Economic Resilience and Community Capitals: A Study in the Estimation and Dynamics of U.S. County Economic Resilience to the Great Recession

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Authorization to Submit Thesis

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Abstract

We develop a quantitative, two-dimensional measure of regional economic resilience and apply it to monthly county-level employment data from 1990 to 2015 to estimate U.S. county economic resilience to the 2007-2009 national recession. This measure reflects aspects of existing single dimension measures of shock responses, like drop and duration, as well as the uneven rate of decline. We include the option of an additional step to adjust for expected variation based on pre-local recession behavior. We use this resilience measure in a structural equation model designed to explain variation in county economic resilience to the 2007-2009 recession in terms of the community capitals framework. While the model estimated produces mixed results, the process of constructing the model and representing the seven community capitals indirectly through the thoughtful selection of observed variables produced valuable insights. We conclude by discussing these observations and ideas for model improvement in future studies.

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Dedication

I would like to thank my family and friends for their love, support, and encouragement throughout the course of my academic career.

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CHAPTER 1 - ECONOMIC RESILIENCE ESTIMATION

1.1 INTRODUCTION

In light of the Great Recession and a spate of natural disasters, researchers are increasingly interested in the causes of observable local variation in responses to these and other shocks. How regions respond to shocks reflects their relative economic resilience, a concept that has enjoyed increased attention in the academic literatures of economics, economic geography, and regional science. Many researchers, however, have indicated a need to formalize the concept of economic resilience in the literature. This has fueled ongoing discussion on how to define economic resilience and how to measure resilience based on proposed definitions, a discussion we seek to contribute to with this paper.

Historically, the often implicit goal of economic development has been to simultaneously encourage income growth while reducing volatility, two goals that some argue are often at odds with one another and are fundamentally different concepts (Spelman, 2006; Chiang, 2009; Lucas, 1987; Quigley, 1998). The concept of economic growth has historically been a central theme of macroeconomic research and has given rise to the sub-discipline of growth theory (Solow, 1956; Romer, 1990). Conversely, the causes and nature of economic volatility and stability, while encompassing a fairly deep literature, have enjoyed less attention than economic growth theory (Deller and Watson, 2016; Wagner and Deller, 1998). The causes of variation in the rate of growth and in a system's responses to shocks have also received relatively little attention but are central to the resilience discussion (Fingleton et al, 2012).

The structure of regional economies is changing, with a growing interconnectedness between regions and the larger global economy, making many regions more susceptible to external shocks than they have been historically. Understanding the varying ability of regional economies to survive disruptive events and persist in a world increasingly characterized by change and uncertainty seems vital to current discussion on how to guide and shape modern economic development strategies.

Currently, there is no single agreed-upon definition of regional economic resilience and much discourse surrounding this topic. Additionally, and by extension, there is also no single agreed-upon method of measuring economic resilience. One definition describes economic resilience as an economy's ability to withstand and recover from shocks (Han and Goetz, 2015; Martin, 2012). While this definition is both useful and limiting in its simplicity, it serves as a good starting point in the discussion of how to define and measure resilience.

We develop a resilience metric that builds on strategies used in existing efforts to measure resilience. We produce scores of relative regional resilience based on the dimensions of regional shock responses as observed in the behavior of an economic statistic representing economic activity (i.e. employment). We create a two-dimensional measure which captures aspects of both the depth and duration of each region's response to the shock, as well as the often uneven rate of decline, by taking into account both first and second moment condition responses. We offer the additional step of adjusting our response measure by accounting for each region's underlying volatility to distinguish the response to the shock from random variation. We demonstrate the use of this resilience metric by applying it to U.S. county-level monthly employment data from 1990 to 2015 to capture the response of counties to the shock of the 2007-2009 national recession. The metric, however, allows for some customization and flexibility in its application, allowing researchers to adapt its use to reflect their adopted definition of resilience.

In the application we use within this paper, we calculate resilience based on total employment behavior during the months from a county's local peak, associated with the beginning of the shock response, to six months after the trough, to include both the magnitude of the impact of the recession locally and the beginning of recovery. We discuss potential alternative applications of this metric, namely how one could use the same calculation process on monthly employment change data to obtain a result that reflects recovery as a return to a pre-shock employment growth rate, rather than a return to a pre-shock employment growth path. Our measure provides a means of comparing the local impact of the recession in each county. We share the results of our application, compare them with results from previous studies on U.S. county resilience to the 2007-2009 recession, and examine spatial, structural and typological differences in how specific groups of counties responded to the Great Recession.

1.2 RELATED LITERATURE

1.2.1 Defining Economic Resilience

One general definition of resilience is "the ability of something to recover from or adjust easily to misfortune or change" (Merriam-Webster, 2016). The application of resilience in theoretical and empirical regional economics research requires that such broad definitions be thoughtfully adapted and refined. This has motivated discussion in regional economics regarding what resilience is, how it relates to existing concepts in the field, how it can be measured, and what forces influence it.

Resilience was introduced into the academic literature in ecology and spread to other disciplines, including behavioral psychology, business, and economics (Holling, 1973; Kaplan, 1999; O'Dougherty Wright et al, 2013; Tompkins, 2007; Perrings, 2006; Rose, 2004). Rose (2004) describes economic resilience as "the inherent and adaptive responses to disasters that enable individuals and communities to avoid potential losses." In the last decade, additional definitions of economic resilience have been proposed, but there is lack of consensus over which definition is most appropriate for describing regional economic resilience (Bristow and Healy, 2015; Martin and Sunley, 2015).

Most definitions of economic resilience relate to an economy's response to a shock, which can be economic, environmental, or even political in nature. We choose to focus specifically on the economic shock of the 2007-2009 national recession in the United States. Economies often undergo change and reorganization in the process of responding to and recovering from such shocks (Walker et al, 2004; Han and Goetz, 2015). In a recession, a region might see a rise in bankruptcies and job loss within some or all industries, resulting the migration of human capital as individuals seek employment outside of the region (Han and Goetz, 2015). Conversely, it can also lead to the creation of new business opportunities and an increase in human capital as individuals migrate to new job opportunities from less resilient regions. Currently, many definitions of resilience relate closely to one of three types of resilience: engineering resilience, ecological resilience, and adaptive (or evolutionary) resilience (Martin, 2012).

Engineering resilience refers to a system's ability to resist a shock and return or recover to its pre-shock state, implying that recovery is a return to the pre-shock development path (Holling, 1973; Martin and Sunley, 2015). Hill et al (2008) describes economic resilience as "the ability of a region…to recover successfully from shocks to its economy that either throw it off its growth path or have the potential to throw it off its growth path." These definitions, in line with assumptions in mainstream economics, suggest that there exists some equilibrium state and that underlying forces will push an economy back toward equilibrium if it shifts out of that state (Fingleton et a,l 2012). By this definition, resilience could be a negative characteristic if a system is on an undesirable development path but is resistant to change (Hill et al, 2011; Bristow and Healy, 2015). The concept of engineering resilience can be restrictive and some argue it is unrealistic to apply the assumptions of this definition to systems as complex as regional economies (Simmie and Martin, 2010; Fingleton et al, 2012; Christopherson et al, 2010). It does, however, lend itself well to measurement.

Ecological resilience refers to the amount of disturbance that a system can absorb before it begins to change form or function (Holling, 1973). Walker et al (2004) describe resilience as "the capacity of a system to absorb disturbance and reorganize while undergoing change to still retain essentially the same function, structure, identity, and feedbacks." This definition does not require a return to the pre-shock path and instead supports the existence of multiple equilibria or stability domains (Martin, 2012;

Fingleton et al, 2012). This introduces the possibility of hysteresis, where a shock can cause a system to move to a new path rather than return to the original (Cross, 1993).

Adaptive (or evolutionary) resilience places added emphasis on a system's ability to continually adapt and evolve in response to change. Under this definition, Simmie and Martin (2010) describe resilience as an "ongoing process rather than a recovery to a (preexisting or new) stable equilibrium state". Research on this type of resilience sometimes borrows from the literature on complex adaptive systems (CAS), employing a CAS framework to analyze the response and adaptation of a system in response to a shock or crisis (Bristow and Healy, 2015).

Not all definitions of resilience fit cleanly into one of these resilience categories, but the differences between engineering resilience, ecological resilience, and adaptive (or evolutionary) resilience represent several central points of tension in the much larger and more nuanced discussion on defining resilience. The existence of other, closely related terms, like stability and robustness, further complicates this discussion. There is currently disagreement as to whether stability, robustness, and resilience should be treated separately or as fully interrelated concepts (Rose, 2004; Han and Goetz, 2015; Bruneau et al, 2003). The relationship of these terms and others to resilience requires greater clarification and agreement. While some have advocated for greater inclusion of adaptability in regional resilience (Pike et al, 2010; Christopherson et al, 2010; Simmie and Martin, 2010; Pendall et al, 2010; Martin et al, 2015), others criticize the use of resilience, in general, when there are existing concepts in the literature, like path dependence and lock-in, relating to regional economic adaptability (Hassink, 2010; Pike et al, 2010). Furthermore, arguments have been made for the inclusion of a political or societal dimension to incorporate the role of government and human agency in resilience (Bristow and Healy, 2015; Davies, 2011; Briguglio et al, 2009; Hassink, 2010; Pike et al, 2010) and others debate whether shocks should also include chronic "slow burn" trends (Pendall et al, 2010; Foster, 2007; Martin et al, 2015). For a more in-depth review of the academic discussion surrounding the concept of regional economic resilience, see Martin and Sunley (2015).

In 2015, Martin and Sunley (2015) proposed the following economic resilience definition with existing definitions and criticisms in mind:

> the capacity of a regional or local economy to withstand or recover from market, competitive and environmental shocks to its developmental growth path, if necessary by undergoing adaptive changes to its economic structures and its social and institutional arrangements, so as to maintain or restore its previous developmental path, or transit to a new sustainable path characterized by a fuller and

> more productive use of its physical, human and environmental resources.
>
> (Martin and Sunley, 2015, p.13)

Our measure most closely relates to engineering and ecological resilience, but we keep this definition in mind as we develop our measure and discuss its limitations.

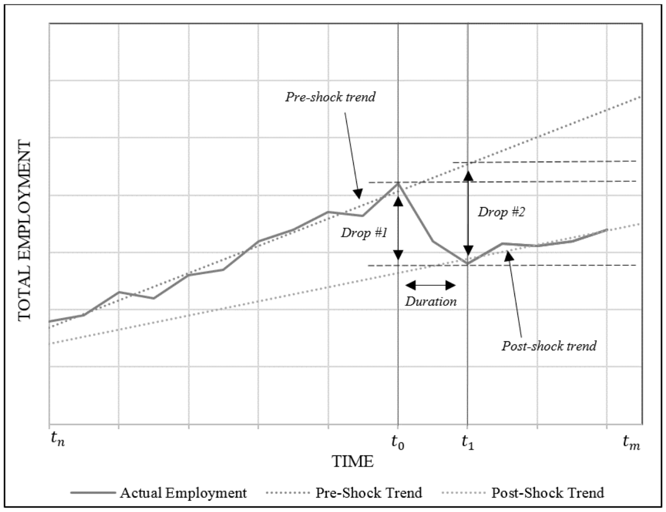
1.2.2 Measuring Economic Resilience

Existing efforts to measure resilience generally follow one of several general approaches. One involves resilience measures based on qualitative characteristics of the regions they are applied to (Briguglio et al, 2009; Kahsai et al, 2015). For example, Briguglio et al (2009) create an economic resilience index based on macroeconomic stability, microeconomic market efficiency, good governance and social development characteristics and Kahsai et al (2015) create a county economic resilience index based on industrial diversity, entrepreneurial activity and business dynamics, human and social capital, scale and proximity, and physical capital. An advantage of a qualitative measure is that it can capture the unique characteristics and complex nature of each region. The primary drawback is that the choice of variables and weighting procedure used in creating the index is subjective (Briguglio et al, 2009).

Another group of resilience measures involves quantifying regional responses to a shock by observing the behavior of an economic statistic representing economic activity. Researchers use such economic statistics as output, unemployment, and employment to observe the shock response of a variety of regional units including countries, regions within countries, metropolitan statistical areas (MSAs), and counties (Fingleton et al, 2012; Davies, 2011; Han and Goetz, 2015; Martin, 2012; Hill et al, 2008). These metrics draw heavily from engineering and ecological definitions of economic resilience and our measure follows this general approach. Such metrics are aimed solely at quantifying regional response to shocks. Any efforts to explain or identify qualities or characteristics distinct to each county that may be affecting local resilience take place in subsequent steps and analysis.

There are several dimensions of a region's response to a shock, as reflected by output or employment data behavior, that are repeatedly discussed in the literature. Martin and Sunley (2015) provide an extensive review of these dimensions and refer to them collectively as the "anatomy of resilience." We will discuss some of those dimensions here as they apply to employment data. These dimensions are illustrated in Figure 1.

Figure 1. Dimensions of an Economy's Response to a Shock



The first dimension is the decline in employment levels following a shock, or the drop. This can be measured as the actual drop from peak employment leading into the recession (actual employment at time t_0) to the trough (actual employment at time t_1) where a region hits its minimum level of employment following the start of the recession (Drop #1) or, following Han and Goetz (2015), as the difference between actual employment and the expected employment at the trough based on pre-recession growth path (the value of pre-shock trend employment at t_1) (Drop #2). Measures of drop capture the depth of the response. The second dimension of the response, duration, measures the time between the employment peak and trough, represented by the difference between t_0 and t_1 in Figure 1. The third dimension is often some measure of recovery, but resilience definitions put forth different views of what recovery means. This makes selecting a method of measuring recovery tricky. Possible measures include a return to the peak level of employment, a return to the original growth path, a return to the original growth rate, or the adoption of a new, favorable growth path (Martin and Sunley 2015). Han and Goetz (2015) represent a region's rebound as the rate of employment change in the six months following a region's trough, rather than defining recovery as a certain employment level to reach or a return to a pre-shock trend.

One element we do not see in existing measures of resilience is an effort to isolate a region's response to a shock from random variation or the variation we might expect to see if that shock had not occurred. County employment volatility varies and one could argue that if a resilience measure generated by observing the response of employment levels to the recession does not account for a county's own expected variation, it could overestimate the impact of the recession locally. We explore the use of an additional step in our resilience score calculation that nets out expected variation and discuss the potential advantages and disadvantages of using this adjustment.

