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# Regional Level Social Capital and Business Survival Rates\*

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**Abstract:** Using two alternative metrics of social capital, we explore how community structure influences the five-year survival rates of businesses started in 2000. Employing a family of spatial estimators to derive a set of global estimates and Geographically Weighted Regression (GWR), we find strong evidence that community-level social capital has a positive influence on business survival rates. Results suggest that while social capital is important in understanding business survival rates, relationships vary significantly across space. From a policy perspective, it would be a mistake to treat social capital as a uniform asset where one approach fits all communities.

*Keywords:* entrepreneurship, social capital, community

*JEL Codes:* R11, O18, L26

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## 1. INTRODUCTION

Healthy, vibrant, local economies hinge on business dynamics—births, deaths, expansions, and contractions (Aquilina et al., 2006; Renski, 2008, 2011; Markley and Low, 2012; Haltiwanger et al., 2013; Hathaway and Litan, 2014; Conroy and Deller, 2015). Most communities, however, focus on the start-up process and look upon businesses that close as failure that reflects poorly on the community. Some, such as Elisinger (1995), Loveridge (1996) and Emery et al. (2004), have argued that this negative perception around business closures has led some communities to favor older economic growth and development strategies such as recruitment over entrepreneurship.

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When an entrepreneur goes through the process of failure it can be a learning experience in terms of what did and did not work relative to the failed business (Minniti and Bygrave, 2001; Shepherd, 2003; Amankwah-Amoah et al., 2018; Fang He et al., 2018; Liu et al., 2019). Though there is a direct cost to the failure of a start-up, it can be an opportunity for the entrepreneur, as well as the broader community, to learn about the market and create successful ventures that support future economic growth and development (Bunten et al., 2015). Rather than a business closure being viewed as a negative reflection on the community, it can be a valuable learning experience that spurs growth and helps inform policy.

Pena (2002) and Hormiga et al. (2011a,b) argue that the success, or failure, of the firm hinges on three types of capital: (1) human capital, (2) structural or organizational capital, and (3) relational capital. Human capital speaks to the skills and experiences of the owner and employees of the business. Structural or organizational capital speaks to characteristics such as how the business is structured, the size of the firm at start-up, financing structure, and the industry sector in which the firm operates.

Relational capital has two interpretations: (1) relationships internal to the firm including customers and suppliers and (2) the explicit recognition that the firm does not operate in isolation and is part of the larger community. Specifically, relational capital speaks to the extent an entrepreneur is integrated into local business and professional and social networks. At both levels of relational capital, internal and external to the firm, the notion of social capital is central. Entrepreneurs that have higher levels of relational capital, or social capital, are better connected to resources and information and thus are more likely to survive and prosper. The information accessed through these networks can help minimize the potential of starting a weak business, which in turn, increases survival rates. While the former notion of relational capital (relations internal to the firm) has been widely studied (Stam et al., 2014; Westlund and Adam, 2010), Huggins et al. (2017, p. 358) observe, “the current research base has largely ignored factors influencing the survival of firms located within a particular region.”

Most studies on business survival rates focus on documenting trends over time, as well as by geography and industry (Phillips and Kirchhoff, 1989; Buss and Lin, 1990; Forsyth, 2005; Deller and Conroy, 2016, 2017), the influence of the individual characteristics of the entrepreneur and firm, as embodied in Pena (2002) and Hormiga et al. (2011a,b), or human, and structural or organizational capital (Reynolds, 1987; Brüderl et al., 1992; Boden Jr and Nucci, 2000; Pena, 2002; Bosma et al., 2004; Esteve-Pérez and Mañez-Castillejo, 2008; Backman et al., 2016). There are few studies that explore the role of the larger community or regional factors outside the control of the firm, including overall growth patterns and unemployment rates, in helping understand business survival (Campbell, 1998; Acs et al., 2007; Strotmann, 2007; Box, 2008; Renski, 2008, 2011; Bosma and Schutjens, 2011; Huggins and Thompson, 2015; Deller and Conroy, 2017; Huggins et al., 2017; Ebert et al., 2019). While these latter studies include community characteristics, none examine the role of community level social capital on survival rates.

Those that do explore the role of social capital (i.e. Bosma et al. (2004)) take a micro approach based on surveys of individual entrepreneurs. Hormiga et al. (2011a,b) analyze 130 new companies in the Canary Islands and found that higher levels of relational capital, defined as levels of connectivity with those outside the firm, reputation of the business owner

within networks, and accessibility to and ability to leverage those networks, are all tied to higher rates of business success (survival). Zhao and Burt (2018) reported a similar finding in a study of Chinese CEOs: higher density of social networks of the CEO has a positive outcome on business survival rates. In a study of 870 companies that were spun-off of 81 universities in the United Kingdom, Prokop et al. (2019) found that the higher levels of connections the leaders of these businesses had to networks outside the business itself increased the survival rate of the business. In a study of 134 spinoff companies from the Massachusetts Institute of Technology, Shane and Stuart (2002) found similar results that the social capital of the founders of the spinoff company plays an important role in firm success.

In this study, we explore how community characteristics, especially community level social capital, influence business survival rates. We maintain that high levels of social capital within a community allow entrepreneurs to better leverage assets for the success of their businesses and is reflective of the community's willingness to embrace entrepreneurship as an economic growth and development strategy. Using the notion of entrepreneurial social infrastructure, as developed by Flora and Flora (1993), one can equate communities with higher levels of social capital as those with higher levels of entrepreneurial behavior. This is not just from a business start-up perspective but also from community leaders and citizenry being more entrepreneurial in community policies and initiatives. Such communities are unlikely to fall into the economic growth and development policy traps as outlined by Elisinger (1995), Loveridge (1996) and Emery et al. (2004).

To test for the hypothesized relationship between community characteristics, with a focus on social capital, and business survival rates, we model five-year survival rates of businesses started in 2000. We pick this time period in order to align with the 2000 U.S. Census and avoid the shocks of the Great Recession. We use the data from the National Establishment Time Series (NETS), a database of U.S. establishments developed by Dun & Bradstreet in partnership with Walls & Associates. The NETS database is uniquely detailed and includes data for every firm in the U.S. For this study, we identify new (start-up) establishments then track them over time to derive five-year survival rates. We then aggregate these firms up to the community level (proxied by counties) to derive the five-year survival rates for new businesses for each community (county) in the U.S. This community level approach differs from most studies that assign community characteristics to individual firms then model those firms. Our approach takes an ecological approach in modeling community level attributes.

For this research, we use a family of spatial estimators under heteroskedastic errors to derive global parameter estimates that are consistent with the majority of studies that employ some form of classical regression analysis. By estimating a global parameter, we assume that the relationships under examination are the same (homogenous) across space. Prior studies of entrepreneurship and community or regional economic performance, however, have found that the key relationships of interest can vary across space (Audretsch and Keilbach, 2007; Deller, 2010; Breitenacker et al., 2017). Within our context, the relationship between community level social capital and business survival rates may be heterogeneous across space: relationships in New England, for example, may be fundamentally different from the Mississippi Delta region. By employing Geographically Weighted Regression (GWR) we can test for spatial variation in how social capital and other community characteristics influence

business survival rates.

## 2. LITERATURE REVIEW

While the concept of social capital was discussed in the social progressive movements of the early 20<sup>th</sup> century, and imagined by the likes of de Tocqueville, Hume, Smith, and Mill, it was not until the work of Granovetter (1985), Coleman (1988), and Putnam (1995) that social capital entered the mainstream of the academic and popular press (Halstead and Deller, 2015). Putnam (1995, p.67) defines social capital as the “...connections among individuals - social networks and the norms of reciprocity and trustworthiness that arise from them.” Putnam (1995) contends that trust is central to the theory of social capital. Without trust, there is no reciprocity, no consideration, and very feeble networks. We would expect individuals who associate with each other socially to have higher levels of interpersonal trust and trustworthiness.

