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A spatial, simultaneous model of social capital and poverty☆

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ABSTRACT

This study explores the interrelationship between social capital and poverty, a negative indicator of well-being, in the Western United States. Econometric models that account for the endogeneity of poverty and social capital, spatial dependence, and cross-equation error correlation were used to explore two questions: is the presence of social capital associated with reduced poverty levels and does the presence of poverty impact social capital stocks? We found evidence that communities with higher social capital levels tend to have lower poverty rates and that poverty may pose barriers to social capital formation. This suggests that policies to reduce poverty will be more effective if coupled with policies to support social capital formation. The study's findings are particularly salient for communities in persistent poverty. These results emerged only after accounting for endogeneity and spatial relationships. Because many factors contributing to well-being are jointly determined with well-being and indicators of well-being are frequently spatially clustered, this situation is likely to be more common than has been typically recognized in the literature.

1. Introduction

Social capital is defined as the norms and networks that facilitate collective action (Woolcock, 2001). In an era of globalization and employment sector transitions (e.g. loss of manufacturing jobs, increase in service and information technology occupations), communities are forced to reconsider their development paths and the types of assets that are needed to adapt in a rapidly changing society. Social capital is an asset that community members can invest in by developing social networks and strengthening societal norms or can allow to be depleted through neglect. It can play a significant role in the ability of a community to face development challenges or shocks. Its presence may lead to better outcomes in terms of community well-being because it is a mobilizing asset that has the potential to improve existing stocks of physical, financial, and natural capital.

It should be recognized that there are two distinct meanings of social capital — individual and community level social capital (Levien, 2015; Portes, 2000). Individual social capital conveys benefits to individuals or families (Bourdieu, 1984) while community social capital enables collective action for larger social units (Putnam, 1993). Shideler and Kraybill (2009, 444) state that “social capital is best described as an impure public good, in that individuals face private incentives to create and preserve social capital but such behavior generates public benefits, or externalities, shared with the community.”

In this study, we explore how community level social capital interacts with community well-being, as reflected in poverty rates, in the Western United States. We test the hypothesis that communities with higher social capital stocks experience greater well-being (lower poverty rates). Recognizing the potential interrelationship between social capital and poverty, we use a spatial simultaneous-equation model to also explore the question of whether poverty impacts the stock of social capital in a given community. Simultaneity arises because the development of social norms and economic class structure is interrelated and occurs simultaneously (Blank, 2005). Ignoring simultaneity in econometric models can result in biased and inconsistent estimates, leading to incorrect inferences. However, few studies have dealt with simultaneity in the relationship between social capital and indicators of well-being. Similarly, largely scant is empirical research considering spatial relationships when studying how social capital and poverty are related. One notable exception is Crandall and Weber (2004), who incorporated a spatial error term and a spatially lagged dependent variable in their study of changes in poverty rates. Overlooking significant spatial relationships when present can lead to unstable parameter estimates and unreliable statistical inference. This study is an attempt to fill this gap in the literature by adopting a comprehensive approach that accounts for feedback simultaneity between community well-being and social

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capital, spatial correlation, and cross-equation correlation. In particular, this study extends the work of Rupasingha and Goetz (2007), who considered the impact of social capital on U.S. county poverty rates but neglected the possible reverse causality of poverty on social capital.

The remainder of the paper is structured as follows. The next section presents a short review of the literature, laying out how this study departs from previous ones. A discussion of our methods and procedures is presented in the third section. Empirical results are presented in the fourth section and concluding remarks in the final section.

2. Literature review

Social capital can be considered a stock of assets (e.g. networks, institutions) which can produce a flow of services (e.g. social participation, collective action) aimed at reinforcing existing social capital and achieving community actions and outcomes (Tiepoh et al., 2004). Social capital theory emphasizes that both individual and group decisions are embedded in a particular social context that includes generalized trust, social norms (i.e. typical patterns of behavior), and networks (Coleman, 1988; Granovetter, 1985; Putnam, 1993). Generalized trust is related to reciprocity and adherence to social obligations, social norms to civic structures, responsibilities, and sanctions, and social networks are crucial to information exchange, as well as the building of trust and social norms (Akcomak and Muller-Zick, 2015).

Economists have traditionally focused on formal rules including laws and property rights with little emphasis on informal customs, codes of conduct, sanctions, and culturally derived norms of behavior (Blasio and Nuzzo, 2009; North, 1991). Social capital, although generally ignored by traditional neoclassical economists, warrants consideration for its role in economic performance, together with conventional factors such as capital, labor, and prices (Stimson et al., 2006). The social capital concept provides a means of bringing communities and other small groups into economic analysis consistent with social theory (Castle, 1998; Kraybill, 1998; Oakerson, 1998; Summers and Brown, 1998).

Knowledge diffusion is at least as important as its creation, and social networks play a critical role in this process (Agrawal et al., 2008; Granovetter, 2005). Early adoption of new technology may allow a region's economy to experience faster growth. Putnam (1993) argues that repeated interactions facilitate communication and amplify information about the trustworthiness and cooperation of others, reducing risk and thereby reducing transaction costs associated with economic exchange. When transaction costs and the costs of gathering and disseminating information are reduced, more exchange takes place, thus enlarging the scope of transactions and interactions (Akcomak and ter Weel, 2012; Zak and Knack, 2001). More and better information exchange channels improve exchange of information regarding funds, technology, market conditions, competitors, and job prospects. For example, if employment opportunities are available, but only a select group of people is aware of them, neither the most qualified nor capable person may apply. Individuals and firms can gather quality information that would be hard and more expensive to obtain in the absence of a social network. The value of social capital rests upon its ability to contribute to a more efficient "round-about" means of production. By investing in relationships that reduce transaction costs, we can reduce the friction in productive activities. Economic actors with low levels of social capital are more likely to experience unwieldy search and information costs, bargaining costs, and decision costs, in addition to lack of coordination, duplications of effort, and costly contractual disputes (Landry et al., 2002; Maskell, 2000).

Another contribution of social capital is that it affects the supply of public goods (Putnam, 1993). The provision of public goods is subject to free riding or shirking if most users do not participate in joint actions to make the provision of public goods a success. When community social capital is present, externalities are internalized, which has the effect of eliminating or reducing the free rider problem and the misuse of public goods while at the same time increasing investments in public goods. For instance, if people take responsibility for voting (which includes being knowledgeable of the ballot issue and how it will affect the individual), a possible civic norm, more effective public services are expected to follow.

Social networks can also create social control among economic actors, leading to reciprocity (i.e. a mutual or cooperative interchange of favors, privileges) and adherence to social obligations. Entrepreneurs and firms are forced to behave in a trustworthy manner to maintain reputation (Rost, 2011). Employees are less likely to shirk. In a low trust environment where few people know one another, or population segments have had experience with unfair treatment, investment will be lower, leading to slower economic growth (Zak and Knack, 2001).

In considering the benefits of social capital, one must also consider the downsides. If social network externalities are like public goods, i.e., non-rival and non-excludable, social capital can accrue to any individual where the network is present. Conversely, if network externalities are like private goods, then the benefits will be confined to those included in the specific network or institution (Iyer et al., 2005). Networks, as well as public and community institutions, may reinforce class patterns and social norms that disadvantage disfavored groups.

