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Jointly Modeling the Community Capitals and Their Influence on Economic Resilience*

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Abstract: The concept of community resilience has garnered a great deal of attention in the past decade and many theoretical constructs have been proposed to model resilience, including the community capitals framework. However, while the community capitals framework has been developed theoretically and subcomponents have been quantified, little research has attempted to address the community capitals framework as a whole and test how well the theorical constructs fit together. Using a structural equation model, we empirically investigate the community capitals framework and test how variables identified in the literature combine to predict community resilience. We find that, while many variables in the theoretical literature perform poorly, the overall framework provides a compelling avenue for addressing economic resilience.
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1. INTRODUCTION

Using the community capitals framework allows us to account for many, diverse community characteristics and their interactions. This provides a snapshot of the local wealth and resources as well as the social, cultural, and political landscape of each area to add qualitative context to analyses of resilience employing our purely quantitative measure. The community capitals framework includes seven community capitals: social, cultural, political, human, financial, built (or physical), and natural capital. However, while these capitals have collectively introduced as a theoretical framework, the individual capitals tend to be empirically studied individually. This paper serves to build out a preliminary empirical framework for investigation how the community capitals interrelate and then extend this empirical framework to estimate the community capitals influence on economic resilience of counties in the United States. To conduct our analysis, we use factor analysis and structural equation modeling (SEM) to create latent variables representative of county community capital stocks and explore the direct and indirect effects of community capitals on regional

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economic resilience. With these methods, we use available data on observable characteristics of each county that we believe relate to or reflect local stocks of community capitals, which are not themselves directly observable. We use exploratory factor analysis (EFA) to observe the general behavior of the social, cultural, and political capital variables to observe how they covary, and see what factors emerge from the dataset before we impose any expectations. With the SEM, which combines concepts from confirmatory factor analysis and path analysis, we test our expectations about the relationships of our observed variables to the seven community capitals and regional economic resilience, included as latent variables, and the relationships of the community capitals to each other and to regional economic resilience to the Great Recession. This work provides a first look at how one might model regional economic resilience in terms of the community capitals framework using data available at the county level. We obtain mixed results overall, in terms of the performance of the model components and interpretability of results, but gain valuable insights and identify opportunities to improve future efforts to model resilience and other regional economic characteristics.

2. RELATED LITERATURE

2.1. The Community Capitals Framework

We are interested in building better understanding of the complex dynamics affecting regional resilience from a perspective that allows for the logical translation into guidance for economic development. The Community Capitals Framework is an existing research and measurement approach used to guide community program and policy design that we believe provides such a perspective. For this reason, we have elected to design a model which applies this framework in explaining variations in regional economic resilience to the Great Recession.

The Community Capitals Framework (CCF) was originally developed by Flora et al. (1992) and includes seven types of community capitals: social, cultural, political, human, financial, natural, and built (or physical) capital. Flora et al. (1992) observed that communities that were successfully supporting sustainable local community and economic development were focusing on these capitals. Since its creation, the CCF has been used as an analysis tool that allows researchers and community leaders alike to adopt a systems view of each community, accounting for resources endowments and institutions that contribute to the functioning of a region (Pender et al., 2012). The CCF is generally applied to guide efforts to promote economic, social, and environmental sustainability, design community development initiatives, and is used as a framework for explaining community development processes and potential investment interactions.

Applying the CCF in our model of resilience allows us to incorporate some of the rich contextual information about our counties that our resilience measure on its own does not. The potential of the CCF as an empirical modeling tool has been limited by a lack of understanding regarding how to quantify community capitals (Pigg et al., 2020). Knowing this, however, we attempt to model community capital stocks and their interactions using county-level data in a structural equation model which, to our knowledge, has not be done. As with most new modeling efforts, we encounter challenges, namely how to bridge the gaps between data availability and construct measurement and theory and empirical results. We do believe, however, that this preliminary work, and its limitations, can move the discussion of how to quantify community capitals forward.

2.2. Community Capital Definitions

The discussion of the community capitals throughout the literature is extensive for some capitals (i.e. social capital) and less developed for others. Here, in defining the community capitals, we focus primarily on the concepts put forth by Flora et al. (1992) and Pender et al. (2012) in their discussion of rural wealth creation.

2.2.1. Social Capital

Social capital refers to the level and nature of interaction among individuals within the same community and with those outside the community. Social capital also involves conceptual qualities like trust, standards of reciprocity and cooperation, shared goals, leadership and networks for collective action (Coleman, 1988; Flora et al., 1992; Putnam, 1995; Woolcock and Narayan, 2000; Woolcock, 2001). Woolcock (2001) describes it as "the norms and networks that facilitate collective action". Some divide social capital into two groups: bonding capital and bridging capital. Bonding capital "consists of connections among individuals and groups of similar backgrounds" (Flora et al., 1992) and bridging capital "connects diverse groups within the community to each other and to groups outside the community" (Flora et al., 1992). When both kinds of social capital are present, they can elevate each other, however, with one or both are absent, communities may find it difficult to adapt and evolve in the ways necessary for sustainable development. Without either form of social capital, individuals fend for themselves. With only bonding capital, a community may have a strong sense of unity but feel against the outside world or homogenous groups may form within the community that are unable to effectively communicate and collaborate for the benefit of the whole community (Flora et al., 1992).

2.2.2. Cultural Capital

Cultural capital has several components, some of which are more abstract, internal, and individual and others which are more observable and can be shared. The internal form of cultural capital refers to the way individuals view the world, what they can achieve within it, what change is possible, and what is important (Flora et al., 1992). In Bourdieu's The Forms of Capital, cultural capital's "embodied state" most closely aligns with this idea and is described as cultural capital's fundamental state, acquired through "work on oneself" or unconsciously through exposure to norms within an individual's society or social class (Bourdieu, 2018). Cultural capital can be reflected as an individual sense of identity, shaped by the values transmitted through families, schools, religious communities, or other social groups or organizations (Flora et al., 1992). Shared forms of cultural capital can be represented more observably in traditions, customs, objects, and media which can forge a shared sense of identity and shared sense of place among groups of people (Fey et al., 2006; Bourdieu, 2018). It is possible for individuals with contrasting cultural capital to exist within the same area, but sometimes a dominant group's values and customs will receive broader validation within the society and other groups may feel that they need to modify their behavior to reflect the other's values to be successful (Flora et al., 1992).

2.2.3. Political Capital

Political capital refers to the ability of citizens to translate the shared values of their community into rules that regulate the use and distribution of community resources (Flora et al., 1992; Emery and Flora, 2020). Citizens may be able to do this through their voting rights, connections to other people within and outside the community, and willingness to participate through avenues that can lead to policy formation and action. Power, however, is not always evenly distributed and political capital can tend to reflect the prevailing cultural capital (Flora et al., 1992). Political capital can also be thought of as political enfranchisement, analogous to the concept of economic enfranchisement presented in Hackett and Watson (2022).

2.2.4. Human Capital

Human capital refers to the personal assets of a community's members, reflected in their health, education, training, skills, and talents, and how these assets contribute to each member's ability to make a living and contribute to the community as a whole (Flora et al., 1992; Emery and Flora, 2020). Human capital is most often represented by formal educational attainment, however, knowledge and skills gained through experience can be as valuable in practice though more difficult to capture (Flora et al., 1992). Health as a form of human capital impacts individuals' ability to apply their education and abilities in work and other personal and community-serving pursuits. Without good health, knowledge-based human capital can be underutilized.

2.2.5. Financial Capital

Financial capital refers to the financial resources and wealth within a community. As community capitals go, financial capital is the most "mobile" (Flora et al., 1992) and available for investment in community capacity-building or business development projects (Lorenz, 1999). It can be represented by savings, access to loans and credit, donations and philanthropy, and income, among others. Income alone, however, is a somewhat convoluted measure of financial capital as it is influenced by characteristics of other capitals, like education, a component of human capital.

2.2.6. Natural Capital

Natural capital refers to the assets associated with a region's environment, geography, climate, and other natural characteristics associated with the region's location. Natural capital can include the land and its characteristics, water resources and quality, biodiversity, geographic isolation, weather, natural beauty, and other natural amenities and resources (Flora et al., 1992; Emery and Flora, 2020). Natural capital can be used to produce financial capital through activities like mining or logging, can affect social and cultural capital by influencing lifestyle behaviors and inspiring traditions, and can attract human capital (Flora et al., 1992; Florida, 2002; McGranahan and Wojan, 2007; Emery and Flora, 2020). Natural capital is in turn affected by political capital and the choices made in the public policy arena regarding land and resource use.

2.2.7. Built Capital

Built (or physical) capital refers to a community's physical, human-made infrastructure that supports production and the quality of life within the community. Four broad categories of built capital include water distribution facilities, solid waste disposal, transportation, and telecommunications (Flora et al., 1992; Emery and Flora, 2020). More specific examples of built capital include water supply systems, wastewater treatment and disposal, utilities, roads, bridges, airports, railways, telephone networks, broadband access, schools, hospitals, housing, and public spaces like parks and playgrounds (Flora et al., 1992). Built capital supports other capitals and more efficiently and inclusively serves the community when other capitals are present and functioning to make that possible (Emery and Flora, 2020).

2.3. Interactions among Community Capitals

The Community Capitals Framework illustrates how communities are dynamic, like an ecosystem, with features and elements that interact rather than existing in isolation from one another. Emery and Flora (2020) discuss these interactions and the ability of community capitals to build on one another (i.e. spiral-up) or initiate a domino-effect of capital loss (i.e. spiral down). For example, an increase in human capital via education can expose individuals to other cultures and ways of life, creating more openness to communication and interaction between groups of people (i.e. growing bridging capital), which could in turn lead to the formation of a stronger shared identity, which relates to both social and cultural capital. Reverse processes, however, are also possible. A shock, like a recession or the closure of a local factory, could lead to job loss that causes part of the population to relocate (i.e. loss of human capital), which could be accompanied by a loss in financial capital, and over time, a decline in the condition of built capital if there are not sufficient financial resources to maintain or update components of the region's physical infrastructure. All community capitals can relate to and influence one another, particularly over the long-term.

2.4. Relating Community Capitals to Resilience

Our work within this paper represents the first attempt to relate the full Community Capitals Framework to regional economic resilience. Existing research on economic resilience includes early efforts to explore and model resilience with the use of qualitative indicators which, in some cases, reflect community characteristics that fit logically within parts of the community capitals framework. Briguglio et al. (2009) employ measures of good governance and social development which are composed of indicators like judicial independence, impartiality of courts, and levels of education and health and relate most closely to the ideas of political and human capital. Kahsai et al. (2015) explicitly incorporate measures of human and physical capital in their resilience index and individual components of their entrepreneurial activity and business dynamics dimension could be viewed as relating to cultural capital (e.g. self-employment). Other efforts to model economic resilience with qualitative measures and indices include indicators of both vulnerability to adverse shocks and ability to recover and adjust in the wake of such shocks (Briguglio et al., 2009). In applying the community capitals framework, we are focusing primarily on the relationship of community capital stock to the ability of counties to respond to this recessionary shock, though future work could account for relative vulnerability to represent economic resilience in relation to level of exposure.

While the discussion of the attributes and community features included in or embodied by each community capital is rich with detail and depth, determining how to accurately and efficiently represent community capitals in an empirical model has its challenges. If we were to focus on a single community, we could generate a fairly comprehensive, qualitative inventory of that single community's capitals stocks, with some exceptions. Some more conceptual components of community capitals, like personal, internal forms of cultural capital, may not be directly measurable and would still require additional analysis techniques to expose and include in such an inventory. In our case, however, we face the added challenge of trying to compare the community capital stocks of all U.S. counties. This requires the collection of existing secondary data that are consistently measured or estimated by county and represent county characteristics that relate closely enough to each county's community capitals that we can use mathematical and statistical techniques to extract estimates of community capital stocks for inclusion in our model. This requires some creative thinking and, in many cases, means that the concepts of each community capital reflected in our model may be more abstract than the descriptions listed above. These descriptions, however, serve as a good basis for thinking about community capitals and the ways that they can be incorporated in empirical models through use of nationwide, county-level datasets.

3. DATA SELECTION, SOURCES, AND SCREENING

The seven community capitals will be incorporated into an empirical model using factor analysis and structural equation modeling (SEM). To do this, we begin with a set of observed, measured variables. In factor analysis, a smaller number of factors can be extracted from these data based on their shared variance and expectations about observed variable relationships to hypothesized constructs can be tested. Structural equation modeling includes the latter use of factor analysis with the addition of expectations regarding the directionality of relationships between variables. While our preliminary SEM will specify all observed variables as being reflective of the community capital they relate to, it is important to keep in mind whether these relationships are likely to be formative or reflective of social capital as more sophisticated SEM methods can feature design elements testing these assumptions.

3.1. Variable Selection and Data Sources

In factor analysis and SEM, it is ideal for each factor to be associated at least three observed variables, so we have identified and collected data for three or more potential variables for each of the seven community capitals. If necessary, two will suffice, but three or more is preferred. While more is generally better, too many observed variables can make it difficult to estimate and fit the model to the data (Bentler, 1980). We believe some observed variables may relate to more than one community capital and explore whether these expectations are supported in preliminary exploratory factor analysis results and our SEM design.