In social network theory, developed and studied by sociologists, not only are networking opportunities and the corresponding flow and trustworthiness of information important but the communication medium of that information is equally important (Stuart and Sorenson, 2007). Information can flow through publications (e.g., trade association journals), electronically (e.g., internet), or face-to-face. Social network theory emphasizes the importance of face-to-face communication. Early work, for example Ryan and Gross’ (1950) study of the adoption of hybrid corn technology or Lee’s (1969) study of the underground network of abortion providers, found that personal communications were vital to information flows.

Networks that facilitate flows of information are more than just professional or business networks. The broader social dimension of economic activity is the essence of Granovetter’s (1985) concept of “embeddedness” which he uses to describe how economic action is rooted in a broader social context. Since economic agents are functioning in a broader social context, specifically the community in which they live and operate their business, they take into consideration more than the immediate business payoff when deciding on a particular strategy or action (Granovetter, 1985; Uzzi, 1996, 1997, 1999; Kwon and Arenius, 2010; Kwon et al., 2013; Molina-Morales et al., 2013). For example, two business owners may have a contractual professional relationship with one another while also attending the same church or their children belong to the same sports team. This level of association suggests shared values and familiarity closer than arm’s length business interactions. Both Granovetter and Uzzi suggest that since the business owners associate with each other in a context outside of their business relations, they will consider these social relationships due to internalized trust and outside social pressures.

In the context of entrepreneurship, Pena (2002) and Hormiga et al. (2011a,b) argue that relational capital recognizes the importance of community characteristics and network connections: entrepreneur and firm do not operate in isolation from the place in which they are located and the people who live there (Box, 2008; Renski, 2008, 2011; Huggins et al., 2017). Cheng and Li (2012), for example, find that cultural diversity, an element of social capital at the community level, has strong spatial spillover effects in new firm formation. Molina-Morales et al. (2013) found, from a social capital perspective, a firm’s sense of embeddedness or “belonging” to an industrial district or cluster can play an important role in performance

of the firm and cluster. Dahl and Sorenson (2012) describe how many entrepreneurs are embedded in their “home community” because of deep local connections. This is consistent with the findings of Conroy and Deller (2014), as well as Halstead and Deller (2015), that the vast majority of firms remain located in the community of their founder because of those local connections. Indeed, Halstead and Deller reference one survey respondent (small rural manufacturers) who stated “find a community you want to raise your family, and that’s where you start your business.” Community embeddedness is fundamental to those local connections.

Kwon and Arenius (2010) and Kwon et al. (2013) argue there are two elements to social capital that are vital to entrepreneurship: information and reduced transactions costs. Relying on the Kirzner (1973) theory of information asymmetry, Kwon and colleagues argue that access to unique information is the key to entrepreneurship. The broader the network of the entrepreneur, the more access to information she has. Equally important is the trustworthiness of the source of that information. With higher levels of social capital and stronger ties, information may be perceived as more reliable and useful to the entrepreneur. Higher levels of both networking and trust results in higher levels of social capital or relational capital in the framework of Pena (2002) and Hormiga et al. (2011a,b). Further, these stronger ties are more likely to form with frequent, face-to-face interaction. Because the probability of face-to-face interactions between two people decreases as the distance between them increases, so too does the likelihood of trusting relationship between them. As a result, networks can be geographically bounded—specific to a place or community (Stuart and Sorenson, 2007). For example, in a study of German regions, Pijenburg and Kholodilin (2014) find strong evidence of entrepreneurial knowledge spillover effects within and across well-defined geographic areas.

One can think of these networks within the context of bridging and bonding social capital. As outlined by Emery and Flora (2006) and Rogers and Jarema (2015), bonding social capital refers to strong ties within a particular network. This could be membership within a specific church, sports team, or social organization. Here, people who are members of that organization build strong internal or bonding networks and often become identified as being a member of that organization. This bonding social capital is inward looking to the organization; networks are dense and trust is high. Bridging social capital refers to relationships across individual networks or heterogeneous groups. An example might be a number of different religious leaders (ministers, priests, rabbis, imams, etc.) coming together to form a “council of ministers” to discuss and address community wide issues. Another example might be different business associations within a community forming an umbrella organization to coordinate efforts.

Kwon and Arenius (2010) note that increased bridging social capital, or interaction across a more diverse and heterogeneous set of networks, not only expands the flow of information, it increases the breadth or diversity of information, leading to more opportunities for entrepreneurs. Indeed, in their meta-analysis Stam et al. (2014) found diversity of networks is perhaps the single strongest predictor of small business success. A wider network of relationships reveals more diverse information for the entrepreneur to process and use to identify opportunities. In a study of entrepreneurial activity in Britain, Huggins and Thompson (2015) found that communities that supported stronger bridging social capital and the openness

to new information and ideas tended to be more resilient and robust over the period of the Great Recession. Strong bonding social capital, however, can place limits on the ability to build bridging social capital (Flache and Macy, 1996; Rosenfeld, 2001; Lambooy, 2010). Strong bonding social capital can lead to “lock-in” and exclusive clubs where networking outside the group is discouraged. Thus, the notion of social cohesion that is fundamental to social capital can actually produce negative outcomes.

This latter case of exclusionary behaviors, described as “lock-in,” is indicative of the third leg of Putnam’s notion of social capital, norms. The norms of acceptable behavior are driven by the culture of the community. Beugelsdijk and Maseland (2010) define the collective identity of the community as a shared set of beliefs, expectations, and values. Huggins and Thompson (2015) define the culture of a community and the businesses within that community as the way that people behave toward each other. As outlined in Markeson and Deller (2015) and Markeson (2016), cultural expectations or norms around success and failure within the community can significantly influence entrepreneurial behavior. For example, if failure is looked down upon, that attitude can stifle entrepreneurial activity or interfere with an existing business’s rational decision to close.

Community norms also can evolve in a way that creates an environment (culture) that discourages risk-taking and differentiation, creating opposition to essential characteristics of entrepreneurship. Rather than celebrating and encouraging individual and group ventures, some communities discourage deviations from the status quo. For example, the “over-achieving” student that is ostracized from their peer network can be analogous to the innovative entrepreneur within the local business community. Those entrepreneurs who break with the exclusionary club can be ostracized, resulting in network constraints that limit their access to valuable resources such as business inputs and information. Such a community culture can be detrimental to entrepreneurship in terms of new business activity or business growth. Similarly, If the culture of the community is to question people from outside the community, the flow of information and ideas from bridging social capital is limited. Alternatively, as Cheng and Li (2012), Stam et al. (2014), and Huggins and Thompson (2015) uncovered, in communities that are open and receptive to diversity, success or resilience is higher.

While there are several empirical studies linking social capital to business outcomes, studies on survival specifically tend to be descriptive in nature with little attention to social capital (e.g. Mayer and Goldstein, 1961; Phillips and Kirchoff, 1989; Buss and Lin, 1990). But with the introduction of new detailed data sets, such as the U.S. Establishment Longitudinal Microdata (USELM) files, along with improved survey collection methods, the current literature seeks to better understand the drivers, both internal and external to the firm, of business survival rates. Human capital-based studies (Van Praag, 2005; Van der Sluis et al., 2008; Parker, 2009; Unger et al., 2011; Millan et al., 2014) focus on the characteristics of the entrepreneur such as education, gender, family experiences in entrepreneurship, and ethnicity among other factors. Studies that focus on the structural or organizational capital of the firm (Kirsch et al., 2009; Esteve-Pérez and Mañez-Castillejo, 2008) explore the structure of the business itself such as the size of the firm at start-up, the financing structure of the business, the industrial sector in which the firm operates, and the management role of the entrepreneur. Others, such as Stewart (1997), argue that these factors (human and

structural capital) cannot be treated independently and that a wider range of factors, both internal and external to the firm, such as the ability to adapt new technologies and market conditions, must be explored.

Building on the work of Thornton (1999) and Littunen (2000), Acs et al. (2007, p.370) argue, "...characteristics of regions and local networks may be more important for survival of entrepreneurial firms than individual initiative." In a meta-analysis of 61 studies exploring the link between relational, or in our context social capital, and small firm performance, Stam et al. (2014) found a strong and consistent positive relationship, and further, the diversity of those relationships mattered most for performance (e.g., survival). They conclude that "[t]here is wide agreement that social capital, or the resources embedded in entrepreneurs' personal networks, is critical for the performance of small firms" (p. 152).