Many economic studies find positive associations between social capital and indicators of well-being. For instance, social capital has been associated with beneficial outcomes for economic development and growth (Beugelsdijk and van Schaik, 2005; Doh and McNeely, 2012; Helliwell and Putnam, 1995; Knack and Keefer, 1997; Peiro-Palomino and Tortosa-Ausina, 2015). Additionally it has been associated with reductions in poverty (Crandall and Weber, 2004), increased incomes (Rupasingha et al., 2000), prosperity (Isserman et al., 2009), innovation (Akcomak and Muller-Zick, 2015; de Dominicis et al., 2013), and employment opportunities (Romero and Yu, 2015).

Metrics used to measure social capital are a source of consternation, and at times, confusion. They vary greatly, adding some complexity to comparing the results of social capital studies. Economic studies typically measure social capital using an aggregation of survey data. Survey questions pertain to social capital indicators like membership in organizations (Crescenzi et al., 2013; Dettori et al., 2012; Iyer et al., 2005), civic norms such as time spent volunteering, charitable giving, and whether the respondent votes (Putnam, 1993; Kim and Kang, 2014), and trust in neighbors, strangers, and institutions (Knack and Keefer, 1997; Shideler and Kraybill, 2009). A latent construct approach has also been used in which several indicators of social capital are merged into an index (Akcomak and ter Weel, 2012; Beugelsdijk and van Schaik, 2005; Doh and McNeely, 2012; Rupasingha and Goetz, 2008).

Qualitative approaches employing methods such as case studies and ethnography do not find a consistent impact of social capital on poverty rates. For example, one outcome of social capital is knowledge transmission among networks and clubs. If the poor are excluded from groups with greater wealth and resources, the networks they belong to may not relay needed information to take advantage of economic opportunities (Cattell, 2001; Pearlin, 1985; Willmott, 1987). Based on his study of rural development in Indian villages, Levien (2015) argued that social capital should be considered an aspect of social inequality that restricts inclusive development. Hence, higher levels of community level social capital, as indicated by organizational membership, may do little to decrease poverty rates. Alternatively, trust and reciprocity, common indicators of social capital, are key norms of behavior for a successful rotating savings and loan association, of which the poor may benefit from and accumulate wealth.

Fewer studies explore the effect of well-being on social capital formation, but their findings are similarly inconsistent. For example, education level, one positive indicator of well-being, appears to positively impact social capital formation (Glaeser et al., 2002; Nie et al., 1996). However poverty, one negative indicator of well-being, has been found to have inconsistent impacts on social capital formation. Higher poverty rates may force community members to spend more time working and less time investing in relationships and network building. Alternatively, the poor may rely on their social networks to make ends meet (Bebbington, 1999; Briggs, 1998). Assensoh (2002) found that civic engagement in terms of community meeting attendance is higher in high poverty areas. Shideler and Kraybill (2009) determined that lower income individuals invest more heavily in social capital than do rich individuals. They theorized that poor households may substitute social capital for formal markets and institutions, whereas rich households are less likely to do so.

One of the challenges in understanding the relations between social capital and poverty is that they are jointly determined (Durlauf, 2002). Only a few studies of social capital and poverty account for simultaneity (i.e., Atemnkeng and Vukenkeng, 2016; Hassan and Birungi, 2011). These studies, set in an African context, find that household income is positively correlated with access to social capital, defined in terms of membership in social organizations, and that access to social capital positively affects household income.

Spatial effects may be important as well. Regional science and economics both emphasize that location—in terms of natural resources, distances to or from markets, and infrastructure—plays a role in determining the success or failure of an area. The spatial diffusion of social capital may be an important factor in determining economic outcomes (Beugelsdijk and van Schaik, 2005; Tabellini, 2010). The clustering of regions with high levels of social capital and regions with low levels of social capital can lead to areas with better or worse economic equilibria (Fazio and Lavecchia, 2013).

Prior studies incorporating spatial effects consider either poverty or social capital, but do not consider them simultaneously. Studies of poverty rates that consider the uneven geographic distribution of poverty rates across the United States have found that poverty rates are highest in the most remote rural counties and in central cities, and persistent poverty is geographically concentrated in isolated rural regions (Partridge and Rickman, 2008; Gundersen and Ziliak, 2004). Rural labor markets are thinner with poorer employer-employee matches compared to urban areas (Davis and Weber, 2002). Inner city skill mismatch is also of concern in that poor people living in inner cities may not be well suited to available urban jobs which require years of formal education and professional training (Blumenberg and Shiki, 2004). Additionally, economically disadvantaged individuals self-select into areas with lower costs of living, cultural similarities, and support networks, concentrating geographically in rural areas and central cities (Fisher, 2007). Prior studies of social capital that explore spatial relationships account for the spatial spillover effects and spatial path dependence of social capital (Fazio and Lavecchia, 2013; Tselios et al., 2015). To the extent that the formation of cultural traits depends on physical human interactions, the strength of social norms and networks attenuate with distance.

3. Methods

We model the interrelationship between poverty and social capital as a system of two simultaneous equations:

$$Pov_i = f_1(SC_i, \boldsymbol{X_i}, \boldsymbol{Y_i})$$

$$SC_i = f_2(Pov_i, \boldsymbol{X_i}, \boldsymbol{Z_i})$$

where the endogenous variables, Pov_i and SC_i, are poverty rate and social capital level in county i, $\boldsymbol{X_i}$ is the set of exogenous control variables that affect both poverty rate and social capital level, and $\boldsymbol{Y_i}$ and $\boldsymbol{Z_i}$ are the sets of exogenous control variables specific to each dependent variable. This structural model permits empirical testing of the relative effect of social capital on poverty and vice versa.

3.1. Empirical model

To model the simultaneous determination of social capital and poverty and account for spatial relationships, we adopted a multi-equation spatial econometric model following Jeanty et al. (2010). Consider the following spatial simultaneous equations system:

$$Pov = \alpha_0 + \alpha_1 SC + \alpha_2 \boldsymbol{X} + \alpha_3 \boldsymbol{Y} + \alpha_4 W(Pov) + u_1$$

$$SC = \beta_0 + \beta_1 Pov + \beta_2 \boldsymbol{X} + \beta_3 \boldsymbol{Z} + \beta_4 W(SC) + u_2$$

$$u_j = \rho_j W u_j + \varepsilon_j \text{ where } j = 1, 2$$

where W is a spatial weights matrix, u_j is the disturbance term, ρ_j is the spatial autoregressive parameter, and ε_j is the independent and identically distributed error term.

There are two types of spatial relations commonly identified in the literature for their potential to introduce bias and/or inefficiency into empirical model estimation if not accounted for properly when present in the data. They can co-exist in a given spatial data set. They can be addressed in econometric models, when appropriate, by incorporating spatially lagged variables and/or spatially correlated error terms.

Spatial lag models deal with the interaction between economic agents that can lead to emergent collective behavior and aggregate patterns. The variable of interest in a spatial lag model is considered to have spatial movement; social capital or poverty spill over from one place to the next – for example, via the spatial diffusion of cultural norms or movement of poor people, respectively. In our model, spatially lagged dependent variables were added on the right-hand side of each regression equation using a spatial weights matrix, W. Therefore, the values of the dependent variable in one geographic area are assumed to be influenced by the values of the dependent variable in neighboring areas. For example, poverty rates in a county may be correlated with poverty rates in an adjacent county if physical proximity facilitates movement of poor people and associated characteristics (e.g. higher crime rates, fewer services, and environmental disamenities) from one community to another. If the influence of spatially lagged terms is ignored, coefficients are biased and standard errors wrong, since the errors cannot be considered to be independent among contiguous counties.