Our resilience measure is based on Ringwood et al. (2019) and is calculated using seasonally-adjusted monthly county employment data from the BLS spanning the years of 1990 to 2015. Because we have just one value of each resilience measure for each county and because we want to test directional relationships between community capitals and regional economic resilience, we use observed variable data from 2005 or closely prior (e.g. 2000) whenever possible to try to represent levels of community capitals prior to the start of local recessions. In some cases, however, our data come from years later than 2005.

3.1.1. Social Capital Observed Variables

Social capital relates to the connectedness and nature of relationships between people within a community, and with the community to the outside world (Flora et al., 1992). This can include concepts like trust, that are tricky to measure directly. Representing social capital is further complicated by the existence of the dual concepts of bonding and bridging social capital and their interactions. While bonding and bridging capital are not treated separately within our model, we are thoughtful of which type of social capital each of our observed variables mostly closely relates to. Additionally, we consider variables that may either relate to the presence or absence of social capital, as some other researchers have in existing studies (Akçomak and Ter Weel, 2012).

Our choice of observed variables related to social capital was guided largely by the work of (Rupasingha et al., 2006). We used several variables involved in the calculation of their Social Capital Index, including aggregate membership organizations and total number of non-profit organizations. Aggregate membership organizations include religious associations, civil and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, and sport clubs, managers, and promoters. These are all membership organizations, fitting with the concept of bonding social capital. Non-profit organizations exclude non-profits with an international approach and could relate to bonding social capital by rallying those who work for, interact with, or are served by a non-profit around a common cause and mission. Certain kinds of non-profits could contribute to bridging capital if their work fosters or strengthens connections between groups that might not otherwise interact. We do not use the social capital index itself because, while we do use some components of the index to represent social capital, there are two components, voter turnout (or voter participation rate) and census response rate, that we treat separately so we can explore their relationship to other capitals in addition to social capital. Following Rupasingha et al. (2006), we represent the aggregate membership organizations value relative to population, in our case, by simply dividing by the county population. Rupasingha et al. (2006) refer to this value as "associational density". Non-profits are left as a total.

The literature on social capital is lively and deep and while we pull from existing studies to identify our other social capital-related observed variables, our coverage represents just a fraction of the discussion on social capital indicators. The observed variables we select reflect crime rates (violent and property), female labor force participation, community attachment, homeownership rates, ethnic fractionalization (or diversity), rural-urban status, and percent family households. Rates of violent and property crimes appear to be negatively associated with social capital based on previous studies suggesting the communities with higher social capital had lower crimes when controlling for other community characteristics like population heterogeneity and education (Akçomak and Ter Weel, 2012).

Theoretically, high crime rates could reflect a lack of bridging capital rather than bonding capital. Youth gangs or mafia families provide classic examples of the presence of bonding social capital and absence of bridging capital (Portes, 1998). We explore the inclusion of female labor force participation rates knowing that the reasons women enter the workforce are highly variable. Putnam (1995) suggested that women as wives and mothers can generate social capital through involvement in school and church groups and time spent with friends and family, and that the movement of more women into the labor force is associated with a reduction in these specific sources of social capital. This relationship, however, was not empirically tested in that paper. Community attachment and homeownership are both viewed as associated with higher levels of social capital and conversely, migration, is considered negatively associated with social capital (Putnam, 1995; Glaeser and Sacerdote, 1999; DiPasquale and Glaeser, 1999). We represent community attachment with two variables. The first is the percent of the local population who, when the data were collected, were living in the same community that they had been living in five years before. The second measure of community attachment, reflecting a broader view of community, is the percent of residents who are native to the state in which the county is located. Even if residents are from different counties originally, if they live in the same state they were born, they may feel more connection to the area than if they were not and may have a more developed social network. Homeownership rates are represented by the percent of occupied housing units that are occupied by their owners. DiPasquale and Glaeser (1999) argue that homeowners have a greater incentive to improve their community and greater mobility barriers. Ethnic fractionalization, which some use as a measure of diversity, is associated with lower social capital (Alesina et al., 1999; Belton et al., 2018). We use the measure of ethnic fractionalization used by Alesina et al. (1999) represented by the following equation

$$Ethnic\ fractionalization_j = 1 - \sum_i (race_{i,j})^2 \tag{1}$$

where $race_i$ refers to the share of the population that self-identifies as Race i in county j. For our calculations, the races represented include white (not Hispanic), African American, Asian, American Indian or Alaska Native, Native Hawaiian or Pacific Islander, or Hispanic. Rural-urban status is included though there are conflicting arguments regarding its relationship to social capital with some suggesting that large cities with people living near one another have higher social capital and others arguing that in rural areas, collective behavior is more essential to providing services to local community (e.g. volunteer fire departments) (Browne, 2001; Glaeser et al., 2002). One study differentiates between bonding and bridging capital and finds that bonding capital is significantly higher in rural areas while bridging capital is marginally higher in urban areas (Sørensen, 2016). We include rural-urban status as an ordinal variable generated from the rural-urban continuum code where the lowest value represents urban (i.e. metro area), the middle value represents suburban (i.e. non-metro area that is metro-adjacent), and the highest value represents rural (i.e. non-metro and not metro-adjacent). Finally, we include percent family households, though like rural-urban status, there are opposing arguments within the literature regarding the relationship of marriage status and families to overall social capital (Putnam, 1995; Alesina and La Ferrara, 2000).

We explore the inclusion of poverty and income inequality variables. Rupasingha et al. (2006) argue that greater income inequality can reduce social capital as those with lower income may feel exploited and disconnected. Following Rupasingha et al. (2006) as well as Alesina and La Ferrara (2000), we use the ratio of mean to median household income to represent income inequality. We also explore the behavior of Gini coefficients and poverty levels in our analysis. Violent and property crimes rates come from 2005 Department of Justice and Federal Bureau of Investigation data. Female labor force participation data comes from 2005-2009 ACS data. Community attachment is measured both as the percent of residents in 2000 who had lived in the same county since 1995 or before, based on 2000 Census data, and as percent of local individuals who are native to their current state of residence, based on 2005-2009 ACS data. Homeownership rates are generated using data from 2005-2009 ACS data as the percent of occupied housing units that were occupied by homeowners. Ethnic fractionalization was calculated using 2000 Census data.

3.1.2. Cultural Capital Observed Variables

Cultural capital relates to how individuals view the world, including their beliefs about what they can achieve and change as well as their sense of identity (Flora, 2018). To capture something akin to the mindset and personal identity of individuals living in a region is a tall order. In addition to the difficulty of representing the internal aspects of cultural capital, we recognize that representing a quality as individual as culture in aggregate is not an ideal representation of this capital. Even direct surveys of all individuals could not capture such complex, internal dynamics, however, we try with the data we have at the county-level to scratch at the surface of the collective cultural orientation of each county. We do this by focusing on variables that capture one of three characteristics: (1) characteristics of firm owners (i.e. how reflective firm owners are of the population) and levels of self-employment, (2) the characteristics and prevalence of entities that serve as conduits of culture, and (3) presence of culture-transmitting professionals and institutions. Data for this capital came from the ACS, Institute of Museum and Library services, and the USDA ERS's Creative Class Codes. Within the first category of cultural-related observed variables, we have one experimental measure representing a deviation in the share of businesses across races and ethnicities, i, in a given region j from the share at the national level; we will refer to this measure as ethnic enfranchisement for simplicity. The goal of this variable is to measure how reflective the firm owners are of the local population in terms of race and ethnicity, or rather how the share of each race or ethnicity within the population compares to the share of each race or ethnicity among firm owners. This variable was calculated using the following equation

$$\text{Ethnic Enfranchisement}_j = -\sum_i \left| \frac{\text{Difference between Firm Owner Share and Population Share}_{i,j}}{\text{mean}\left(\left|\text{Difference between Firm Owner Share and Population Share}_i\right|\right)} \right| \tag{2}$$

where i represents each race or ethnicity group, which includes white (non-Hispanic), African American, Asian, American Indian or Alaska Native, Native Hawaiian or Pacific Islander, and Hispanic or Latino, j represents each county, and where

$$\left|\text{Difference between Firm Owner Share and Population Share}_{i,j}\right| = \left|\left(\frac{\text{Population}_{i,j}}{\text{Total Population}_j}\right) - \left(\frac{\text{Firm owners}_{i,j}}{\text{Total Firm Owners}_j}\right)\right| \tag{3}$$

The value of the measure, based in this calculation, is likely to be higher among counties with more racially homogenous population. For example, if all residents belong to one race, all firm owners residing in this county will be of that race as well and that county will score high in ethnic enfranchisement, or rather, will have a value close to zero. We recognize that this is a major limitation of this measure represented in this way. We argue, however, that this calculation, while correlated with ethnic fractionalization (or diversity), tells us something beyond that. We use it experimentally in our analysis, but are interested in exploring improvements to this measure and other ways to get at cultural capital implicitly. Additional measures within this first category of cultural observed variables include percent women firm owners and ratio of proprietor to wage and salary employment.

For the second category of cultural-related observed variables, those reflective of local conduits of culture, we include average household size and rate of religious adherence as households and churches are both avenues for the spread of cultural capital.

For the final category of cultural-related observed variables, we include museums per capita and artistic share of the workforce. “Museums” include a wide variety of institutions and community features including art, history, natural history, science and children’s museums as well as arboretums, botanical gardens, historical societies, zoos, and aquariums, among others. Artistic share of the workforce includes individuals working as fine, performing, and applied artists.

3.1.3. Political Capital Observed Variables

Political capital relates to the level of political engagement of citizens and how well shared values can be incorporated and translated into the policies and rules governing the community (Flora, 2018). We measure this with observed variables including voter turnout, census response rates, political contributions per capita (count and total value), and political organizations per capita. Data on political contributions are obtained from the Sunlight Foundation where location-based analysis was performed using federal campaign finance data. All political observed variables relate to the political engagement of citizens, however, in theory there are lower costs to voting and completing a census than to contributing to political campaigns or organizations. Both voter turnout and census response rates have been tied to social capital in other studies, but since our analysis includes political capital, we will assign these variables to political capital, though we explore their relationship to social and cultural capital in our exploratory factor analysis (Rupasingha et al., 2006). Voter participation, for example, could be reflective of political capital in the choice of citizens to participate politically, but it also reflects a belief that one's vote matters and can contribute to changing (or maintaining) one's community environment and the options of individuals who live there. This quality has conceptual ties to cultural capital.

3.1.4. Human Capital Observed Variables

Human capital refers to the personal assets of a community's members and their ability to contribute to the community as a whole (Flora and Flora, 2013). In our analysis, human capital is represented primarily through education and health-related data. Human capital variables include the dependency ratio and alternatively, the percent of the population age 18 to 64 only, total labor force participation, percent of the population who completed high school, percent of the population with bachelor's degrees or higher, drop-out rates, creative share of the workforce, population without health insurance, obesity rates, diabetes prevalence (diagnosed), mortality rates, physical activity, and life expectancy. We expect many of these variables to be highly correlated given the consistently strong association of education and health represented by a variety of measures (Kitagawa and Hauser, 1973; Cutler and Lleras-Muney, 2006). The dependency ratio is one way of representing the age distribution of the population as a ratio of the non-working age population (i.e. children and elderly) to the working-age population. The World Bank uses this measure and represents dependents as those ages 0 to 14 and 65 and older and working-age individuals as those ages 15 to 64. We represent dependents as those under the age of 18 and over the age of 65 and working-age individuals as those ages 18 to 64. We would expect that as the value of the dependency ratio decreases (number of dependents relative to working-age population decreasing), we would see greater human capital. We know, however, that some communities may have people who are classified as dependents according to this measure who contribute greatly in the form of human knowledge and skills, through the labor force or other avenues. All other variables are obtained from the Census and the Centers for Disease Control (CDC) and are represented as rates or percentages. We expect higher levels of education and higher levels of health and access to health care to be associated with higher levels of human capital.

3.1.5. Financial Capital Observed Variables

Financial capital relates to the monetary resources and assets held by community members. It is the capital that can be most easily converted into other forms of capital. Our observed variables related to financial capital include dividends per capita, interest per capita, and deposits per capita which are reflective of investments and savings. Data on dividends, interest, and rents per capita are generated from 2005 data from the Internal Revenue Service (IRS). Deposits data come from Federal Deposits Insurance Corporation (FDIC) and measure the number of deposits in the month of June 2005. We choose to exclude measures like personal income per capita as this is influenced by non-financial characteristics of individuals like level of education.