Indeed, social capital is likely a key element to business performance and survival specifically. It is perhaps most straightforward to think of social capital in terms of strong networks, particularly in the form of bridging social capital, and high levels of trust, that can increase the flow of information and reduce transactions costs, both of which can enhance the success or survival rate of entrepreneurs. In some communities, cultural norms promote openness, celebrate success and look at failures as a learning opportunity. Durlauf (1999, 2002) and Besser and Miller (2015), however, argue that social capital is a two edged sword with both positive and negative elements. In some communities, it is possible that social capital is strong but establishes norms and behavior that is antithetical to entrepreneurship. For example, looking outside (bridging social capital) of the group (bonding social capital) may be discouraged behavior that prevents new ideas and experimentation. Failure, and/or over-achieving, can also be discouraged. For this latter community one could argue that social capital is high, but behaviorally averse to entrepreneurship.<sup>1</sup> While we hypothesize a positive relationship, we certainly acknowledge the potential for a negative effect. These competing theories motivate our empirical work detailed in the following section.

### 3. MODELS AND METHODS

For this study, we use the National Establishment Time Series (NETS) database of U.S. establishments maintained by Wall & Associates. Building on the Dun & Bradstreet (D&B) database of individual establishment as a core foundation, Walls & Associates introduces other sources of individual establishments data to build a comprehensive database of all businesses in the U.S. Dunn & Bradstreet's Duns Marketing Information file is widely used for business marketing and credit scoring and as a profit oriented firm D&B has strong incentives to compile creditable data because their customers use this data for marketing and establishing credit worthiness. Walls & Associates then build on this base data by complementing it with individual business data from federal sources, such as the Census Bureau's County Business Patterns and Nonemployer Statistics, as well as the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. Unfortunately, the specific methods used by Wall & Associates are proprietary and as such, key details remain unknown. In a detailed assessment of the quality of this data, Barnatchez et al. (2017, p. 1) find that the

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<sup>1</sup>For a more stylized deductive theory of social capital and entrepreneurship, see Deller et al. (2018)

largest weakness of the NETS data is in the smallest of firms (e.g., homebased businesses) but they conclude that the “NETS microdata can be useful and convenient for studying static business activity in high detail.”

To derive five-year survival rates, we identify the number of new (start-up) establishments in 2000 as well as the number still operating five years later. We elect to use data from 2000 because we can use detailed socioeconomic data from the 2000 Census and it is the most current year of survival rate data before the effects of the Great Recession introduced significant noise into the data. The five-year survival rate is not randomly selected. First, studies (Berryman, 1983; Boeri and Cramer, 1992; Weyh, 2006) that seek to understand business survival rates tend to use five years as a threshold. Second, and perhaps more fundamental, start-up businesses are generally held to two benchmarks: businesses should be able to cash flow their operations by the end of year three and should be offering a fair rate of return (i.e., profitability) by the end of year five. If those benchmarks are not met, the entrepreneur should consider significantly altering the business (year three benchmark) or close the business (year five benchmark). Following the logic of Renski (2008, 2011) one could reasonably interpret firms that survive through five years as a success.

### 3.1. Model Specification

Building on the framework of Deller and Conroy (2017), our model can be expressed as:

$$SR = \beta LG + \alpha SDE + \pi SC + \varepsilon \quad (1)$$

$SR$  is the five-year survival rate for businesses that were started in 2000 (share of firms still operating in 2005),  $LG$  are lagged growth rates in general economic metrics from 1990 to 2000,  $SDE$  is a set of measures capturing the socio-demographic and economic characteristics of the community, and  $SC$  reflects social capital. Following the results of Portugal et al. (2003); Fritsch et al. (2006), who find that the conditions prevailing at the time of the business startup had a longer lasting effect on the survival rate than conditions in a later time period, our control variables and social capital measures reflect 2000 data. Our selection of specific control variables, specifically within the set of socio-demographic and economic characteristics ( $SDE$ ), is based on prior ecological studies of business survival rates including Fritsch et al. (2006); Acs et al. (2007); Renski (2008); Cader and Leatherman (2011).

The lagged growth variables include population, employment, and per capita income. Studies have generally found that higher rates of lagged growth have a positive effect on survival rates as a growing regional economy can create opportunities for these businesses. Income of the community is captured by median household income along with the overall poverty rate. Income characteristics can have concurrently opposing effects on business survival rates. Higher income communities can represent both stability to the business enhancing survival rates, but also represent new opportunities creating greater competition within the community. Poverty is generally thought of as having a dampening effect on survival rates because higher poverty reflects weaker markets for the business. At the same time, it could be the case that communities with higher rates of poverty have lower opportunity costs for existing businesses. With lower opportunity costs, businesses may be forced



to accept lower rates of return and remain in business.

We also include the percent of persons in the community receiving public assistance income as well as the percent of persons receiving retirement income. States that have more generous public assistance programs increase the opportunity cost of business owners with underperforming businesses. In other words, states with relatively modest public assistance programs have lower opportunity costs to the business owner and they may find that maintaining a marginal business is their best option. At the same time, the injections of these benefit payments into poorer communities could create some market opportunities by increasing demand in communities with a higher propensity to consume. Retirement income captures both the age profile of the community and the injections of money into the region. There is a growing pool of research (Kautonen et al., 2017) that many retirees elect to start businesses for either financial or personal reasons including satisfaction from work but on one's own terms. Many of these "late life businesses" are not growth businesses nor under market pressures to be profitable. Normal market forces that may cause businesses to close may not apply to these "late life businesses" thus increasing survival rates.

We measure the stability of the community with three metrics, the percent of persons residing in the same house (1995-2000), the unemployment rate, and the percent of persons who speak English less than very well. Residential stability speaks to levels of embeddedness in the community, unemployment is a simple measure of economic stress, and the English language variable controls for the ability of people to integrate into the broader community.

Our economic structure variable is a standard Herfindahl Index of economic diversity across industrial employment shares. If  $s_i$  is the share of total employment in the community, the Herfindahl Index is  $HI = \sum_{i=1}^k s_i^2$  where  $k$  is the number of industry sectors. Higher values of the index are associated with more specialized economies in terms of industry employment patterns. We also measure education by looking at the distribution of formal education across seven education categories from those age 25 and over with less than a 9<sup>th</sup> grade education to those with graduate or professional degrees. Here, we compute the third moment (skewness) of the distribution where positive values suggest lower levels of education and a negative value suggests higher levels of education. We also include a measure of population density to capture the rural-urban spectrum. Analysis by Stearns et al. (1995); Renski (2008, 2011); Yu et al. (2011); Rupasingha and Contreras (2014); Deller and Conroy (2016, 2017) find that business survival rates are consistently higher in more rural settings compared to urban. These rural-urban differences may hinge on lower opportunity costs and less competition in rural areas.

In order to address the central question of the effects of social capital on business survival rates, it is necessary to build a set of social capital metrics from secondary data. Social capital, like human capital, is not easily measured directly (Halstead and Deller, 2015). Durlauf (1999) and Durlauf (2002) argue that developing proxy measures of social capital is fraught with theoretical and empirical difficulties and is highly critical of much of the early social capital empirical literature. Durlauf is particularly critical of aggregate measures at the community or regional levels because any measure, by definition, is a crude proxy and subject to researcher biases. In essence, there is a type of modeling uncertainty where the possible number of proxy measures of social capital can be overwhelming and there is no theoretical justification for one set of proxy measures over another.

As noted by Friedman and Fraser (2015) and Hutchinson and Vidal (2004) social capital is a “meta-construct” because it is a collection of nebulous elements describing an elusive phenomenon. Goetz and Rupasingha (2006), Rupasingha et al. (2006), and Rupasingha and Goetz (2007) tackle the problem by using principal component analysis to combine several proxy measures such as number of religious organizations, professional and labor organizations, recreational organizations, and voter turn-out rates, among others, into a single scalar index of social capital. This is similar in approach to Putnam (2000) who combines measures such as the number of civic and social organizations per capita, number of non-profits per capita, and presidential voter turn-out rates into a social capital index. Alternatively, one can use a number of different measures of social capital to better understand the effects of specific aspects of social capital such as in the case of local crime (Deller, 2010) or labor productivity Sabatini (2008).

