreneurship. Communities are not just pipes for information and resource mobilization, but also through its underlying distribution of outcomes, resources, and demographics, key lenses for interpreting stimuli as targets for solutions. For example communities where income disparities and racial divisions coincide with high levels of spatial segregation, even a need that s experienced widely

might not drive entrepreneurial effort. When portions of the community that might have the resources and social capital to found organizations to solve salient problems are more segregated from those lacking the same, prospective local social entrepreneurs might have a harder time mobilizing resources and assembling the spaces, capital, people and routines to found such organizations.

Second, individual well-being is not merely a function of human or social capital, but is inextricably tied to the places and spaces that people inhabit: organizations that can improve local community health are therefore key partners whose emergence is worthy of attention. The locus of local civic action in recent times has shifted away from traditional voluntary associations and one-off protest to modern goal-driven forms of organized voluntary association such as local nonprofits engaging in pro-bono care, counseling and advocacy (e.g.; Wuthnow, 1998; Sampson et al, 2005; Strolovitch, 2007; Walker, McCarthy, and Baumgartner, 2011). Structural features of communities that allow its members to perceive a shared fate with physically and socially distant others are not merely boundary conditions but instead ought to be seen as key inputs into understanding why some communities contribute more to improve the collective's outcomes. In that way, the paper contributes to the emerging literature bridging urban and organizational sociology through the study of founding of local healthcare advocacy and support organizations. With the increasing reach of pandemics and public health crises on one hand, and healthcare costs skyrocketing owing to the market structure of the healthcare sector on the other hand, social entrepreneurship in healthcare is set to become paramount, as a way to address the challenges of well-being amid rising gaps between the haves and the have-nots. As key vectors of knowledge and skills unique to serving the community, and carriers of institutionalized roles where exceptional individuals can volunteer their time, such organizations often end up having impacts

much larger than their formal size and structure would indicate.

Finally, the study, through the additional analyses presented in the extensions and robustness checks section, offers a window into some key points of difference between commercial and social entrepreneurship. The individual-opportunity nexus in social entrepreneurship is complicated by the nuance that social entrepreneurship, particularly of the local kind in developed economies, is a response to needs unmet by both formal institutions and informal civic engagement of professionals and domain-experts in their communities. Our study for example suggests that the presence of a large pool of medical professionals in a community—presumably representing a larger pool of people with the skills, knowledge and connections to found such organizations—don't always amplify the impact of external stimuli (or opportunities) on foundings. Instead, the value of such individuals lies in being sources of action when the community at large might be indifferent to emerging problems that are concentrated in hot spots instead of being perceived widely as a cause for action. Additionally, outside of baseline second-order ecological processes of density dependence that affect foundings, stimuli driving social entrepreneurship in particular problem areas might be less potent when there is already a higher density of such organizations in the community. Furthermore, even geographic spillovers show a negative trend, in that solutions to emergent problems in neighboring communities, have possibly crowding out effects on the same solutions emerging in a focal community. Together these suggest that unlike commercial entrepreneurship, where foundings follow at a faster clip once the market has been shown as viable by the founding and existence of other organizations in the same domain, social entrepreneurial efforts are more likely to emerge in response to problems when pre-existing pathways of addressing those problems are absent.

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TABLES

TABLES

Table 1: Summary Statistics and Pairwise Correlations between Variables (N=1083) Note that RHS variables are lagged one year, so the period for the below observations is 1995-2013. Some variables such as zipcode mortality, and % insured in two sparsely populated counties (Alpine and Sierra) are missing in some years due to lack of data. As a result, instead of 58 counties x 19 years, i.e. 1102 observations, the non-missing sample contains only 1083 observations.