3.1.6. Natural Capital Observed Variables

Natural capital relates to the climate, natural amenities, and resources of a region. We represent this primarily through the inclusion of the individual components of the USDA's Natural Amenity scale (i.e. average January temperature, average days of sun in January, average July temperature, average July humidity, topographic variation, and water area as proportion of total county area)[1] with the addition of measures of air pollution, percent area in farms, value of crop sales per acre, and ratio of federal land to total land (McGranahan and Wojan, 2007). Air pollution is represented as the number of days in a year (i.e. 2005) when air quality was considered unhealthy due to particulate matter or ozone. Percent area in farms is included a one representation of the use of local land resources as an input to production. Value of crop sales per acre is included to represent, where crop farming exists, the relative value per acre of production. Conservation efforts and outdoor recreational opportunities are lumped into some discussions of natural capital, so the ratio of federally-owned land was included for its relationship to conservation and public access for recreation. Natural capital encompasses many types of resources and area characteristics, some of which may not strongly covary, which may make it difficult to represent as a latent variable.

3.1.7. Built Capital Observed Variables

Built capital includes man-made features and infrastructure, including those related to housing, transportation, and communication. Our built capital observed variables include county proximity to major airports, number of public-use airports which provide air-taxi services (i.e. transport passengers and/or mail), housing units, Amtrak miles and stations, road miles of Interstates, U.S. and state highways, and county roads, total hospitals, and broadband coverage represented by prevalence of broadband service with download speeds of 3 megabytes per second (mbps) or higher. In our models, all but proximity to major airports and broadband coverage are adjusted for area and represented as per square mile values.

[1]https://www.ers.usda.gov/data-products/natural-amenities-scale/documentation/

4. EXPLORATORY FACTOR ANALYSIS: METHOD AND RESULTS

We use exploratory factor analysis (EFA) as an intermediate step in our analysis to explore the relationships between our observed variables for social, cultural, and political capital as they may be related to more than one community capital or may require recategorization. In general, we want to observe how these data move in relation to each other and observe their clustering tendencies. As mentioned before, voter turnout has been used in measures of social capital, but we are opting to include voter turnout as a measure associated with political capital and want to see how it relates to cultural capital variables (Rupasingha et al., 2006). We will also look at the behavior of poverty levels and income inequality. Inequality surfaces in the literature as potentially relating to social capital, but we want to explore its behavior before deciding whether to include it in our SEM.

4.1. EFA Method

In factor analysis, we identify relationships between observed variables and a smaller set of underlying variables. These underlying variables, which go by several terms including latent variables or factors, often represent ideas or concepts that cannot be directly measured or observed. Factor analysis is useful, therefore, for several purposes. Researchers can use factor analysis to extract factors that can summarize the variation among many observed variables with relatively fewer latent variables and it can provide a method for indirectly measuring latent constructs through careful selection and analysis of observed variables believe to be related to or reflective of these underlying concepts.

There are two types of factor analysis: exploratory factor analysis and confirmatory factor analysis. The concept of confirmatory factor analysis is rolled into structural equation modeling methods and will be discussed more in the next section. We are using exploratory factor analysis here as an intermediate step in our analysis to look more closely at the behavior of the observed variables we have collected related to social, cultural, and political capital.

Constructing a set of observed variables from secondary data available at the county-level that successfully captures the abstractness, multidimensionality, and interconnectedness of these capitals is challenging. We believe the observed variables we have collected and created relate to and reflect these capitals, but are aware that they may relate to more than one community capital and may reflect other community characteristics outside of the scope of the community capitals framework. EFA allows us to explore the behavior of these variables more, particularly how they cluster and covary, prior to the imposing any expectations in our structural equation model (Alavifar et al., 2012).

In exploratory factor analysis, each observed variable is modeled as a dependent variable explained by a series of underlying factors, serving as explanatory variables. The following set of equations illustrates these relationships

$$
\begin{aligned}
v_1 &= a_{11}F_1 + a_{12}F_2 + \ldots + a_{1m}F_m + a_1u_1 \\
v_2 &= a_{21}F_1 + a_{22}F_2 + \ldots + a_{2m}F_m + a_2u_2 \\
&\vdots \\
v_n &= a_{n1}F_1 + a_{n2}F_2 + \ldots + a_{nm}F_m + a_nu_n
\end{aligned} \tag{4}
$$

where each v represents an observed variable, each F represents an underlying factor, and each u represents the uniqueness of the observed variable, or the portion of the observed variable's variation that is not explained by the factors that have been extracted. With factor analysis, we are essentially trying to find the values of the coefficients (a_{11} to a_{nm}) which best reproduce the values of the observed variables from the extracted factors. These coefficients are called factor loadings. They can be interpreted similarly to regression coefficients. If the factors are uncorrelated, the coefficients can be interpreted as correlations and the sum of the squared loadings represents the amount of that variable's variance that is accounted for by the factors. This value is known as the communality. The sum of the squared loadings, or coefficients, by factor represents the amount of variance accounted for by that specific factor and is referred to as a factor's eigenvalue.

There are several methods of extracting factors from the correlation or variance-covariance matrix. Two of the primary methods are principal axis factoring and principal component analysis. We use principal axis factoring which analyzes shared variance and allows for there to be some amount of unique variance that is not accounted for by the factors. Principal component analysis, on the other hand, will continue extracting factors until virtually all variance has been accounted for. This is more useful as a variable reduction technique.

In initial factor extraction, variables often load most heavily on the first factor and some rotation is generally performed. There are numerous rotation methods and two primary categories of rotation: orthogonal and oblique. Orthogonal rotation methods assume that factors are uncorrelated and oblique rotation methods assume that factors are correlated.

In our use of exploratory factor analysis, we use the principal axis extraction method and compare the results from four EFAs, two using the original data (one using orthogonal and one using oblique rotation methods) and two using the data with log transformations applied to variables with issues of non-normal distribution (one using orthogonal and one using oblique rotation methods). We focus our interpretation of these results on the eigenvalues, factor loadings, and uniqueness values associated with the rotated factors to gain more information about the behavior of our social, cultural, and political observed variables. Also, it is worth noting that since we are not specifying a model or testing any expectations, factors extracted in this process are not assumed to represent these community capitals specifically.

4.2. EFA Results

The primary observations that we make looking at the results from our four EFAs are

The primary observations that we make looking at the results from our four Exploratory Factor Analyses (EFAs) are

1. Our observed variables for social, political, and cultural capital do not clearly cluster along the lines of their hypothesized community capital associations.

2. In each EFA, seven or more factors had eigenvalues greater than 1.0, suggesting the presence of patterns in the variances and covariances within the data well beyond the number of capitals we want to measure.

3. Repeated clustering occurs (based on factor loadings) between measures of poverty and inequality (in all EFAs), museums per capita and average household size (loadings inversely related in three of four EFAs), violent crime rates and property crime rates (in all EFAs), both measures of community attachment (in all EFAs), and ethnic enfranchisement and ethnic fractionalization have high loadings on the same factors but in opposite directions.

4. Percent of women-owned firms and political organizations per capita have high uniqueness values in all EFAs, which suggests that their variation behavior is relatively unexplained by the first ten factors extracted in each of these EFAs.

The results of our exploratory factor analyses demonstrate that representing and differentiating between these three community capitals in not a clear-cut task and that there are numerous undercurrents affecting the values and variance of these data. The strong association between the three variables representing poverty and income equality may offer an argument for excluding them from the SEM or relating them to multiple capitals. If they are all assigned to measure the same single capital, their strong relationships will reinforce each other and potentially overpower the relationships between other observed variables within the capital, causing the associated capital to reflect measures of inequality and poverty, more than anything else.

The behavior of voter participation and census response rates based on these EFAs did not show many repeated or potentially meaningful patterns to argue for or against recategorization. We will keep it as a political capital observed variable as we believe it is a theoretically strong measure of levels of political engagement in a region.

5. STRUCTURAL EQUATION MODEL: METHODS AND RESULTS

Structural equation modeling, like many statistical analysis techniques, is part art and part science. We conduct our analysis recognizing the limitations of our data and the complexity of the issues we are tackling. We are motivated by the desire to assess the potential use of existing available data in applying the community capital framework in an empirical model of resilience. We expect to obtain results that do not perfectly back existing theory and research findings and hope that such mixed results will spur discussion of ways to improve future modeling efforts applying the community capitals framework to answer community and regional level questions.

5.1. SEM Method

Structural equation modeling combines the methods of path analysis, confirmatory factor analysis, and multiple regression. Structural equation models include a structural model and a measurement model. Concepts from path analysis apply to the structural model which consists of directional relationships between variables to test causal hypotheses (Maruyama, 1997). Confirmatory factor analysis pertains to the measurement model within a structural equation model where covariances or correlations among observed variables are used to indirectly measure latent constructs, in our case, the community capitals and regional economic resilience. Traditional path analysis requires the use of observed variables exclusively, but the marriage of path analysis and confirmatory factor analysis methods within SEM allows us to test relationships and causal hypotheses involving latent variables. Multiple regression practices are used in the process of estimating parameters.

In our preliminary model, the seven community capitals and regional economic resilience will be represented as latent variables. Regional economic resilience, as a latent variable, loads on several resilience-related observed variables, including our own measure of resilience as well as our expected variation measure and dimensions of resilience in the existing literature, like *drop* and *rebound* (Han and Goetz, 2015). Since we include the rebound from Ringwood et al. (2019) in this model, our resilience observed variable (and expected variation) has been recalculated for just the local recession months. The drop measure used in this model represents the difference between long-term trend predicted employment and actual employment at the trough. Measures of drop are made comparable by dividing by peak employment. *Rebound* is calculated using the method proposed by Han and Goetz (2015) which represents the velocity of each region's recovery after a shock and represented in their paper by the equation below:

$$Rebound = \frac{y_{t_3} - y_{t_2}}{y_{t_2}} \times \frac{1}{t_3 - t_2} \tag{5}$$

here y represents employment levels, t_2 represents the trough month, and t_3 takes place after the trough month ($t_3 > t_2$). For the calculation of *rebound* used by Han and Goetz (2015), t_3 represents six months beyond the trough month. We use this same six-month time span to calculate our value of *rebound*. Our calculation of *rebound* therefore looks like the following

$$Rebound = \frac{Emp_{trough+6m} - Emp_{trough}}{Emp_{trough}} \times \frac{1}{t_{trough+6m} - t_{trough}} \tag{6}$$

Our full measurement model consists of the connections of observed variables to their associated community capital or regional economic resilience. Our structural model includes covariances between the community capitals and direct effects of the community capitals on regional economic resilience. Our preliminary model includes all observed variables previously discussed, except for those dropped in the data screening process for exhibiting correlations higher than 0.90 with other observed variables. This model serves as starting point for exploring the use of SEM to model the community capitals framework and the potential causal relationships between each of the community capitals as resilience and we explore modifications to improve overall model fit and characteristics.

Structural equation models can include exogenous and endogenous variables among both latent and observed variables. Endogenous variables are presumed to be determined, at least in part, by causes within the model. Endogenous variables include all our observed variables, which we model initially as being reflective of their associated community capital or regional economic resilience rather than formative.[2]. Our resilience latent variable is also endogenous to the model as we are testing the existence of causal relationships between the community capitals and resilience. Each observed variable has an associated error term, representing measurement error, or the amount of variance not explained by its associated community capital(s). Regional economic resilience has a disturbance term, representing the variance in resilience not explained by its direct causes, our community capitals.

Once parameters have been estimated, one can analyze both the direct and indirect effects within the model. Indirect effects are the effects of one variable that are passed through an intermediate variable. For example, we might hypothesize that local stock of human capital directly affects regional economic resilience. We might also argue that an individual's decision of whether to go to college and earn a bachelor's degree is affected by an individual's view of the world and what he or she can achieve in it, implying that cultural capital directly affects human capital. If we were to model our SEM to reflect these potential connections, then our model would include an indirect effect of cultural capital on regional economic resilience. In other words, if cultural capital influences human capital and human capital influences resilience, then cultural capital influences resilience via human capital, our intermediate variable. If cultural capital also has a direct effect on economic resilience, its total effect would be the sum on its direct effect and all indirect effects tracing back to cultural capital within the model. Indirect effects also allow us to control for common causes within our model. For example, say social capital and cultural capital are both influenced by education, a form of human capital. If we do not account for their mutual connection to human capital, we might think they are highly correlated because they are similar to one another when, in fact, they may be highly correlated because they share a common cause. In this way, indirect effects also allow us to differentiate between meaningful and spurious correlations. The models in this paper are not specified in a way that allows for these indirect effects to be calculated (e.g. the indirect effect of human capital on resilience via other community capitals, like social or cultural), however, alternative models could estimate such effects.