For the first measure we follow the approaches of Deller (2010), Keene and Deller (2015), and Markeson and Deller (2015) and use the concentration of organizations that facilitate networking or reflect the charitable nature of the community. Saxton and Benson (2005), along with Kim (2017), find that the concentration of nonprofits and organizations generally associated with more socially active communities increases as social capital of the community expands. This interpretation would be consistent with the findings of Huggins and Thompson (2015) and small business resiliency. Using data from County Business Patterns we look at the total concentration (number of organizations per 10,000 persons) of:

- Religious Organizations
- Business and Professional Organizations
- Child, Elderly, Food Bank, Other Related Services
- Voluntary Health Organizations
- Civic and Social Organizations
- Labor Unions and Similar Labor Organizations

We maintain that the concentration of community organizations in any of these categories is associated with higher levels of social capital. Communities that have higher concentrations of these types of organizations are more pro-active (i.e., creation and supporting these types of organizations) and have greater opportunities for new connections thus facilitating networking, mentoring, and flows of information. We also use the social capital index developed by Rupasingha et al. (2006) as a simple alternative measure to ours.<sup>2, 3</sup> The variables along with simple descriptive statistics and sources of the data are provided in Table 1.

<sup>2</sup>While one could argue the merits of principal component analysis as having no rigorous criteria for construction or final selection of the weighting scheme, or that the final index explains a relatively modest amount of the variation in the data, the Rupasingha, Goetz, and Freshwater index has been used in 478 studies to date.

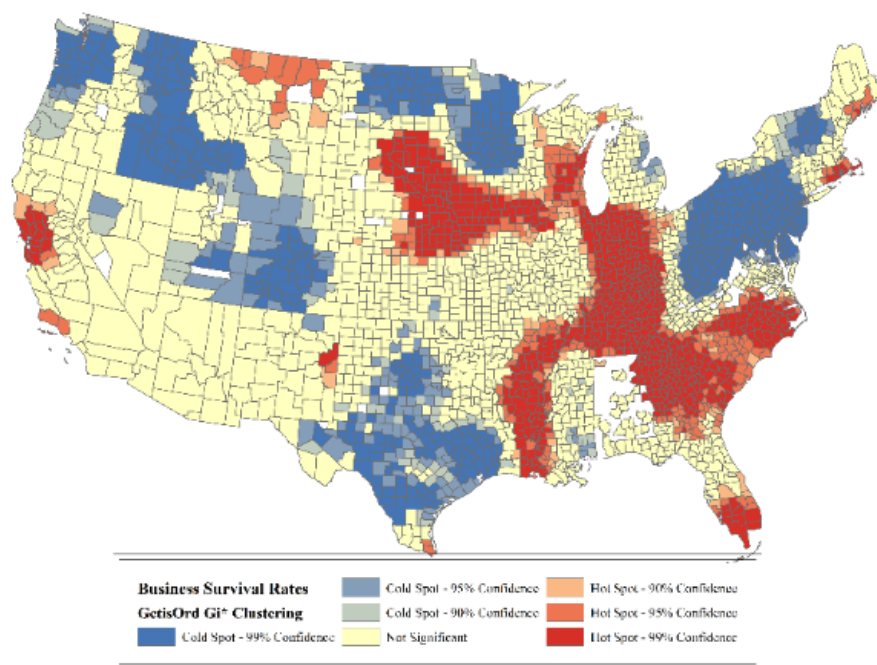
<sup>3</sup>We estimate the models separately for each measure of social capital. Because of the overlap of several key elements of both measures, they are highly correlated ( $r= 0.7068$ ,  $p=0.0001$ ) and including both in one model would unnecessarily introduce collinearity. Rather, using the two different measures of social capital allows for a form of robustness test of our results.

Table 1: Descriptive Statistics

Dependent Variable	Mean	Standard Deviation	Median	Source
Five Year Survival Rates	0.596	0.081	0.603	National Establishment Time Series (NETS)
Growth Lags				
Percent Change in Population 1990-2000	0.111	0.161	0.083	BEA, Regional Economic Information System
Percent Change in Employment 1990-2000	0.208	0.267	0.168	BEAs, Regional Economic Information System
Percent Change in Per Capita Income 1990-2000	0.544	0.147	0.543	BEA, Regional Economic Information System
Socio-Economics				
Median Household Income (\$10,000s)	3.528	0.871	3.377	U.S. Bureau of the Census
Percent of Persons in Same House 1995-2000	0.589	0.073	0.595	U.S. Bureau of the Census
Percent of Persons who Speak English Less than Very Well	0.034	0.049	0.016	U.S. Bureau of the Census
Unemployment Rate	0.034	0.013	0.032	U.S. Bureau of the Census
Economic Diversity Index	2.119	0.149	2.132	U.S. Bureau of the Census
Percent of Persons with Public Assistance Income	0.034	0.019	0.030	U.S. Bureau of the Census
Percent of Persons with Retirement Income	0.168	0.043	0.166	U.S. Bureau of the Census
Poverty Rate	0.141	0.064	0.129	U.S. Bureau of the Census
Distribution of Education Index	1.185	0.610	1.276	U.S. Bureau of the Census
Population Density	0.228	1.686	0.042	U.S. Bureau of the Census
Social Capital Metric				
Organizational Density	13.576	6.259	12.581	County Business Patterns
RGF Social Capital Index	0.004	1.279	-0.107	Rupasingha, Goetz, and Freshwater (2006)
Sample Size: 2,994				

The five year survival rate, economic diversity index, distribution of education index, and organizational density were calculated by the authors.

**Figure 1:** Spatial Clusters of Five Year Business Survival Rates (Start-ups 2000)



The limitation to our approach to measuring social capital is that the final indices represent an ordinal, as opposed to a cardinal, ranking. At best we can conclude that social capital has a positive, negative, or no impact on business survival rates. We cannot conclude, for example, working on increasing the number of nonprofits within the community by ten percent will increase (or decrease) the average business survival rate by five percent. In addition, these are indirect measures of social capital and are argued to be associated with the characteristics of social capital.

### 3.2. Modeling Estimators

The first step in our analysis is to estimate the model using a family of estimators that yield a global parameter estimate after controlling for spatial dependency within the data. It is widely accepted that there are significant spatial variations in entrepreneurship and the relationship between local economies and entrepreneurship (Armington and Acs, 2002; Glaeser and Kerr, 2009; Deller, 2010; Bosma and Schutjens, 2011; Trettin and Welter, 2011; Rupasingha and Contreras, 2014). Huggins and Thompson (2015) and Huggins et al. (2017) argue that studies at the national or state/provincial or even metropolitan areas mask important characteristics that can only be captured at the local or community level. A simple mapping of the Getis-Ord  $G_i^*$  statistic of spatial patterns of five-year survival rates reveals strong spatial cluster of hot and cold spots across the U.S. (Figure 1).

Following Cheng and Li (2012), we use three specifications including a spatial lag (SAR), spatial error (SEM), and spatial Durbin (SDM) specifications as a simple robustness check,

respectively:<sup>4</sup>

$$y = \rho W y + \beta x + \varepsilon \quad (2)$$

$$y = \beta x + \varepsilon; \quad \varepsilon = \lambda W \varepsilon + \mu \quad (3)$$

$$y = \rho W y + \beta x + \delta W x + \varepsilon \quad (4)$$

Here the spatial weight matrix ( $W$ ) explicitly captures the spatial dependency between observations (counties) defined as a row-stochastic Rook contiguity spatial weigh matrix.<sup>5</sup> In the spatial lag model, business survival rates ( $y$ ) in one community (county) are influenced by nearby counties ( $\rho W y$ ) in a structural manner. The spatial error model treats the spatial dependency in the data mostly as a nuisance that must be corrected. The spatial Durbin model suggests that there is not only a structural relationship across space in business survival rates but also in terms of the control variables and, for this study, social capital. Not only do business survival rates spillover across communities but social capital in neighboring communities influences business survival rates in the host community. LeSage and Pace (2009) have argued that the spatial Durbin is perhaps the most flexible of the three specifications outlined above and thus the most general.