	Mean	St Dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Time Trend (Year-1995)	9.00	5.48	0.00	18.00																	
2 Population Density (thousands per square mile)	0.65	2.24	0.00	17.89	0.01																
3 Racial Diversity	1.22	0.36	0.42	1.80	0.22	0.23															
4 Residential Segregation by Race (Isolation Index)	0.66	0.15	0.19	0.92	-0.21	-0.19	-0.91														
5 Income Dispersion Across Zip Codes in County (\$'000)	16.01	7.08	5.19	45.56	-0.14	0.31	0.24	-0.06													
6 Median Household Income in County (\$'000)	5.18	2.01	2.59	13.34	-0.22	0.36	0.12	-0.03	0.60												
7 Political Diversity	1.11	0.07	0.90	1.31	0.30	-0.03	-0.50	0.57	0.05	0.03											
8 Percent Uninsured Children (age 0 to 17)	3.16	1.47	0.61	9.28	-0.60	-0.19	0.20	-0.28	-0.08	-0.12	-0.57										
9 Percent Uninsured Adults (age 18 to 65)	13.79	2.71	6.94	22.70	-0.08	-0.11	0.30	-0.38	-0.18	-0.40	-0.37	0.69									
10 Percent Enrolled in Medicare	14.92	4.41	6.65	45.16	0.12	-0.08	-0.73	0.69	-0.28	-0.29	0.46	-0.32	-0.23								
11 Percent Enrolled in Medicare Advantage Plans	2.80	2.16	0.08	8.49	0.08	0.29	0.31	-0.14	0.50	0.47	-0.05	-0.21	-0.29	-0.18							
12 Total Hospital Bed Capacity in the County (thousands)	1.45	3.45	0.01	28.81	-0.03	0.29	0.36	-0.24	0.36	0.11	-0.09	0.08	0.19	-0.26	0.31						
13 Number of Hospitals in the County	8.96	18.33	0.00	198.00	-0.05	0.21	0.36	-0.22	0.35	0.09	-0.09	0.11	0.21	-0.27	0.30	0.98					
14 Density of Healthcare Nonprofits (thousands)	0.07	0.16	0.00	1.29	0.05	0.36	0.38	-0.25	0.39	0.14	-0.02	-0.03	0.14	-0.26	0.34	0.94	0.92				
15 Square of above Density of Healthcare Nonprofits	0.03	0.17	0.00	1.65	0.04	0.17	0.23	-0.15	0.20	-0.02	0.00	0.01	0.20	-0.14	0.14	0.87	0.86	0.92			
16 Total Medical-Cause Mortality Rate in County	7.05	2.12	0.23	13.47	-0.02	-0.05	-0.48	0.49	-0.27	-0.25	0.20	-0.15	-0.16	0.70	-0.08	-0.15	-0.15	-0.16	-0.10		
17 Spatial Dispersion of Medical-Cause Mortality	2.27	1.05	0.00	5.49	0.01	0.28	0.49	-0.31	0.51	0.31	-0.17	0.00	0.05	-0.33	0.61	0.66	0.67	0.68	0.46	-0.09	
18 Diversity of Medical Causes of Mortality in County	1.80	0.10	1.04	2.00	0.52	0.04	0.41	-0.37	-0.04	-0.05	-0.05	-0.22	0.03	-0.11	0.21	0.08	0.07	0.13	0.07	0.11	0.29