1.3 DATA

We use U.S. county-level monthly employment data from the U.S. Department of Labor's Bureau of Labor Statistics for the years of 1990 through 2015.[1] We use monthly employment data for all counties and county equivalents with a few exclusions, using a total of 3,137 U.S. counties in our analysis.[2] We seasonally adjust the monthly employment data using the U.S. Census Bureau's X-13 ARIMA prior to the application of our resilience metric.

We choose to use employment data because of the availability and completeness of employment data for the past 25 years at the county-level and because it provides an opportunity to observe how the 2007-2009 recession affected county economic growth. Han and Goetz (2015) also use county-level employment data to observe region responses and measure resilience to the shock of the 2007-2009 recession. One primary limitation of using employment is its dependence on population. While this does not necessarily compromise our efforts to measure resilience, it does influence the behavior of total employment levels. In using counties as our regional units, we can observe in greater detail the spatially unbalanced nature of local responses to the national recession. Limitations to using counties are that these are not economically autonomous regions. Geographic regions are increasingly interwoven economically, on a national and global scale, which poses a challenge to all research in regional economics over how to define economic regions. Looking at recession responses in county employment data can, however, help to map how this particular shock rippled through the United States economy and provide an opportunity to observe response patterns. We can use these surface-level observations to expose the currents and underlying forces that are not bound by geography.

1.4 METHODS

The central goal of our resilience measure is to capture the variation in employment in response to the recession that exceeds what we can attribute to random variation. To do this, we must first identify the central tendency (first moment) of the data and variation around this central tendency (second

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[1] As of July 2016, this data can be accessed online at http://www.bls.gov/cew/datatoc.htm.

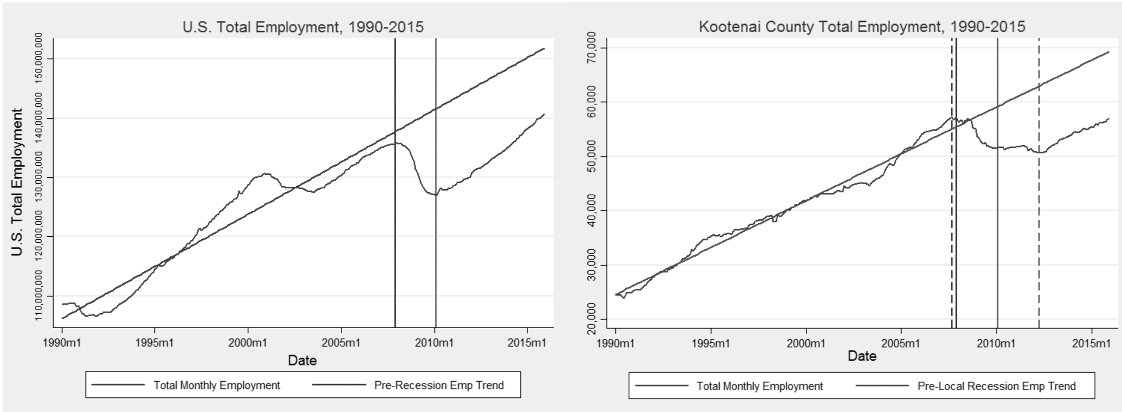
[2] Over the years of 1990 to 2015, there have been some code and county definition changes and we merged and appended data series to match these changes. We merged eight counties and excluded four for insufficient data or definitional changes. Following Han and Goetz (2015), we merged two counties into the Skagway-Hoonah-Angoon Census Area, Alaska which was split in 2007 and merged two counties into the Wrangell-Petersburg Census Area, Alaska which was split in 2008. We merged two pairs of counties that underwent name changes during this time period (Wade Hampton Census Area, Alaska became Kusilvak Census Area, Alaska and Shannon County, South Dakota became Oglala Lakota County, South Dakota in July 2015). We also merged two pairs of counties that retained their names but whose FIPs codes changed during the period (Ste. Genevieve County, Missouri and Park County, Montana). We excluded Clifton Forge City, Virginia, Broomfield County, Colorado, Prince of Wales-Hyder Census Area, Alaska and Prince of Wales-Outer Ketchikan Census Area, Alaska.

moment). We have elected to measure variation around a pre-local recession long-term growth trend. We calculate this trend by performing a simple linear regression of monthly employment levels over time from January 1990 up to the month of local peak employment.

To generate pre-local recession trends for each county, we first identify each county's month of peak employment that is followed by entry into a local recession. To do this, we begin by following a method used by Han and Goetz (2015) and identify peak employment by county as the maximum level of employment occurring between two years before and two years after the national employment peak. This allows for the fact that some counties led in this recession, entering a local recession before the nation, and some counties lagged, entering local recession after the nation. For consistency, we also use employment data to identify the start of the national recession. The National Bureau of Economic Research (NBER) defines the 2007-2009 recession as beginning in December 2007 and lasting until June 2009. This definition is based in large part on the behavior of real gross domestic product (real GDP) and real gross domestic income (real GDI) data. We find, according to our seasonally-adjusted employment data, that national employment levels peaked in December 2007 and experienced a trough, or end to the national recession, in February 2010. The NBER confirms the employment levels began to recover later than the real GDP and real GDI (NBER, 2010). For the purposes of this paper, we therefore define the national recession as beginning after December 2007 and lasting until February 2010 and identify peak employment for the counties as maximum local employment occurring between December 2005 and December 2009.

We identify each county's trough as the point of minimum employment after peak employment and prior to the end of 2015. Figure 2 shows total employment and the pre-recession employment trend for the United States on the left and on the right, one example county: Kootenai County, Idaho. In the graph showing United States employment the first solid vertical line (left) marks the national peak followed by entry into recession and the second solid vertical line (right) marks the end of the national recession. In the graph of Kootenai County, Idaho, the beginning and end of the national recession are again represented by the solid lines and the dashed lines represent the beginning and end of Kootenai County's local recession, based on our criteria.

Figure 2. Comparison of Local Recession for Kootenai County, Idaho to National Recession

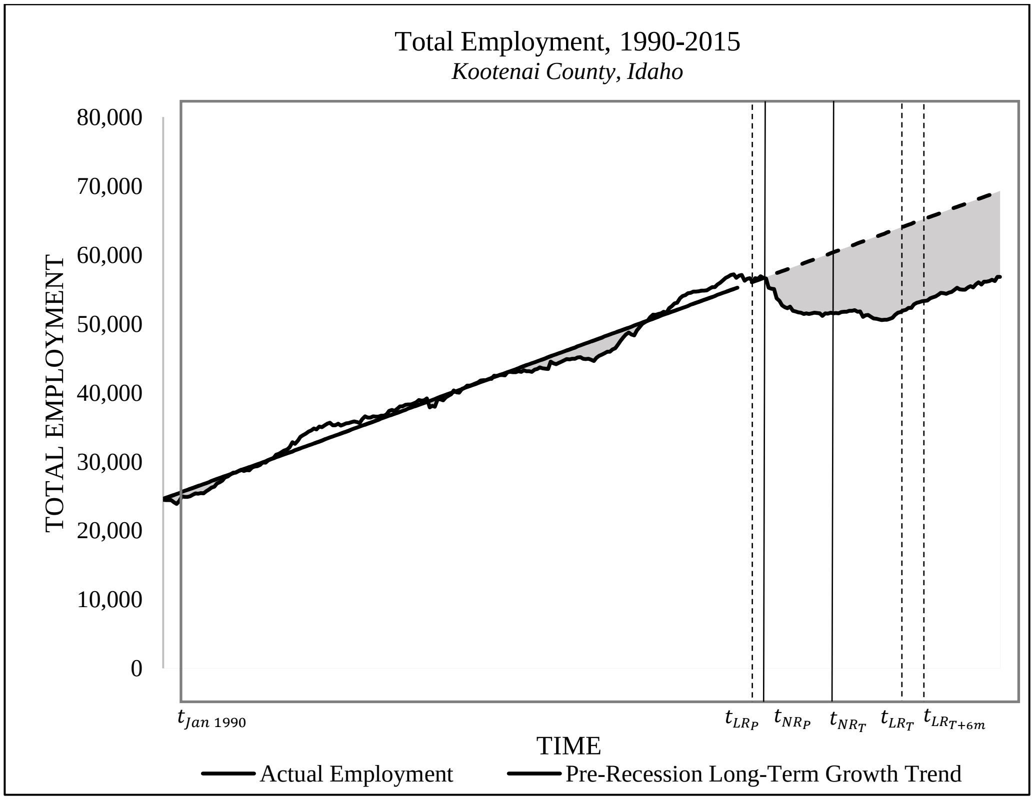


We seek to combine elements of drop and duration into one two-dimensional measure, by calculating the area of the deviation of actual employment below expected employment (based on a pre-local recession trend) during a specified time period following the start of the local recession. This application of our metric reflects engineering resilience and the idea that a resilient economy is one that returns to its original growth path. Alternatively, if we were to use employment change data rather than total employment to represent economic activity, a resilient economy could be one that returns to its pre-recession growth rate, or a higher one, rather than to its original growth path. Based on our application, both the U.S. and Kootenai County, Idaho are penalized for each month that they have not returned to their original path, but both return to a similar or improved growth rate following their employment troughs which some would argue is one form of recovery.

In applying this metric, one must decide what criteria to use to determine the period for response measurement. During the months from January 1990 to December 2015, counties exhibit a wide variety of behaviors. Some were in overall steady decline prior to the recession while others grew steadily over the entire period. Some are incredibly volatile and some counties experienced a double-dip, entering a short recovery and then falling into recession again (Han and Goetz, 2015). It is difficult to design a "one size fits all" set of criteria to identify county-specific time periods for measuring county responses to the recession while also including some element of recovery. We elect to measure resilience over the period from the local peak to six months, or two quarters, beyond the local trough in demonstrating one application of our metric. This window relies on our criteria for identifying local peaks and troughs and other researchers might choose to vary these criteria and their window for measuring resilience.

We begin by calculating the area under the trend during the months from the local peak to six months after the local trough. Figure 3 illustrates this area for Kootenai County, Idaho, represented by the shaded region between the local peak and start of the local recession (t_{LR_P}) and six months beyond the end of the local recession ($t_{LR_{T+6m}}$).

Figure 3. Example of Area Calculations for Kootenai County, Idaho



To calculate the gross area of these shaded regions, we calculate the difference between the integral of the plotted actual employment line and the integral of the trend line for each one month to month period. We then sum all of the individual month to month integral differences, or areas, for which actual employment was less than the pre-local recession trend. The value of the difference during these time periods is therefore, negative. This process in represented by Equation 1.[3]

$$A_{LR+6m} = \sum_{i=t_{LR_P}}^{t_{LR_{T+6m}}} A_i \qquad where\ A_i \begin{bmatrix} \int_{t_{i-1}}^{i} E_{actual} - \int_{t_{i-1}}^{i} E_{trend} & if\ negative \\ 0 & if\ positive \end{bmatrix} \tag{1}$$

[3] NOTE: Periods when actual employment crosses from above to below or below to above the trend line are handled differently. The portion of each of these periods where actual employment was below the trend is isolated and the area below the trend and above actual employment is calculated separately and included in the summations that yield our A_{LR+6m} values. This also applies to the process we use to calculate expected variation.

Here we add the optional step of adjusting the gross area by netting out expected variation. We calculate an area representative of the expected variation for a time period the length of the local recession plus six months (A_{EV}) for each county. We base our calculation of expected variation on pre-local recession behavior and begin with the same process used to perform the gross area below trend calculations explained above. We sum up the areas of all dips of actual employment below the pre-recession long-term growth trend occurring from January 1990 up to the month of each county's local peak employment (the shaded regions between $t_{Jan\ 1990}$ and t_{LP} in Figure 3), which will be cumulative but not continuous. We then divide this total by the number of months from January 1990 to each county's local peak ($t_{Jan\ 1990}$ to t_{LP}) to get an average area below the trend per month up to the month of peak employment. We then multiply this pre-local recession average monthly below-trend area by the number of months in each county's local recession plus six months. These values represent the area below the trend that we would expect to see and attribute to random variation. The process of calculating this expected variation for each time period is represented by Equation 2.

$$A_{EV} = \left(\sum_{i=t_{Jan1990}}^{t_{LR_P}} A_i \Big/ (t_{LR_P} - t_{Jan\ 1990}) \right) \times (t_{LR_P} - t_{LR_T+6m}) \tag{2}$$

We adjust our gross area (A_{LR+6m}) by netting out the expected variation for each time period. To do this, we subtract the expected variation (A_{EV}) from the gross area (A_{LR+6m}). This process is represented by Equation 3 below.

$$A_{LR+6m} - A_{EV} = Net\ Area\ of\ Local\ Recession\ Response\ (t_{LR_P} to\ t_{LR_T+6m}) \tag{3}$$

To make the area of recession impact comparable between counties of different sizes, we take an additional step and divide each net area of recession response by each county's respective employment level at its peak.

$$R_{LR+6m} = \frac{A_{LR+6m} - A_{EV}}{Employment_{peak}} \tag{4}$$

The resulting value, R_{LR+6m}, shown in Equation 4 is our resilience measure. A positive value signifies that the variation of actual employment below the expected employment (based on a pre-local recession trend) was less than the amount of variation that could be attributed to randomness. A negative value signifies that the amount of variation observed in actual employment dipping below the pre-precession trend exceeded that which could be attributed to random variation. Therefore, negative values signify that there was an observable response to the shock of the recession in county employment levels. If a county has a positive resilience score, it was resilient to this recessionary shock. If two counties have negative resilience scores, the county with the smaller absolute value would be considered relatively more resilient to the recession than the county with the larger absolute value.