To allow the greatest flexibility it seems reasonable that the error structure in the three spatial model specifications outlined above is unlikely to be homoskedastic but rather heteroskedastic.<sup>6</sup> Given the spatial clustering reported in Figure 1, it seems reasonable to assume that the error variance will be different across those identified hot and cold spots. As outlined in detail by LeSage and Pace (2009), the maximum likelihood function under heteroskedastic errors becomes intractable and we must turn to Bayesian methods. Specifically, placing priors on the expected underlying distributions and using Markov Chain Monte Carlo (MCMC) estimation approaches we can generate parameter estimates that are consistent with the underlying data generating processes.<sup>7</sup>

<sup>4</sup>We could implement a series of tests, such as those outlined by Elhorst (2014), to more formally compare and contrast the SAR, SEM, and SDM specifications but we elect to focus on the consistency of results related to social capital. If we find consistency across specifications, this lends a certain level of confidence to the results. If results are inconsistent, then formally testing which specification is superior is appropriate.

<sup>5</sup>While some researchers express concern over the specification of the spatial weight matrix, we follow the advice of LeSage and Pace (2014) who argue that if the model is properly specified and the coefficients interpreted correctly (specifically for the spatial lag and spatial Durbin models) then the estimators are not sensitive to changes in the spatial weight matrix.

<sup>6</sup>Specifically, for the SAR and SDM we have:

$$\varepsilon \sim N(0, \sigma^2 V) \quad V = \text{diag}(v_1, \dots, v_n)$$

and for the SEM model,

$$\mu \sim N(0, \sigma^2 V) \quad V = \text{diag}(v_1, \dots, v_n)$$

Here the set of variance scalars ( $v_1, v_2, \dots, v_n$ ) are unknown parameters that need to be estimated.

<sup>7</sup>Following LeSage and Pace (2009, Chapter 5) we assume the prior distributions:

The spatial clustering (Figure 1) patterns also suggest that the the underlying data generating process behind social capital and business survival rates and the relationship between them varies across space. For example, the relationship between the specific measures of survival rates and social capital used in this study may differ across the region defined as the Boston to Washington DC corridor and the Mississippi Delta region. While the spatial estimators outlined above allow for immediate spatial spillovers (neighboring communities influence each other) and the error structure varies across space, the final parameter estimate between social capital and survival rates is a “global” estimate or average across the study geography. These spatial estimators cannot capture the differences between the northeast coastal region and the Mississippi Delta region. While we could attach a regional dummy variable (either intercept and/or slope shifting), even this would only allow variation based on the defined regions that may or may not capture actual regional variations in our focal variables.

An alternative approach is to use Geographically Weighted Regression (GWR) as outlined by Fotheringham et al. (2003). This approach estimates a separate OLS equation for every location in the dataset, which incorporates the dependent and explanatory variables of locations falling within a certain “bandwidth” (distance or proximity) of each target location. The GWR model can be written as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (5)$$

where  $(u_i, v_i)$  is the location of the  $i^{th}$  point and  $\beta_k(u_i, v_i)$  is a realization of the function  $\beta_k(u, v)$  at point  $i$  or the value of the parameter for each observation. As the estimator “moves across space or geography” in the study area, a unique regression estimate is established for each observation. The spatial patterns in these individual parameter estimates can expose insights into the underlying data generating process and the hypothesis under consideration. See Appendix A for additional details. In essence, rather than relying on a global parameter that is constant across space, we allow the parameter to vary across space. Because we are using U.S. county level data, the geographic size of the units varies significantly. For example, in the northeast, the counties tend to be much smaller geographically than in the western U.S. Following Fotheringham et al. (2003) the use of the adaptive spatial bi-square kernels approach corrects for this issue. Here,  $d$  is the Euclidean distance between observation  $i$  and location  $j$ , and  $\theta$  is a fixed bandwidth and  $\theta_{i(k)}$  is an adaptive bandwidth size defined by the distance measure. The latter is estimated using a golden section search process, a technique of finding the extremum values, by minimizing the Bayesian Information Criterion (BIC).

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$$\pi(\beta, \delta) \sim N(c, N), \pi(r/v_i) \sim \text{IID } \chi^2(r), \pi(1/\sigma^2) \sim \Gamma(d, v), \pi(\rho) \sim U[0, 1]$$

The prior distribution for the  $v_i$  terms takes the form of an independent  $x^2(r)/r$  distribution where  $x^2$  is a single parameter distribution with  $r$  as the parameter. By adding the single parameter  $r$ , this allows the estimation of the  $n$  parameters  $v_i$ . The prior distributions are indicated using  $(\pi)$ , a normal-gamma conjugate prior for  $\sigma$  a uniform prior for  $\rho$ . For the MCMC process, we use 25,000 draws and allow a burn-in rate of 1,000 to allow for the possibility of poor starting points in the Markov Chain.

**Table 2:** Five Year Business Survival Rates: Global Parameter Estimates

(Direct Effects Reported)	Spatial Lag	Spatial Error	Spatial Durbin	Spatial Lag	Spatial Error	Spatial Durbin
<b>Growth Lags</b>						
Percent Change Pop 1990-2000	0.0376 (0.2617)	0.0062 (0.3502)	0.1123* (0.0561)	0.1162* (0.0589)	-0.0046 (0.3911)	0.1147* (0.0619)
Percent Change Emp 1990-2000	-0.0052 (0.7862)	0.0062 (0.2184)	-0.0650* (0.0876)	-0.0702* (0.0702)	0.0066 (0.2030)	-0.0689* (0.0743)
Percent Change Income Per Cap 1990-2000	0.0480* (0.0859)	0.0102 (0.2170)	0.0545 (0.2216)	0.0469 (0.2970)	0.0073 (0.2917)	0.0461 (0.3022)
<b>Socio-Economics</b>						
Median HH Income	0.0254** (0.0013)	0.0243*** (0.0001)	0.0340** (0.0045)	0.0285** (0.0111)	0.0225*** (0.0001)	0.0286** (0.0115)
Percent in Same HH 1995-2000	0.1941*** (0.0008)	0.2156*** (0.0001)	0.1001 (0.2585)	0.1251 (0.1536)	0.2374*** (0.0001)	0.1231 (0.1596)
Percent Speak Eng. less than Very Well	0.0175 (0.8268)	-0.0087 (0.4263)	0.0721 (0.4771)	0.1074 (0.2840)	-0.0128 (0.3939)	0.1086 (0.2789)
Unemployment Rate	-0.4635 (0.1696)	-0.1649 (0.1587)	-0.3876 (0.4370)	-0.6660 (0.1735)	-0.2027 (0.1122)	-0.6626 (0.1787)
Economic Diversity Index	0.1595*** (0.0001)	0.1530*** (0.0001)	0.1510*** (0.0001)	0.1732*** (0.0001)	0.1621*** (0.0001)	0.1735*** (0.0001)
Percent w/ Public Assist. Income	-1.1806*** (0.0001)	-0.6601*** (0.0001)	-0.3903 (0.3137)	-0.4686 (0.2237)	-0.7098*** (0.0001)	-0.4666 (0.2283)
Percent w/ Retirement Income	-0.2276** (0.0116)	-0.0857* (0.0578)	-0.3712** (0.0033)	-0.3927** (0.0017)	-0.0919** (0.0471)	-0.3941** (0.0018)
Poverty Rate	0.6210*** (0.0001)	0.5029*** (0.0001)	0.5960*** (0.0004)	0.6371*** (0.0006)	0.4959*** (0.0001)	0.6385*** (0.0007)
Dist. of Education Index	0.0108 (0.1310)	0.0046 (0.1070)	0.0392*** (0.0002)	0.0417*** (0.0002)	0.0041 (0.1395)	0.0418*** (0.0002)
Population Density	-0.0012 (0.5411)	-0.0004 (0.3324)	-0.0039 (0.1581)	-0.0043 (0.1173)	-0.0004 (0.3566)	-0.0044 (0.1085)
<b>Social Capital Metric</b>						
Org. Density Social Capital Index	0.0017** (0.0133)	0.0013*** (0.0001)	0.0023** (0.0269)	-	-	-
RGF Social Capital Index	-	-	-	0.0093* (0.0877)	0.0012 (0.2781)	0.0093* (0.0876)
spatial $\rho$	0.6586*** (0.0001)	-	0.6332*** (0.0001)	0.6324*** (0.0001)	-	0.6341*** (0.0001)
spatial $\lambda$	-	0.5279*** (0.0001)	-	-	0.5323*** (0.0001)	-