Table 2: Tests of Hypotheses. Models 1, 2, 3 & 5 use a negative binomial specification with Random Effects on County (QML Est.), Model 4 is a pooled negative binomial specification with SE clustered on County (ML Est.) Two-tailed tests. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)
Model Specification:	RE-NB	RE-NB	RE-NB	Pooled NB	RE-NB
Dependent Variable:	Founding of healthcare nonprofit organizations	Founding of healthcare nonprofit organizations	Founding of non-branch organizations only (subset)	Founding of healthcare nonprofit organizations	Founding of healthcare nonprofit organizations
<i>Lagged RHS Variables</i>					
Time Trend (Year-1995)	0.001 (0.011)	-0.004 (0.011)	-0.001 (0.011)	0.007 (0.016)	0.017 (0.010)
Population Density (thousands per square mile)	0.039 (0.058)	0.051 (0.029)	0.045 (0.029)	0.047*** (0.009)	0.039 (0.028)
Racial Diversity	1.063 (0.722)	0.425 (0.496)	0.546 (0.496)	0.143 (0.376)	0.329 (0.496)
Residential Segregation by Race (Isolation Index)	-0.416 (2.044)	1.126 (1.169)	1.395 (1.155)	1.221 (0.754)	0.606 (1.188)
Income Dispersion Across Zip Codes in County (\$'000)	-0.003 (0.011)	-0.002 (0.010)	-0.002 (0.010)	-0.001 (0.008)	-0.001 (0.010)
Median Household Income in County (\$'000)	-0.003 (0.026)	0.000 (0.024)	0.005 (0.024)	0.021 (0.019)	0.007 (0.024)
Political Diversity	-0.575 (0.620)	-0.129 (0.575)	-0.257 (0.580)	1.075 (1.055)	-0.252 (0.593)
Percent Uninsured Children (age 0 to 17)	-0.053 (0.043)	-0.012 (0.039)	-0.008 (0.039)	0.018 (0.050)	-0.031 (0.040)
Percent Uninsured Adults (age 18 to 65)	0.012 (0.022)	-0.022 (0.021)	-0.022 (0.021)	-0.033 (0.026)	-0.012 (0.021)
Percent Enrolled in Medicare	-0.020 (0.029)	0.001 (0.026)	-0.002 (0.026)	-0.053 (0.028)	-0.026 (0.024)
Percent Enrolled in Medicare Advantage Plans	0.062 (0.032)	0.054* (0.027)	0.048 (0.027)	0.086** (0.031)	0.050 (0.028)
Total Hospital Bed Capacity in the County (thousands)	-0.019 (0.025)	-0.031 (0.022)	-0.033 (0.022)	-0.021 (0.020)	-0.042 (0.022)
Number of Hospitals in the County	-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.003 (0.003)	-0.000 (0.003)
Density of Healthcare Nonprofits (thousands)	5.002*** (1.204)	2.899** (1.067)	3.516** (1.069)	3.924*** (0.785)	3.043** (1.057)
Square of above Density of Healthcare Nonprofits	-2.096*** (0.624)	-1.426* (0.557)	-1.744** (0.558)	-1.941*** (0.428)	-1.503** (0.551)
Total Medical-Cause Mortality Rate in County	0.038 (0.040)	-0.048 (0.040)	-0.042 (0.040)	0.006 (0.041)	§ 0.006 (0.005)
Spatial Dispersion of Medical - Cause Mortality in County		1.056*** (0.121)	1.015*** (0.120)	0.921*** (0.101)	§ 1.079*** (0.122)
Diversity of Medical Causes of Mortality in County		2.357*** (0.503)	2.253*** (0.506)	2.074*** (0.582)	§ 0.032 (0.075)
Constant	2.025 (2.256)	-4.872** (1.737)	-4.689** (1.755)	-7.294*** (1.711)	-0.719 (1.457)
Number of Observations	1083	1083	1083	1083	1083
Log-likelihood	-1583.28	-1546.11	-1533.80	-1569.78	-1553.59
Akaike Information Criterion	3204.56	3134.22	3109.60	3179.57	3149.18
Wald Chi-Squared Statistic	248.5***	632.5***	643.3***	32682.6***	621.1***

§ For Model 5 these variables are computed over a moving window of last 5 years instead of last year alone