The inclusion of the step adjusting for expected variation is optional and one should consider the characteristics that they would like their measure of resilience to reflect before deciding whether to make such an adjustment. If the gross area goes unadjusted, then there may be two counties who receive the same resilience score (based on gross area) but who have very different pre-recession behavior, where one shows relatively stable employment growth, sticking closely to its long-time growth trend, and the other has highly variable employment levels. Without accounting for these divergent behaviors, we might be overestimating the impact of the recession in the characteristically volatile county and, in terms of relativity, not representing that the local recession response was a more dramatic departure in behavior for the stable county than the volatile one. With that said, using the calculation methods we propose, some of the variability that goes into the estimation of expected variation counts employment behavior during prior recessions. One could argue that such an adjustment gives counties that have been adversely affected in prior recessions some extra credit in the calculation of its resilience to this recession, which may seem counterintuitive. It is not, however, unlike some effects of using pre-local recession trends to generate expected levels of employment that observed levels of employment during the recession can be measured against. Two counties with the same absolute drop, measured as the difference between peak and trough employment levels as a percent of peak employment, may have very different values in other drop measures calculated as the difference between expected employment and actual employment during the trough month, based on the pre-local recession trends. By the second measure, the drop for a county with a negative pre-local recession trend would be smaller than the drop for a county with a positive pre-local recession trend, even if their absolute drop from peak to trough was the same. This too may seem counterintuitive, but if a county is already in decline going into the recession, we do not want to credit all the absolute decline during the time of shock response to the shock itself. With this measure of resilience, we are trying to differentiate the specific response to this recession from larger trends occurring in each county. Any measure applied to all counties, each with their own unique behaviors and peculiarities, will work more effectively for some than others. For this reason, we honor both arguments about the inclusion of such an adjustment and while we focus more extensively on the results of the adjusted measure, we compare the results of the adjusted (net area) with the unadjusted (gross area) resilience measure by observing differences in the spatial distribution of relative resilience scores.

1.5 RESULTS

According to our seasonally adjusted employment data, national peak employment occurred in December 2007 and hit a trough in February 2010, marking the beginning and end of a 26-month national recession. In discussing our peak, trough, and duration results, we exclude counties whose maximum employment between December 2005 and December 2009 was not a local peak and those counties whose identified trough was not a confirmed local minimum. Of those counties excluded for not meeting the traditional local peak criteria, 117 hit maximum employment in December 2005, the first month of our peak identification period, but were already in decline from the previous month(s) and 11 counties hit maximum employment in December 2009, the last month of this period, but had employment levels increase in the month that followed. All 106 counties whose troughs were not confirmed local minima experienced their troughs in December 2015, the last month within our dataset, so we cannot confirm that employment increased in the subsequent month. After excluding counties in these two categories (229 total, 5 appeared in both), we have 2,908 counties that we use to produce summary statistics and analyze patterns in county peaks, troughs, and recession duration.

The majority of U.S. counties, 54.9 percent, entered a local recession prior to the start of the national recession. Of the remaining counties, 4.5 percent hit peak employment in December 2007, entering a local recession at the same time as the nation, and 40.6 percent hit peak employment after December 2007, entering a local recession after the start of the national recession. The months with the most counties hitting peak employment are December 2007 (4.5 percent) and August 2008 (3.9 percent). By year, 3.5 percent hit peak employment in 2005, 27.9 percent in 2006, 28.0 percent in 2007, 31.9 percent in 2008, and 8.7 percent in 2009.

The majority of U.S. counties, 61.1 percent, experienced their trough and end to their local recession after the nation. Of the remaining counties, 6.3 percent experienced their trough in the same month as the nation and 32.6 percent experienced their trough after the nation. The greatest number of counties, like the nation, hit their trough in February 2010 (6.3 percent), followed by December 2009 (4.3 percent). By year, 0.2 experienced their trough in 2006, 0.8 percent in 2007, 1.9 percent in 2008, 25.6 percent in 2009, 24.5 percent in 2010, 13.0 percent in 2011, 8.3 percent in 2012, 7.9 percent in 2013, 7.6 percent in 2014, and 10.3 percent in 2015.

On average, county local recessions lasted longer than the national recession, but varied greatly. On average, local recessions for counties lasted 46.6 months compared to the nation’s 26 months. The distribution of county recession durations, however, is widespread, with a minimum of 1 month, a maximum of 119 months, and a standard deviation of 28.1 months. Considering duration in years, 7.8 percent of county recessions lasted one year or less, 18.7 percent lasted between one and two years, 17.4 percent lasted between two and three years, 15.9 percent lasted between three and four years, 10.6 percent lasted between four and five years, 8.9 percent lasted between five and six years, and 20.8 percent lasted more than six years. It is possible that counties that show particularly long recessions, based on these criteria, may have been experiencing other trends that were contributing to their long-term decline.

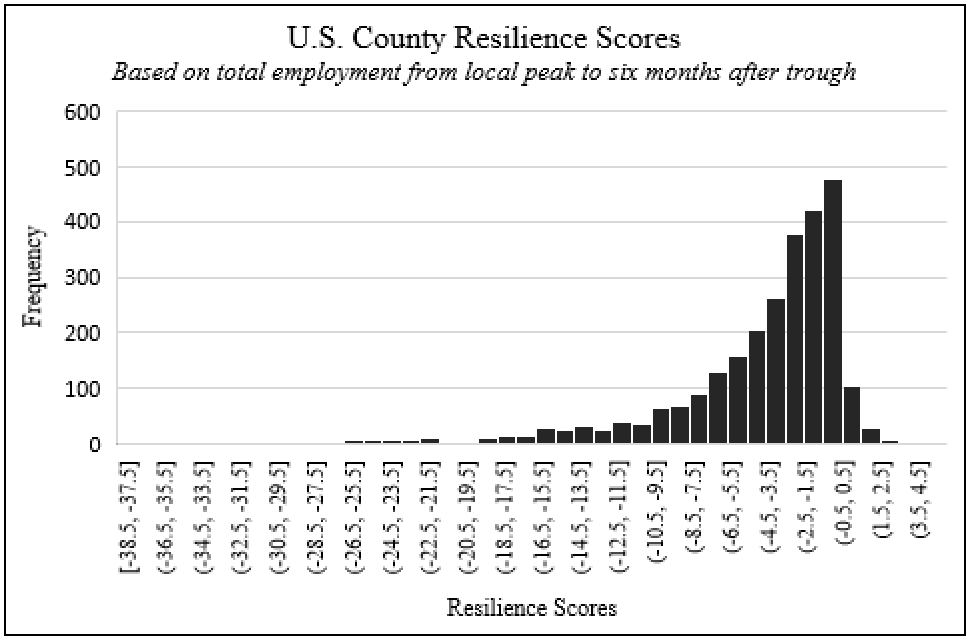
Prior to the start of the national recession, the nation had a positive long-term growth trend. Out of all 3,137 counties, 84.6 percent of counties had positive long-term growth trends and 15.4 percent of counties had negative long-term growth trends. Of the 3,009 counties that experienced peak employment meeting the local peak criteria, 85 percent had positive long-term growth trends and 15 percent had negative long-term growth trends prior to their local recession.

We also calculated post-recession trends using a simple regression of employment over the time in the months following each local recession to the end of 2015. To calculate post-local recession trends for counties, counties who had not experienced a trough by June 2015 are excluded to ensure that post-local recession trends are calculated with at least six months of available data. There are 2,710 counties that satisfy these criteria of the 2,908 that satisfied local peak and trough criteria. Of these, 37.8 had lower post-local recession growth rates and 62.2 percent of counties had higher growth rates after the end of their local recession than they had going into their local recession.

Our application of our resilience metric reflects the wide variation of responses to the 2007-2009 recession observed at the county level. Here again we look at the 2,710 counties that met local peak and trough criteria and hit their trough by June 2015 so the full local recession plus six-month window is captured. The resilience score for the nation was -1.94 and the average county resilience score was -3.92 with a standard deviation of 5.19, a minimum of -38.47 (Manassas Park City, Virginia), and a maximum of 5.40 (Nicholas County, Kentucky). Many counties with high positive scores have negative pre-local recession trends and some dramatic variation, often a drop, in employment during their pre-local recession years causing expected variation values to be relatively high. A strongly negative pre-local recession trend can result in actual employment being above the trend-projected employment for the entire period of our resilience calculation. Out of the 2,710 counties whose resilience scores we analyzed, a total of 148 counties were above their pre-local recession trend for the entire response measurement period.

Figure 4 shows the distribution of the resilience scores based on our application. Once again, a positive value signifies that the variation of actual employment below expected employment (based on a pre-local recession trend) was less than the amount of variation that could be attributed to randomness whereas a negative value means that the amount of variation observed in actual employment dipping below the pre-local recession trend exceeded that which could be attributed to randomness.

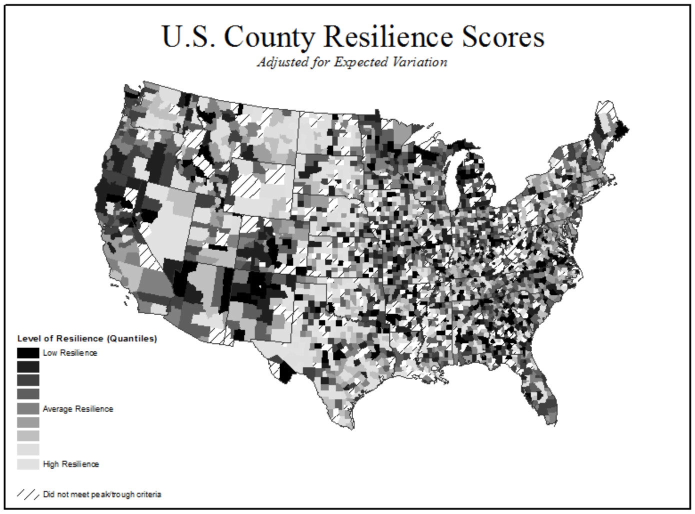
Figure 4. Distribution of U.S. County Resilience Scores

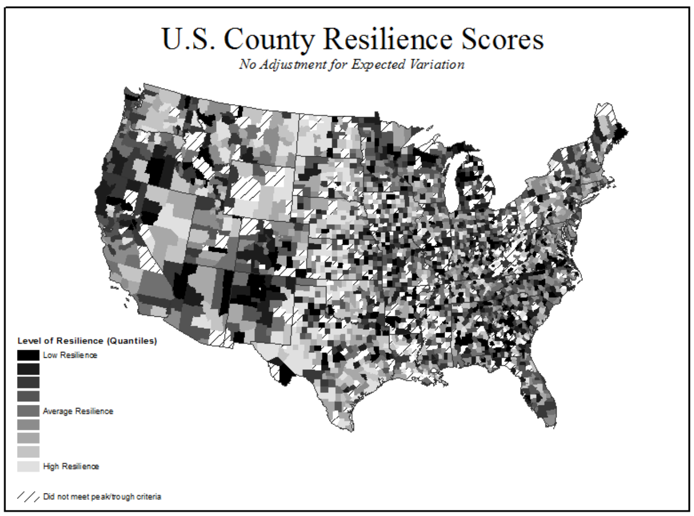


We use regions from the Bureau of Economic Analysis (BEA), rural-urban continuum codes developed by the United States Department of Agriculture's Economic Research Service (ERS), and county typology information from the ERS to see how different subsets of counties performed compared to one another. Based on mean resilience scores, the Mideast (-2.61), Southwest (-2.81), and Far West (-3.03) regions appeared to be the most resilient to this recession and the Great Lakes (-5.27), Southeast (-4.79), and Rocky Mountain (-3.71) appeared to be the least resilient. For comparison, Han and Goetz (2015) found that the Southwest and Plains had great resilience based on their resilience measure, which incorporates measures of drop and rebound, and found that New England and the Mideast had low resilience due to small rebounds while the Far West had low resilience due to large drops and smaller rebounds.

The spatial distribution of our resilience scores with and without the adjustment for expected variation are represented in the maps provided in Figure 5. The differences between these maps are minor and take some studying to find. This suggests that our adjustment for expected variation does not cause major shifts in the relative resilience of counties. In fact, the correlation between the unadjusted and adjusted resilience scores is very high (0.993). Both maps show the wide variation in the resilience scores of counties within the same BEA regions, observable in the standard deviations of scores within each BEA region and the visible variation seen in the maps in Figure 5.

Figure 5. Spatial Distribution of U.S. County Resilience Scores





With the use of the rural-urban continuum codes, we can observe how resilience scores differed between metropolitan counties of varying population size and nonmetropolitan counties classified by their population size and whether they are adjacent to metropolitan areas (ERS USDA 2015). Based on each group's mean score, nonmetro, not metro-adjacent counties with urban populations of 20,000 or more appeared to be the most resilient (-2.74) while nonmetro, but metro-adjacent counties with an urban population between 2,500 and 19,999 appeared to be the least resilient (-4.95). When we divide counties into metro counties, nonmetro counties that are metro adjacent, and nonmetro counties that are not metro-adjacent, disregarding population size, metro counties appear to be the most resilient (mean resilience score equal to -3.41) while nonmetro, metro-adjacent counties appear to be the least resilient (mean resilience score equal to -4.55). With that said, there is still great variation within each of these categories and when comparing the mean resilience scores for all metro counties with all nonmetro counties using a t-test (for all U.S. counties and counties by BEA region), we do not find that their means are statistically different.

The industries that a region depends on can influence its resilience to economic shocks and retrospective analyses of the Great Recession have found that U.S. agriculture appeared to fair relatively well as an industry through the 2007-2009 recession (Sundell and Shane, 2012). Our resilience results reflect this. Farming-dependent counties tended to fair better than non-farming-dependent counties. The ERS provides typology data for two periods occurring within our 25-year dataset: 1998-2000 and 2010-2012. In the data for 1998-2000, farming-dependent counties are those that either had an annual average of 15 percent or more total county earnings coming from farming or 15 percent or more of employed residents working in farming. There are 350 counties out of our 2,710 that classify as farming-dependent during this period. In the 2010-2012 data, farming-dependent counties were those where farming accounted for 25 percent or more of total county earnings or 16 percent or more of employment. There are 415 counties out of our 2,710 that classify as farming-dependent during this period. Among counties classified as farming-dependent during the 1998-2000 timeframe, the average resilience score was -2.71, compared with an average resilience score of -4.11 for non-farming-dependent counties. Among counties classified as farming-dependent during the 2010-2012 timeframe, the average resilience score was -2.92, compared with an average score of -4.11 for those that were not farming-dependent.