\*\*\*: Significant at 99.9 percent level. \*\*: Significant at 95.0 percent level. \*: Significant at 90.0 percent level

#### 4. RESULTS

Turn first to the results using the more traditional spatial estimators (Table 2).<sup>8</sup> There are six sets of results, across two measures of social capital and three spatial estimators. Again, we use these different estimators as a simple robustness test of our results and, in general, the results are consistent across the different spatial estimators. Based on the spatial lags

<sup>8</sup>Based on estimated variance inflation factors (VIF) and the condition index (CI) of the design matrix, there appears to be modest levels of collinearity amongst the control variables. Specifically, the CI is slightly larger than 90, suggesting a borderline issue with collinearity with VIF between four and five for median household income (4.23) and poverty rates (4.89), which should not be unexpected. This reinforces the rationale for not including both measures of social capital into one model.

( $\rho$  and  $\lambda$ ), there appears to be spatial dependency within the data. Before turning to the results on social capital, we explore the results on the control variables to gain insights in the underlying relationships between community characteristics and business survival rates.

The lagged population and employment growth variables have statistically weak and mixed influences on business survival rates, whereas income growth is insignificant. Positive population growth can correspond to higher survival rates but at the same time growth in employment corresponds to lower survival rates. The latter result on employment growth is likely explained by increasing opportunity costs of operating an underperforming business; if the community is experiencing employment growth the business owner may have a better wage-and-salary opportunity available; it may be rational to close the business and pursue the alternative.

Of the control variables, several are statistically significant across all models, namely median household income, the economic diversity index, percent of persons receiving retirement income, and the poverty rate. Somewhat surprisingly, both higher median household income levels and individual poverty rates are associated with higher survival rates. While one might expect these two variables to have opposite impacts on survival rates, the empirical results are consistent with our theoretical understanding of business survival rates. Communities with higher overall income levels generate more demand to support businesses. At the same time, if higher poverty rates are correlated with few attractive employment options and thus lower opportunity costs for business owners, they may choose to remain in business longer (higher survival rates).

Higher levels of the economic diversity index, which indicate more specialized economies, are associated with higher business survival rates. This is again consistent with our central line of thinking around opportunity costs: communities that are more specialized present fewer opportunities (hence lower opportunity costs) to shift from one business to another. A more diversified economy, on the other hand, creates greater opportunities for owners of underperforming business to close and pursue another venture or wage-and-salary employment.

As the share of persons with retirement income increases, business survival rates tend to decline. This is likely due to the unique phenomena that a growing number of retirees elect to start a small business in their retirement years. During the study time-period many people were retiring early from formal work (hence drawing retirement income) with the intent of starting their own business (Shields et al., 2003). Indeed, Lambert et al. (2007) find a strong positive relationship between in-migration of retirees and new business growth. Many of these businesses, however, are short-term enterprises thus placing downward pressure on overall business survival rates. Alternatively, the inverse relationship between the share receiving retirement income and survival rates may be demand driven. Retirees often live on a lower level of income than during their peak-earning years thus their spending habits may be relatively modest, reducing demand.

Residential stability, percent of the population with public assistance income, and educational patterns influence survival rates, though are inconsistently estimated across the different spatial estimators. More stable communities, as measured by the percent of persons in the same house over the 1995-2000 period, tend to have higher business survival rates but the results are statistically significant in only three of the six models. A higher



share of persons receiving public assistance is associated with lower survival rates, possibly because public assistance is an indicator of low-income groups who face some additional constraints on their spending that limit demand and stifle local businesses. Additionally, with higher assistance levels, the opportunity cost of remaining in an underperforming business may be too high. Potentially, higher assistance levels raise the reservation wage for (self-) employment. In terms of the distribution of education, we find that counties that tend to have lower overall levels of education tend to have higher survival rates which is consistent with the notion of lower opportunity costs. This result, though only weakly robust, is also consistent with a labor supply argument suggested by Acs et al. (2007): businesses may benefit from a relatively large pool of low-skill workers.

The percent of the population that speaks English less than very well, the unemployment rate, and population density had no influence on survival rates. The results suggest that once accounting for the density of social capital generating organizations, the population stability and density have little influence on business survival. Similarly, the unemployment rate, at any given point in time, is understandably less relevant to long-term business survival. Instead, sustained high unemployment over a period may be more relevant than a simple snapshot.

The two variables of core interest, the social capital measures, are largely consistent and complementary in the results: higher levels of social capital are associated with higher business survival rates. The organizational density index is statistically significant across all three spatial estimators and the Rupasingha, Goetz, and Freshwater index is weakly significant in two of the three models. These results support the notion that higher levels of social capital correspond to higher five-year survival rates across U.S. counties.<sup>9</sup> These results are consistent with the argument that social capital can enhance the flow of information and reduce transactional costs. As outlined by Kwon and Arenius (2010), communities with higher levels of social capital provide a context for entrepreneurs to make more informed decisions within a more supportive environment. The data suggest that business owners are able to tap into a greater flow of information and access resources at the formation of the businesses (decision to start-up) and through the early stages of business development. These enhanced networks also allow new business owners to lower the costs of operations due to lower transactions costs.

The results provided in Table 2 are global parameter estimates and assume that the underlying relationships do not vary across space. To allow and test for spatial heterogeneity, we employed the GWR estimator as outlined above and provide a summary of the results in Tables 3 and 4. Included in the tables are the results from a simple classical regression (OLS), the median GWR value of the spatially varying parameter estimate, and the lower and upper quartile values. Following Nakaya et al. (2017), the key statistic for this analysis is the diff-Criterion: a positive difference greater than two indicates that the coefficient on the  $k_{TH}$  variable is global, meaning the spatial estimator(s) are more appropriate than the GWR estimator. Thus values less than two, and particularly those that are negative, suggest that the spatially heterogeneous GWR estimates are an improvement over the global estimates. A test of consistent underlying relationships between community characteristics

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<sup>9</sup>Because the social capital index is at best an ordinal ranking, as opposed to cardinal absolutes, the best that can be stated is whether the key relationship is positive, negative or zero.

and business survival across space (i.e., the global parameter is correct), rejects the null hypothesis indicating that these underlying relationships vary across space.

Consider first the model containing the Organizational Density Social Capital Index (Table 3). Among the majority of the control variables, there is sufficient evidence based on the diff-criterion to suggest that the global parameter estimates may be misleading. Rather than exploring the spatial patterns for all estimated parameter values, consider the focal social capital variables. We find that the Organization and RGF indices of social capital are similar in that the OLS global estimates are positive and statistically significant which is consistent with the spatial estimator(s) results in Table 2. The diff-criteria, however, are both large and negative suggesting that there is significant spatial heterogeneity in the underlying relationship between community level social capital and business survival rates. Note that the median and lower quartile values are negative, suggesting that for many parts of the U.S. higher levels of social capital are associated with lower business survival rates.

To help better understand the spatial pattern between social capital and business survival rates, consider Figures 2 and 3. Here, we map the statistical significance of the t-statistics for the individual parameter estimates across three categories: positive and statistically significant, not significant, and negative and statistically significant. The spatial patterns in the two mappings are largely similar with three of four clear regions where higher levels of social capital are associated with higher survival rates and smaller handful of regions where the negative relationship dominates. The positive relationship is concentrated in Florida, parts of Texas, and the Pacific Northwest with a very small cluster around the Missouri-Iowa border region. In parts of the heartland of the U.S., there is a negative relationship between social capital and survival rates. For the RGF index, the negative relationship exists in large sections of the West and in Texas along with small pockets in the southern U.S. Notice, however, for northern New England the two separate measures of social capital provide contradictory results. Interestingly, there are also large sections of the U.S. where the social capital and business survival relationship is statistically insignificant.