Table 3: Tests of Hypotheses: Interaction Effects. Negative Binomial Models with Random Effects on County (QML Estimates) Predicting Founding of Healthcare Nonprofit Organizations. Two-tailed tests. RHS Variables are lagged 1 year. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(6)	(7)	(8)	(9)
Time Trend (Year-1995)	-0.004 (0.011)	-0.003 (0.011)	-0.004 (0.011)	-0.003 (0.011)
Population Density (thousands per square mile)	0.051 (0.029)	0.039 (0.030)	0.048 (0.028)	0.051 (0.028)
Racial Diversity	0.427 (0.502)	0.130 (0.305)	0.646 (0.491)	0.526 (0.491)
Residential Segregation by Race (Isolation Index)	1.165 (1.754)		1.110 (1.123)	1.239 (1.133)
Income Dispersion Across Zip Codes in County (\$'000)	-0.002 (0.010)	-0.000 (0.010)	0.060* (0.024)	-0.002 (0.009)
Median Household Income in County (\$'000)	0.000 (0.024)	0.006 (0.024)	0.008 (0.024)	0.103 (0.083)
Political Diversity	-0.130 (0.575)	-0.112 (0.573)	0.158 (0.582)	-0.130 (0.573)
Percent Uninsured Children (age 0 to 17)	-0.012 (0.039)	0.002 (0.040)	0.010 (0.040)	-0.009 (0.039)
Percent Uninsured Adults (age 18 to 65)	-0.022 (0.021)	-0.028 (0.021)	-0.041 (0.022)	-0.022 (0.020)
Percent Enrolled in Medicare	0.001 (0.026)	0.004 (0.026)	0.007 (0.026)	0.006 (0.026)
Percent Enrolled in Medicare Advantage Plans	0.054* (0.027)	0.050 (0.027)	0.048 (0.026)	0.052* (0.026)
Total Hospital Bed Capacity in the County (thousands)	-0.031 (0.022)	-0.019 (0.022)	-0.003 (0.023)	-0.025 (0.022)
Number of Hospitals in the County	-0.001 (0.002)	-0.000 (0.002)	-0.000 (0.002)	-0.000 (0.002)
Density of Healthcare Nonprofits (thousands)	2.886* (1.152)	3.190** (1.078)	2.712* (1.077)	2.757* (1.073)
Square of above Density of Healthcare Nonprofits	-1.421* (0.579)	-1.566** (0.560)	-1.441** (0.558)	-1.497** (0.560)
Total Medical-Cause Mortality Rate in County	-0.048 (0.040)	-0.045 (0.040)	-0.037 (0.040)	-0.045 (0.040)
Spatial Dispersion of Medical -Cause Mortality in County	1.066** (0.348)	1.040*** (0.123)	1.394*** (0.173)	1.206*** (0.166)
Diversity of Medical Causes of Mortality in County	2.356*** (0.503)	2.085*** (0.516)	2.154*** (0.508)	2.366*** (0.505)
Spatial Dispersion of Mortality X Residential segregation by Race	-0.015 (0.512)			
Supernormal Residential Segregation By Race (residual)		7.879* (3.340)		
Spatial Dispersion of Mortality X Supernormal Res Segr by Race		-2.675* (1.235)		
Spatial Dispersion of Mortality X Income Dispersion			-0.022** (0.008)	
Spatial Dispersion of Mortality X Median Household Income				-0.031 (0.024)
Constant	-4.899* (1.953)	-3.221* (1.292)	-6.040*** (1.742)	-5.736** (1.821)
Number of Observations	1083	1083	1083	1083
Log-likelihood	-1546.11	-1543.66	-1542.36	-1545.27
Akaike Information Criterion	3136.22	3131.33	3128.72	3134.55
Wald Chi-Squared Statistic	632.1***	632.1***	689.4***	667.3***