For our spatial lag model, we used an inverse distance decay spatial weights matrix W where nearby neighboring counties are weighted more heavily than neighbors farther away. The weight given to county j in observation i is $w_{ij} = 1/d_{ij}$, where d_{ij} is the distance between the centroids of counties i and j. We tested other forms of spatial weights matrices such as the 100-mile cut-off spatial weights matrix (which assumes that counties that are more than 100 miles apart do not influence one another) and the queen contiguity spatial weights matrix (which assumes that counties only influence one another if they share edges; hence, there is no influence beyond the first ring). We obtained similar results across formulations and report only the distance decay model here.

Spatial error models account for spurious spatial correlation, which can occur when there is measurement error associated with the spatial boundaries, e.g. when the aggregation level of geographic data is not the same as the level at which the process under study acts. For example, if community level social capital is a neighborhood or town-level process, but is measured at the county level, spatial error autocorrelation may be introduced. Spatial error autocorrelation can also occur when omitted variables are spatially clustered. Suppose that y is explained entirely by two explanatory variables x and z, where $x, z \sim N(0, I_n)$ and are independent:

$$y = x\beta + z\theta$$

If z is not observed, the vector $z\theta$ is nested into the error term ε

$$y = x\beta + \varepsilon$$

Examples of the latent variable, z, that might follow a spatial autoregressive process include culture, neighborhood prestige, distance to markets, and natural resource endowments. If we ignore the resulting

Table 1
Variables used in the poverty and social capital models – definition, mean, standard deviation (SD), and range.

Poverty model				
Control variable	*Definition*	*Mean*	*SD*	*Range*
Social Capital	Composite index as defined in Rupasingha et al. (2008)	−0.02	1.70	−2.99–9.74
Metro	Dummy variable: Metropolitan = 1, Non-metropolitan = 0	0.31	0.46	0.00–1.00
Metro Adjacent	Dummy variable: Metro-adjacent = 1, Metropolitan or rural = 0	0.29	0.46	0.00–1.00
Non-white	Percentage of population that identifies as a race/ethnicity other than white	24.78	19.75	0.30–89.40
Population under 19	Percentage of population below the age of 19	26.89	5.15	7.25–39.68
Population over 65	Percentage of population above the age of 65	14.99	4.95	4.95–32.29
Married w/Children	Percentage of households married with children	20.71	6.29	3.90–42.00
Bachelor Degree	Percentage of population ≥ 25 years of age with a bachelor's degree	22.70	9.73	5.30–64.00
Unemployed	Percentage of labor force unemployed	7.19	3.08	0.00–17.64
Female Labor Force	Percentage of females ≥ 16 years of age in the labor force	56.64	6.90	32.60–81.40
Industry Diversity	Shannon Weaver diversity index for industry employment	2.28	0.13	1.61–2.45
FIRE Jobs	Percentage of employed population working in finance, insurance, real estate	4.70	2.07	0.00–14.31
Natural Amenity	Categorical variable of natural amenities: Highest = 7, Lowest level = 1	5.03	1.06	2.00–7.00
Social capital model				
Control variable	*Definition*			
Poverty	Percentage of population at or below the poverty line	14.65	5.41	2.90–41.70
Metro	Dummy variable: Metropolitan = 1, Non-metropolitan = 0	0.31	0.46	0.00–1.00
Metro Adjacent	Dummy variable: Metro-adjacent = 1, Metropolitan or rural = 0	0.29	0.46	0.00–1.00
Ethnic Heterogeneity	Diversity index for race/ethnicity	32.90	17.58	0.60–74.57
Median Age	Median age	39.85	6.50	22.50–58.60
Median Age Squared	Median age squared	1630.01	526.91	506.25–3433.96
Population over 65	Percentage of population above the age of 65	14.99	4.95	4.95–32.29
Same County	Percentage of population that lived in the same county one year ago	92.55	2.94	78.48–99.91
Bachelor Degree	Percentage of population ≥ 25 years of age with a bachelor's degree	22.70	9.73	5.30–64.00
Unemployed	Percentage of labor force unemployed	7.19	3.08	0.00–17.64
Female Labor Force	Percentage of females ≥ 16 years of age in the labor force	56.64	6.90	32.60–81.40
Income Inequality	Gini index of income inequality	0.41	0.03	0.31–0.58

spatial autocorrelation in the residuals, coefficient estimates are unbiased, but standard errors may be underestimated.

Simultaneity of social capital and poverty can be addressed in a spatial model using instrumental variables in econometric frameworks such as spatial two or three stage least squares (2SLS/3SLS), and generalized spatial 2SLS/3SLS (Kelejian and Prucha, 2004). The procedure is outlined in Jeanty et al. (2010) and Irwin et al. (2014).

3.2. Data

Counties define community boundaries in our study. We chose the western region of the contiguous United States as the geographic focus of the study for several reasons. First, we wanted to provide complementary data to existing case studies of social capital development in the same area (Harrison et al., 2016). Second, the western region is geographically distinct from the U.S. as a whole in county size and population density; average county size in the West is 3700 square miles, compared to 1000 square miles for the U.S. as a whole and average population density in the West was 41.1 people per square mile in 2010, compared to 87.4 per square mile in the U.S. as a whole. Social capital works at multiple geographic scales. Some aspects of social capital are town-specific, some better reflect a county, and some represent an entire region. In densely populated eastern counties, social capital is more likely to operate on a neighborhood or city scale, with social norms and networks varying from neighborhood to neighborhood. In the sparsely populated West, social capital is more likely to be a county-level process and people more likely to share cultural norms across large distances. Therefore, the geographic scale at which social capital works is more likely to match the unit of observation (the county) and, hence, the spatial auto-correlation described above is less likely to occur in the West than in the U.S. as a whole. For our study, the units of analysis are 414 counties from Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming.

3.2.1. Social capital

We used the 2005 social capital index developed by Rupasingha and Goetz (2008), which includes data for continental U.S. counties to represent social capital. It was created using principal components analysis. The variables used in the principal components analysis are: total associations (i.e. bowling centers, civic and social associations, physical fitness facilities, public golf courses, religious organizations, sports and recreation clubs, political organizations, professional organizations, business associations, labor organizations) per 10,000 people, number of not-for-profit organizations per 10,000 people, census mail response rate for the year 2000, and number of votes cast for president in 2004 divided by total population of age 18 and over in 2004. The first principal component explained about 46% of the variation and is considered the index of social capital. Total associations and non-profit organizations represent networks of people in each county, whereas the census response rate and voting rate represent civic norms. The index is standardized around a mean of zero, so that counties with higher levels of social capital than the average county have a positive value and counties with lower levels of social capital than the average county have a negative value.

3.2.2. Poverty

Poverty is represented by the poverty rate – the percentage of population at or below the poverty line as defined by U.S. Bureau of the Census. County-level data for poverty rates and most of the model control variables were sourced from the American Community Survey (ACS), the first cycle of which covers the five year period 2006–2010 (U.S. Census, 2010). The ACS five-year estimates were used because this product is the only U.S. Census Bureau survey that collects data for geographic areas with small populations (20,000 people or less). Many western U.S. counties are sparsely populated and are not surveyed extensively in the decennial census. Data were collected between the years 2006–2010 and the control variables are assumed to generally represent this time period. The control variables “Metro” and “Metro-adjacent" are from ERS (2005) and the Natural Amenity scale is from McGranahan (1999).