When we reintroduce the rural-urban continuum codes while accounting for farming-dependency, we begin to see statistically significant differences between groups that we did not see when looking at rural-urban status alone. Using our three, broad rural-urban categories (i.e. metro counties; nonmetro, metro-adjacent counties; nonmetro, not metro-adjacent counties), we perform pairwise comparisons of the means of county groups based on which rural-urban category they belong to and whether they are farming-dependent (see Table 1 for results of all comparisons). We find that farming-dependent counties outperformed their non-farming-dependent counterparts within every rural-urban category. Nonmetro, metro-adjacent, farming-dependent counties and nonmetro, not metro-adjacent, farming-dependent counties both showed positive mean differences that are statistically significant at the 0.05 level when compared with non-farming-dependent counties of the same rural-urban status. When nonmetro, metro-adjacent and nonmetro, not metro-adjacent farming-dependent counties were compared with one another based on the 1998-2000 typology data, nonmetro, not metro-adjacent, farming-dependent counties appeared to be more resilient with a statistically significant mean difference.

Among non-farming counties, metro counties strongly outperformed both groups of nonmetro counties with mean differences that are statistically significant at the 0.01 level for groups using both the 1998-2000 and 2010-2012 typology data. Interestingly, however, these non-farming-dependent metro counties were not more resilient than nonmetro, not metro-adjacent counties that were farming-dependent. Nonmetro, not metro-adjacent farming-dependent counties appeared to be more resilient than non-farming-dependent metro counties with a mean difference that is statistically significant at the 0.05 level using both time periods of typology data. In the results of all these pairwise comparisons of means (Table 1), we can see that these rural, remote, farming-dependent counties consistently showed higher levels of resilience compared with all other groups, often with statistically significant mean differences.

Table 1. Pairwise Comparison of Means, Rural-Urban and Farming-Dependency Status

Group 1	Group 2	Typo. Data	Diff.	Std. Err	P > |t|
Metro counties, Farming-dependent	Metro counties, Not Farming-dependent	1998-2000 2010-2012	0.254 0.256	0.923 0.739	0.783 0.728
Nonmetro, Metro-adjacent counties, Farming-dependent	Nonmetro, Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	1.120 1.451	0.544 0.508	0.040** 0.004**
Nonmetro, Not Metro-adjacent counties, Farming-dependent	Nonmetro, Not Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	2.386 1.850	0.413 0.400	0.000*** 0.000***
Metro counties, Farming-dependent	Nonmetro, Metro-adjacent counties, Farming-dependent	1998-2000 2010-2012	0.397 0.132	1.043 0.862	0.703 0.879
Metro counties, Farming-dependent	Nonmetro, Not Metro-adjacent counties, Farming-dependent	1998-2000 2010-2012	-0.917 -0.468	0.973 0.792	0.346 0.555
Nonmetro, Metro-adjacent counties, Farming-dependent	Nonmetro, Not Metro-adjacent counties Farming-dependent	1998-2000 2010-2012	-1.314 -0.600	0.619 0.575	0.034** 0.297
Metro counties, Not Farming-dependent	Nonmetro, Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	1.263 1.326	0.244 0.247	0.000*** 0.000***
Metro counties, Not Farming-dependent	Nonmetro, Not Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	1.215 1.125	0.272 0.278	0.000*** 0.000***
Nonmetro, Metro-adjacent counties, Not Farming-dependent	Nonmetro, Not Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	-0.048 -0.201	0.288 0.294	0.868 0.495
Metro counties, Farming-dependent	Nonmetro, Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	1.517 1.582	0.927 0.745	0.102 0.034**
Metro counties, Farming-dependent	Nonmetro, Not Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	1.469 1.382	0.935 0.756	0.116 0.068*
Nonmetro, Metro-adjacent counties, Farming-dependent	Metro counties, Not Farming-dependent	1998-2000 2010-2012	-0.143 0.125	0.536 0.499	0.790 0.803
Nonmetro, Metro-adjacent counties, Farming-dependent	Nonmetro, Not Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	1.072 1.250	0.557 0.524	0.054* 0.017**
Nonmetro, Not Metro-adjacent counties, Farming-dependent	Metro counties, Not Farming-dependent	1998-2000 2010-2012	1.171 0.725	0.384 0.366	0.002*** 0.048**
Nonmetro, Not Metro-adjacent counties, Farming-dependent	Nonmetro, Metro-adjacent counties, Not Farming-dependent	1998-2000 2010-2012	2.434 2.050	0.395 0.378	0.000*** 0.000***

* signifies significance at 0.10 level, ** at 0.05 level, *** at 0.01 level

Manufacturing, an industry that was already experiencing long-term decline going into the 2007-2009 recession, experienced accelerated job loss during the national recession (Barker 2011, Flora and Flora 2013). This too is reflected in our resilience scores, though not as strongly as the relative resilience of farming-dependent over non-farming-dependent counties. In the ERS typology data for 1998-2000, manufacturing-dependent counties are those where manufacturing accounted for an annual average of 25 percent or more total earnings during the associated time period. There are 780 counties out of our 2,710 that meet these criteria during this period. In the 2010-2012 data, manufacturing-dependent counties were those where manufacturing accounted for 23 percent or more of the county's earnings or 16 percent of the average employment of that time period. There are 447 counties out of our 2,710 that meet these criteria during this period. Among counties classified as manufacturing-dependent during the 1998-2000 timeframe, the average resilience score was -4.93, compared with an average resilience score of -3.52 for non-manufacturing-dependent counties. Among counties classified as manufacturing-dependent during the 2010-2012 timeframe, the average resilience score was -4.41, compared with an average score of -3.84 for those that were not manufacturing-dependent.

When we perform pairwise comparisons of the means of county groups based on their rural-urban status and whether they are manufacturing-dependent, we find further evidence that manufacturing-dependent counties were particularly hard hit by this recession (see Table 2 for results of all comparisons). Non-manufacturing-dependent metro counties appear more resilient than all manufacturing-dependent counties, regardless of rural-urban status, with statistically significant mean differences for both sets of ERS typology data. Nonmetro, not metro-adjacent manufacturing-dependent counties appeared to be less resilient than their non-manufacturing-dependent counterparts, though the pairwise mean difference was only statistically significant using the 1998-2000 typology data. Among manufacturing-dependent counties, metro counties appeared to be the most resilient, however the mean differences were statistically significant only when compared to both groups of nonmetro counties based on the 1998-2000 typology data.

Table 2. Pairwise Comparison of Means, Rural-Urban and Manufacturing-Dependency Status

Group	Group 2	Typ. Data	Diff.	Std. Err	P > |t|
Metro counties, Manufacturing-dependent	Metro counties, Not Manufacturing-dependent	1998-2000 2010-2012	-0.996 -1.044	0.345 0.467	0.004*** 0.026**
Nonmetro, Metro-adjacent counties, Manufacturing-dependent	Nonmetro, Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	-0.100 0.120	0.357 0.407	0.005*** 0.768
Nonmetro, Not Metro-adjacent counties, Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	-2.734 -0.554	0.484 0.572	0.000*** 0.333
Metro counties, Manufacturing-dependent	Nonmetro, Metro-adjacent counties, Manufacturing-dependent	1998-2000 2010-2012	1.058 0.144	0.405 0.561	0.009*** 0.797
Metro counties, Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties, Manufacturing-dependent	1998-2000 2010-2012	2.077 0.121	0.521 0.691	0.000*** 0.860
Nonmetro, Metro-adjacent counties, Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties Manufacturing-dependent	1998-2000 2010-2012	1.019 0.023	0.521 0.643	0.051* 0.972
Metro counties, Not Manufacturing-dependent	Nonmetro, Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	1.054 1.308	0.288 0.263	0.000*** 0.000***
Metro counties, Not Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	0.339 0.611	0.277 0.262	0.222 0.020**
Nonmetro, Metro-adjacent counties, Not Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	-0.716 -0.697	0.301 0.283	0.017** 0.014**
Metro counties, Manufacturing-dependent	Nonmetro, Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	0.058 0.264	0.364 0.264	0.872 0.582
Metro counties, Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	-0.657 -0.433	0.355 0.479	0.065* 0.366
Nonmetro, Metro-adjacent counties, Manufacturing-dependent	Metro counties, Not Manufacturing-dependent	1998-2000 2010-2012	-2.054 -1.188	0.338 0.393	0.000*** 0.003***
Nonmetro, Metro-adjacent counties, Manufacturing-dependent	Nonmetro, Not Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	-1.715 -0.577	0.349 0.407	0.000*** 0.156
Nonmetro, Not Metro-adjacent counties, Manufacturing-dependent	Metro counties, Not Manufacturing-dependent	1998-2000 2010-2012	-3.073 -1.165	0.476 0.562	0.000*** 0.038**
Nonmetro, Not Metro-adjacent counties, Manufacturing-dependent	Nonmetro, Metro-adjacent counties, Not Manufacturing-dependent	1998-2000 2010-2012	-2.018 0.143	0.490 0.572	0.000*** 0.803

* signifies statistical significance at 0.10 level, ** at 0.05 level, *** at 0.01 level

There are many ways that we can divide counties into categories based on their shared attributes in attempt to excavate the factors that influence resilience. Other researchers have already begun to do this. We look at the presence of agriculture and manufacturing as a first glance at the relationships of two large U.S. industries to resilience to the 2007-2009 recession. Undoubtedly, there are much deeper and less visible forces that contribute to community resilience and vulnerability that will require further and more complex analysis to uncover.

The choices that we made in the application of our resilience metric inform the type of resilience that our results reflect. Our use of total employment data and choice to compare actual employment to a long-term employment trend based on pre-local recession behavior, treating those that stick closely to or even above their growth path as more resilient, reflects the engineering definition of resilience. Again, we could choose to use other economic statistics, or in this case, even different forms of employment data, like monthly employment change. In running the same calculation process, but with employment change data, we obtain slightly altered resilience rankings as this method places more emphasis on the idea of recovery being a return to an original growth rate or adoption of a higher one. If counties deviate from the original growth path, but return to or exceed their original growth rate, they are no longer penalized in this alternative application even if they never return to their original growth path. This would reflect an idea of resilience that is closer to the concept of ecological resilience and is an example of just one alternative application of our resilience metric.

1.6 CONCLUSIONS

Describing and quantifying regional variation in resilience is a critical first step to understanding what factors contribute to a region's ability to resist and recover from economic shocks. In understanding how to foster the desirable attributes of resilience, we can provide better guidance to policy makers and community leaders as they try to strengthen their communities and prepare them for internal and external shocks that they may not be able to predict.

A single, agreed-upon definition of resilience does not yet exist, just as there is no single measure of resilience that all researchers in regional economics endorse. This is a crucial and ongoing area of research that requires further development and discussion if a unified approach to economic resilience is to be attained.

Our measure of resilience builds on previous literature and proposes a two-dimensional response to a shock based on first and second moment conditions in the data and subtracting out variation due to randomness. This metric offers a step to correct estimates of resilience in counties which have endogenously higher volatility, therefore disentangling behavior due to this general volatility from resilience. The two-dimensional nature of our measure combines both the central trend (first moment condition) and variance around that trend (second moment condition) into a singular measure of resilience. Our measure of resilience is neither deviations from a growth path or volatility, but rather an interaction between these two measures that nets out expected volatility based on historic variation.

The primary limitations of the work and results that we have shared in this paper are related to specific choices we have made in the application of our metric. Our choice of using total employment to measure economic activity and a long-term, linear pre-recession trend to project expected employment in the absence of the 2007-2009 recessionary shock make this measure of resilience most reflective of equilibrium-based definitions, particularly concepts of engineering resilience. Our choice to measure resilience over the months of each county's local recession and the six months following allows us to capture the beginning of recovery, but somewhat minimally. Some existing resilience metrics measure recovery or post-local recession behavior separately or as a rate. Alternative applications of this metric may be able to credit counties more for strong recovery behavior, or at least reduce the penalization to regions for the absolute loss in response to the recession if a similar or improved growth rate develops in the time of recovery. Finally, this measure of resilience does not speak to the overall resilience of regions, but rather to the resilience of U.S. counties to this particular shock, the 2007-2009 recession. Changes in the application of this metric can ameliorate some, but not all, of these limitations.

Developing measures of resilience allows us to identify how regions perform relative to one another when exposed to the same shock. With this ability to compare responses, we can begin to explore the possible explanations for variation among responses which could ultimately inform recommendations for fostering resilience through targeted economic development strategies.

In this paper, we only begin to explore how different counties, grouped by shared characteristics like location in the same BEA region, rural-urban status, and farming- or manufacturing-dependency, performed relative to one another. We found the most pronounced differences when looking at farming-dependency and manufacturing-dependency, confirming other studies findings on the strong performance of agriculture and waning manufacturing industry leading up to and during the recession. Farming-dependent counties largely outperformed non-farming-dependent counties of the same rural-urban status and nonmetro, not metro-adjacent farming-dependent counties appeared the most resilient of these, also on average, performing better than metro counties that were not farming-dependent. Among manufacturing-dependent counties, metro counties appeared the most resilient, but all manufacturing counties were outperformed by not manufacturing-dependent metro counties. In addition, both metro and nonmetro, not metro-adjacent manufacturing-dependent counties were outperformed by their non-manufacturing-dependent counterparts of the same rural-urban status.

While we recognize that this is far from the last and definitive word on the topic, we hope that this measure of resilience will further the discussion of what it means for a region to be "resilient" and how we can effectively measure that quality. We also believe that this measure provides some insights into geographic differences in resilience and, with further development, can be used in future research exploring the causes and nature of this geographic variation in regional economic resilience scores.

CHAPTER 2 – APPLYING THE COMMUNITY CAPITALS FRAMEWORK TO COUNTY ECONOMIC RESILIENCE

2.2 INTRODUCTION

The previous chapter contributes to the discussion on how to measure regional economic resilience. Its proposed method was applied to U.S. county monthly employment data leading up to, during, and after the 2007-2009 national recession to produce scores representing each county's relative regional resilience based on employment level behavior. Identifying the relative resilience of regions to the same shock is a necessary precursory step for those interested in exploring the forces and community characteristics associated with regional resilience based on empirical evidence in addition to theory. The resilience scores from the previous chapter are carried over into this one as we explore the relationship of resilience to the 2007-2009 recession to the various forms of community wealth represented in the community capitals framework. We use our adjusted resilience measure in addition to existing single-dimension measures of resilience, including drop and rebound, to represent regional economic resilience within our model.