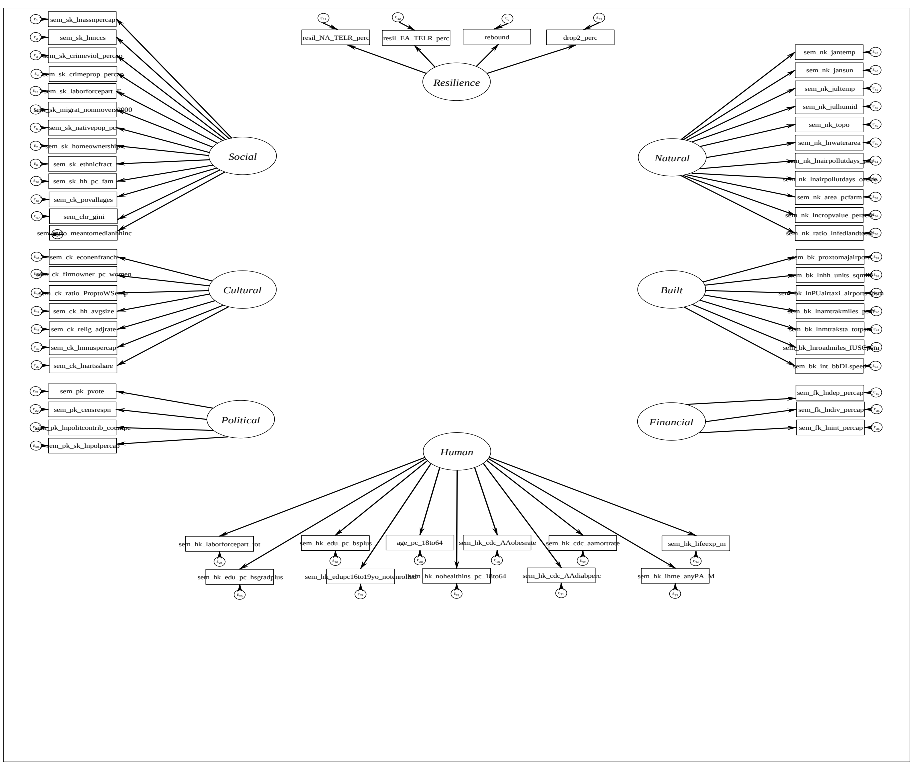
The value of structural equation modeling over other forms of analysis, like multiple regression, depends partly on the purpose or goal of analysis. If the goal of analysis is prediction, multiple regression is just as, or more, appropriate than SEM. If the goal of analysis is explanation, SEM becomes more valuable because not only can it explain how well predictors explain variation in the predictor variable, but it can also be used to distinguish between the relationship of predictor variables to the variables they explain as well as to each other (Maruyama, 1997). Also, the use of latent variables in SEM can put situations of high correlations between predictors or observed variables that might cause multicollinearity issues in multiple regression to use in the identification and representation of constructs (Maruyama, 1997).

[2]Observed variables can be viewed as reflective or formative and there are SEM models that allow for the inclusion of both reflective and formative observed variables assigned to a single community capitals. One example of such models is the "Multiple Indicator, Multiple Cause" (MIMIC) model (Kline, 2012)

5.2. The SEM Model and Modifications

The first step of structural equation modeling is to specify a model. The individual components of our initial measurement model are summarized below in Figure 1 which includes all latent variables and observed variables. Rectangles represent observed variables and ovals represent latent variables and circles represent error or disturbance terms. Single-headed arrows moving from a latent variable to an observed variable signify that the observed variable is reflective of the community capital stock. A single-headed arrow moving from an error term to an observed variable signifies the relationship of that observed variable to its omitted causes. In the process of running our SEM, path coefficients are estimated for each of these arrows and are analogous to the estimation of a coefficient associated with an explanatory variable (i.e. each community capital, resilience latent variable, or error term) in a regression equation where the observed variable is the dependent variable.

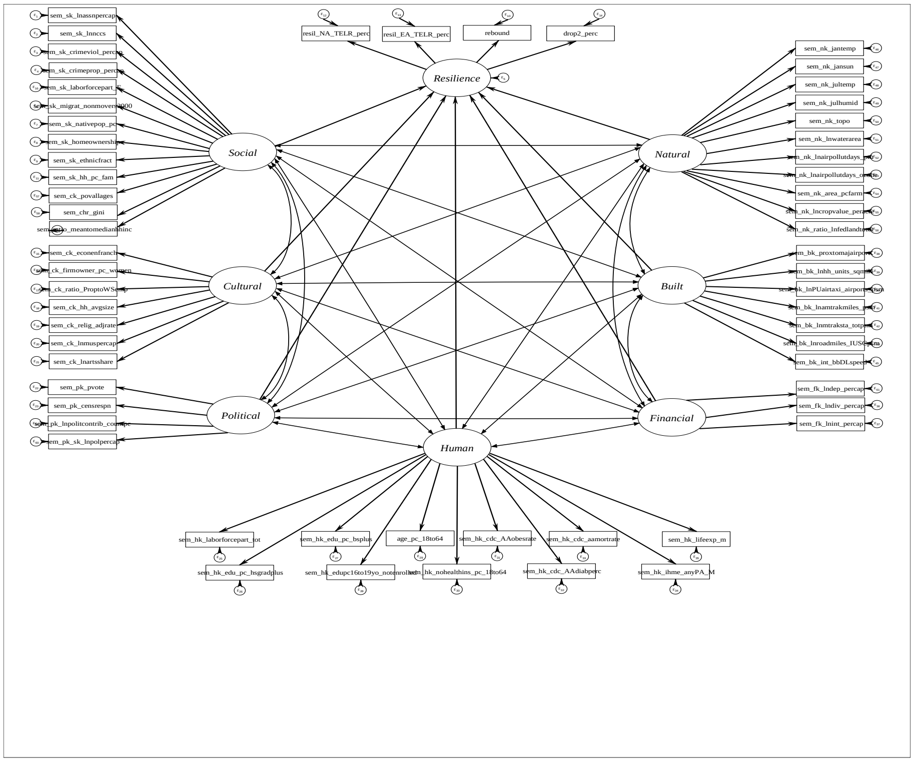
Figure 1: Measurement Model Components of SEM



For the structural model, we connect our community capitals to each other and to resilience, based on our expectations about their relationships. Connections with a single-headed arrow signify a direct effect and connections with a double-headed arrow signify a covariance. The arrows for covariance allow the model to account for the covariance between the two variables without imposing any expectations about their relationship or causality. We connect each of the community capitals to one another in this way. Figure 2 below shows the full SEM, combining the measurement and structural models.

The second step in structural equation modeling, once a model has been specified, is to

Figure 2: Full SEM



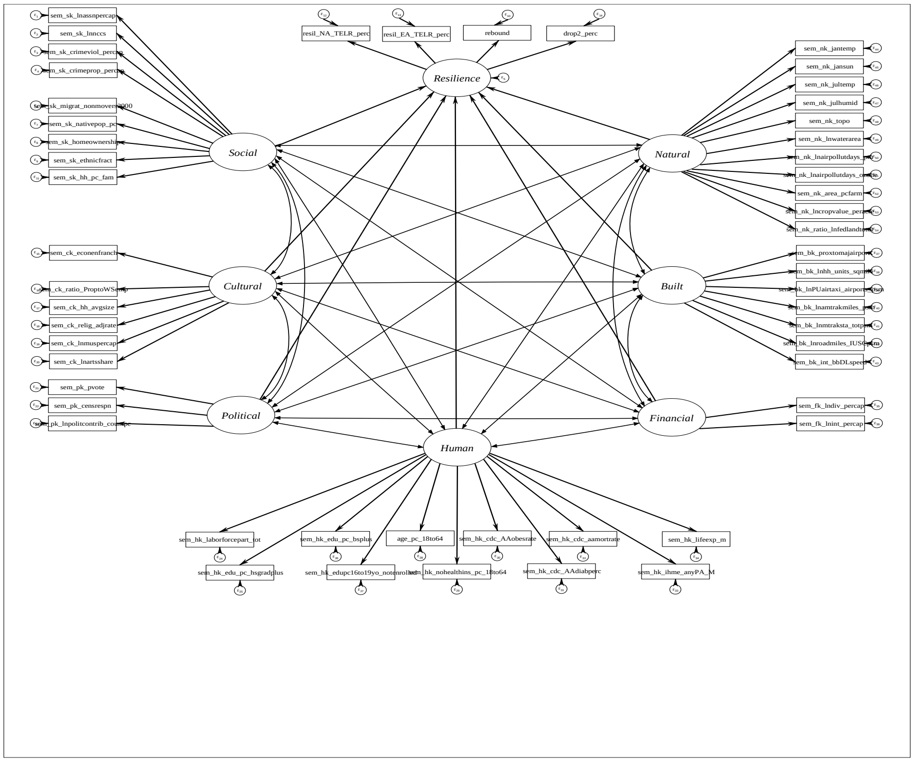
determine if the model is identified. If a model is identified, it means that it will be possible to calculate a unique estimate for each of our parameters. To do this, our model must have at least as many knowns and unknowns, where knowns are the unique values of the correlation or variance-covariance matrix (including diagonal and upper or lower triangle) and unknowns are the number of parameters we are trying to estimate. We can calculate the number of known values as $v(v+1)/2$ where v is the number of observed variables. A model is said to be just-identified if the number of knowns is equal to the number of unknowns, over-identified if there are more knowns than unknowns, and under-identified if there are fewer knowns than unknowns. A model's degrees of freedom are calculated as the difference between the unique variance-covariance or correlation matrix values and the number of parameters to be estimated.

The third step is to select our variables and prepare and screen the data. We did this previously to perform our exploratory factor analysis and based on the observations we made about the data in that process, we have elected to run our preliminary SEM with log transformations applied to the variables that are severely right-skewed.

The fourth step is to run the model and generate parameter estimates for all U.S. counties. We find that the model, as specified, is not able to converge on a unique solution, so we move directly into options for respecification.

We choose to explore options for modifying and respecifying the overall model by looking at the individual measurement components first. From the EFA, we have some ideas about variables that may not be representative of the corresponding community capital they were

Figure 3: Modified SEM



included to explain (e.g. percent female firm owners for cultural capital given high uniqueness value in EFA) or ones that may cluster due to a shared characteristic other than the concept of the community capital we intend to measure (e.g. strong associations between poverty levels, Gini coefficient, and mean to median income ratio reflecting inequality). In the case of the latter, the EFA suggested that the strong representation of inequality through the inclusion of three highly related observed variables could potentially overpower other associations and the latent variable we designate to represent social capital might become most reflective of inequality levels. In running mini-SEMs for each of the community capital measurement models, we compare the initial SEMs measurement model for each to modified ones and then, based on comparative goodness of fit tests (i.e. AIC and BIC, standardized root mean squared residual, and coefficient of determination), replace the individual community capital measurement models in the overall SEM with the specified individual models that performed best based on goodness of fit. Changes to create this SEM included dropping female participation rate, poverty levels, Gini coefficients, and mean to median income ratio for social capital, percent female firm owners for cultural capital, and political organization per capita for political capital. For human capital, dependency ratio was replaced with one of its calculation components, individuals ages 18 to 64, and creative share of the workforce was excluded for greater parsimony given its high correlation with another observed variable, percent of the population with a bachelor's degree or higher. Deposits per capita (log) are dropped from financial capital due to convergence issues. The resulting respecified SEM is shown below (Figure 3)

It would be ideal to compare to original SEM with the modified SEM, but due to convergence issues with the full model, we run each without the inclusion of our resilience latent variable and the associated direct effects of each community capital on resilience, in essence, testing how well each represent the community capitals framework overall, on its own. In comparing the goodness of fit of each of these models, we find that the modified community capitals SEM outperforms the initial, full community capitals SEM based on the standardized root mean squared residual values (SRMR), 0.173 and 0.182 respectively. A "good" model, however, that fits the data well would have an SRMR value of 0.08 or lower, so we cannot say that either of these are particularly strong models (Hu and Bentler, 1999). Also, both models produce a fitted model that is not full rank, so other measures of goodness of fit cannot be run.

We move forward to reintroduce the resilience latent variable and the direct effects of the community capitals on resilience and estimate the model (represented in Figure 4). This model produces has an SRMR value of 0.167, improving slightly over our modified SEM with the community capitals alone (Table 1 shows goodness of fit tests for the three models we ran), but still not low enough to be considered a good fit for the data.