3.2.3. Control variables

While the primary coefficients of interest in this study are those estimated for social capital in the poverty equation and for poverty in the social capital equation, the equations are specified to control for variation in the dependent variables due to correlation with other socio-economic determinants. We selected control variables from those shown to be potentially important in earlier studies: Partridge and Rickman (2008), Blank (2005), Crandall and Weber (2004), Levernier et al. (2000), and Duncan (2000) for the poverty equation; Brehm and Rahn (1997), Charles and Kline (2006), Fazio and Lavecchia (2013), Glaeser et al. (2002), Glaeser et al. (2000), Iyer et al. (2005), and Rupasingha et al. (2006) for the social capital equation. The variables are listed and defined in Table 1. Although analytical models do not provide a theoretical basis to predict direction of influence on the dependent variables for the control variables, previous studies – both qualitative and quantitative – give some indication of which variables are likely to be important and of the direction of influence to expect.

Location with respect to the *rural-urban continuum* appears to be important. Individuals living in urban areas are in close proximity to markets and, hence, may experience lower rates of poverty. Geographic isolation alternatively can hinder economic development by limiting market exchange and curtailing access to employment opportunities (Blank, 2005). However, there is also evidence that counties in metropolitan areas have higher poverty rates due to chronic impoverished conditions in central cities. The evidence for social capital in metropolitan counties is also inconclusive. While residency in urban areas presents numerous opportunities to join organizations and be civically engaged, there is also the possibility of isolation in a densely populated city of strangers (Iyer et al., 2005). Rupasingha et al. (2006) found that urban areas are associated with lower levels of social capital, compared to rural areas where collective behavior may be essential to provide basic services that might be provided institutionally in urban areas. Residents of metropolitan-adjacent areas often commute to work and live in "bedroom" communities that are isolated from civic and social gathering places and, hence, may be less invested in social capital (Flora et al., 1997). Because there are fewer people in rural areas, it can be a quicker process to determine what networks are available and which to join, as well as more opportunities to run into the same people in public areas; also, more isolated rural communities may have more deeply inculcated social norms due to less in-migration (Blank, 2005).

Poverty rates have long trended higher for most *racial and ethnic minority* groups in the U.S. (Levernier et al., 2000). Discrimination in hiring by employers, as well as greater returns to participating in the informal economy and lower levels of education among racial and ethnic minorities are a few of the reasons why this trend continues. Employment spatial mismatch, in which jobs and employees are located in different areas, has also been an issue for African-Americans who were or are disproportionately concentrated in inner cities (Blumenberg and Shiki, 2004). Iyer et al. (2005) note that an association of ethnically diverse populations with low levels of social capital is emerging in the literature, partially because people tend to fear association with others who they perceive to be different (see also Charles and Kline, 2006).

Age and family status (e.g. married with children) have been found to be important factors in both poverty and investment in social capital. Percent of the population over 65 and under 19 are included as control variables to represent populations not in the work force. However, people in the over-65 age group may have had opportunity to amass wealth over their lifetimes, reducing poverty rates among their ranks. They may also have narrower social networks as they leave the workforce, but more time (and need) to invest in networking activities than before. Young people who are working are more likely to receive lower wages than are more experienced workers. Young people also have had less time to invest in social capital and are often more mobile. Previous studies have found that social capital increases as the population ages, but at a decreasing rate (Glaeser et al., 2002; Tselios et al., 2015). Married households have the benefit of two potential income earners as well as someone to depend upon if an economic calamity ensues and, hence, are less likely to experience poverty than single-head-of-household families (Levernier et al., 2000). Also, financial stability is often a precursor to marriage and marriage can provide a form of financial insurance.

One of the most consistent results in social capital studies is the strong association between *education* and indicators of social capital (Glaeser et al., 2002; Putnam, 2000). Iyer et al. (2005) explain how education requires the development of social skills. Public education in particular requires working in groups, learning to cooperate, and being aware of the needs and attitudes of others. Additionally schools afford numerous opportunities to grow a social network and associate with people that an individual might otherwise never interact with. Education increases access to high-skilled employment that, in turn, yields relatively high income and job security. Therefore, education level is expected to be negatively correlated with poverty.

The *structure of the local economy and attributes of the labor force* have been shown to be important determinants of poverty (Blank, 2005). Levernier et al. (2000) found that above-average employment shares in FIRE (finance, insurance, and real estate) jobs were associated with lower poverty rates. Watson and Deller (2017) found evidence that industry diversity contributes to lower rates of unemployment and resulting higher economic well-being. We included female labor force participation in both equations, expecting that more wage-earning women will alleviate poverty, particularly in single-head households with children. With respect to social capital, employment offers work-based networking opportunities but presents time constraints for participating in networking opportunities outside of work. Obviously, unemployment is positively correlated with poverty in most studies and has been found to be associated with low levels of social capital. Income inequality can be a source of social division and, hence, might be a detriment to social capital formation (Alesina and Ferrara, 2000). Individuals find it hard to cooperate when the distribution of material wealth is visibly skewed (Nishi et al., 2015).

The variable *natural amenity* refers to the level of natural amenities in a county, such as the number of days with sunshine, miles of coastline, and varied topography. Migration flows are increasingly explained by natural amenity and quality of life differences across regions (Deller et al., 2001; Irwin et al., 2010). Because natural amenities are a normal or superior good, it makes sense that they are associated with relatively low levels of poverty.

3.2.4. Instrumental variables

Instrumental variables serve as proxies for endogenous variables in 2SLS and 3SLS. The set of instruments used in each equation is given by exclusion restrictions. Excluded variables from the poverty equation (control variables in the first-stage regression on social capital, Z_i) are ethnic heterogeneity, median age, median age squared, income inequality, and same county. The same county variable is defined as the percentage of the population that lived in the same county one year ago. We used it to indicate length of household residency, which has served as an instrument for poverty in previous social capital studies that use individual survey response data (Aker, 2007; Atemnkeng and Vukenkeng, 2016; Glaeser et al., 2000; Hassan and Birungi, 2011). Variables excluded from the social capital equation (control variables in the first-stage regression on poverty, Y_i) are nonwhite, population under 19, married with children, industry diversity, FIRE jobs, and natural amenity. We included poverty rates in 1995 as an additional external instrument for poverty to capture inertia. Finally, the instruments are supplemented with their first and second order spatial lags (Kelejian and Prucha, 2004).

4. Model estimation and results

All estimations were computed using the statistical software package Stata. The spatial model estimations used Stata programming code developed by Jeanty (2013). We estimated the model in three stages. We first estimated a non-spatial 2SLS model as a baseline to compare with the spatial models. We then added the spatial lagged dependent variables, *W*(*Pov*) and *W*(*SC*), to account for spatial dependency and estimated each equation with 2SLS. We also estimated the spatial 2-equation system using 3SLS because 3SLS can be more efficient (i.e., the variance is "more" minimized) than 2SLS if error terms are correlated across equations. We conducted tests for endogeneity and spatial dependence in each respective equation using the IV Moran's I and Lagrange multiplier tests and, based on the results, we rejected the null hypotheses of no endogeneity and no spatial dependence (Anselin and Kelejian, 1997; Hausman, 1978). Finally after estimating the spatial lag models, we tested the residuals for any remaining spatial correlation. The test results suggested none in either equation. Therefore, we did not consider the spatial error component of the models, $u_j = \rho_j W u_j + \varepsilon_j$. The 2SLS, spatial 2SLS, and spatial 3SLS estimations are reported in Table 2 for the *poverty* model and Table 3 for the *social capital* model. All three model estimations are reported in order to compare across models and assess the robustness of our conclusions.

4.1. Poverty model estimation results

Goodness-of-fit measures (adjusted R^2 for nonspatial model and square of the correlation coefficient between the observed and predicted values of the dependent variable for spatial models) indicate that the models explain from 65% to 74% of the variation in poverty rates. The poverty model is robust in that it passes the strong sign test; all control variable coefficient estimates that are significant at $p < 0.05$ have the same sign and are similar in magnitude across equations.