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.

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 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 (EFA) to observe the general behavior of the potential observed variables we collect to related to social, cultural, and political capital, 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 capital 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.

2.3 RELATED LITERATURE

The goal of the previous chapter was to develop a quantitative measure of U.S. county economic resilience to the Great Recession based solely on the behavior of monthly employment levels leading up to, during, and after the shock. The method we proposed results in a two-dimensional metric, reflective of local recession depth, duration, and variable rate of decline from the local employment peak to its trough, marking the end of the recession. We chose to measure six months beyond the end of the local recession to capture early recovery behavior. We also added an optional additional step correcting for expected variation, essentially netting out the amount of variation in employment that one might expect to see in the absence of the shock of the Great Recession, based on pre-local recession behavior.

In this chapter, we utilize our metric in a structural equation model designed to explore the relationships of community capital stocks to relative regional economic resilience. Representing community capital stocks of U.S. counties using secondary data presents its own challenges although factor analysis and structural equation modeling allow us to incorporate them into our analysis and model despite not being able to directly measure them. To begin, we must clarify what we mean by community capitals, discuss options for representing community capitals in our model using methods like factor analysis and the thoughtful selection of relevant observed variables, and articulate our expectations regarding the relationships between observed variables, community capitals, and ultimately, regional economic resilience based on theory and previous research.

2.3.1 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 (2004) and includes seven types of community capitals: social, cultural, political, human, financial, natural, and built (or physical) capital. Flora et al (2004) 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 “various elements, resources, and relationships within a community and their contribution to the overall functioning of the community” (Mattos, 2015). 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 (Gasteyer, 2014). 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.

2.3.2 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 and Flora (2013) in their discussion of rural wealth creation.

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 and Flora, 2013; Putnam, 1995; Woolcock and Narayan, 2000). 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 and Flora 2013) and bridging capital “connects diverse groups within the community to each other and to groups outside the community" (Flora and Flora, 2013). 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 and Flora, 2013).

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 and Flora, 2013). 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, 1986). 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 and Flora, 2013). 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, 1986). 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 and Flora, 2013).

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 (Emery and Flora, 2006; Flora and Flora, 2013). 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 and Flora, 2013).

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 and Flora, 2013; Emery and Flora, 2006). 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 and Flora, 2013). 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.

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 and Flora, 2013) 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.

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 and Flora, 2013; Emery and Flora, 2006). 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 and Flora, 2013; Emery and Flora, 2006; Florida, 2002; McGranahan and Wojan, 2007). Natural capital is in turn affected by political capital and the choices made in the public policy arena regarding land and resource use.

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 (Emery and Flora, 2006; Flora and Flora, 2013). 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 and Flora, 2013). 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, 2006).

2.3.2.1 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 (2006) 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.

2.3.2.2 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.

2.4 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.

2.4.1 Observed Variable Selection

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.

2.4.1.1 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 and Flora, 2013). 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 (Akçomack and ter Weel, 2008).

Our choice of observed variables related to social capital was guided largely by the work of Rupasingha, Goetz, and Freshwater (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, Goetz, and Freshwater (2006), we represent the aggregate membership organizations value relative to population, in our case, by simply dividing by the county population. Rupasingha, Goetz, and Freshwater (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 crimes 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 (Akçomack and ter Weel, 2008). 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 (Glaeser, 2002; DiPasquale and Glaeser, 1999; Glaeser et al, 2000; Putnam, 1995). 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 (Belton, Huq, Oyelere, 2014; Alesina et al, 1999). We use the measure of ethnic fractionalization used by Alesina et al (1999) represented by the following equation

$$Ethnic\ fractionalization = 1 - \sum_i (Race_i)^2 \tag{5}$$

where $Race_i$ refers to the share of the population that self-identifies as $Race\ i$. 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) (Glaeser et al, 2002; Browne, 2001). One recent 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, 2014). 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, Goetz, and Freshwater (2006) argue that greater income inequality can reduce social capital as those with lower income may feel exploited and disconnected. Following Rupasingha, Goetz, and Freshwater (2006) as well as Alesina et al (1999), 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.

2.4.1.2 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 and Flora, 2013). 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.

Within the first category of cultural-related observed variables, we have one experimental measure representing the economic enfranchisement across races and ethnicities, although we will refer to this measure as economic 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

$$Economic\ enfranchisement_j = -\sum \frac{|Difference\ between\ Firm\ Owner\ Share\ and\ Population\ Share_{i,j}|}{mean(|Difference\ between\ Firm\ Owner\ Share\ and\ Population\ Share_i|)} \tag{6}$$

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

$$\left|Difference\ between\ Firm\ Owner\ Share\ and\ Population\ Share_{i,j}\right| = \left|\left({Population_{i,j}}/{Total\ Population_j}\right) - \left({Firm\ owners_{i,j}}/{Total\ Firm\ Owners_j}\right)\right| \quad (7)$$

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 economic 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.

2.4.1.3 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 and Flora, 2013). 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. 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.

2.4.1.4 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 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.

2.4.1.5 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. We choose to exclude measures like personal income per capita as this is influenced by non-financial characteristics of individuals like level of education.

2.4.1.6 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 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)[4] 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. 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.

2.4.1.7 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.

2.4.2 Data Sources

Our resilience measures come from the previous chapter and were 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

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

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.

2.4.2.1 Social Capital Data Sources

The social capital index and data used to generate it comes from the 2005 Social Capital Index, available through the Northeast Regional Center for Rural Development at Pennsylvania State University (Rupasingha et al, 2006). 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. Three groups representing county rural-urban status were generated using the 2013 Rural-Urban Continuum Codes produced by the USDA’s ERS. The number and percent of family households was generated using 2005-2009 ACS data. Data on the percent of people all ages living below the poverty level comes from the Census Bureau’s Small Area Income and Poverty Estimates (SAIPE) data. Gini coefficients were accessed via the County Health Rankings and were generated using 2000 Census data and 2005-2007 ACS data. The ratio of mean to median household income was generated using 2005-2009 ACS data.

2.4.2.2 Cultural Capital Data Sources

Our economic enfranchisement variable is generated using population data from the 2000 Census and firm ownership data from the Census 2007 Survey of Business Owners and Self-Employed Person. The percent of firms owned by women also comes from 2007 SBO data. The ratio of wage and salary employment to proprietor employment was generated using 2005 employment data from the Bureau of Economic Analysis (BEA). Average household size data comes from 2005-2009 ACS data. Museums per capita is generated using data from the Institute of Museum and Library services. Artistic share of the workforce data comes from the 2007-2011 USDA ERS’s Creative Class Codes

2.4.2.3 Political Capital Data Sources

Data on the number of local political organizations, voter turnout, and census response rate come from the Northeast Regional Center for Rural Development at Pennsylvania State University. Data on political contributions come from a project conducted by the Sunlight Foundation where location-based analysis was performed using federal campaign finance data. For our project, we used data on political contributions occurring within the 2004 election cycle.

2.4.2.4 Human Capital Data Sources

Population age data comes from the 2000 Census and is used for the generation of the dependency ratios. Share of employment in the creative class is provided by the 2007-2011 USDA ERS's Creative Class Codes. Labor force participation and education data come from 2005-2009 ACS data. Dropout rates are generated using 2000 Census data. Percent of individuals ages 18 to 64 without health insurance comes from the U.S. Census Bureau's 2005 Small Area Health Insurance Estimates (SAHIE) data. Obesity, diabetes, and mortality rates come from 2005 CDC data and are available in age-adjusted and not age-adjusted forms. We use age-adjusted rates. Physical activity and life expectancy estimates are for 2005 and come for the Institute for Health Metrics and Evaluation.

2.4.2.5 Natural Capital Data Sources

The Natural Amenity scale is a measure produced and provided at the county level by the USDA's ERS and last published in 1999. Levels of air pollution are represented by 2005 data and were obtained via the 2010 County Health Rankings, though they come originally from 2005 CDC-Environmental Protection Agency collaboration data. Data on total area, total land area, and total water area comes from the 2000 Census, while data on federally-owned land comes from the 2014 National Atlas and data on land in farms comes from 2002 USDA-NASS datasets. The values of crop sales per acre were generated using 2002 data from USDA-NASS.

2.4.2.6 Financial Capital Data Sources

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.

2.4.2.7 Built Capital Data Sources

Total housing units comes from 2005-2009 ACS data, while data pertaining to transportation infrastructure (i.e. airports, Amtrak, road miles) come from 2011 and 2014 National Atlas data. Some variables were generated using this data in ArcGIS. Broadband coverage data come from the Federal Communications Commission (FCC).

Screening the Data

As with any statistical analysis, it is important to screen the data to identify violations of method assumptions that can affect results, introducing bias or limiting their robustness. To prepare for exploratory factor analysis and structural equation modeling, we look for issues of non-normal distributions and check for high correlations (over 0.9) among variables to guide our decision of which variables to use in our analysis and of those, identify which may require transformation. Certain methods of SEM estimation (i.e. maximum likelihood) can produce estimates that are robust even when variables are not normally distributed, however, severe cases can still potentially introduce errors so we want to be aware of the characteristics of the data and identify potential problem areas.

Among our social capital observed variables, the primary issues concern nonnormality among the aggregate social associations per capita, number of non-profits (total and per capita), and violent crimes per capita. All these variables are right-skewed, the social associations and non-profits variables severely enough to consider transformation or exclusion. Among our cultural capital variables, issues with nonnormality arise with the number of museums per capita and artistic share of the workforce (both right-skewed). Among our political capital observed variables, the simple correlation between of political contributions per capita and the number of political contributions per capita is high (0.92). Of these two, we choose to exclude the value of political contributions per capita from our analysis as this reflection of political capital is slightly more correlated with financial capital and the number of political contributions per capita may, at least in theory and definition, be more reflective of wider participation of county residents in the political process via financial support irrespective of the value of total donations. The political organizations per capita is highly right-skewed and has 2,345 counties with zero organizations. We explore the behavior of this variable in our analysis, but exclude it when problems arise. Among our human capital observed variables, we can see that simple correlations move as we might expect, with education and heath related variables showing strong, but not problematic, correlations with each other. We have physical activity and life expectancy by gender and will keep the male variable for each for consistency. There are also no major violations of normal distribution (e.g. no skewness values greater than |2|). Among our financial capital observed variables, dividends and interest per capita are highly correlated but this correlation does not exceed 0.90 so we will keep both to ensure that financial capital has three observed variables. All variables are right-skewed enough to consider transformation. Among our natural capital observed variables, our temperature variables (January and July) are the only variables with correlations exceeding 0.5, the remaining correlations are lower. Issues with non-normal distributions arise with our air pollution, value of crops sale per acre, and ratio of federally-owned land variables. Of these, all but the value of crop sales per acre have a high proportion of zero values and all may be better represented in our analysis after transformation. Among our built capital observed variables, total housings units per square mile and hospitals per square mile are highly correlated (0.98). We choose to exclude hospitals per square mile. Most of the built capital variables are not normally distributed and are severely right-skewed except for proximity to a major airport and broadband coverage. Table 14 in Appendix A summarizes all potential actions based on data screening.

2.5 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.

2.5.1 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

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

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.

Not all of the results are discussed here, but tables summarizing some of the main results for each of these EFAs, including information about initial factor extraction, rotated factors, factor loadings, and uniqueness (where applicable) can be found in Appendix B.

2.5.2 Results

The primary observations that we make looking at the results from our four 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 economic 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 the 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.

2.6 STRUCTURAL EQUATION MODEL: METHOD 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.

2.6.1 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, 1998). 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). In the previous chapter, our resilience measure was calculated using data from the local recession plus six months to include some measure of recovery. Since we include rebound in this model, our resilience observed variable (and expected variation) has been recalculated for just the local recession months. This variable is highly correlated (0.997) with the resilience measure calculated for the previous chapter over the longer time period. 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:

$$Rebound = \frac{y_{t_3} - y_{t_2}}{y_{t_2}} \times \frac{1}{t_3 - t_2} \qquad (8)$$

where 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

$$Rebound = \frac{Emp_{trough+6m} - Emp_{trough}}{Emp_{trough}} \times \frac{1}{t_{trough+6m} - t_{trough}} \qquad (9)$$

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 discussed in this chapter, 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.[5] 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

[5] 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, 2005).

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.

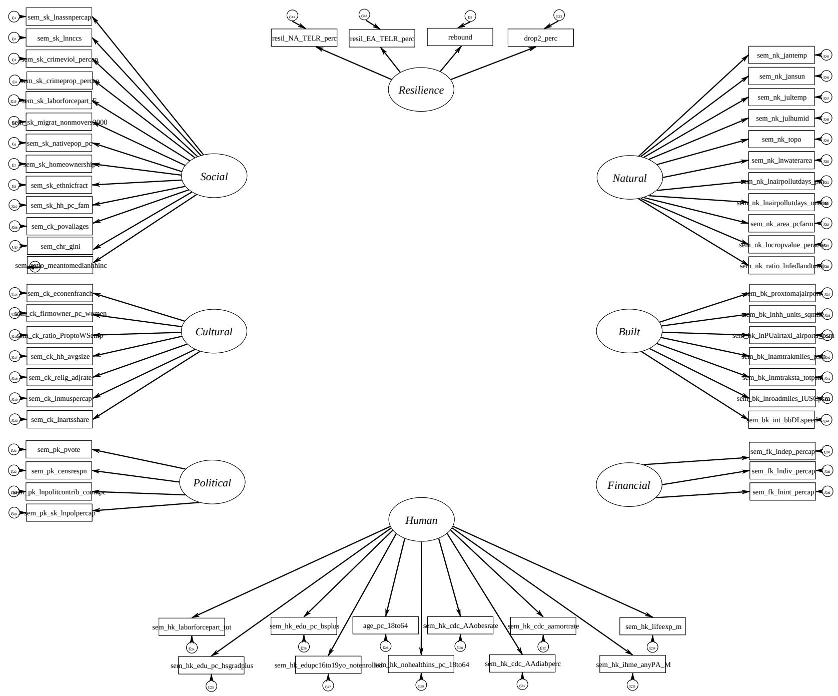
2.6.2 Advantages of Structural Equation Modeling

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, 1998). 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, 1998).

