Measuring United States County-Level Economic Resilience to a Recession

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by

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Authorization to Submit Thesis

This thesis of Anna Brown, submitted for the degree of Master of Science with a Major in Applied Economics and titled "Measuring United States County-Level Economic Resilience to a Recession," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

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Abstract

I use a Cox proportional hazards model to determine factors contributing toward a county's resilience to the external shock of a recession. Emphasis is placed on the rural nature of the county and its levels of community capitals and economic structure. I find residents with bachelor's degrees and within the 30-49 year old age band, as well as local government jobs and federal funding for defense and space functions, mitigate a county's entrance to recession. Certain topographical features, namely hills and mountains, also protect against a recession. On the other hand, concentrations in certain industries, such as transportation equipment manufacturing and finance, hinder a county's ability to withstand a recession.

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Introduction

The goal of this research is to identify economically resilient regions and to isolate the factors that help them withstand an economic downturn. The "Great Recession" resulted in many areas experiencing a downturn, with the national economy experiencing a 2.9% annual decrease in Gross Domestic Product (GDP) from the fourth quarter of 2007 to the second quarter of 2009 (BEA 2013).[1] Roughly 82% of all United States counties experienced employment losses during that time. Some areas fared better than others, with rural counties seeing earlier and greater rates of employment decline compared to metro counties (Hertz et al. 2014). This creates the question of whether certain factors contribute toward a community's ability, or resilience, to weather a recession.

What is Resilience?

There are many pieces to the definition of resilience. I find the term resilience in a regional economic sense refers not just to a region's ability to recover from external shocks, but to also withstand these shocks. The negative shock can result from a natural disaster, such as a hurricane or tornado, or from a human-made disaster, such as a national economic recession or large employer leaving a rural region. I therefore define resilience as the capacity of a region to resist external shocks or disturbances and to continue to develop or regain functions (Han and Goetz 2013).

Resilience often refers to the ability of a region to return to its pre-shock state after experiencing a negative shock. Researchers have found that economic structures can be rearranged and/or economic agents changed following a negative shock. These differ by

[1] According to the National Bureau of Economic Research (NBER), the official dates of the recession were from December 2007-June 2009.

region due to unique recovery patterns of hysteresis, growth paths, rebounds, and realignment. Economic output is often used as the measure of how the structures change (Simmie and Martin 2010, Martin 2011, Han and Goetz 2013). Using this definition, attention is placed on how a region is able to recover, where it finds a new stabilization, and the length of time it takes to reach the new norm (Brown 2014).

My definition differs since I account for a county's resistance to an external shock in addition to its recovery. In this research, I have narrowed my focus from this definition to revolve around how a region mitigates its entrance into recession, not how long it takes to recover from a recession. Further research can expand upon the latter piece of the resilience definition.

The study of economic resiliency is by no means a new area of study. Some researchers take a conceptual approach towards the study of economic resiliency by forming a preliminary framework of measuring resilience (Briguglio, Cordina, Bugeja, and Farragia 2004) and borrowing from how resiliency works in other fields (Ficenec 2014). While not making a deep connection to economic theory, Hill (2011) outlines earlier statistical exercises from several older studies on economic resilience and develops a quantitative framework. Brown (2014) goes a step further by exploring the relationship between industry diversity and economic resilience. These studies search for patterns across a wide spatial area. Other resiliency studies focus on how particular events, such as Hurricane Katrina, affect one region. Such studies offer a qualitative approach through policy suggestions in how communities can better prepare for and recover from external shocks (Dabson 2012).

The types of models used in resiliency studies widely differ. Some studies develop models such as computable general equilibrium (CGE) models measuring the lost income a region faced during a disaster (Rose 2004). Other studies keep a broad focus through a national application of econometric models, such as factor analyses, that analyze a vast number of variables potentially contributing toward economic resiliency. The variables in each study range from workforce characteristics to regional capital levels to industrial diversity. The authors then pick up and discuss certain patterns, often with case studies of specific regions (Briguglio, Cordina, Bugeja, and Farragia 2004; Brown 2014). Of particular interest to my research from such studies is the use of the Cox proportional hazards model (Hill 2011), which provides a method for measuring resilience of a region suffering from an external shock.

Missing from previous studies is the tie from economic growth theory to resiliency, particularly the direct link between regional levels of capital assets and resilience. Few studies have yet to be done following the 2007-2009 recession, nonetheless with a focus on rural areas. I provide the theoretical link between economic growth theory and resiliency, and empirically measure through the Cox proportional hazards model how investment in regional capitals leads to economic resiliency to a recession.