Table 1: Overall Goodness of Fit Comparison of SEMs

Fit statistic	SEM 1	SEM 2	SEM 3 (Mod. SEM)	Description
Information criteria				
AIC	329290.204	282611.756	275081.704	Akaike's information criterion
BIC	330290.485	283490.933	275972.448	Bayesian information criterion
Size of residuals				
SRMR	0.182	0.173	0.167	Standardized root mean squared residual
CD	1.000	1.000	1.000	Coefficient of determination

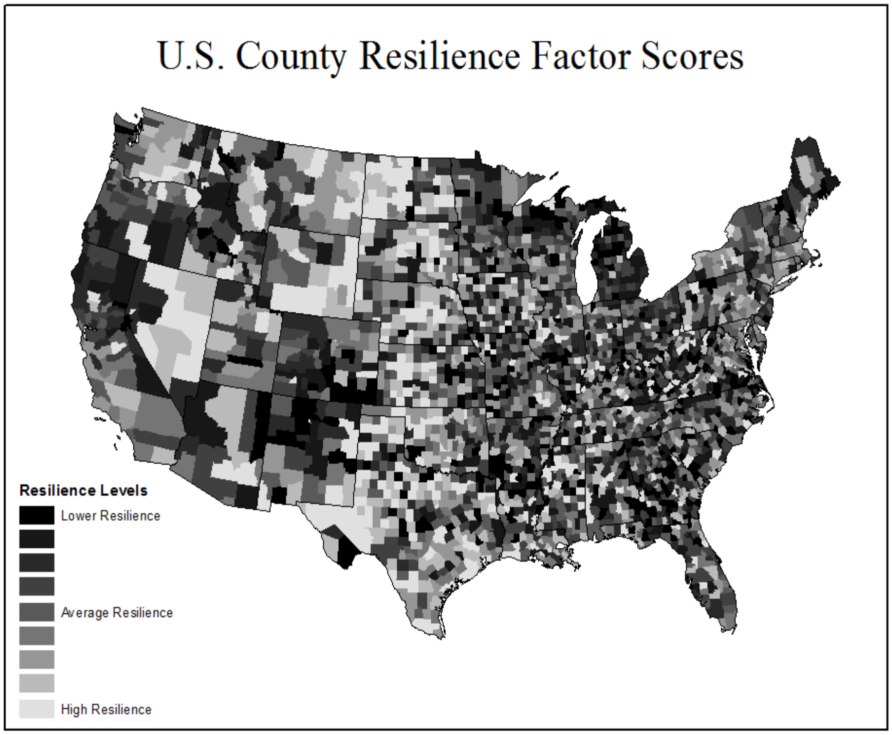
** Fitted model was not full rank, so not all goodness of fit measures could be calculated.*

This is the model that we will use, however, in our full results analysis and exploration of the relationships between observed variables and latent variables, community capitals and resilience. Once we assess the performance of the individual components of this model, we discuss potential avenues for improvement to the model based on limitation we see in these results.

6. RESULTS OF MODIFIED SEM

In analyzing the estimates produced by our modified SEM, we begin by looking at our measurement model parameter estimates. In looking at the parameter estimates for the regional economic resilience measurement (Table 2 below), we find that this SEM has estimated the latent variable in a way that represents the opposite of resilience. In Table 2, our adjusted resilience measure and expected variation are negatively associated with this latent variable, which loads most heavily on our adjusted resilience measure (-0.971) out of all the observed variables. Drop is positively associated with the latent variable, meaning a larger drop is associated with high values in the latent variable. All coefficients appear to be statistically significant. If we run an EFA with these same variables, the first factor, with the highest eigenvalue, has oppositely signed loadings on each of the variables. The relationships from our modified SEM result suggest that our latent variable represents lower resilience as it gets higher in value and higher resilience as it gets lower in value. The fact that rebound seems

Figure 4: Regional Economic Resilience Factor Scores derived from Modified SEM



to be positively correlated with low resilience, based on this interpretation, even though we theoretically consider higher rebounds characteristic of higher resilience, is not entirely unexpected. It represents a different dimension and stage of resilience and, in any case, has a low-valued coefficient in terms of magnitude which suggests that the relationship is not strong. We will keep the reverse representation of resilience in this model in mind when we assess the direct effects of the community capitals on this variable. For this point forward, when we refer to resilience as measured by this SEM model, we will be referring to lower values of this latent variable.

Table 2: Standardized Estimates relating to Regional Economic Resilience Measurement Model

Measurement, Regional Economic Resilience	Coef.	Std. Err.	z	P>z	[95% Conf. Int.]
Resilience Measure (Adjusted)	-0.971	0.009	-109.080	0.000	[-0.988, -0.953]
Constant	-0.720	0.023	-31.450	0.000	[-0.765, -0.675]
Expected Variation	-0.560	0.015	-37.820	0.000	[-0.589, -0.531]
Constant	-1.101	0.026	-42.570	0.000	[-1.151, -1.050]
Rebound	0.085	0.022	3.840	0.000	[0.042, 0.129]
Constant	1.035	0.025	40.930	0.000	[0.985, 1.084]
Drop	0.859	0.009	92.960	0.000	[0.841, 0.877]
Constant	1.403	0.029	48.810	0.000	[1.346, 1.459]

The fact that our latent variable loads most heavily on our adjusted resilience measure means that the latent variable's representation of resilience is closely related to our adjusted resilience measure's representation of resilience on its own. To illustrate, the map below (Figure 4) shows resilience based on the factor scores produced from this SEM with lighter shade of gray representing higher resilience and dark shades of gray representing lower resilience. Note, this map does differ for the other in showing the estimated resilience of all counties, including those that were not involved in the estimation of this model.

Our social capital latent variable is positively associated with associational density (log), both community attachment variables (percent of residents residing locally for five years or more and percent of residents who are native to the state in which the county is located), homeownership rates, and percent family households. Of those, it loads most heavily on associational density (0.966). The social capital latent variable is negatively associated with total number of non-profits, violent and property crimes per capita, and ethnic fractionalization, with all loadings greater than 0.3 (absolute value). In some ways, this latent variable reflects our expectations regarding social capital based on the existing literature discussed in previous sections. The interpretation of the negative coefficient for total nonprofits is unclear and may behave differently if represented as a density. Measures of bonding capital, like associational density and community attachment or investment of time as resident or financial resources (e.g. homeownership), are expected to relate to greater levels of social capital while a higher prevalence of crime can occur where there is a lack of bridging capital, regardless of the levels of bonding social capital. Standardized estimates relating to the social capital measurement model are in Table 3.

The map in Figure 5 shows the social capital factor scores generated from the modified SEM estimates. Higher levels of social capital are represented by lighter shades of gray while lower levels of social capital are represented by dark shades. This map shares some similarities with the associational density map generated in Rupasingha et al. (2006), understandably given the high standardized coefficient for associational density, but shows patterns which differ from their overall social capital index. One of the primary reasons for this are likely our inclusion of observed variables that could represent (lack of) bridging capital. Areas marking lower social capital that appear to correspond with cities could be reflect the influence of high crime rates in cities on this latent variable (Glaeser and Sacerdote, 1999). Another reason for differences between our representation of social capital and the Social Capital index performance could relate to our reassignment of voter participation and census response rate to political capital.

Our cultural capital latent variable is positively associated with ethnic enfranchisement, the ratio of proprietor to wage and salary employment (our measure of self-employment), religious adherence rate, and museums per capita (log). It is negatively associated with average household size and artistic share of the workforce (log). All appear to be statistically significant. No one single observed variable dominates, though museums per capita (log) and average household size have the highest correlations (0.457 and -0.458 respectively). Our expectations regarding the relationship of our observed variables to cultural capital were less defined, but the positive relationships of ethnic enfranchisement and the ratio of proprietor to wage and salary employment to this latent variable are consistent with the idea that the prevalence and patterns of business ownership could say something about the beliefs of individuals within the population regarding what they can achieve economically. Our inclusion of household size and religious adherence were to represent the presence of

Table 3: Standardized Estimates relating to Social Capital Measurement Model

Measurement, Social Capital	**Coef.**	**Std. Err.**	**z**	**P > z**	**[95% Conf. Int.]**
Log, associational density	0.966	0.003	297.050	0.000	[0.959, 0.972]
Constant	-6.563	0.097	-67.760	0.000	[-6.752, -6.373]
Log, number of non-profit orgs.	-0.881	0.006	-158.260	0.000	[-0.892, -0.870]
Constant	4.080	0.062	65.490	0.000	[3.958, 4.202]
Violent crimes per capita	-0.477	0.016	-29.250	0.000	[-0.509, -0.445]
Constant	1.073	0.026	41.890	0.000	[1.022, 1.123]
Property crimes per capita	-0.593	0.014	-42.840	0.000	[-0.620, -0.566]
Constant	1.471	0.029	49.960	0.000	[1.413, 1.528]
Community attachment					
Local resident, 5+ years	0.101	0.021	4.850	0.000	[0.060, 0.141]
Constant	12.899	0.187	68.900	0.000	[12.532, 13.266]
Community attachment					
Native to state of residence	0.307	0.019	16.170	0.000	[0.270, 0.344]
Constant	4.723	0.071	66.400	0.000	[4.583, 4.862]
Homeownership rate	0.365	0.018	19.930	0.000	[0.329, 0.401]
Constant	10.399	0.151	68.680	0.000	[10.102, 10.696]
Ethnic fractionalization	-0.353	0.018	-19.130	0.000	[-0.389, -0.317]
Constant	1.387	0.029	48.530	0.000	[1.331, 1.443]
Percent, family households	0.023	0.021	1.080	0.280	[-0.019, 0.065]
Constant	13.662	0.198	68.940	0.000	[13.274, 14.050]

groups and institutions that can transmit cultural values, though we had no expectations about what kind of cultural values would spread via these avenues. The presence of cultural and historical institutions, represented by museums per capita, can also serve to spread culture and, in theory, to foster a share sense of history and identity, which provides some interpretation of this positive value. With that said, we acknowledge that these estimates are limited in their explanatory power, due to the difficulty in getting to the root of the internal and individual aspects of cultural capital. All cultural capital measurement model estimates are shown below in Table 4.

Looking at the spatial patterns of cultural capital in Figure 6, as represented by this latent variable, cultural capital appears to be higher in the center of the country and lower around cities and the coasts. Several issues could be driving down the value of cultural capitals in cities. This could be due, in part, to the representation of the presence of museums as a per capita value, dividing the number of institutions by many more people in the cities. Museums and other entities included might be considered non-rivalrous goods where being shared by more people does not necessarily affect the value of each person's experience. It might be worth considering if this adjustment is appropriate or if creating a museum density be more appropriate. Another potential issue within this estimation is that our measure of ethnic enfranchisement is calculated using information about the ethnic makeup of the population and is therefore affected by changes in population composition. We expect ethnic diversity, which is negatively correlated with ethnic enfranchisement (-0.67) to be higher in cities, generally.