The coefficient estimate for the spatial lag variable *W*(*Pov*) is positive and significant at $p < 0.01$ in both spatial models, suggesting that spillover effects from neighboring counties do exist. The coefficient estimate for the key variable of interest in this model, *social capital*, is not significantly different from zero when spatial interactions are omitted, but is negative and significant at $p < 0.01$ when the spatially lagged variables are added in both the 2SLS and the 3SLS models – evidence that supports the hypothesis that building social capital may help alleviate poverty.

The spatial estimations further indicate that not only is poverty level in a given county affected by poverty levels in neighboring counties, but also by social capital in neighboring counties. To decompose the interactions of social capital on poverty rates, we calculate the direct ("own" effect), indirect (spatial spillover effect), and total impacts of social capital (shown in Table 4). In the spatial 3SLS model, a one unit increase in own-county social capital index (7.8% of its sample range) would result in a decline of 0.745 percentage points in own-county population at or below the poverty rate on average. When considering the indirect effects, the response of poverty to social capital is significant as well; a one unit increase in the social capital index in nearby counties is related to a 0.360 percentage point decrease in poverty rate in a particular county on average. A key implication of the indirect effects is that because social capital is so spatially interconnected, a decline in social capital in one county could increase poverty rates across a much wider geographical area, holding other factors constant. Combining direct and indirect impacts results in an estimated total impact of 1.105% of social capital on poverty rate on average. It is worth noting that all the impact measures are significant at $p < 0.01$.[1]

[1] Statistical inferences were derived using Krinsky and Robb procedure as in Jeanty et al. (2010).

Coefficient estimates for the remaining control variables are mostly significant at $p < 0.01$ and have signs that are consistent with our expectations as described in Section 3.2. There appears to be lower poverty rates in metropolitan areas, as well as counties with relatively older populations, households that are married with children, a higher proportion of women participating in the labor force, employment in finance, insurance, and real estate (FIRE), and relatively high natural amenities. Higher poverty rates appear in counties with relatively large nonwhite populations and relatively large populations of youth.

Education level, as measured by proportion of the population with college degrees at the bachelor level or above, does not appear to be correlated with poverty. This result countering intuition could be due to endogeneity. We tried other proxies for education—such as percentage of individuals with an associate degree or higher, or number of years of schooling—with the same result. It could be that counties with more residents with higher education levels also have large numbers of current students, who are below the poverty line if considered independent from their families.

4.2. Social capital model estimation results

Goodness-of-fit measures indicated that the models explain from 54% to 62% of the variation in social capital as measured by the Rupasingha and Goetz index. The social capital model is robust in the sense that the control variable coefficient estimates that are significant at $p < 0.05$ in all three models have the same sign and are similar in magnitude across models. However, coefficients for four variables – ethnic heterogeneity, median age, unemployed, and female labor force – became statistically insignificant in the models with spatially lagged variables. This is to be expected if there are strong spillover effects between these variables in adjacent counties that are captured in the spatial lag model when it is added to the social capital equation.

The coefficient estimate for the spatial lag variable *W*(*SC*) is positive and significant at $p < 0.01$ in the spatial models, again suggesting that spillover effects from neighboring counties exist. The coefficient on the key variable of interest in this model, *poverty*, is negative as expected but not significantly different from zero when spatial interactions are omitted. In the spatial 2SLS it is still negative but now significant at $p < 0.05$. Also, in the spatial 3SLS model, which accounts for cross-equation correlation, it is negative and significant at $p < 0.01$ with an increase in the magnitude. The results provide evidence that supports the hypothesis that poverty may present barriers to social capital formation, at least as it is measured in this study. The marked changes from standard 2SLS to the spatial 2SLS and 3SLS estimations provide credence to the adequacy of our holistic approach that allows for feedback simultaneity, spatial autocorrelation in the form of a lag, and cross-equation correlation. Our results are consistent with findings in previous studies. For instance, Jeanty et al. (2010) noted a reversal of sign and significance of the coefficient estimates after accounting for feedback simultaneity and spatial autocorrelation. Similarly, in a simulation study, Baltagi and Deng (2015) found that the structural parameter increases in magnitude significantly when accounting for cross-equation correlation.

As in the poverty model, not only is social capital in a given county affected by social capital levels in neighboring counties, but also by poverty in neighboring counties. In the spatial 3SLS model, our preferred model, a one percentage point increase in own-county poverty results in a decline of 0.064 units of the social capital index in a given county on average. When considering the spatial spillover, or indirect effects, a one percentage point increase in poverty in nearby counties is related to a 0.053 decrease in the social capital index of a given county on average. Combining direct and indirect impacts into total impact reveals that a one percentage point increase in poverty lowers the social capital index by 0.116 on average.

Coefficient estimates for the remaining control variables that are significant at $p < 0.05$ in every spatial model include being a

Table 2
Coefficient estimates for poverty models.

Poverty	2SLS			Spatial 2SLS		Spatial 3SLS	
	Coef.	St Error		Coef.	St Error	Coef.	St Error
Social Capital	−0.372	0.255		−0.526***	0.200	−0.721***	0.199
Poverty Spatial Lag				0.366***	0.054	0.348***	0.054
Metro	−1.956***	0.543		−1.681***	0.495	−1.930***	0.494
Metro Adjacent	−0.036	0.454		−0.146	0.417	−0.306	0.417
NonWhite	0.096***	0.011		0.068***	0.011	0.067***	0.011
Population under 19	0.262***	0.060		0.181***	0.058	0.177***	0.058
Population over 65	−0.219***	0.069		−0.240***	0.064	−0.218***	0.064
Married w/Children	−0.444***	0.047		−0.369***	0.046	−0.373***	0.045
Bachelor Degree	−0.011	0.027		−0.009	0.025	−0.003	0.025
Unemployed	0.117	0.072		0.069	0.068	0.055	0.068
Female Labor Force	−0.244***	0.038		−0.194***	0.036	−0.187***	0.036
Industry Diversity	−2.416	1.535		−1.628	1.455	−1.592	1.445
FIRE jobs	−0.225**	0.106		−0.255**	0.100	−0.252**	0.100
Natural Amenity	−1.233***	0.200		−0.872***	0.192	−0.907***	0.190
Constant	44.288***	4.878		34.621***	4.829	34.560***	4.811
R^2	0.657		Sq. Corr.	0.645			
Adjusted R^2	0.646		Var. Ratio	0.740			
N	414		*N*	414		414	

** $p < 0.05$,
*** $p < 0.01$.

Table 3.
Direct, Indirect, and Total Impacts for the Spatial 3SLS Model.

	Social capital (in the poverty model)		Poverty (in the social capital model)	
	Coef.	St Error	Coef.	St Error
Direct	−0.745***	0.201	−0.064***	0.022
Indirect	−0.360***	0.143	−0.053*	0.031
Total	−1.105***	0.326	−0.116**	0.050

* $p < 0.10$,
** $p < 0.05$,
*** $p < 0.01$.

metropolitan county, being adjacent to a metropolitan county, same county, and education level. Being a metropolitan county and being adjacent to a metropolitan county are both negatively correlated with social capital in our models, supporting the notion that social capital tends to be higher in rural areas. Education and percentage of population that are residents for at least one year are positively correlated with social capital, an outcome consistent with previous studies.