Table 4: Robustness checks: Negative Binomial Models with Random Effects on County (QML Estimates) Predicting Founding of Healthcare Nonprofit Organizations. Two-tailed tests. RHS Variables are lagged 1 year. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(10)	(11)	(12)	(13)	(14)
Time Trend (Year-1995)	-0.004 (0.011)	-0.001 (0.011)	-0.000 (0.011)	-0.004 (0.011)	0.003 (0.011)
Population Density (thousands per square mile)	0.053 (0.028)	0.036 (0.029)	-0.001 (0.030)	0.053 (0.028)	0.050 (0.027)
Racial Diversity	0.369 (0.491)	0.361 (0.487)	0.252 (0.449)	0.350 (0.523)	0.480 (0.515)
Residential Segregation by Race (Isolation Index)	1.064 (1.150)	1.234 (1.133)	0.992 (1.027)	1.045 (1.181)	1.044 (1.157)
Income Dispersion Across Zip Codes in County (\$'000)	-0.001 (0.009)	-0.002 (0.009)	-0.002 (0.009)	-0.001 (0.010)	0.000 (0.009)
Median Household Income in County (\$'000)	-0.003 (0.024)	-0.002 (0.024)	0.001 (0.023)	-0.004 (0.024)	0.000 (0.024)
Political Diversity	0.118 (0.601)	0.152 (0.601)	0.371 (0.602)	0.104 (0.608)	0.322 (0.613)
Percent Uninsured Children (age 0 to 17)	-0.008 (0.039)	-0.006 (0.039)	-0.004 (0.039)	-0.009 (0.040)	0.013 (0.041)
Percent Uninsured Adults (age 18 to 65)	-0.022 (0.020)	-0.022 (0.020)	-0.029 (0.020)	-0.022 (0.021)	-0.031 (0.021)
Percent Enrolled in Medicare	-0.003 (0.026)	-0.003 (0.026)	-0.005 (0.025)	-0.002 (0.027)	-0.004 (0.026)
Percent Enrolled in Medicare Advantage Plans	0.062* (0.027)	0.052 (0.027)	0.055* (0.025)	0.060* (0.028)	0.066* (0.027)
Total Hospital Bed Capacity in the County (thousands)	-0.022 (0.022)	-0.013 (0.023)	0.027 (0.027)	-0.021 (0.023)	-0.020 (0.022)
Number of Hospitals in the County	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Density of Healthcare Nonprofits (thousands)	2.947** (1.067)	3.092** (1.058)	13.253*** (3.365)	2.929** (1.101)	2.991** (1.087)
Square of above Density of Healthcare Nonprofits	-1.338* (0.559)	-1.257* (0.555)	0.761 (0.887)	-1.331* (0.578)	-1.260* (0.573)
Total Medical-Cause Mortality Rate in County	-0.049 (0.040)	-0.045 (0.039)	-0.047 (0.038)	-0.048 (0.040)	-0.040 (0.040)
Spatial Dispersion of Medical - Cause Mortality in County	1.075*** (0.121)	1.023*** (0.123)	1.030*** (0.114)	1.065*** (0.126)	1.042*** (0.124)
Diversity of Medical Causes of Mortality in County	2.442*** (0.508)	2.344*** (0.508)	2.219*** (0.510)	2.423*** (0.512)	2.225*** (0.515)
Num. of medical professionals in county (thousands)	-0.007 (0.005)	0.065* (0.031)	-0.002 (0.005)	-0.006 (0.005)	-0.008 (0.005)
Spatial Dispersion of Mortality X Num. Medical Professionals		-0.014* (0.006)			
Spatial Dispersion of Mortality X Density of Healthcare Nonprofits			-2.524** (0.801)		
<i>For Neighboring Counties:</i>					
Number of Foundings of Healthcare Nonprofit Orgs				-0.000 (0.002)	
Density of Healthcare Nonprofits				0.068 (0.256)	0.087 (0.251)
Spatial Dispersion of Mortality				0.002 (0.027)	0.009 (0.026)
Foundings Predicted by Spatial Disp. of Mortality					-0.010* (0.005)
Residual Foundings (not explained by above)					-0.000 (0.002)

Constant	-5.215** (1.742)	-5.114** (1.720)	-4.978** (1.632)	-5.145** (1.763)	-5.116** (1.748)
Number of Observations	1083	1083	1083	1083	1083
Log-likelihood	-1545.15	-1542.57	-1540.46	-1545.10	-1542.33
Akaike Information Criterion	3134.30	3131.15	3126.93	3140.20	3136.67
Wald Chi-Squared Statistic	656.1***	681.4***	857.3***	650.6***	688.8***

FIGURES

Figure 1: Founding of community healthcare nonprofit organizations. Average foundings, and standard deviation of foundings by year. The Y-axis units are number of foundings.