Figure 5: Standardized Estimates relating to Social Capital Measurement Model

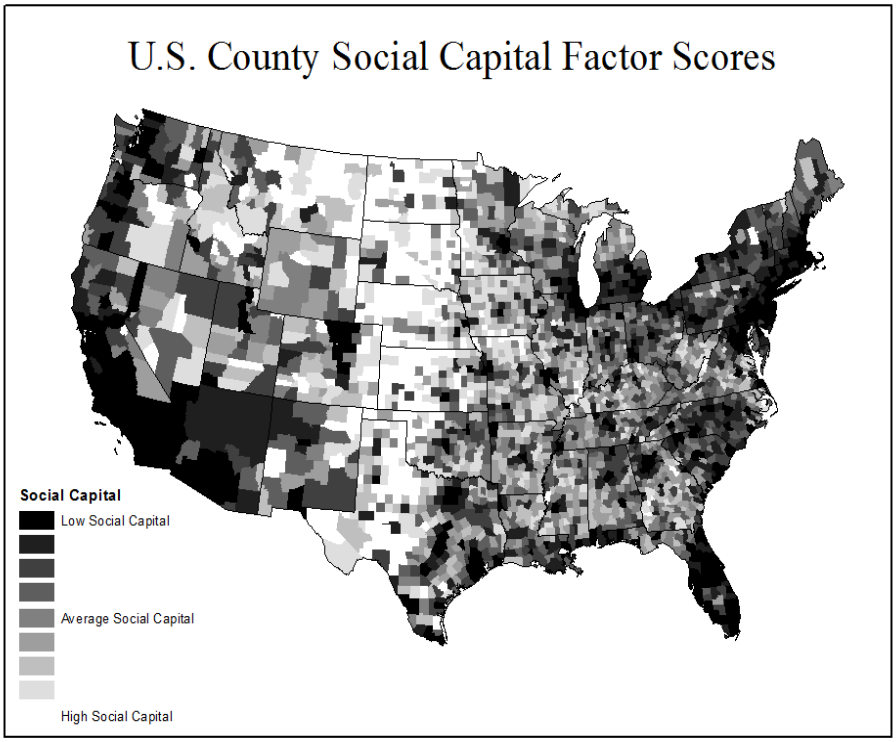


Figure 6: Cultural Capital Factor Scores derived from Modified SEM

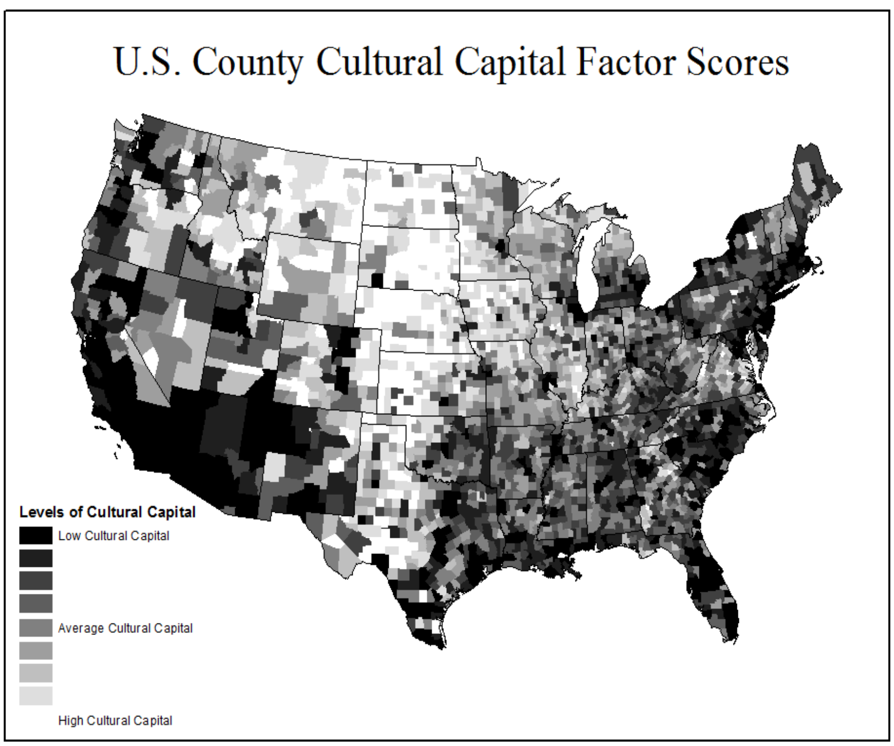


Table 4: Standardized Estimates relating to Cultural Capital Measurement Model

Measurement, Cultural Capital	**Coef.**	**Std. Err.**	**z**	**P > z**	**[95% Conf. Int.]**
Ethnic enfranchisement	0.255	0.023	10.890	0.000	[0.209, 0.301]
Constant	-1.031	0.025	-40.840	0.000	[-1.081. -0.982]
Ratio, proprietor to wage and salary employment	0.534	0.017	32.280	0.000	[0.502, 0.567]
Constant	1.971	0.035	56.320	0.000	[1.903, 2.040]
Average household size	-0.458	0.019	-23.570	0.000	[-0.496, -0.420]
Constant	9.890	0.144	68.610	0.000	[9.607, 10.173]
Religious adherence rate	0.202	0.020	10.090	0.000	[0.163, 0.241]
Constant	3.083	0.049	63.000	0.000	[2.987, 3.178]
Log, museums per capita	0.457	0.020	23.370	0.000	[0.419, 0.495]
Constant	-16.805	0.243	-69.070	0.000	[-17.282, -16.328]
Log, artistic share of workforce	-0.273	0.022	-12.340	0.000	[-0.316, -0.229]
Constant	-4.256	0.065	-65.770	0.000	[-4.382, -4.129]

The behavior of the political capital latent variable is consistent with our expectations. All our politically-related observed variables produce positive coefficient estimates. Voter participation is slightly dominant (0.546), followed by political contribution count per capita (log) (0.445), and census response rate (0.347). All appear to be statistically significant. These results are shown below in Table 5.

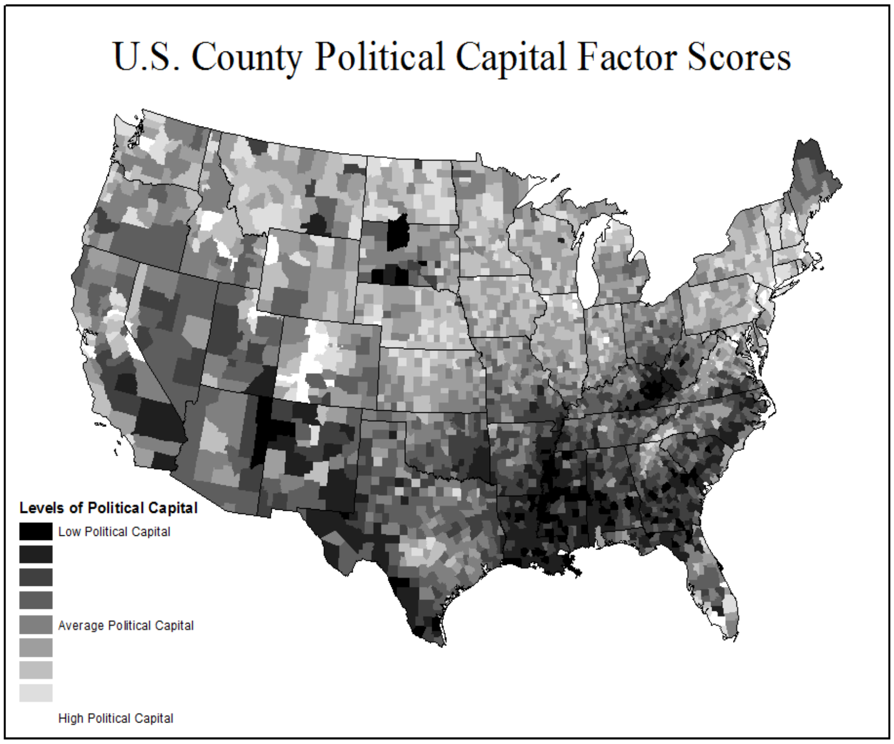
Table 5: Standardized Estimates relating to Political Capital Measurement Model

Measurement, Political Capital	**Coef.**	**Std. Err.**	**z**	**P > z**	**[95% Conf. Int.]**
Voter participation	0.546	0.021	26.260	0.000	[0.505, 0.586]
Constant	6.517	0.096	67.730	0.000	[6.328, 6.706]
Census response rate	0.347	0.019	17.920	0.000	[0.309, 0.385]
Constant	7.442	0.109	68.090	0.000	[7.228, 7.657]
Log, number of political contributions per capita	0.445	0.019	23.330	0.000	[0.408, 0.483]
Constant	-7.236	0.106	-68.020	0.000	[-7.444, -7.027]

Figure 7 shows some interesting patterns in political capital, particularly in the concentration of low political capital in areas parts on the Southeast and Appalachia. Also, some counties that have relatively low populations but attract wealthy residents and tourists (e.g. Blaine County, Idaho and Teton County, Wyoming) may have political capital values that are driven up by the political contributions variable. (Sibley et al., 2013)

The behavior of the human capital latent variable is consistent with our expectations. Education and health variables move together. Observed variables positively associated with human capital, based on this latent variable, include total labor force participation, percent of the population ages 18 to 64, percent of population (age 25 and older) who are high school graduates, percent of population with a bachelor's degree or higher, physical activity levels, and life expectancy. Observed variables negatively associated with human capital include

Figure 7: Political Capital Factor Scores derived from Modified SEM



drop-out rate, lack of health insurance, obesity rate, prevalence of diagnosed diabetes, and mortality rate. Human capital loads most heavily on life expectancy (0.927), physical activity (0.879), the percent of the population who are high school graduates (0.841), and mortality rate (-0.811). All coefficient estimates appear to be statistically significant. Full results for this measurement model are included in Table 6.

From the spatial distribution of other human capital factor scores, shown in Figure 8, we can see that lower levels of human capital are concentrated in the southeastern United States and counties near major cities tend to have higher levels of human capital.

Our financial capital latent variable relates to its observed variables in ways that match our expectations. Both dividends per capita (log) and interest per capita (log) load heavily on the financial capital variable and have positive estimated coefficients. Both are statistically significant. Ideally, we would have more than two financial capital observed variables. Deposits per capita was dropped due to convergence issues. Full results of this measurement model are shown in Table 7 below.

Some spatial patterns of financial capital stocks, based on this latent variable, are observable in the map in Figure 9. There are some similarities between this map and the map of human capital, with the southeastern United States and Appalachia exhibiting lower levels of financial capital.

The observed variables associated with built capital all have positive and statistically significant coefficient estimates, in line with our expectations. Results for this measurement model are shown in Table 8 below.

Figure 8: Human Capital Factor Scores derived from Modified SEM

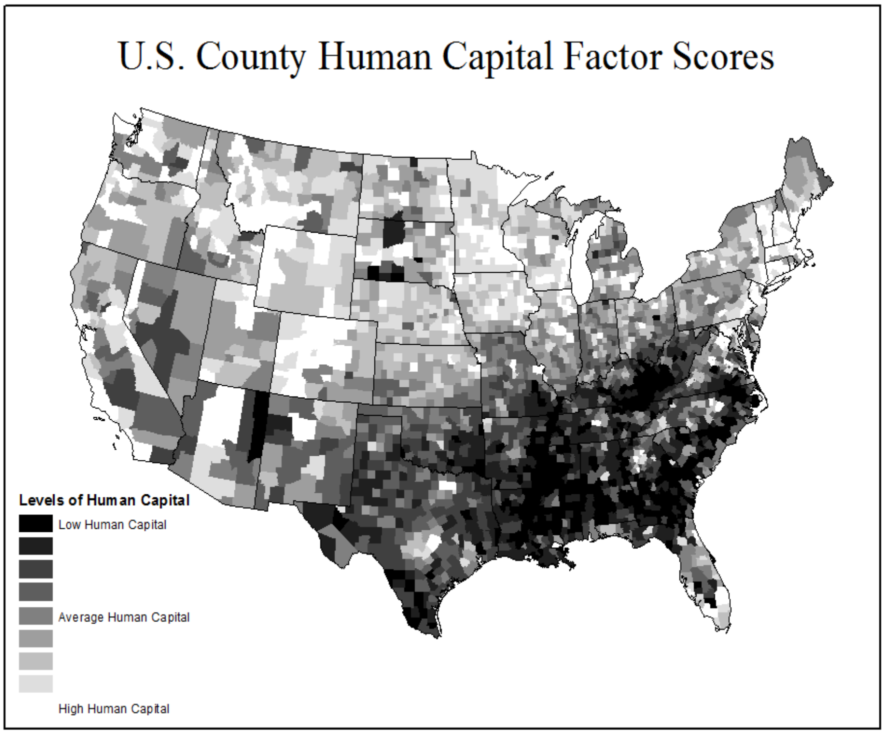


Figure 9: Financial Capital Factor Scores derived from Modified SEM

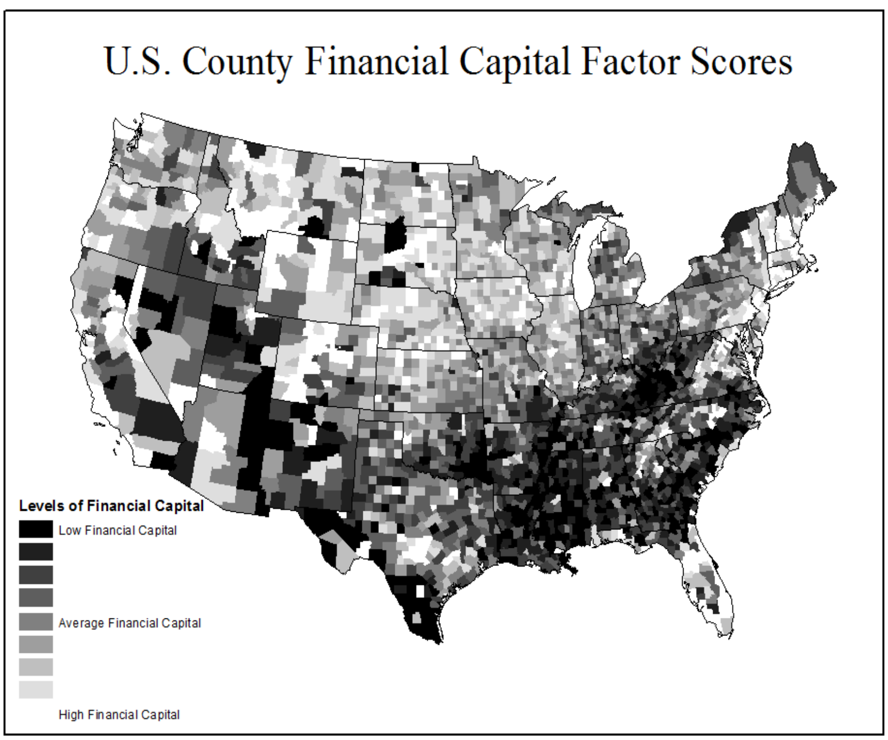


Table 6: Standardized Estimates relating to Human Capital Measurement Model

Measurement, Human Capital	Coef.	Std. Err.	z	P > z	[95% Conf. Int.]
Total labor force participation	0.648	0.012	52.160	0.000	[0.623, 0.672]
Constant	8.766	0.128	68.430	0.000	[8.515, 9.018]
% population ages 18 to 64	0.111	0.021	5.330	0.000	[0.070, 0.152]
Constant	15.682	0.227	69.030	0.000	[15.237, 16.127]
%, high school graduates	0.841	0.007	121.540	0.000	[0.828, 0.855]
Constant	11.464	0.167	68.790	0.000	[11.137, 11.790]
%, bachelor's degree or higher	0.725	0.010	69.090	0.000	[0.704, 0.745]
Constant	2.231	0.038	58.540	0.000	[2.156, 2.305]
Drop-out rate	-0.522	0.015	-33.960	0.000	[-0.552, -0.492]
Constant	1.898	0.034	55.580	0.000	[1.831, 1.965]
No health insurance (ages 18 to 64)	-0.247	0.020	-12.440	0.000	[-0.286, -0.208]
Constant	3.163	0.050	63.270	0.000	[3.065, 3.261]
Obesity rate	-0.677	0.012	-57.970	0.000	[-0.700, -0.654]
Constant	7.750	0.114	68.180	0.000	[7.527, 7.973]
Prevalence of diagnosed diabetes	-0.771	0.009	-83.820	0.000	[-0.789, -0.753]
Constant	5.073	0.076	66.770	0.000	[4.924, 5.222]
Mortality rate	-0.811	0.008	-100.510	0.000	[-0.827, -0.795]
Constant	6.931	0.102	67.910	0.000	[6.731, 7.131]
Physical activity, male	0.879	0.006	153.360	0.000	[0.868, 0.890]
Constant	13.852	0.201	68.950	0.000	[13.458, 14.246]
Life expectancy, male	0.927	0.004	229.830	0.000	[0.919, 0.934]
Constant	33.484	0.484	69.250	0.000	[32.536, 34.432]

Table 7: Standardized Estimates relating to Financial Capital Measurement Model

Measurement, Financial Capital	Coef.	Std. Err.	z	P > z	[95% Conf. Int.]
Log, dividends per capita	0.871	0.007	120.100	0.000	[0.856, 0.885]
Constant	-2.173	0.037	-58.090	0.000	[-2.246, -2.100]
Log, interest per capita	0.945	0.006	153.420	0.000	[0.933, 0.957]
Constant	-1.903	0.034	-55.640	0.000	[-1.971, -1.836]

The spatial distribution of built capital (Figure 10) shows more populated areas east of the Mississippi and along the West Coast exhibiting higher levels of built capital. With the observed variables we have included we are reflecting built capital primarily in terms of density and do not have observed variables that reflect quality. The inclusion of observed variables that reflect built infrastructure quality would contribute valuable information over what we currently have, as built infrastructure in decline can be a source of problems for the local communities that depend on it.