5. Conclusion

The key findings from our analysis are twofold. Once spatial autocorrelation and the endogeneity of poverty and social capital are accounted for, estimation results support the hypotheses that (1) building social capital is associated with lower levels of poverty and (2) the presence of poverty is a deterrent to building community-wide social capital, at least as it is defined in this study. With respect to the first finding, social networks may advance the diffusion of information about employment prospects, while social norms foster behavioral expectations (e.g. replicating neighbors' consumption patterns). Communities with more individuals that trust one another may be more likely to work together and initiate a new business or simply employ

Table 4
Coefficient estimates for social capital models.

Social capital	2SLS			Spatial 2SLS		Spatial 3SLS	
	Coef.	St Error		Coef.	St Error	Coef.	St Error
Poverty	−0.017	0.022		−0.043**	0.021	−0.059***	0.021
Social Capital Spatial Lag				0.515***	0.081	0.490***	0.080
Metro	−0.998***	0.173		−0.757***	0.173	−0.837***	0.173
Metro Adjacent	−0.713***	0.150		−0.474***	0.152	−0.492***	0.152
Ethnic Heterogeneity	−0.008*	0.005		−0.006	0.005	−0.004	0.005
Median Age	0.156*	0.094		0.107	0.092	0.132	0.092
Median Age Squared	−0.001	0.001		−0.001	0.001	−0.001	0.001
Population over 65	0.031	0.033		0.032	0.032	0.029	0.032
Same County	0.026	0.020		0.041**	0.020	0.043**	0.020
Bachelor Degree	0.027***	0.010		0.031***	0.009	0.030***	0.009
Unemployed	−0.067***	0.024		−0.032	0.024	−0.030	0.024
Female Labor Force	0.031**	0.014		−0.000	0.015	−0.005	0.015
Income Inequality	3.361	2.418		2.424	2.352	2.083	2.335
Constant	−12.859***	2.653		−8.550***	2.685	−8.694***	2.672
R^2	0.544		Sq. Corr.	0.516			
Adjusted R^2	0.530		Var. Ratio	0.616			
N	414		*N*	414		414	

* $p < 0.10$,
** $p < 0.05$,
*** $p < 0.01$.

local people versus sourcing labor from other places.

With respect to the second finding, individuals in poorer communities may be less likely to engage in activities conducive to strong social capital because they lack the material resources to do so. There are financial costs to joining some networks and groups, as well as social norms that differ based on economic class. Joining a golf club for example involves fees, particular attire, and customs that differ greatly from participating in a pick-up game of basketball. In addition, individuals focused on making ends meet may not have the time or wherewithal to participate in demanding civic organizations. Finally lower levels of trust among low income individuals (Iyer et al., 2005) may preclude involvement in income enhancing activities like higher education. In a case study of two impoverished London neighborhoods, Cattell (2001) found that social networks enabled access to coping resources; however, not all networks produced the same outcomes. Even if poor people participate in strong social networks, those networks may be less institutionalized and have fewer linkages to those with resources. The types of networks available depend on the social organization to which a person belongs and the forms of poverty a person faces. Willmott (1987) suggested that middle class people generally have wider, looser networks, and Pearlin (1985) found they have more resourceful social networks. Working class people have fewer opportunities to broaden theirs (Cattell, 2001).

These results only emerged when accounting for spatial correlation and simultaneity between poverty and social capital. The results are even stronger when the more efficient 3SLS estimator was used to account for cross-equation error correlation that may occur when the same omitted spatial variables affect both poverty and social capital. For example, religious affiliations in some areas (which tend to be geographically clustered in some parts of the western U.S.) may lead to a strong commitment to community involvement and support for community members in times of need, while also advocating a simple way of life that limits material accumulation. Other examples include social norms associated with a historical economic base such as cattle, timber, and mining or degrees of remoteness not captured by our metropolitan and metropolitan-adjacent variables.

Our analysis reveals the possibility that poverty and social capital are interconnected in a way that could lead either to more wealthy, civic, and networked communities or to a downward spiral of poverty with low levels of interaction among community members. These results especially have implications for policy-makers seeking to help communities that are trapped in a pattern of persistent poverty. In particular, policies for the alleviation of persistent poverty may be more effective if coupled with policies for building social capital, such as providing childcare and facilitators/organizers for community-building events or projects.

Our results are in line with findings in previous studies when it comes to potential determinants of poverty and social capital. Variables that stand out in our analysis include education, racial/ethnic relations, and female labor force participation. Investment in education may contribute to building social capital, considering the overwhelming evidence of their positive association. Policies that enhance tolerance for differences and that reverse historic and current policies of racial and ethnic discrimination can mitigate barriers to building trust and, hence, encourage investment in social capital in racially/ethnically diverse areas. A lack of paid parental leave and affordable childcare present barriers to female labor force participation that can be addressed by policy.

Our analysis also highlights the importance of accounting for spatial dimensions in studies of community well-being. The statistical significance of the spatial lag model in the poverty equation indicates that counties with high poverty levels are associated geographically with other high poverty counties. These results are consistent with other studies regarding the role of spatial dimensions on poverty and economic growth (de Dominicis et al., 2013; Duncan, 2000). Spatial proximity can foster opportunities to engage in market transactions and be in employer-employee relationships. Yet if there is a deficit of market activity or employment prospects in one community, a neighboring community receives no benefit from this adjacent place, reducing the amount of total economic activity that occurs. Likewise, the statistical significance of the spatial lag model in the social capital equation indicates that counties with high social capital levels are associated geographically with other high social capital counties. Spatial proximity can foster communication and learning among individuals. Hence, social networks and norms likely spread more easily between adjacent communities.

Because many factors that contribute to well-being are jointly determined with well-being, and because indicators of well-being are frequently spatially clustered, this situation is likely to be more common than has been typically recognized in the literature. Many of the control variables in the poverty and social capital models likely have some spatial dependence; thus, without accounting for geographic diffusion effects, those control variables appear to be more important than they truly are. The implication of our results for future research is that failure to adequately model the interrelationship between community well-being and social capital might result in erroneous statistical inferences and misleading policy recommendations.

One caveat to this study is its static nature; the model provides a snapshot in time. This static analysis provides new insights by addressing spatial relations and endogeneity at a point in time, thereby identifying the potential interconnectedness of the level of social capital and poverty. In fact, in studies of social capital development and poverty formation, it appears that spatial influences overwhelm temporal changes or fluctuations. Poverty generally persists over time in particular places in the U.S. (Call and Voss, 2016; Labao and Saenz, 2002). Social norms do not change rapidly either (Duncan, 2000). In their study of temporal and spatial variation in childhood poverty rates for example, Call and Voss (2016) show how over a 20-year period from 1990 to 2010, coefficient estimates are stable. Even immense changes in the U.S. economy did not much alter the fundamental relationships at work in their model. Rupasingha et al. (2006) used panel estimation to assess the factors that contribute to social capital using the same social capital index used here. They confirmed the majority of results obtained in separate regressions for two distinct time periods (i.e., 1980–1990 and 1990–1997).

That said, a recently released 2nd cycle of the American Community Survey and updated measurements of the social capital index may offer an opportunity to begin to explore some of the dynamics underlying the relationship our static analysis reveals. The dynamic relations are likely to be complex and only apparent by analyzing long-term data (i.e. more than a few decades) once such data become available. Nonetheless, the policy relevance of this work would be enhanced by an improved understanding of the time frame over which one might expect a community to respond to policies aimed at reducing poverty through investment in social capital.

Another important caveat is that the measure of social capital used here is not a comprehensive proxy for social capital. By relying on an accessible dataset on organizational membership, voting rates, and census response rates, other forms of social capital were not explored. Cohen (2001, p. 270) contends that poor community members are "creating new political and social formations invisible to social scientists looking for social capital in all the old places (national data sets) and in all the traditional forms." Civic organizations in the social capital index used here like public golf courses, professional organizations, and business associations are unlikely to represent or strongly benefit the poor.