Figure 2: Sample Certificate of Death (1989 version, Source CDC)

TYPE/PRINT IN PERMANENT BLACK INK FOR INSTRUCTIONS SEE OTHER SIDE AND HANDBOOK		U.S. STANDARD CERTIFICATE OF DEATH										
		LOCAL FILE NUMBER				STATE FILE NUMBER						
DECEDENT	1. DECEDENT'S NAME (First, Middle, Last)					2. SEX	3. DATE OF DEATH (Month, Day, Year)					
	4. SOCIAL SECURITY NUMBER	5a. AGE—Last Birthday (Years)	5b. UNDER 1 YEAR Months Days	5c. UNDER 1 DAY Hours Minutes	6. DATE OF BIRTH (Month, Day, Year)	7. BIRTHPLACE (City and State or Foreign Country)						
	8. WAS DECEDENT EVER IN U.S. ARMED FORCES? (Yes or no)	9a. PLACE OF DEATH (Check only one; see instructions on other side) HOSPITAL ☐ Inpatient ☐ ER/Outpatient ☐ DOA ☐ OTHER ☐ Nursing Home ☐ Residence ☐ Other (Specify)										
	9b. FACILITY NAME (If not institution, give street and number)					9c. CITY, TOWN, OR LOCATION OF DEATH			9d. COUNTY OF DEATH			
PARENTS	10. MARITAL STATUS—Married, Never Married, Widowed, Divorced (Specify)	11. SURVIVING SPOUSE (If wife, give maiden name)			12a. DECEDENT'S USUAL OCCUPATION (Give kind of work done during most of working life. Do not use retired.)			12b. KIND OF BUSINESS/INDUSTRY				
	13a. RESIDENCE—STATE	13b. COUNTY	13c. CITY, TOWN, OR LOCATION			13d. STREET AND NUMBER						
	13e. INSIDE CITY LIMITS? (Yes or no)	13f. ZIP CODE	14. WAS DECEDENT OF HISPANIC ORIGIN? (Specify No or Yes—If yes, specify Cuban, Mexican, Puerto Rican, etc.) ☐ No ☐ Yes			15. RACE—American Indian, Black, White, etc. (Specify)		16. DECEDENT'S EDUCATION (Specify only highest grade completed) Elementary/Secondary (0-12) College (1-4 or 5+)				
	17. FATHER'S NAME (First, Middle, Last)					18. MOTHER'S NAME (First, Middle, Maiden Surname)						
INFORMANT	19a. INFORMANT'S NAME (Type/Print)	19b. MAILING ADDRESS (Street and Number or Rural Route Number, City or Town, State, Zip Code)										
	20a. METHOD OF DISPOSITION ☐ Burial ☐ Cremation ☐ Removal from State ☐ Donation ☐ Other (Specify)	20b. PLACE OF DISPOSITION (Name of cemetery, crematory, or other place)			20c. LOCATION—City or Town, State							
DISPOSITION	21a. SIGNATURE OF FUNERAL SERVICE LICENSEE OR PERSON ACTING AS SUCH	21b. LICENSE NUMBER (of Licensee)			22. NAME AND ADDRESS OF FACILITY							
	23a. To the best of my knowledge, death occurred at the time, date, and place stated. Signature and Title	23b. LICENSE NUMBER			23c. DATE SIGNED (Month, Day, Year)							
PRONOUNCING PHYSICIAN ONLY	24. TIME OF DEATH M	25. DATE PRONOUNCED DEAD (Month, Day, Year)			26. WAS CASE REFERRED TO MEDICAL EXAMINER/CORONER? (Yes or no)							
	27. PART I. Enter the diseases, injuries, or complications that caused the death. Do not enter the mode of dying, such as cardiac or respiratory arrest, shock, or heart failure. List only one cause on each line. IMMEDIATE CAUSE (Final disease or condition resulting in death) → a. _____ DUE TO IOR AS A CONSEQUENCE OF: Sequentially list conditions, if any, leading to immediate cause. Enter UNDERLYING CAUSE (Disease or injury that initiated events resulting in death) LAST b. _____ DUE TO IOR AS A CONSEQUENCE OF: c. _____ DUE TO IOR AS A CONSEQUENCE OF: d. _____										Approximate Interval Between Onset and Death	