Our natural capital latent variable does not appear to represent all the various components of natural capital cohesively and accurately, in terms of each of their contributions to natural capital (Table 9). The likely reason for this is that natural capital consist of many diverse components, some the preferred types of land topography, like hills and mountains. Three of our variables representing desirable climate attributes are negatively correlated

Figure 10: Built Capital Factor Scores derived from Modified SEM

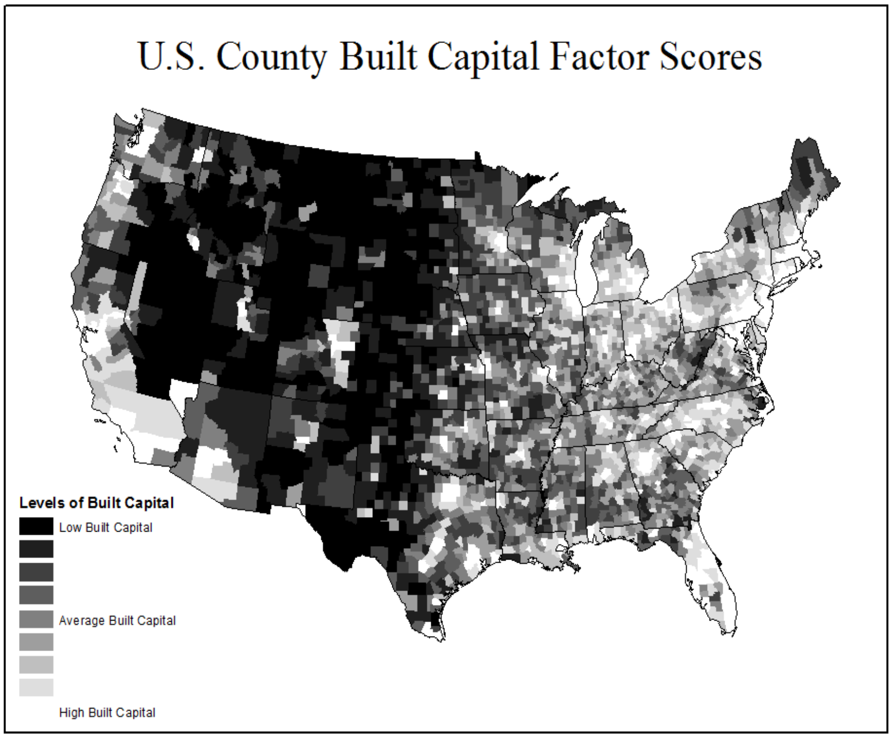


Figure 11: Natural Capital Factor Scores derived from Modified SEM

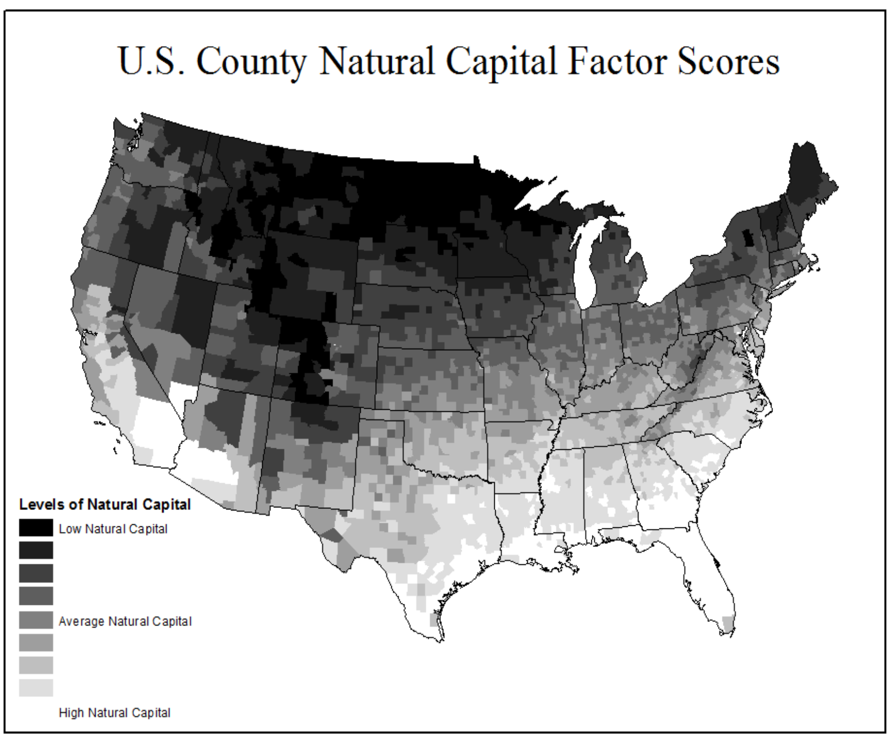


Table 8: Standardized Estimates relating to Built Capital Measurement Model

Measurement, Built Capital	Coef.	Std. Err.	z	P > z	[95% Conf. Int.]
Proximity to major airport	0.582	0.014	40.880	0.000	[0.554, 0.609]
Constant	1.250	0.027	45.900	0.000	[1.196, 1.303]
Log, housing units per square mile	0.968	0.005	192.420	0.000	[0.958, 0.978]
Constant	2.122	0.037	57.670	0.000	[2.050, 2.194]
Log, public use airports with air taxi services per square mile	0.422	0.018	24.010	0.000	[0.387, 0.456]
Constant	-5.357	0.080	-67.020	0.000	[-5.514, -5.201]
Log, Amtrak miles per square mile	0.332	0.020	17.030	0.000	[0.294, 0.371]
Constant	-3.161	0.050	-63.270	0.000	[-3.259, -3.064]
Log, Amtrak stations per square mile	0.432	0.018	23.970	0.000	[0.397, 0.468]
Constant	-7.970	0.117	-68.240	0.000	[-8.199, -7.741]
Log, road miles per square mile	0.662	0.012	53.410	0.000	[0.638, 0.687]
Constant	-2.532	0.042	-60.510	0.000	[-2.614, -2.450]
Broadband coverage	0.445	0.017	26.270	0.000	[0.411, 0.478]
Constant	7.956	0.117	68.240	0.000	[7.727, 8.184]

Table 9: Standardized Estimates relating to Natural Capital Measurement Model

Measurement, Natural Capital	Coef.	Std. Err.	z	P > z	[95% Conf. Int.]
Average January temperature	0.888	0.014	63.570	0.000	[0.860, 0.915]
Constant	2.732	0.044	61.550	0.000	[2.645, 2.819]
Average January days of sun	0.290	0.023	12.700	0.000	[0.245, 0.334]
Constant	4.656	0.070	66.320	0.000	[4.519, 4.794]
Average July temperature	0.754	0.012	62.670	0.000	[0.731, 0.778]
Constant	14.275	0.207	68.970	0.000	[13.870, 14.681]
Average July humidity	0.395	0.025	15.890	0.000	[0.346, 0.444]
Constant	3.882	0.060	65.120	0.000	[3.765, 3.999]
Land topography	-0.242	0.024	-10.050	0.000	[-0.289, -0.195]
Constant	1.346	0.028	47.790	0.000	[1.291, 1.402]
Log, percent water area	0.117	0.024	4.950	0.000	[0.071, 0.164]
Constant	2.647	0.043	61.130	0.000	[2.562, 2.732]
Log, days of high level air pollution, particulate matter	0.360	0.022	16.650	0.000	[0.317, 0.402]
Constant	-0.339	0.021	-16.150	0.000	[-0.380, -0.298]
Log, days of high level air pollution, ozone	0.146	0.024	5.990	0.000	[0.098, 0.194]
Constant	-0.725	0.023	-31.620	0.000	[-0.770, -0.680]
%, area in farms	-0.217	0.022	-9.660	0.000	[-0.261, -0.173]
Constant	1.676	0.032	52.970	0.000	[1.614, 1.738]
Log, crop value per acre	0.123	0.024	5.210	0.000	[0.077, 0.170]
Constant	3.972	0.061	65.300	0.000	[3.853, 4.091]
Log, ratio of federally-owned land to total	-0.162	0.028	-5.830	0.000	[-0.216, -0.107]
Constant	-4.363	0.066	-65.930	0.000	[-4.492, -4.233]

with land topography, which increases in value as topographic variation increases. In our measurement model results, our natural capital latent variable is positively associated with January temperatures, January sun, July temperatures, July humidity, water area, air pollution (i.e. particulate matter and ozone), and crop value per acre (log) when humidity and air pollution should not, based on our definition of natural capital, have a positive relationship here. The latent variable is negatively associated with land topography, area in farms, and amount of federally-owned land. The main violation of our expectation here is in the negative relationship of land topography to this latent variable. Upon closer look, we see that overall this measure loads heavily on January and July temperatures (0.888 and 0.754) and in reality, is most representative of temperature patterns. The map in Figure 12 reinforces this as the pattern of natural capital, as represented by this latent variable, looks more like a temperature map.

Standardized path estimates from the structural model, which represent direct effects, within our modified SEM are shown in Table 10. We have specified in the table that these coefficients estimate relationships to low resilience due to the observations we made regarding the behavior of this latent variable's measurement model estimates. If we interpret the relationships of these community capitals to regional economic resilience (high levels of resilience) as being represented with the opposite coefficient signs, we see that this model estimates a positive effect of social capital, human capital, financial capital and built capital on resilience, with social, cultural, and human capital being statistically significant at the 0.05 level, and estimates a negative effect of cultural and political on resilience, also statistically significant. These results reflect no effect of our natural capital variable (dominated by temperatures) on resilience.

The fact that we observe higher levels of cultural and political capital to be associated with lower economic resilience is unexpected and could potential come from two different sources. The first could be that the great recession did tend to impact urban and suburban areas more than rural areas. Urban and suburban areas tend to also have higher levels of political and cultural capital. Therefore, due to the nature of the Great Recession, these areas of high cultural and political capital may have been, in fact, less resilient. Conversely, it must be acknowledged that there is little precedence for empirically combining all of the community capitals into one systematic framework. While the variables that were chosen are consistent with the literature on political and cultural capital, it could be that the theory needs to be modified in light of the empirical findings and new variables that relate to political and cultural capital need to be posited. Either way, we hope that these findings encourage additional analysis on how we measure community capitals, especially related to cultural and political capital.

Table 10: Standardized Estimates of Structural Model

Structural Model (Direct Effects)		**Coef.**	**Std. Err.**	**z**	**P > z**	**[95% Conf. Int.]**
Low Resilience <	**Social**	-0.722	0.242	-2.980	0.003	[-1.196, -0.248]
	Cultural	0.637	0.189	3.370	0.001	[0.267, 1.006]
	Political	0.260	0.066	3.980	0.000	[0.132, 0.389]
	Human	-0.430	0.093	-4.630	0.000	[-0.612, -0.248]
	Financial	-0.337	0.115	-2.930	0.003	[-0.563, -0.111]
	Built	-0.120	0.096	-1.260	0.208	[-0.308, 0.067]
	Natural	0.000	0.070	0.000	0.999	[-0.137, 0.137]

The indirect effects of each of the community capitals on the individual observed variables associated with resilience can be interpreted directly and are shown in Table 11 below.

According to this model, our adjusted resilience measure and expected variation (where higher values actually present lower expected variation) are positively indirectly affected by social, human, financial, and built capital and negatively indirectly affected by cultural and political capital. The indirect effects of the community capitals on rebound are all low in magnitude (all standardized estimates have absolute values less than 0.10) and it is positively indirectly affected by cultural and political capital and negatively indirectly affected by social, human, financial, and built capital. Finally, drop is positively indirectly affected by cultural and political capital and negatively indirectly affected by social, human, financial, and built capital. All estimates of indirect effects stemming from social, cultural, political, human, and financial capital are statistically significant at the 0.05 level. Indirect effects associated with built and natural capital are not statistically significant.