A more refined concept of social capital may help us understand its effects. Some social capital studies have differentiated between bonding, bridging, and linking social capital (Woolcock, 2001). Bonding social capital refers to relations with people of *similar* backgrounds (e.g. education levels, ethnicity/race, language, political beliefs, and wealth) *within* your community, while bridging social capital refers to relations with people of *different* backgrounds *within* your community. Linking social capital is the relations with people *outside* your community who can influence community outcomes. Power dynamics of social relationships may be better understood by differentiating social capital into these three types. Recent case study research (Harrison et al., 2016) illustrates how these different types of social capital interact in three rural communities in the Pacific Northwest. Moving away from one-size-fits-all approaches to social capital measurement may help parse out the various dimensions of social norms and networks and facilitate analysis of how they interact.

In summary, our analysis demonstrated that social capital and poverty may be related in ways that are relevant in the quest to understand and to find ways to alleviate persistent poverty. We believe that there are at least two pathways to further our understanding of the nature of this relationship: first, by examining more carefully how the different forms of social capital interact with poverty in a community and, second, by exploring more carefully how these relationships evolve over time.

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References

Akcomak, I.S., Muller-Zick, H., 2015. Trust and inventive activity in Europe: causal, spatial and nonlinear forces. Ann. Reg. Sci. 1–40.
Akcomak, I.S., ter Weel, B., 2012. The impact of social capital on crime: evidence from the Netherlands. Reg. Sci. Urban. Econ. 42, 323–340.
Aker J.C. 2007. Social networks and household welfare in Tanzania: working together to get out of poverty. Available at SSRN: https://ssrn.com/abstract=995941 or http://dx.doi.org/10.2139/ssrn.995941.
Agrawal, A., Kapur, D., McHale, J., 2008. "How do spatial and social proximity influence knowledge flows?" Evidence from patent data. Urban Econ. 64, 258–269.
Alesina, A., La Ferrara, E., 2000. Participation in heterogeneous communities. Q. J. Econ. 115 (3), 847–904.
Anselin, L., Kelejian, H.H., 1997. Testing for spatial error autocorrelation in the presence of endogenous regressors. Int. Reg. Sci. Rev. 20 (1–2), 153–182.
Assensoh, Y., 2002. Inner city contexts, church attendance, and African–American political participation. J. Polit. 63, 886–901.
Atemnkeng, J.T., Vukenkeng, A.W., 2016. Does social capital really determine poverty? Evidence from a Cameroon household survey. Afr. J. Sci. Technol. Innovation Dev. 8 (1), 97–110.
Baltagi, B.H., Deng, Y., 2015. EC3SLS estimator for a simultaneous system of spatial autoregressive equations with random effects. Econometric Rev. 34 (6–10), 659–694.
Bebbington, A., 1999. Capitals and capabilities: a framework for analyzing peasant viability, rural livelihoods, and poverty. World Dev. 27 (12), 2021–2044.
Beugelsdijk, S., van Schaik, T., 2005. Social capital and growth in European regions: an empirical test. Eur. J. Polit. Econ. 21 (2), 301–324.
Blank, R.M., 2005. Poverty, policy, and place: how poverty and policies to alleviate poverty are shaped by local characteristics. Int. Reg. Sci. Rev. 28 (4), 441–464.
Blasio, G., Nuzzo, G., 2009. Historical traditions of civicness and local economic development. J. Reg. Sci. 50 (4), 833–857.
Blumenberg, E., Shiki, K., 2004. Spatial mismatch outside of large urban areas: an analysis of welfare recipients in Fresno County, California. Environ. Plann. C 22, 401–421.
Bourdieu, P., 1984. Distinction: A social Critique of the Judgment of Taste. Routledge, London.
Brehm, J., Rahn, W., 1997. Individual-level evidence for the causes and consequences of social capital. Am. J. Polit. Sci. 41 (3), 999–1023.
Briggs, X.S., 1998. Brown Kids in White Suburbs: housing mobility and the multiple faces of social capital. Hous. Policy Debate 9 (1), 177–221.
Call, M.A., Voss, P.R., 2016. Spatio-temporal dimensions of child poverty in America, 1990–2010. Environ. Plann. A 48 (1), 172–191.
Castle, E.N., 1998. A conceptual framework for the study of rural places. Am. J. Agric. Econ. 80 (3), 621–631.
Cattell, V., 2001. Poor people, poor places, and poor health: the mediating role of social networks and social capital. Soc. Sci. Med. 52, 1501–1516.
Charles, K.K., Kline, P., 2006. Relational costs and the production of social capital: evidence from carpooling. Econ. J. 116 (511), 581–604.
Cohen, C., 2001. Social capital, intervening institutions, and political power. In: Seagert, S., Thompson, P., Warren, M. (Eds.), Social Capital in Poor Communities. Russell Sage, New York, pp. 267–289.
Coleman, J.S., 1988. Social capital in the creation of human capital. Am. J. Sociol. 94, 95–120.
Crandall, M.S., Weber, B.A., 2004. Local social and economic conditions, spatial concentrations of poverty, and poverty dynamics. Am. J. Agric. Econ. 86 (5), 1276–1281.
Crescenzi, R., Gagliardi, L., Percoco, M., 2013. "Social capital and the innovative performance of Italian provinces. Environ. Plann. A 45, 908–929.
Davis, E.E., Weber, B.A., 2002. How much does local job growth improve employment outcomes of the rural working poor? Rev. Reg. Stud. 32, 255–274.
De Dominicis, L., Florax, R.J.G.M., de Groot, H.L.F, 2013. Regional clusters of innovative activity in Europe: are social capital and geographical proximity key determinants? Appl. Econ. 45, 2325–2335.
Deller, S.C., Tsai, T., Marcouiller, D.W., Donald, B.K., 2001. The role of amenities and quality of life in rural economic growth. Am. J. Agric. Econ. 83 (2), 352–365.
Dettori, B., Marrocu, E., Paci, R., 2012. Total factor productivity, intangible assets and spatial dependence in the European regions. Reg. Stud. 46 (1), 1401–1416.
Doh, S., McNeely, C.L., 2012. A multi-dimensional perspective on social capital and economic development: an exploratory analysis. Ann. Reg. Sci. 49, 821–843.
Duncan, C.M., 2000. Worlds Apart: Why Poverty Persists in Rural America. Yale University Press, New Haven, CT.
Durlauf, S., 2002. On the empirics of social capital. Econ. J. 112, F459–F479.
ERS [U.S. Department of Agriculture, Economic Research Service], 2005. Rural-urban commuting area codes. Accessed, 15 September 2011.. www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/.
Fazio, G., Lavecchia, L., 2013. Social capital formation across space: proximity and trust in European regions. Int. Reg. Sci. Rev. 36 (3), 296–321.
Fisher, M., 2007. Why is U.S. poverty higher in nonmetropolitan than in metropolitan areas? Growth Change 38, 56–76.
Flora, J.L., Sharp, J., Flora, C., Newlon, B., 1997. Entrepreneurial social infrastructure and locally initiated economic developing in the nonmetropolitan United States. Sociol. Q. 38 (4), 623–645.
Glaeser, E.L., Laibson, D., Sacerdote, B., 2002. An economic approach to social capital. Econ. J. 112 (483), F437–F458.
Glaeser, E.L., Laibson, D.I., Scheinkman, J.A., Soutter, C.L., 2000. Measuring trust. Q. J. Econ. 115 (3), 811–846.
Granovetter, M., 2005. The impact of social structure on economic outcomes. J. Econ. Perspect. 19, 33–50.
Granovetter, M., 1985. Economic action and social structure: the problem of embeddedness. Am. J. Sociol. 91 (3), 481–510.
Gundersen, C., Ziliak, J.P., 2004. Poverty and macroeconomic performance across space, race, and family structure. Demography 41 (1), 61–86.
Harrison, J.L., Montgomery, C.A., Bliss, J.C., 2016. Beyond the monolith: the role of bonding, bridging, and linking social capital in the cycle of adaptive capacity. Soc. Nat. Resources 29 (5), 525–539.
Hassan, R., Birungi, P., 2011. Social capital and poverty in Uganda. Dev. South. Afr. 28 (1), 19–37.
Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46 (6), 1251–1271.
Helliwell, J.F., Putnam, R.D., 1995. Economic growth and social capital in Italy. Eastern Econ. J. 21 (3), 295–307.
Irwin, E.G., Jeanty, P.W., Partridge, M.D., 2014. Amenity values versus land constraints: The spatial effects of natural landscape features on housing values. Land Econ. 90 (1), 61–78.
Irwin, E.G., Isserman, A., Kilkenny, M., Partridge, M., 2010. A century of research on rural development and regional issues. Am. J. Agric. Econ. 92 (2), 522–553.
Isserman, A., Fesser, E., Warren, D., 2009. Why some rural places prosper and others do not. Int. Reg. Sci. Rev. 32 (3), 300–342.
Iyer, S., Kitson, M., Toh, B., 2005. Social capital, economic growth and regional development. Reg. Stud. 39 (8), 1015–1040.
Jeanty, P.W., 2013. Stasacode. Accessed. www.stasacode.com 12 January 2013.
Jeanty, P.W., Partridge, M.D., Irwin, E.G., 2010. Estimation of a spatial simultaneous equation model population migration and housing price dynamics. Reg. Sci. Urban. Econ. 40, 343–352.
Kelejian, H.H., Prucha, I.R., 2004. Estimation of simultaneous systems of spatially interrelated cross sectional equations. Econometrics 118 (1-2), 27–50.
Kim, B-Y., Kang, Y., 2014. "Social capital and entrepreneurial activity: a pseudo-panel approach. Econ. Behav. Organ. 97, 47–60.
Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. Q. J. Econ. 112 (4), 1251–1288.
Kraybill, D.S., 1998. The view from economics: discussion of Castle's conceptual framework. Am. J. Agric. Econ. 80, 635–636.
Labao, L., Saenz, R., 2002. Spatial inequality and diversity as an emerging research area. Rural Sociol. 67 (4), 497–511.
Landry, R., Amara, N., Lamari, M., 2002. Does social capital determine innovation? To what extent? Technol. Forecasting Soc. Change 69 (7), 681–701.
Levernier, W., Partridge, M.D., Rickman, D.S., 2000. The causes of regional variations in U.S. poverty: a cross-country analysis. J. Reg. Sci. 40 (3), 473–497.
Levien, M., 2015. Social capital as obstacle to development: brokering land, norms, and trust in rural India. World Dev. 74, 77–92.
Maskell, P., 2000. Social capital, innovation, and competitiveness. In: Baron, S., Field, J., Schuller, T. (Eds.), Social Capital: Critical Perspectives. Oxford University Press, UK, pp. 111–123.
McGranahan, D., 1999. Natural Amenities Drive Rural Population Change. Agricultural Economic Report No. 781. www.ers.usda.gov/publications/aer781.
Nie, N., Junn, J., Stehlik-Barry, K., 1996. Education and Democratic Citizenship in America. University of Chicago Press, Chicago.
Nishi, A., Shirado, H., Rand, D.G., Christakis, N.A., 2015. "Inequality and visibility of wealth in experimental social networks. Nature 526, 426–429.