2.6.3 The Model and Modifications

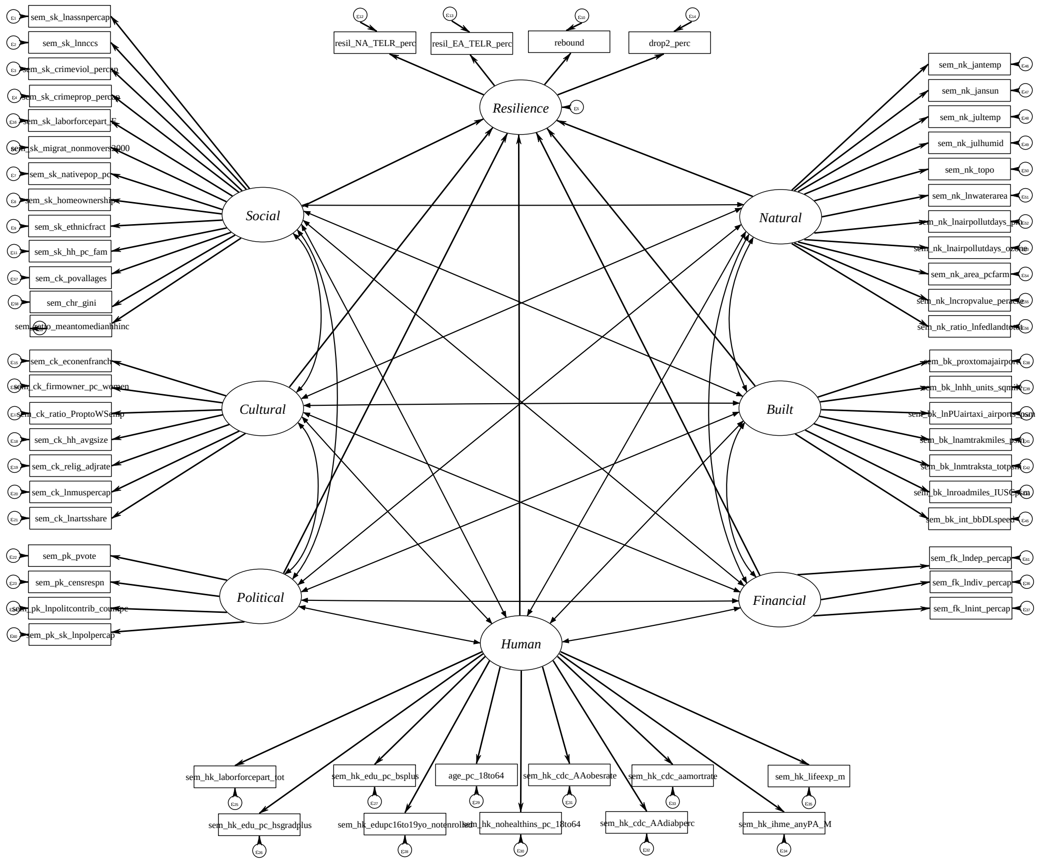
The first step of structural equation modeling is to specify a model. The individual components of our initial measurement model are summarized below in Figure 6 which includes all latent variables and observed variables. Rectangles represent observed variables and ovals represent latent variables and 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 6. 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 7 below shows the full SEM, combining the measurement and structural models.

Figure 7. Full SEM



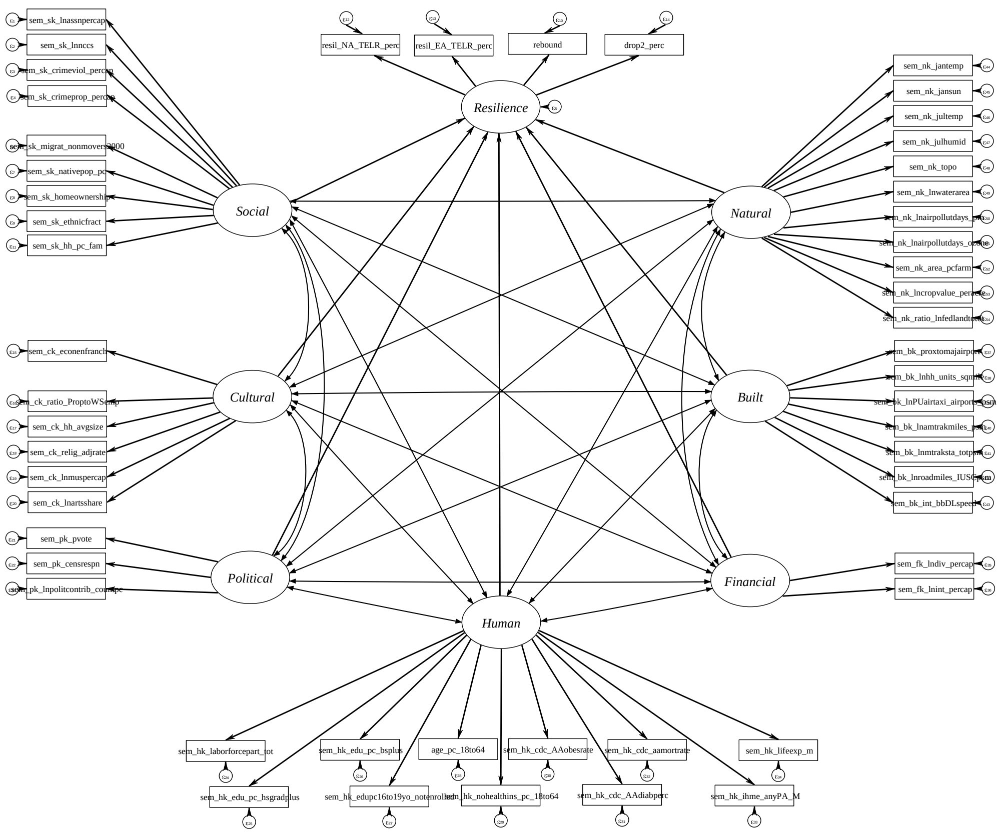
The second step in structural equation modeling, once a model has been specified, is to determine if the model is identified. If a model is identified, it means that it will be possible to calculate a unique estimate for each of our parameters. To do this, our model must have at least as many knowns 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. We run the model using the 2,710 counties in Chapter 1 that met peak and trough criteria including transformed version of variables with severely non-normal distributions. 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 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 8).

Figure 8. Modified SEM



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 8). This model produces has an SRMR value of 0.167, improving slightly over our modified SEM with the community capitals alone (Table 3 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 3. 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.

2.6.4 Results of Modified SEM

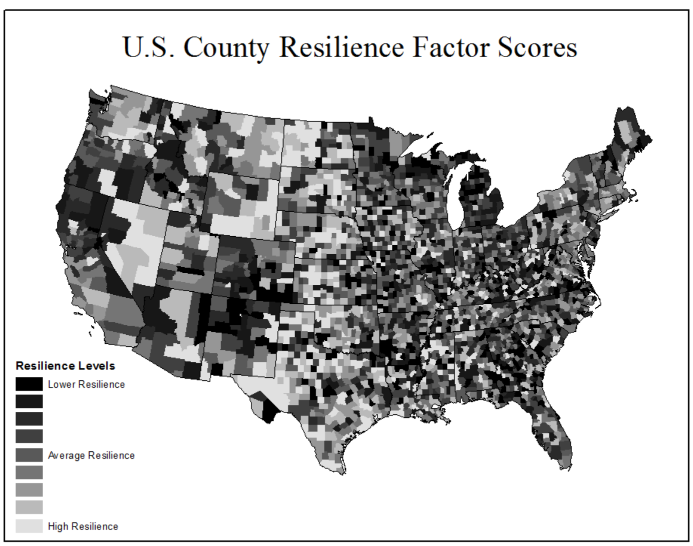
In analyzing the estimates produced by our modified SEM, we begin by looking at our measurement model parameter estimates. In looking at the parameter estimates for the regional economic resilience measurement (Table 4 below), we find that this SEM has estimated the latent variable in a way that represents the opposite of resilience. In Table 4, 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 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 4. 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 9) 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. When compared to the map of resilience in Chapter 1, these results are clearly similar. 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.

Figure 9. Regional Economic Resilience Factor Scores derived from Modified SEM



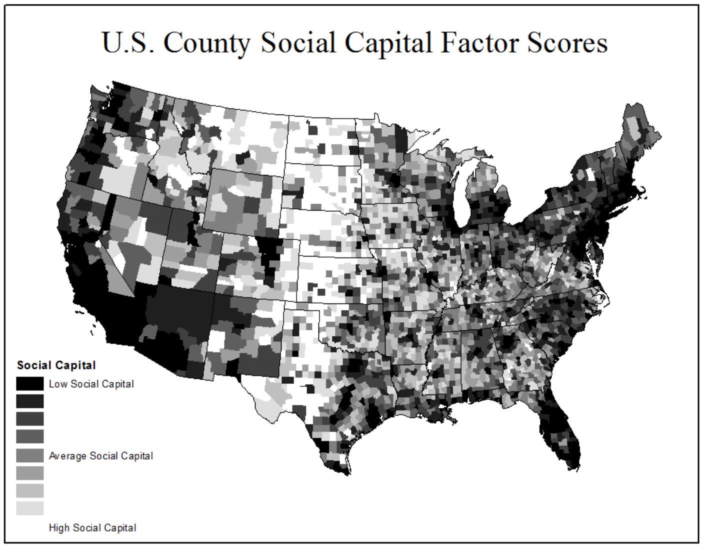
Our social capital latent variable is positively associated with associational density (log), both community attachment variables (percent of residents residing locally for five years or more and percent of residents who are native to the state in which the county is located), homeownership rates, and 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 5.

Table 5. 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

The map in Figure 10 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, Goetz, Freshwater's paper (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, 1996). 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.

Figure 10. Social Capital Factor Scores derived from Modified SEM



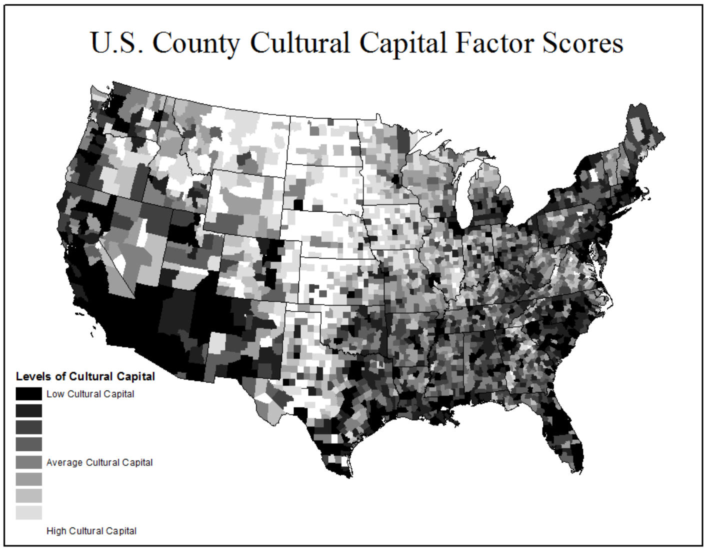
Our cultural capital latent variable is positively associated with economic enfranchisement, the ratio of proprietor to wage and salary employment (our measure of self-employment), religious adherence rate, and museums per capita (log). It is negatively associated with average household size and artistic 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 economic 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 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 6.

Table 6. Standardized Estimates relating to Cultural Capital Measurement Model

Measurement, Cultural Capital	Coef.	Std. Err.	z	P > z	[95% Conf. Int.]	
Economic 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

Looking at the spatial patterns of cultural capital in Figure 11, 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 economic 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 economic enfranchisement (-0.67) to be higher in cities, generally.

Figure 11. Cultural Capital Factor Scores derived from Modified SEM



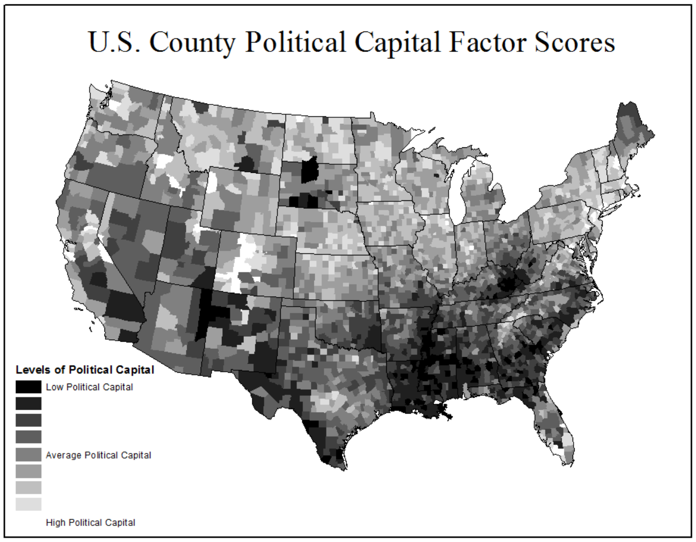
The behavior of the political capital latent variable is consistent with our expectations. All our politically-related observed variables produce positive coefficient estimates. Voter participation is slightly dominant (0.546), followed by political contribution count per capita (log) (0.445), and census response rate (0.347). All appear to be statistically significant. These results are shown below in Table 7.

Table 7. 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 12 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, Lannon, and Chartoff, 2013).