Table 11: Standardized and Unstandardized Estimates of Indirect Effects

Indirect Effects	**(Resil. Ob. Var. < Comm. Cap.)**	**Coef. (Standard.)**	**Coef. (Unstandard.)**	**Std. Err**	**z**	$P > \|z\|$
Resilience Measure (Adj.)						
	Social	0.701	2.132	0.715	2.98	0.003
	Cultural	-0.618	-2.197	0.646	-3.4	0.001
	Political	-0.253	-23.702	5.703	-4.16	0
	Human	0.418	41.705	9.117	4.57	0
	Financial	0.327	2.492	0.851	2.93	0.003
	Built	0.117	0.86	0.684	1.26	0.209
	Natural	0	0	0.029	0	0.999
Expected Variation						
	Social	0.405	0.177	0.06	2.96	0.003
	Cultural	-0.357	-0.182	0.054	-3.36	0.001
	Political	-0.146	-1.966	0.479	-4.11	0
	Human	0.241	3.459	0.763	4.53	0
	Financial	0.189	0.207	0.071	2.9	0.004
	Built	0.067	0.071	0.057	1.26	0.209
	Natural	0	0	0.002	0	0.999
Rebound						
	Social	-0.062	0	0	-2.32	0.021
	Cultural	0.054	0	0	2.48	0.013
	Political	0.022	0.002	0.001	2.76	0.006
	Human	-0.037	-0.004	0.001	-2.93	0.003
	Financial	-0.029	0	0	-2.26	0.024
	Built	-0.01	0	0	-1.19	0.233
	Natural	0	0	0	0	0.999
Drop						
	Social	-0.62	-0.043	0.015	-2.97	0.003
	Cultural	0.547	0.045	0.013	3.37	0.001
	Political	0.224	0.482	0.117	4.13	0
	Human	-0.369	-0.848	0.186	-4.57	0
	Financia	-0.29	-0.051	0.017	-2.91	0.004
	Built	-0.103	-0.017	0.014	-1.26	0.209
	Natural	0	0	0.001	0	0.999

There are many additional results and tests that can be run on this model. The error variances indicate how much of the variance in each observed variable and our resilience-related latent variable are unexplained, or influenced by omitted causes. Several observed variables have high standardized

While we cannot rely heavily on the results of this particular model, if these results were reproduced by a more robust future model that better fit the data, we could draw some new insights from these results. Specifically, the positive effects of social and human capital on regional economic resilience could encourage the use of resilience-fostering strategies and policies which invest in the development of these capitals. Because we have included indicators of both bonding and bridging capital, our social capital factor scores reflect both and in looking specifically at the performance of individual indicators at the county level, we could identify where there is a strong presence of bonding capital but lack of bridging capital. Strategies that target to development of bridging social capital in these areas could elevate the overall level of social capital locally and potentially contribute to greater resiliency. This is the kind of information we could gain from the continued development of the use of structural equation modeling and the community capitals framework in efforts to explain variation in regional economic resilience.

7. CONCLUSIONS AND OPTIONS FOR FUTURE IMPROVEMENT OF MODEL AND METHODS

The collection of data related to the community capitals framework and estimation of a structural equation model using those data to explain regional economic resilience in terms of community capitals were the primary goals of this paper. This had not been undertaken in previous research and we faced challenges related to data availability, representation of community capitals, and model specification in attempting to model the complex dynamics within U.S. counties which influence the regional economic resilience construct. With all that said, we do feel there are avenues worth exploring that could lead to the production of an improved and more informative model. These include the collection and incorporation of additional or alternative observed variables associated with community capitals, alternative techniques for dealing with data that are severely non-normally distributed or which include outliers, the inclusion of non-community capital related variables within the model that provide information about county vulnerability to this specific recessionary shock, and the use of more sophisticated structural equation modeling methods that will allow, for example, the inclusion of categorical and binary variables.

There are always alternative measures to explore and in this case, when some components of the existing model are not performing well, such exploration is likely necessary to model improvement. While we recognize room for improvement in this model, we maintain that an SEM approach is likely to be a fruitful methodology for investigating community capitals and their influence on regional outcomes. Of all the community capitals represented in this model, human capital seems to be the best represented in terms of robustness, producing the relationships we would expect to see based on previous research and theory. With that said, the theory of human capital includes forms of knowledge and skills that are acquired outside of the formal education system, and exploring measures reflective of that would be valuable qualitatively. It is also possible that pairing down the number of observed variables representing human capital, particularly when there are strong intercorrelations, may improve the model goodness of fit measures. Financial capital, while appearing to be well-represented by dividends and interest per capita, could be improved by the inclusion of at least one more observable variable to reach the ideal three observed variables per latent variable rule of thumb in factor analysis. Data on access to credit or charitable donations may be options to explore. The measurement model for built capital in the modified SEM, exhibits the relationships we would expect between the observed variables and the built capital latent variable, but the inclusion of measures reflecting quality and condition of built infrastructure rather than simple density might represent built capital in a way that is more in line with the ability of this capital to positively contribute to the functioning of a community. The natural capital latent variable performed poorly in terms of its ability to embody all the characteristics that contribute to natural capital. This issue might be addressed with the inclusion of additional or alternative observed variables or the use of more advanced SEM techniques. It is also possible that modeling natural capital as a latent construct might not be necessary or even the best method for representing natural capital in this. We would also like to see the incorporation of variables representing harvestable resources, as this is another aspect of natural capital.

The inclusion of other variables that are not necessarily related to community capital stocks but which may help explain variation in resilience to the 2007-2009 recession could be essential to improving future model fit. Such variables could include concentration of employment in most adversely affected industries, region and state variables to account for regional and state effects, dependence on manufacturing or agriculture, and variables associated with stability like industry mix (Deller and Watson, 2016).

We hope this preliminary effort to model regional economic resilience in terms of measured community capital stocks, along with its limitations, will contribute to the discussion of how to effectively identify factors that influence resilience and apply that knowledge to the creation of community development strategies and interventions.

REFERENCES

Akçomak, İ Semih and Bas Ter Weel. (2012) "The Impact of Social Capital on Crime: Evidence from The Netherlands," *Regional Science and Urban Economics*, 42(1-2), 323–340.

Alavifar, A., M. Karimimalayer, and M. K. Anuar. (2012) "Structural Equation Modeling vs Multiple Regression," *IRACST – Engineering Science and Technology: An International Journal*, 2(2), 326–239.

Alesina, Alberto, Reza Baqir, and William Easterly. (1999) "Public Goods and Ethnic Divisions," *The Quarterly Journal of Economics*, 114(4), 1243–1284.

Alesina, Alberto and Eliana La Ferrara. (2000) "Participation in Heterogeneous Communities," *The Quarterly Journal of Economics*, 115(3), 847–904.

Belton, Willie James, Ruth Uwaifo Oyelere, and Yameen Huq. (2018) "Diversity and Social Capital in The US: A Tale of Conflict, Contact or Total Mistrust?," *Review of Economics and Institutions*, 9(2), 39.

Bentler, Peter M. (1980) "Multivariate Analysis with Latent Variables: Causal Modeling," *Annual Review of Psychology*, 31(1), 419–456.

Bourdieu, Pierre. (2018) "The Forms of Capital," In *The Sociology of Economic Life*. Routledge: pp. 78–92.

Briguglio, Lino, Gordon Cordina, Nadia Farrugia, and Stephanie Vella. (2009) "Economic Vulnerability and Resilience: Concepts and Measurements," *Oxford Development Studies*, 37(3), 229–247.

Browne, William Paul. (2001) *The Failure of National Rural Policy: Institutions and Interests*. Georgetown University Press.

Coleman, James S. (1988) "Social Capital in The Creation of Human Capital," *American Journal of Sociology*, 94, S95–S120.

Cutler, David M and Adriana Lleras-Muney. (2006) "Education and Health: Evaluating Theories and Evidence," *National Poverty Center Working Paper Series*, (06-19).

Deller, Steven and Philip Watson. (2016) "Did Regional Economic Diversity Influence the Effects of The Great Recession?," *Economic Inquiry*, 54(4), 1824–1838.

DiPasquale, Denise and Edward L Glaeser. (1999) "Incentives and Social Capital: Are Homeowners Better Citizens?," *Journal of Urban Economics*, 45(2), 354–384.

Emery, Mary and Cornelia Flora. (2020) "Spiraling-Up: Mapping Community Transformation with Community Capitals Framework," In *50 Years of Community Development Vol I*. Routledge: pp. 163–179.

Fey, Susan, Corry Bregendahl, and Cornelia Flora. (2006) "The Measurement of Community Capitals Through Research," *Online Journal of Rural Research & Policy*, 1(1), 1.

Flora, Cornelia Butler. (2018) *Rural Communities: Legacy and Change*. Routledge.

Flora, Cornelia Butler, Jan L Flora, Jacqueline D Spears, and Louis E Swanson. (1992) *Rural Communities: Legacy and Change*. Westview Press.

Florida, R. (2002) "The Rise of The Creative Class and How It's Transforming Work, Leisure, Community and Everyday Life," *New York City: Basic Books*.

Glaeser, Edward L, David Laibson, and Bruce Sacerdote. (2002) "An Economic Approach to Social Capital," *The Economic Journal*, 112(483), F437–F458.

Glaeser, Edward L and Bruce Sacerdote. (1999) "Why Is There More Crime in Cities?," *Journal of Political Economy*, 107(S6), S225–S258.

Hackett, Susan and Philip Watson. (2022) "Economic Enfranchisement, Goal Setting, and Rural Development," *Journal of Agricultural and Applied Economics*, 54(4), 634–655.

Han, Yicheol and Stephan J Goetz. (2015) "The Economic Resilience of US Counties During The Great Recession," *Review of Regional Studies*, 45(2), 131–149.

Hu, Li-tze and Peter M Bentler. (1999) "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives," *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55.

Kahsai, Mulugeta, Junbo Yu, Mark Middleton, Peter V Schaeffer, and Randall Jackson. (2015) "A Framework for Measuring County Economic Resilience," *Regional Research Institute Working Paper Number*, (2015-03).

Kitagawa, Evelyn M and Philip M Hauser. (1973) *Differential Mortality in The United States: A Study in Socioeconomic Epidemiology*. Harvard University Press.

Kline, Rex B. (2012) "Assumptions in Structural Equation Modeling," *Handbook of Structural Equation Modeling*, 111, 125.

Lorenz, Edward. (1999) "Trust, Contract and Economic Cooperation," *Cambridge Journal of Economics*, 23(3), 301–315.

Maruyama, Geoffrey. (1997) *Basics of Structural Equation Modeling*. Sage.

McGranahan, David and Timothy Wojan. (2007) "Recasting The Creative Class to Examine Growth Processes in Rural and Urban Counties," *Regional Studies*, 41(2), 197–216.

Pender, John, Alexander Marré, and Richard Reeder. (2012) "Rural Wealth Creation Concepts, Strategies, and Measures," *USDA-ERS Economic Research Report*, (131).

Pigg, Kenneth, Stephen P Gasteyer, Kenneth E Martin, and Godwin P Apaliyah. (2020) "The Community Capitals Framework: An Empirical Examination of Internal Relationships," In *50 Years of Community Development Vol I*. Routledge: pp. 117–127.

Portes, Alejandro. (1998) "Social Capital: Its Origins and Applications in Modern Sociology," *Annual Review of Sociology*, 24(1), 1–24.

Putnam, Robert D. (1995) "Tuning In, Tuning Out: The Strange Disappearance of Social Capital in America," *PS: Political Science & Politics*, 28(4), 664–683.

Ringwood, Lauryn, Philip Watson, and Paul Lewin. (2019) "A Quantitative Method for Measuring Regional Economic Resilience to The Great Recession," *Growth and Change*, 50(1), 381–402.

Rupasingha, Anil, Stephan J Goetz, and David Freshwater. (2006) "The Production of Social Capital in US Counties," *The Journal of Socio-Economics*, 35(1), 83–101.

Sibley, Ryan, Bob Lannon, and Ben Chartoff. (2013) Political Influence by County: A New Way to Look at Campaign Finance Data. https://sunlightfoundation.com/2013/10/23/political-influence-by-county-a-new-way-to-look-at-campaign-finance-data. Accessed: 2017-03-21.

Sørensen, Jens FL. (2016) "Rural–Urban Differences in Bonding and Bridging Social Capital," *Regional Studies*, 50(3), 391–410.

Woolcock, Michael. (2001) "The Place of Social Capital in Understanding Social and Economic Outcomes," *Canadian Journal of Policy Research*, 2(1), 11–17.

Woolcock, Michael and Deepa Narayan. (2000) "Social Capital: Implications for Development Theory, Research, and Policy," *The World Bank Research Observer*, 15(2), 225–249.