CAUSE OF DEATH	PART II. Other significant conditions contributing to death but not resulting in the underlying cause given in Part I.										28a. WAS AN AUTOPSY PERFORMED? (Yes or no)	28b. WERE AUTOPSY FINDINGS AVAILABLE PRIOR TO COMPLETION OF CAUSE OF DEATH? (Yes or no)
	29. MANNER OF DEATH ☐ Natural ☐ Pending Investigation ☐ Accident ☐ Suicide ☐ Could not be Determined ☐ Homicide	30a. DATE OF INJURY (Month, Day, Year)	30b. TIME OF INJURY M	30c. INJURY AT WORK? (Yes or no)	30d. DESCRIBE HOW INJURY OCCURRED							
CERTIFIER	30e. PLACE OF INJURY—At home, farm, street, factory, office building, etc. (Specify)			30f. LOCATION (Street and Number or Rural Route Number, City or Town, State)								
	31a. CERTIFIER (Check only one) ☐ CERTIFYING PHYSICIAN (Physician certifying cause of death when another physician has pronounced death and completed item 23) To the best of my knowledge, death occurred due to the cause(s) and manner as stated. ☐ PRONOUNCING AND CERTIFYING PHYSICIAN (Physician both pronouncing death and certifying to cause of death) To the best of my knowledge, death occurred at the time, date, and place, and due to the cause(s) and manner as stated. ☐ MEDICAL EXAMINER/CORONER On the basis of examination and/or investigation, in my opinion, death occurred at the time, date, and place, and due to the cause(s) and manner as stated.											
	31b. SIGNATURE AND TITLE OF CERTIFIER				31c. LICENSE NUMBER			31d. DATE SIGNED (Month, Day, Year)				
	32. NAME AND ADDRESS OF PERSON WHO COMPLETED CAUSE OF DEATH (ITEM 27) (Type/Print)											
REGISTRAR	33. REGISTRAR'S SIGNATURE									34. DATE FILED (Month, Day, Year)		

PHS-T-003

Figure 3: Spatial dispersion of medical-cause mortality by year (standardized, z-score): Scatterplot for San Francisco County (urban, coastal, densely populated, diverse, high income). The Y-axis scale is the standardized value of spatial dispersion of mortality across zip codes in a county in a year.

Figure 4: Spatial dispersion of medical-cause mortality by year (standardized, z-score): Scatterplot for Butte County (rural, inland, sparsely populated, middling to low diversity, middling to low income). The Y-axis scale is the standardized value of spatial dispersion of mortality across zip codes in a county in a year.

Figure 5: Comparison of the foundings dependent variable, with that calculated by subtracting foundings of branches of multi-unit nonprofits (typically large national or regional agencies)

Figure 6: Interaction of spatial dispersion of mortality with the ‘supernormal’ measure of residential segregation by race (i.e. with residual from linear prediction of residential isolation index by aggregate (space-free) measure of racial diversity).

Figure 7: Interaction of spatial dispersion of mortality with income disparity between zip codes in a county