Figure 12. Political Capital Factor Scores derived from Modified SEM



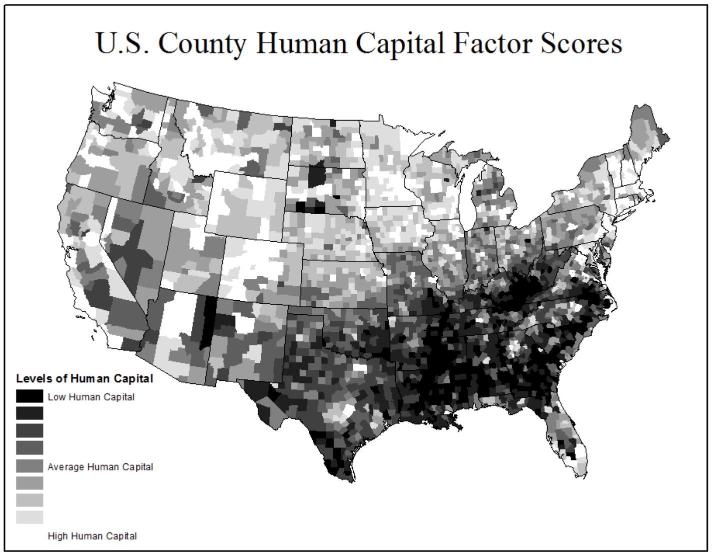
The behavior of the human capital latent variable is consistent with our expectations. Education and health variables move together. Observed variables positively associated with human capital, based on this latent variable, include total labor force participation, percent of the population ages 18 to 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 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 8.

From the spatial distribution of other human capital factor scores, shown in Figure 13, 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.

Table 8. Standardized Estimates relating to Political 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

Figure 13. Human Capital Factor Scores derived from Modified SEM



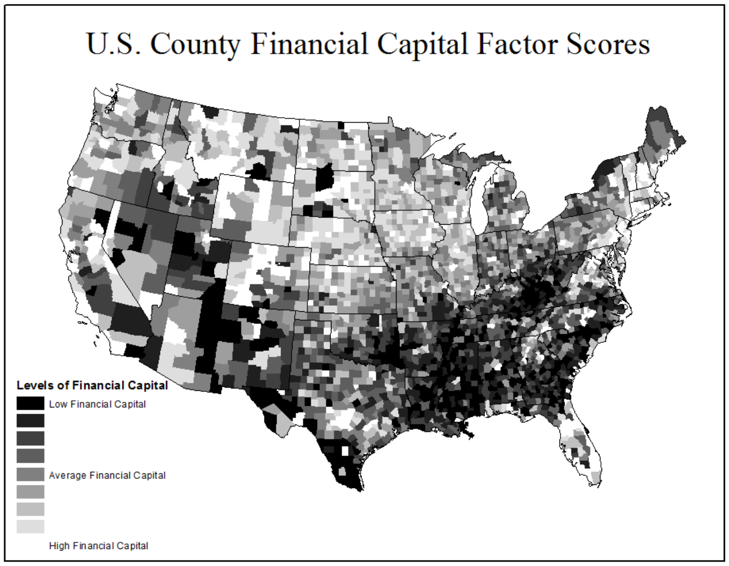
Our financial capital latent variable relates to its observed variables in ways that match our expectations. Both dividends per capita (log) and interest per capita (log) load heavily on the financial capital variable and have positive estimated coefficients. Both are statistically significant. Ideally, 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 9 below.

Table 9. 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

Some spatial patterns of financial capital stocks, based on this latent variable, are observable in the map in Figure 14. 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.

Figure 14. Financial Capital Factor Scores derived from Modified SEM



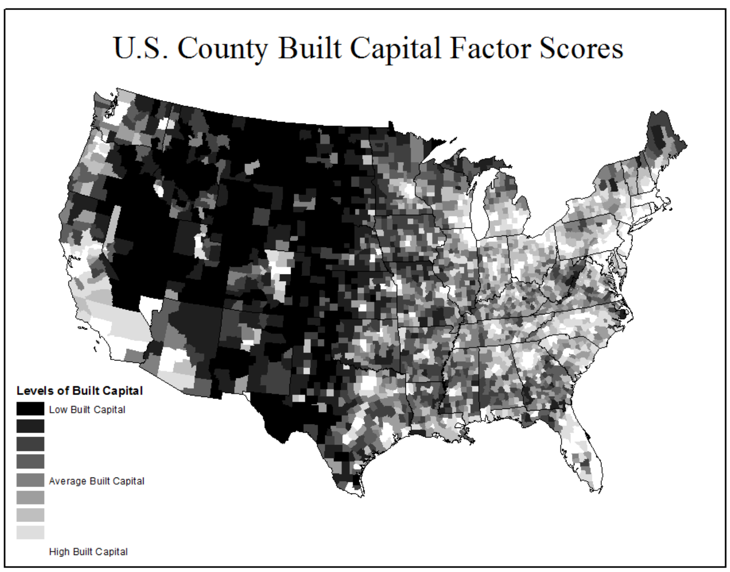
The observed variables associated with built capital all have positive and statistically significant coefficient estimates, in line with our expectations. Results for this measurement model are shown in Table 10 below.

The spatial distribution of built capital (Figure 15) 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.

Table 10. 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

Figure 15. Built Capital Factor Scores derived from Modified SEM

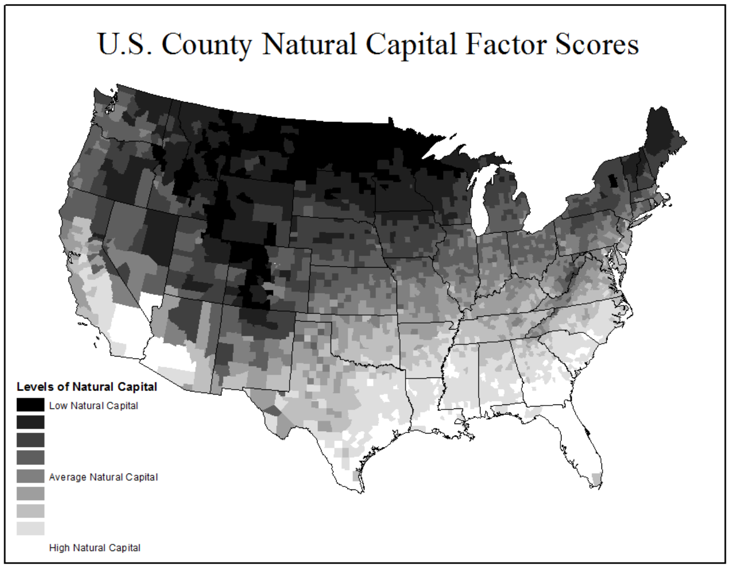


Our natural capital latent variable does not appear to represent all the various components of natural capital cohesively and accurately, in terms of each of their contributions to natural capital. The likely reason for this is that natural capital consist of many diverse components, some of which move opposite each other despite both contributing to natural capital. For example, measures of preferred climate, like warmer temperatures and more days of sun in January may be negatively associated with the preferred types of land topography, like hills and mountains. Three of our variables representing desirable climate attributes are negatively correlated 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 16 reinforces this as the pattern of natural capital, as represented by this latent variable, looks more like a temperature map.

Table 11. 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

Figure 16. Natural Capital Factor Scores derived from Modified SEM



Standardized path estimates from the structural model, which represent direct effects, within our modified SEM are shown in Table 12. 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.

Table 12. 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 13 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 13. 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	2.980	0.003
	Cultural	-0.618	-2.197	0.646	-3.400	0.001
	Political	-0.253	-23.702	5.703	-4.160	0.000
	Human	0.418	41.705	9.117	4.570	0.000
	Financial	0.327	2.492	0.851	2.930	0.003
	Built	0.117	0.860	0.684	1.260	0.209
	Natural	0.000	0.000	0.029	0.000	0.999
Expected Variation	Social	0.405	0.177	0.060	2.960	0.003
	Cultural	-0.357	-0.182	0.054	-3.360	0.001
	Political	-0.146	-1.966	0.479	-4.110	0.000
	Human	0.241	3.459	0.763	4.530	0.000
	Financial	0.189	0.207	0.071	2.900	0.004
	Built	0.067	0.071	0.057	1.260	0.209
	Natural	0.000	0.000	0.002	0.000	0.999
Rebound	Social	-0.062	0.000	0.000	-2.320	0.021
	Cultural	0.054	0.000	0.000	2.480	0.013
	Political	0.022	0.002	0.001	2.760	0.006
	Human	-0.037	-0.004	0.001	-2.930	0.003
	Financial	-0.029	0.000	0.000	-2.260	0.024
	Built	-0.010	0.000	0.000	-1.190	0.233
	Natural	0.000	0.000	0.000	0.000	0.999
Drop	Social	-0.620	-0.043	0.015	-2.970	0.003
	Cultural	0.547	0.045	0.013	3.370	0.001
	Political	0.224	0.482	0.117	4.130	0.000
	Human	-0.369	-0.848	0.186	-4.570	0.000
	Financial	-0.290	-0.051	0.017	-2.910	0.004
	Built	-0.103	-0.017	0.014	-1.260	0.209
	Natural	0.000	0.000	0.001	0.000	0.999

There are many additional results and tests that can be run on this model. Additional results regarding error variances and covariances between community capital variables are included for reference in Appendix C. 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 error variances (over 0.8) and the error variance for our resilience-related variable is larger than 1, which is not a feasible solution. This is further indication that this model is not doing a satisfactory job of representing and fitting the data and would need to be addressed in future work.

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 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.

2.6.5 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 chapter. 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.

The collection of data and their inclusion, either directly or indirectly through use in calculating observed variables, in a model of this nature can (and in some cases should) be a process that gets repeated. There are always alternative measures to explore and in this case, when the existing model is not performing well, such exploration is likely necessary to model improvement. 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 (which we began to look at in the previous chapter), 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.

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APPENDIX A. POTENTIAL ACTIONS BASED ON DATA SCREENING

Table 14. Recommended Actions After Screening Data

Original Observed Variables	Potential Actions
Social capital variables	
Aggregate social organizations per capita	Log transformation
Number of non-profit organizations, total	Log transformation
Crime	
Violent crimes per capita	Log transformation
Property crimes per capita	
Percent, female labor force participation	
Community Attachment	
% of population residing locally for 5+ years	
% of population native to state of residence	
Homeownership	
Ethnic Fractionalization	
Rural-urban status	
Percent, family households	
Cultural Capital	
Economic enfranchisement	
Percent, women-owned firms	
Ratio, proprietor to wage and salary employment	
Average household size	
Museums per capita	Log transformation
Artistic share of workforce	Log transformation
Percent, living in poverty	
Inequality	
Gini coefficient	
Ratio, mean to median income	
Political Capital	
Voter participation rate	
Census response rate	
Political contributions, value per capita	*Drop*
Political contributions, count per capita	Log transformation
Number of political organizations	Log transformation
Human Capital	
Dependency ratio	
Labor force participation, total	
Percent, high school graduates	

Percent, bachelor's degree or higher	
Drop-out rate	
Creative share of workforce	
Percent without health insurance	
Obesity rate	
Diagnosed diabetes rate	
Mortality rate	
Percent, any physical activity (by gender)	*Drop female*
Life expectancy (by gender)	*Drop female*
Financial Capital	
Deposits per capita	Log transformation
Dividends per capita	Log transformation
Interest per capita	Log transformation
Natural Capital	
Temperature, January	
Days of sun, January	
Temperature, July	
Humidity, July	
Land topography	
Log, percent water area	
Air pollution, particulate matter	Log transformation
Air pollution, ozone	Log transformation
Value of crop sales per acre	Log transformation
Ratio of federally-owned land	Log transformation
Percent, land in farms	
Built (Physical) Capital	
Housing units (per sq. mile)	Log transformation
Hospitals (per sq. mile)	*Drop*
Transportation Infrastructure	
Proximity to major airport	
Total public use airports with air-taxi services (per sq. mile)	Log transformation
Amtrak miles (per sq. mile)	Log transformation
Amtrak stations (per sq. mile)	Log transformation
Road miles (per sq. mile)	Log transformation
Broadband coverage	

APPENDIX B. EXPLORATORY FACTOR ANALYSIS RESULTS

Table 15. Extracted Factors from Cultural, Political, Social Observed Variables with Orthogonal Rotation, No Data Transformations

	Initial Extraction				After Orthogonal Rotation			
Factor	Eigenvalue	Diff.	Proportion	Cumulative	Variance	Diff.	Proportion	Cumulative
Factor 1	4.457	0.988	0.334	0.334	**2.978**	1.111	0.223	0.223
Factor 2	3.469	1.250	0.260	0.594	**1.868**	0.076	0.140	0.363
Factor 3	2.219	0.865	0.166	0.761	**1.792**	0.268	0.134	0.498
Factor 4	1.354	0.390	0.102	0.862	**1.524**	0.016	0.114	0.612
Factor 5	0.964	0.169	0.072	0.934	**1.508**	0.030	0.113	0.725
Factor 6	0.795	0.224	0.060	0.994	**1.478**	0.107	0.111	0.836
Factor 7	0.571	0.216	0.043	1.037	**1.371**	0.330	0.103	0.939
Factor 8	0.355	0.099	0.027	1.064	**1.041**	0.215	0.078	1.017
Factor 9	0.256	0.076	0.019	1.083	0.826	0.591	0.062	1.079
Factor 10	0.180	0.049	0.014	1.096	0.234	.	0.018	1.096

Extraction Method: Principal Axis Factoring, Rotation Method: Varimax

Table 16. Extracted Factors from Cultural, Political, Social Observed Variables with Oblique Rotation, No Data Transformations

	Initial Extraction				After Oblique Rotation			
Factor	Eigenvalue	Diff.	Proportion	Cumulative	Variance	Diff.	Proportion	Cumulative
Factor1	4.457	0.988	0.334	0.334	**3.468**	0.260	Rotated factors are correlated	
Factor2	3.469	1.250	0.260	0.594	**3.189**	0.239		
Factor3	2.219	0.865	0.166	0.761	**2.868**	0.215		
Factor4	1.354	0.390	0.102	0.862	**2.834**	0.213		
Factor5	0.964	0.169	0.072	0.934	**2.490**	0.187		
Factor6	0.795	0.224	0.060	0.994	**2.313**	0.173		
Factor7	0.571	0.216	0.043	1.037	**2.259**	0.169		
Factor8	0.355	0.099	0.027	1.064	**2.222**	0.167		
Factor9	0.256	0.076	0.019	1.083	**1.625**	0.122		
Factor10	0.180	0.049	0.014	1.096	0.995	0.075		