North, D.C., 1991. Institutions. J. Econ. Perspect. 5 (1), 97–112.
Oakerson, R.J., 1998. Politics, culture, and the rural academy: a response to Castle. Am. J. Agric. Econ. 80, 632–634.
Partridge, M.D., Rickman, D.S., 2008. Distance from urban agglomeration economies and rural poverty. J. Reg. Sci. 48 (2), 285–310.
Pearlin, L.I., 1985. Social structure and processes of social support. In: Cohen, S., Syme, S.L. (Eds.), Social Support and Health. Academic Press, New York, pp. 43–60.
Peiro-Palomino, J., Tortosa-Ausina, E., 2015. Social capital investment and economic growth: evidence for Spanish provinces. Spatial Econ. Anal. 10 (1), 102–126.
Portes, A., 2000. The two meanings of social capital. Sociol. Forum 15 (1), 1–12.
Putnam, R.D., 2000. Bowling Alone: The collapse and Revival of American Community. Schuster & Schuster, New York.
Putnam, R.D., 1993. Making Democracy Work: Civic Traditions in Modern Italy. Princeton University Press, Princeton.
Romero, I., Yu, Z., 2015. Analyzing the influence of social capital on self-employment: a study of Chinese immigrants. Ann. Reg. Sci. 54, 877–899.
Rost, K., 2011. The strength of strong ties in the creation of innovation. Res. Policy 40, 588–604.
Rupasingha, A., Goetz, S.J., 2008. US county-level social capital data, 1990-2005. The Northeast Regional Center for Rural Development. Penn State University, University Park, PA.
Rupasingha, A., Goetz, S.J., 2007. Social and political forces as determinants of poverty: a spatial analysis. J. Soc. Econ. 36 (4), 650–671.
Rupasingha, A., Goetz, S.J., Freshwater, D., 2006. The production of social capital in US counties. J. Soc. Econ. 35, 83–101.
Rupasingha, A., Goetz, S.J., Freshwater, D., 2000. Social capital and economic growth: a county-level analysis. J. Agric. Appl. Econ. 32 (3), 565–572.
Shideler, D.W., Kraybill, D.S., 2009. Social capital: an analysis of factors influencing investment. J. Soc. Econ. 38, 443–455.
Stimson, R.J., Stough, R.R., Roberts, B.H., 2006. Regional Economic Development. Springer-Verlag, Berlin.
Summers, G.F., Brown, D.L., 1998. A sociological perspective on rural studies. Am. J. Agric. Econ. 80 (3), 640–643.
Tabellini, G., 2010. Culture and institutions: economic development in the regions of Europe. J. Eur. Econ. Assoc. 8 (4), 677–716.
Tiepoh, M., Nah, G., Reimer, B., 2004. Social capital, information flows, and income creation in rural Canada: a cross-community analysis. J. Soc. Econ. 33, 427–448.
Tselios, V., Noback, I., van Dijk, J., McCann, P., 2015. Integration of immigrants, bridging social capital, ethnicity, and locality. J. Reg. Sci. 55 (3), 416–441.
U.S. Census Bureau, 2010. ACS 5-year estimates: United States Counties. Accessed, 15 March 2012,. www.factfinder2.census.gov.
Watson, P., Deller, S., 2017. Economic diversity, unemployment and the great recession. Q. Rev. Econ. Finance 64, 1–11.
Willmott, P., 1987. Friendship Networks and Social Support. Policy Studies Institute, London.
Woolcock, M., 2001. The place of social capital in understanding social and economic outcomes. Can. J. Policy Res. 2 (1), 1–17.
Zak, P.J., Knack, S., 2001. Trust and growth. Econ. J. 111, 295–321.