The variation in the effect of social capital on business survival rates is consistent with the observations of Durlauf (1999), Durlauf (2002), and Besser and Miller (2015) who argue that social capital is multifunctional with both positive and negative elements. Further, social capital is meant to measure networks, behavioral norms, and trust, but their existence alone does not necessarily lead to better business outcomes. It could be that the culture that arises out of these elements of social capital sustains behaviors such as risk aversion that are antithetical to entrepreneurship and business ownership. Durlauf makes three additional points that highlight the difficulty of ecological studies of social capital. The three core elements of social capital (networks, trust and norms) are difficult to quantify and measure. Cultural norms vary so greatly within and across communities that the conceptual idea cannot be easily measured. Third, these relationships change over time thus making the measurement of social capital a moving target. More concisely, (Woolcock, 2001, p. 69) warns that "...social capital [has] become all things to all people and hence nothing to anyone..."

**Table 3: Five Year Business Survival Rates: Organizational Social Capital**

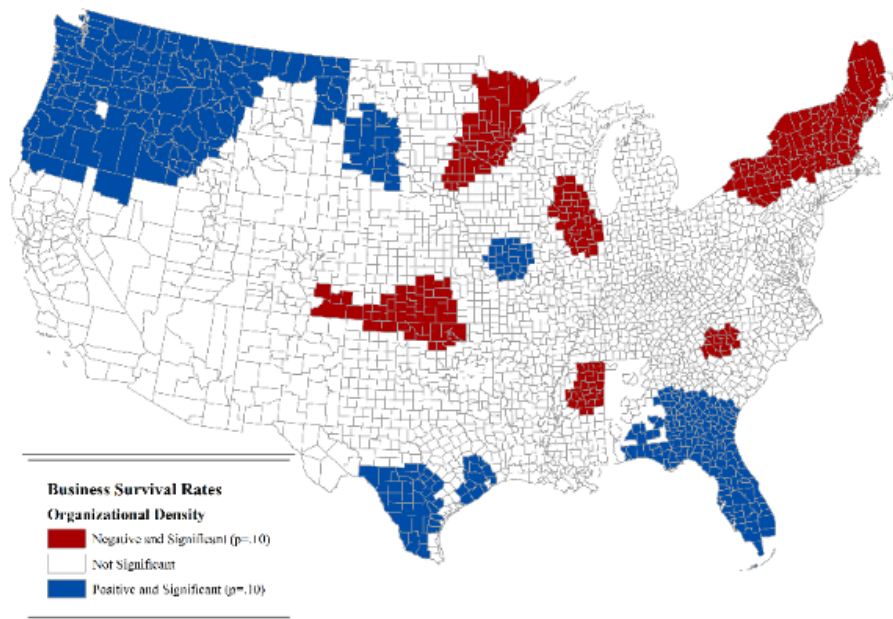
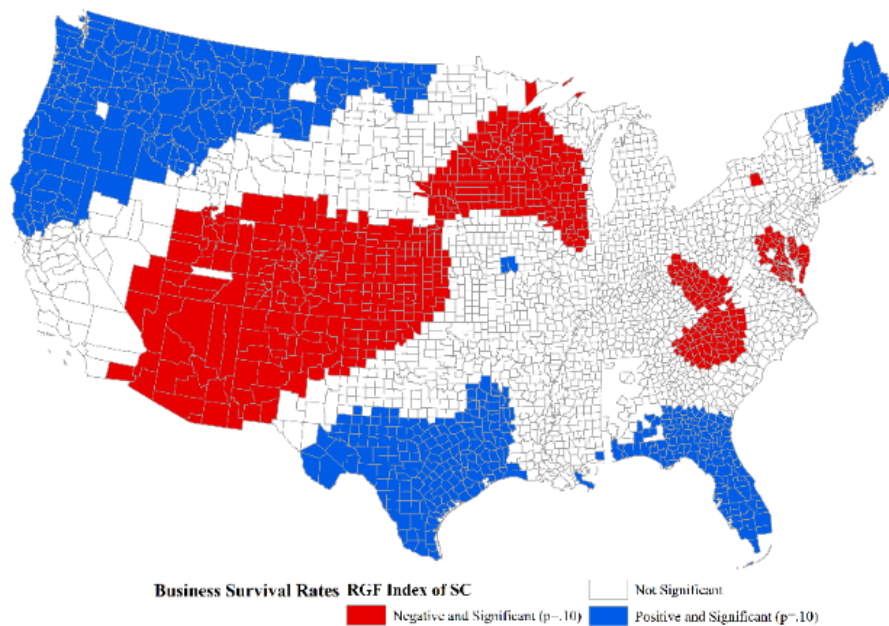
	Global OLS	p-value	Lower Quartile	Median	Upper Quartile	Diff-Criterion
<b>Growth Lags</b>						
Percent Change in Population 1990-2000	0.0309	(0.0399)**	-0.0756	-0.0115	0.0544	5.913
Percent Change in Employment 1990-2000	-0.0030	(0.6977)	-0.0147	0.0069	0.0505	5.173
Percent Change in Per Capita Income 1990-2000	0.0251	(0.0268)**	-0.0246	0.0196	0.0583	3.888
<b>Socio-Economics</b>						
Median Household Income	0.0248	(0.0001)***	-0.0189	0.0069	0.0209	-72.049
Percent of Persons in Same House 1995-2000	0.2028	(0.0001)***	-0.1221	-0.0328	0.0591	-559.665
Percent of Persons who Speak English Less than Very Well	-0.0124	(0.7341)	-0.1228	0.0455	0.2440	-12.650
Unemployment Rate	-0.3594	(0.0173)**	-0.7602	-0.1347	0.3854	4.025
Economic Diversity Index	0.1438	(0.0001)***	-0.1028	-0.0269	0.0471	-78.809
Percent of Persons with Public Assistance Income	-0.5958	(0.0001)***	-0.7882	-0.2553	0.4109	-8.392
Percent of Persons with Retirement Income	-0.1949	(0.0001)***	-0.2457	-0.1018	0.0572	4.772
Poverty Rate	0.5330	(0.0001)***	-0.1758	0.0822	0.4118	-43.981
Distribution of Education Index	0.0106	(0.0011)**	-0.0191	-0.0001	0.0171	-11.088
Population Density	-0.0017	(0.0687)*	-0.0057	0.0032	0.0133	23.677
<b>Social Capital Metric</b>						
Organizational Density	0.0018	(0.0001)***	-0.0014	-0.0003	0.0009	-30.945
Intercept	0.0202	(0.0023)**	0.4394	0.6854	0.8797	-185.169
Adj R <sup>2</sup>	0.6977			0.7974		
Sample Size: 2,994						

\*\*\*: Significant at 99.9 percent Level. \*\*: Significant at 95.0 percent Level. \*: Significant at 90.0 percent Level