Extraction Method: Principal Axis Factoring, Rotation Method: Promax

Table 17. Variable Factor Loadings, Orthogonal Rotation, No Data Transformations

	Factors									
Variable	**1**	2	3	4	5	6	7	8	9	Uniq.
Econ. enfranchise.		-0.782								0.316
%, female firm owners										0.724
Ratio, prop. to wage and salary emp.			-0.323		0.391				0.415	0.463
Average household size		0.340		-0.639						0.411
Religious adherence rate						0.532				0.571
Museums per capita				0.339	0.404					0.631
Artistic share of workforce								0.418		0.612
Voter participation	-0.386							0.302		0.403
Census response rate	-0.554									0.463
Number of political contributions per capita								0.590		0.485
Political organizations per capita										0.974
Associational density					0.750					0.402
Number of non-profit organizations							0.801			0.280
Violent crimes per capita			0.756							0.320
Property crimes per capita			0.755							0.319
Female labor force participation rate	-0.703									0.340
Community attachment										
Local resident, 5+ years						0.725				0.408
Native to state of residence						0.601				0.512
Homeownership rate		-0.392		-0.304					0.547	0.288
Ethnic fractionalization		0.744	0.3219							0.219
Rural-urban status					0.584		-0.58			0.100

Table 17. Variable Factor Loadings, Orthogonal Rotation, No Data Transformations (continued)

	Factors									
Variable	1	2	3	4	5	6	7	8	9	Uniq.
%, family households				-0.764						0.318
Poverty rate	0.790									0.177
Inequality										
Gini coefficient	0.778									0.257
Ratio, mean to median income	0.673									0.387

Extraction Method: Principal Axis Factoring, Rotation Method: Varimax

Table 18. Variable Factor Loadings, Oblique Rotation, No Data Transformation

	Factors									
Variable	1	2	3	4	5	6	7	8	9	Uniq.
Econ. enfranchise.			0.816							0.316
%, female firm owners										0.724
Ratio, prop. to wage and salary employment				0.438						0.463
Average household size								0.734		0.411
Religious adherence rate									0.463	0.571
Museums per capita								-0.302		0.631
Artistic share of workforce						0.503				0.612
Voter participation	-0.316			0.349		0.348				0.403
Census response rate	-0.479			-0.313						0.463
Number of political contributions per capita						0.708				0.485
Political organizations per capita										0.974
Associational density					0.874					0.402
Number of non-profit organizations							0.832			0.280
Violent crimes per capita		0.839								0.320
Property crimes per capita		0.793								0.319
Female labor force participation rate	-0.712									0.340
Community attachment										
Local resident, 5+ years									0.761	0.408
Native to state of residence									0.519	0.512
Homeownership rate				0.761						0.288

Table 18. Variable Factor Loadings, Oblique Rotation, No Data Transformation (continued)

Variable	Factors 1	2	3	4	5	6	7	8	9	Uniq.
Ethnic fractionalization			-0.703							0.219
Rural-urban status					0.576		-0.468			0.100
%, family households				0.322				0.813		0.318
Poverty rate	0.726									0.177
Inequality										
Gini coefficient	0.856					0.305				0.257
Ratio, mean to median income	0.755					0.385				0.387

Extraction Method: Principal Axis Factoring, Rotation Method: Varimax

Table 19. Extracted Factors from Cultural, Political, Social Observed Variables with Orthogonal Rotation with Data Transformations

	Initial Extraction				After Orthogonal Rotation			
Factor	Eigenvalue	Diff.	Proportion	Cumulative	Variance	Diff.	Proportion	Cumulative
Factor 1	5.402	1.433	0.381	0.381	**4.296**	1.548	0.303	0.303
Factor 2	3.968	1.803	0.280	0.662	**2.748**	0.661	0.194	0.497
Factor 3	2.166	0.831	0.153	0.815	**2.087**	0.341	0.147	0.645
Factor 4	1.335	0.481	0.094	0.909	**1.746**	0.328	0.123	0.768
Factor 5	0.854	0.229	0.060	0.969	**1.418**	0.251	0.100	0.868
Factor 6	0.625	0.107	0.044	1.013	**1.167**	0.086	0.082	0.951
Factor 7	0.518	0.287	0.037	1.050	**1.081**	0.680	0.076	1.027
Factor 8	0.231	0.069	0.016	1.066	0.401	0.134	0.028	1.055
Factor 9	0.162	0.024	0.011	1.077	0.268	0.084	0.019	1.074
Factor 10	0.137	0.047	0.010	1.087	0.184	.	0.013	1.087

Extraction Method: Principal Axis Factoring, Rotation Method: Varimax

Table 20. Extracted Factors from Cultural, Political, Social Observed Variables with Oblique Rotation with Data Transformations

	Initial Extraction				After Oblique Rotation			
Factor	Eigenvalue	Diff.	Proportion	Cumulative	Variance	Diff.	Proportion	Cumulative
Factor 1	5.402	1.433	0.381	0.381	**4.785**	0.338	Rotated factors are correlated	
Factor 2	3.968	1.803	0.280	0.662	**3.533**	0.250		
Factor 3	2.166	0.831	0.153	0.815	**3.503**	0.247		
Factor 4	1.335	0.481	0.094	0.909	**3.169**	0.224		
Factor 5	0.854	0.229	0.060	0.969	**2.981**	0.211		
Factor 6	0.625	0.107	0.044	1.013	**2.451**	0.173		
Factor 7	0.518	0.287	0.037	1.050	**2.438**	0.172		
Factor 8	0.231	0.069	0.016	1.066	**2.257**	0.159		
Factor 9	0.162	0.024	0.011	1.077	**2.095**	0.148		
Factor 10	0.137	0.047	0.010	1.087	**1.847**	0.130		

Extraction Method: Principal Axis Factoring, Rotation Method: Promax

Table 21. Variable Factor Loadings, Orthogonal Rotation with Data Transformations

	Factors							
Variable	1	2	3	4	5	6	7	Uniq.
Econ. enfranchise.			-0.785					0.320
%, female firm owners	0.483							0.690
Ratio, prop. to wage and salary employment	-0.537							0.465
Average household size			0.377	-0.629				0.370
Religious adherence rate					0.563			0.557
Log, Museums per capita				0.412				0.603
Log, Artistic share of workforce	0.467							0.677
Voter participation			-0.386				0.444	0.397
Census response rate		-0.484						0.453
Log, Number of political contributions per capita	0.390						0.568	0.428
Log, Political organizations per capita	0.502							0.707
Log, Associational density	-0.939							0.053
Log, Number of non-profit organizations	0.918							0.062
Violent crimes per capita	0.351					0.674		0.323
Property crimes per capita	0.462					0.641		0.310
Female labor force participation rate		-0.585					0.333	0.349
Community attachment								
Local resident, 5+ years					0.698			0.463
Native to state of residence					0.603			0.508
Homeownership rate	-0.319		-0.447	-0.396				0.285
Ethnic fractionalization			0.744					0.216
Rural-urban status	-0.698							0.287
%, family households				-0.790				0.301
Poverty rate		0.703	0.334				-0.395	0.151
Inequality								
Gini coefficient		0.818						0.255
Ratio, mean to median income		0.738						0.376

Table 22. Variable Factor Loadings, Oblique Rotation with Data Transformations

Variable	Factors 1	2	3	4	5	6	7	8	Uniq.
Econ. enfranchise.				0.851					0.320
%, female firm owners					-0.319				0.690
Ratio, prop. to wage and salary employment					0.500				0.465
Average household size									0.370
Religious adherence rate								0.554	0.557
Log, Museums per capita									0.603
Log, Artistic share of workforce	0.362								0.677
Voter participation						0.454			0.397
Census response rate		-0.342					-0.349		0.453
Log, Number of political contributions per capita						0.680			0.428
Log, Political organizations per capita	0.455								0.707
Log, Associational density	-0.981								0.053
Log, Number of non-profit organizations	0.969								0.062
Violent crimes per capita			0.781						0.323
Property crimes per capita			0.732						0.310
Female labor force participation rate		-0.469				0.358	-0.404		0.349
Community attachment									
Local resident, 5+ years								0.783	0.463
Native to state of residence								0.614	0.508

Table 22. Variable Factor Loadings, Oblique Rotation with Data Transformations (continued)

Variable	Factors 1	2	3	4	5	6	7	8	Uniq.
Homeownership rate							0.542		0.285
Ethnic fractionalization				-0.749					0.216
Rural-urban status	-0.655								0.287
%, family households									0.301
Poverty rate		0.635				-0.447			0.151
Inequality									
Gini coefficient		0.896							0.255
Ratio, mean to median income		0.841							0.376

APPENDIX C. ADDITIONAL RESULTS FROM MODIFIED SEM ESTIMATION

Table 23. Error Variance on Endogenous Variables in Modified SEM

Endogenous Variable, Error Variance	Coef.	Std. Err.	[95% Confid. Int.]	
Log, Associational density	0.067	0.006	0.056	0.081
Log, Number of non-profit organizations	0.224	0.010	0.206	0.244
Violent crimes per capita	0.773	0.016	0.743	0.804
Property crimes per capita	0.649	0.016	0.617	0.682
Community attachment				
Local resident, 5+ years	0.990	0.004	0.982	0.998
Community attachment				
Native to state of residence	0.906	0.012	0.883	0.929
Homeownership rate	0.867	0.013	0.841	0.893
Ethnic fractionalization	0.876	0.013	0.850	0.901
%, family households	0.999	0.001	0.998	1.001
Rebound	0.993	0.004	0.985	1.000
Resilience Measure (Adjusted)	0.058	0.017	0.032	0.104
Expected variation	0.686	0.017	0.654	0.719
Drop	0.262	0.016	0.233	0.295
Econ. enfranchise.	0.935	0.012	0.912	0.959
Ratio, prop. to wage and salary employment	0.714	0.018	0.680	0.750
Average household size	0.790	0.018	0.756	0.826
Religious adherence rate	0.959	0.008	0.943	0.975
Log, Museums per capita	0.791	0.018	0.757	0.827
Log, Artistic share of workforce	0.926	0.012	0.902	0.950
Voter participation	0.702	0.023	0.659	0.748
Census response rate	0.880	0.013	0.854	0.906
Log, Number of political contributions per capita	0.802	0.017	0.769	0.836
Labor force participation, total	0.581	0.016	0.550	0.613
% high school graduates	0.292	0.012	0.271	0.316
% bachelor’s degree or higher	0.475	0.015	0.446	0.505
Drop-out rate	0.728	0.016	0.697	0.760
% population age 18 to 64	0.988	0.005	0.979	0.997
% without health insurance	0.939	0.010	0.920	0.958
Obesity rate	0.541	0.016	0.511	0.573
Diagnosed diabetes rate	0.405	0.014	0.379	0.434
Mortality rate	0.342	0.013	0.318	0.369
%, any physical activity	0.227	0.010	0.208	0.248
Life expectancy	0.141	0.007	0.128	0.157

Table 23. Error Variance on Endogenous Variables in Modified SEM (continued)

Endogenous Variable, Error Variance	Coef.	Std. Err.	[95% Confid.	Int.]
Log, dividends per capita	0.242	0.013	0.218	0.268
Log, interest per capita	0.107	0.012	0.086	0.132
Proximity to major airport	0.662	0.017	0.630	0.695
Log, housing units per square mile	0.063	0.010	0.046	0.085
Log, public use airports with air taxi services per square mile	0.822	0.015	0.794	0.852
Log, Amtrak miles per square mile	0.889	0.013	0.864	0.915
Log, Amtrak stations per square mile	0.813	0.016	0.783	0.844
Log, road miles per square mile	0.561	0.016	0.530	0.594
Broadband coverage	0.802	0.015	0.773	0.832
Average January temperature	0.212	0.025	0.168	0.266
Average January days of sun	0.916	0.013	0.890	0.942
Average July temperature	0.431	0.018	0.397	0.468
Average July humidity	0.844	0.020	0.807	0.883
Land topography	0.942	0.012	0.919	0.965
Log, percent water area	0.986	0.006	0.975	0.997
Log, days of high level air pollution, particulate matter	0.871	0.016	0.841	0.902
Log, days of high level air pollution, ozone	0.979	0.007	0.965	0.993
%, area in farms	0.953	0.010	0.934	0.972
Log, crop value per acre	0.985	0.006	0.973	0.996
Log, ratio of federally-owned land to total	0.974	0.009	0.956	0.992
Resilience	1.039	0.033	0.976	1.106

Table 24. Covariances between Community Capitals in Modified SEM

Covariances	Coef.	Std. Err.	z	P > z	[95% Conf. Int.]	
cov(Social,Cultural)	0.951	0.022	44.030	0.000	0.908	0.993
cov(Social,Political)	-0.130	0.039	-3.320	0.001	-0.207	-0.053
cov(Social,Human)	-0.259	0.021	-12.260	0.000	-0.301	-0.218
cov(Social,Financial)	-0.167	0.024	-6.950	0.000	-0.214	-0.120
cov(Social,Built)	-0.876	0.007	-119.830	0.000	-0.890	-0.862
cov(Social,Natural)	-0.295	0.023	-12.830	0.000	-0.340	-0.250
cov(Cultural,Political)	0.500	0.049	10.180	0.000	0.404	0.597
cov(Cultural,Human)	0.148	0.034	4.320	0.000	0.081	0.215
cov(Cultural,Financial)	0.319	0.034	9.410	0.000	0.253	0.386
cov(Cultural,Built)	-0.754	0.027	-28.390	0.000	-0.806	-0.702
cov(Cultural,Natural)	-0.551	0.029	-19.100	0.000	-0.608	-0.495
cov(Political,Human)	1.108	0.025	44.080	0.000	1.059	1.158
cov(Political,Financial)	1.097	0.029	38.170	0.000	1.041	1.154
cov(Political,Built)	0.238	0.037	6.460	0.000	0.166	0.310
cov(Political,Natural)	-0.756	0.030	-24.980	0.000	-0.815	-0.696
cov(Human,Financial)	0.789	0.010	81.900	0.000	0.770	0.808
cov(Human,Built)	0.193	0.021	9.030	0.000	0.151	0.235
cov(Human,Natural)	-0.611	0.016	-39.070	0.000	-0.641	-0.580
cov(Financial,Built)	0.205	0.023	8.900	0.000	0.160	0.251
cov(Financial,Natural)	-0.356	0.021	-17.060	0.000	-0.397	-0.315
cov(Built,Natural)	0.332	0.027	12.390	0.000	0.280	0.385