**Table 4:** Five Year Business Survival Rates: RGF Social Capital Index

	Global OLS	p-value	Lower Quartile	Median	Upper Quartile	Diff-Criterion
<b>Growth Lags</b>						
Percent Change in Population 1990-2000	0.0204	(0.1784)	-0.0657	-0.0260	0.0261	9.35
Percent Change in Employment 1990-2000	-0.0021	(0.7827)	-0.0172	0.0070	0.0518	6.68
Percent Change in Per Capita Income 1990-2000	0.0204	(0.0726)*	-0.0257	0.0218	0.0545	2.15
<b>Socio-Economics</b>						
Median Household Income	0.0211	(0.0001)***	-0.0119	0.0092	0.0195	-18.53
Percent of Persons in Same House 1995-2000	0.2344	(0.0001)***	-0.1470	-0.0373	0.0527	-350.95
Percent of Persons who Speak English Less than Very Well	0.0042	(0.9106)	-0.1369	0.0509	0.2920	-24.79
Unemployment Rate	-0.4696	(0.0019)**	-0.6689	-0.2107	0.4020	3.79
Economic Diversity Index	0.1572	(0.0001)***	-0.0992	-0.0309	0.0435	-59.87
Percent of Persons with Public Assistance Income	-0.6531	(0.0001)***	-0.6656	-0.1553	0.3788	-11.80
Percent of Persons with Retirement Income	-0.2109	(0.0001)***	-0.2420	-0.0930	0.0618	4.23
Poverty Rate	0.5305	(0.0001)***	-0.2313	0.0817	0.4207	-22.28
Distribution of Education Index	0.0109	(0.0014)**	-0.0142	-0.0001	0.0172	0.71
Population Density	-0.0019	(0.0364)**	-0.0045	0.0035	0.0129	24.82
<b>Social Capital Metric</b>						
RGF Social Capital Index	0.0047	(0.0025)**	-0.0098	-0.0025	0.0095	-84.55
Intercept	0.0223	(0.0008)***	0.4626	0.6924	0.8670	-192.35
AdjR <sup>2</sup>	0.6948			0.8005		
Sample Size: 2,994						

\*\*\*: Significant at 99.9 percent Level. \*\*: Significant at 95.0 percent Level. \*: Significant at 90.0 percent Level

**Figure 2:** GWR Results Organizational Social Capital**Figure 3:** GWR Results RGF Social Capital

Halstead and Deller (2015) argue that the obstacles to understanding how social capital influences economic outcomes should not discourage empirical work. The challenge for applied researchers is to disentangle the elements of social capital and their relationship to economic outcomes. From a purely theoretical perspective, social capital should help new businesses in their start-up and early phases of operation. From our global parameter anal-

ysis (Table 2) the data tend to support this notion: higher levels of social capital tend to be associated with higher business survival rates. The GWR results, however, indicate that the relationship varies significantly across space. In some parts of the U.S., the relationship is positive as hypothesized, but there are some parts of the U.S. where social capital impedes business survival (the second edge of the two edged sword argued by Durlauf (1999), Durlauf (2002), and Besser and Miller (2015) and large parts of the U.S. where the relationship appears inconsequential.

## 5. CONCLUSIONS

This study takes an ecological approach to examining how community-level social capital influences the five-year survival rates of new businesses. Businesses do not operate in isolation from the community in which they are located and theory suggests that communities with higher levels of relational or social capital should be more conducive to entrepreneurial activity. This is captured in network advantages, enhanced information exchanges, and lower transaction costs that foster a supportive environment for businesses in their early stages of operation. Thus, business survival rates should be higher in communities with higher levels of social capital.

To test this relationship, we used the National Establishment Time Series (NETS) to calculate five-year survival rates of businesses started in 2000 for each county in the U.S. We use two measures of social capital. Drawing on the work of Saxton and Benson (2005), Deller (2010), Keene and Deller (2015), Markeson and Deller (2015), and Kim (2017), we use the concentration of organizations that facilitate networking and reflect the charitable nature of the community. Second, we use the measure constructed and used by Goetz and Rupasingha (2006), Rupasingha et al. (2006), and Rupasingha and Goetz (2007) who combine fourteen separate measures commonly associated with social capital into a single scalar index through principal component analysis.

Our first set of results, using three spatial econometric estimators that allow for a heteroskedastic error structure, supports the notion that higher levels of community level social capital tend to be associated with higher business survival rates. In addition, our control variables generally perform as expected and the results tend to be largely robust across the different spatial estimators. If we allow for spatial heterogeneity in the underlying relationship between social capital and business survival via a Geographically Weighted Regression estimator, we find significant spatial heterogeneity. While the global parameter estimates tend to support the notion that social capital supports higher rates of business survival, the GWR results suggest that the parameter varies across counties in the contiguous U.S. Indeed, in some regions, higher levels of social capital are tied to lower business survival rates and, in many parts of the U.S., the relationship is statistically insignificant.

The warnings of Durlauf (1999, 2002) and Besser and Miller (2015) come to bear; the underlying relationship between community level social capital and business survival rates is complex. Social capital is clearly an important factor to the business climate, but additional work is required before we can completely untangle the relationship and draw conclusive policy insights. The results suggest that, on one level, the economic growth and development strategy of building public-private partnership to foster networking, flows of information, and

enhanced levels of trust or social capital, is worth pursuing. But, again we are reminded that strategies that work in one community may not work in another because community attitudes matter.

The stark spatial differences between social capital and business survival rates across the U.S. identified by the GWR results have an alternative interpretation to spatial variation in the relationship between social capital and business survival rates that is motivated by the observations of Durlauf (1999, 2002) and Besser and Miller (2015). Specifically that the measure of social capital, either the organizational density or the RGF index, does not reflect spatial variation in what constitutes proxy measures of social capital. For example, the individual variable weighting schemes used to build the RGF index needs to vary across space. For example, in some regions of the U.S. the density of religious organizations may be more important than other regions. Indeed, Deller et al. (2018) found significant differences across various religious traditions and entrepreneurial activity.

As this line of research relating community level social capital and entrepreneurship moves forward, it will be necessary to better establish how to measure social capital, including identifying the elements of social capital that are most important. The geographic unit of analysis used here, the county, is used primarily because of data conveniences/ limitations. Our understanding of social capital would likely benefit from sub-county analysis. For this study, we aggregated businesses to the county level and used a county average survival rate. We do not control for the business variation within the county, thus losing characteristics of individual firms. For example, are manufacturing firms influenced by social capital different that say personal service-oriented firms? An alternative approach may be to explore individual firms and match those firms to community characteristics an approach used in a handful of micro business survival rate studies. In addition, we assume a linear relationship between social capital and survival rates, which might be masking important underlying relationship.

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## A. APPENDIX: THE GEOGRAPHICALLY WEIGHTED REGRESSION ESTIMATOR

As outlined by Fotheringham et al. (2003), the GWR model can be written as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \quad (\text{A.1})$$

where  $(u_i, v_i)$  is the location of the  $i^{\text{th}}$  point and  $\beta_k(u_i, v_i)$  is a realization of the function  $\beta_k(u, v)$  at point  $i$  or the value of the parameter for each observation.

One potential issue in this general specification is that there are more unknowns than observed variables. Fotheringham et al. (2003) acknowledge this and note that they do not consider the coefficients to be random; rather they view them as a function of locations in space. In this model, the data closer to location  $i$  are weighted more heavily in the estimation than those further from  $i$ . The model is very similar to weighted least squares in its operation. The weighting scheme can be written as follows:

$$\hat{\beta}(i) = (\mathbf{X}'W(i)\mathbf{X})^{-1} \mathbf{X}'W(i)\mathbf{Y} \quad (\text{A.2})$$

where  $i$  represents a row in the matrix and  $W(i)$  is an  $n \times n$  spatial weighting matrix of the form,

$$W(i) = \begin{pmatrix} w_{i1} & 0 & 0 \\ 0 & w_{i2} & 0 \\ 0 & 0 & w_{in} \end{pmatrix} \quad (\text{A.3})$$

$w_{in}$  is the weight given to data point  $n$  for location  $i$ . The function for the weighting scheme is adaptive bi-square kernel with the  $i^{\text{th}}$  observation being defined as:

$$w_{ij} = \begin{cases} (1 - d_{ij}^2/\theta_{i(k)}^2) & d_{ij} < \theta_{i(k)} \\ 0 & d_{ij} > \theta_{i(k)} \end{cases} \quad (\text{A.4})$$

Because we are using U.S. county level data, the geographic size of counties varies significantly, particularly if we compare counties in the northeastern to western regions. In the northeast, the counties tend to be much smaller geographically than in the western U.S. Following Fotheringham et al. (2003), the use of the adaptive spatial bi-square kernels approach corrects for this issue. Here  $d$  is the Euclidean distance between observation  $i$  and location  $j$ , and  $\theta$  is a fixed bandwidth and  $\theta_{i(k)}$  is an adaptive bandwidth size defined by the distance measure. The latter is estimated using a golden section search process, a technique of finding the extremum values, by minimizing the Bayesian Information Criterion (BIC).