Community Economic Growth

In order to understand resiliency, I first look at economic growth theory. Each region has a growth path based on previous performance and its availability of resources. This can be seen as the first moment condition, or the expected value of future levels of output based on previous levels of output. Resilience looks at how a region deviates from its growth path. In other words, it is the second moment condition of variance around a growth path. By understanding the relationship between economic growth and economic resilience, I form a link between a region's production function in terms of its capitals, and how it reacts to an external shock.

Theoretical Background

Economic growth theory has a long history, with much of the mainstream work beginning in the 1950s and 1960s. Solow (1956) estimated regional growth to be a function of financial capital, labor, and technology. By treating the rate of population change and technology as exogeneous variables, he posited the only way to achieve growth was through investing in financial capital, eventually resulting in a steady state.

Romer (1986) advanced the role of increasing returns to scale, which create efficiencies, but also expose communities to risk. He found knowledge to be a public good that is often underproduced, bringing about the role of patents and similar intellectual property instruments in protecting knowledge-creation. The role of human capital became known as an important driver of technological progress and economic growth.

Lucas (1988) built upon this model by highlighting the clustering effect of human capital. He found that high concentrations of people, such as in cities, enable new ideas to rapidly spread, which in turn create new knowledge. A number of researchers have empirically documented the role of human capital in growth. For example, Glaeser (2000) found firms gain competitive advantages when they locate in regions with high levels of human capital. Moretti (2004) discovered the presence of a land grant education institution increases the skill level of the region. This in turn increases wages across various levels of educational attainment, even for less skilled workers.

Kaldor (1970) introduced agglomeration effects, or benefits businesses gain from being in close proximity to each other and sharing inputs such as labor and technology, stemming from a region's economies of scale and comparative advantages. Krugman (1991) was the first to effectively model these effects. He identified centrifugal forces that cause economic activity to spread out and centripetal forces that pull economic activity together. These cause a challenge for rural development because economies of scale tend to favor large places at the expense of small places.

Recently, the community development literature has emphasized seven forms of capital in which development strategies are devised. These forms of capital are: natural, cultural, human, social, political, financial, and built (Flora and Flora 2004, Emory and Flora 2006). With these capital forms, I have a production function that determines regional output as a function of stocks of capital.

Community Wealth

Emory and Flora (2006) provide a community capitals framework for identifying assets and interaction among regional capitals. Pender et al. (2012) created a similar framework but for wealth creation strategies in rural areas.

Before I delve into the definitions of capital contributing toward community wealth, I must recognize a few attributes of capital. According to Pender et al. (2012), capital must be a durable asset, is reliant upon consumption and investment decisions, and must factor in to production. In this way, stocks of capital lead to regional wealth. Income generated from returns to capital increase capital stocks, whereas consumption of capital depletes capital stocks.

Traditionally, capital referred to wealth with a productive return and was seen mostly in terms of physical goods and financial assets. As discussed above, capital has evolved to include intangible assets such as human capital (Pender et al. 2012). The full list of capitals recognized and defined by Pender et al. (2012) are below.[2] I rely upon these definitions throughout my analysis.

1. **Physical capital:** capital goods used by firms to produce outputs; infrastructure used by firms and households to reduce costs of commerce; and durable goods used by households for either production or consumption purposes.
2. **Natural capital:** renewable or non-renewable, naturally occurring assets that yield a flow of valuable goods or services into the future.
3. **Financial capital:** money and other liquid financial assets, such as stocks and bonds, net of financial liabilities.
4. **Human capital:** investments that improve skills, knowledge, or health, and thereby raise incomes of people.
5. **Social capital:** features within a social organization, such as trust, that facilitate coordination and cooperation for mutual benefit.
6. **Cultural capital:** people's understanding of society and their role in it, as well as their values, symbols, and rituals.
7. **Political capital:** ability of a group to influence the distribution of resources through a political process.

The level and combination of each capital stock differs by region. This leads to how community members make decisions regarding their region's economic development. They will each face different risks, constraints, costs, and returns. As a result, each region faces

[2] Pender et al. (2012) included one more capital, intellectual capital, which reflects knowledge and innovation. It differs from human capital since it is not embodied in individuals. I decided not to include intellectual capital given its similarity to human capital, deciding instead to focus on human capital.

unique outcomes in terms of employment and income, and how these outcomes will be affected by a recession (Pender et al. 2012).

Theoretical Model

Following my previous discussion, I can establish regional output is generated via the following production function:

$$Y = f(AK) \tag{1}$$

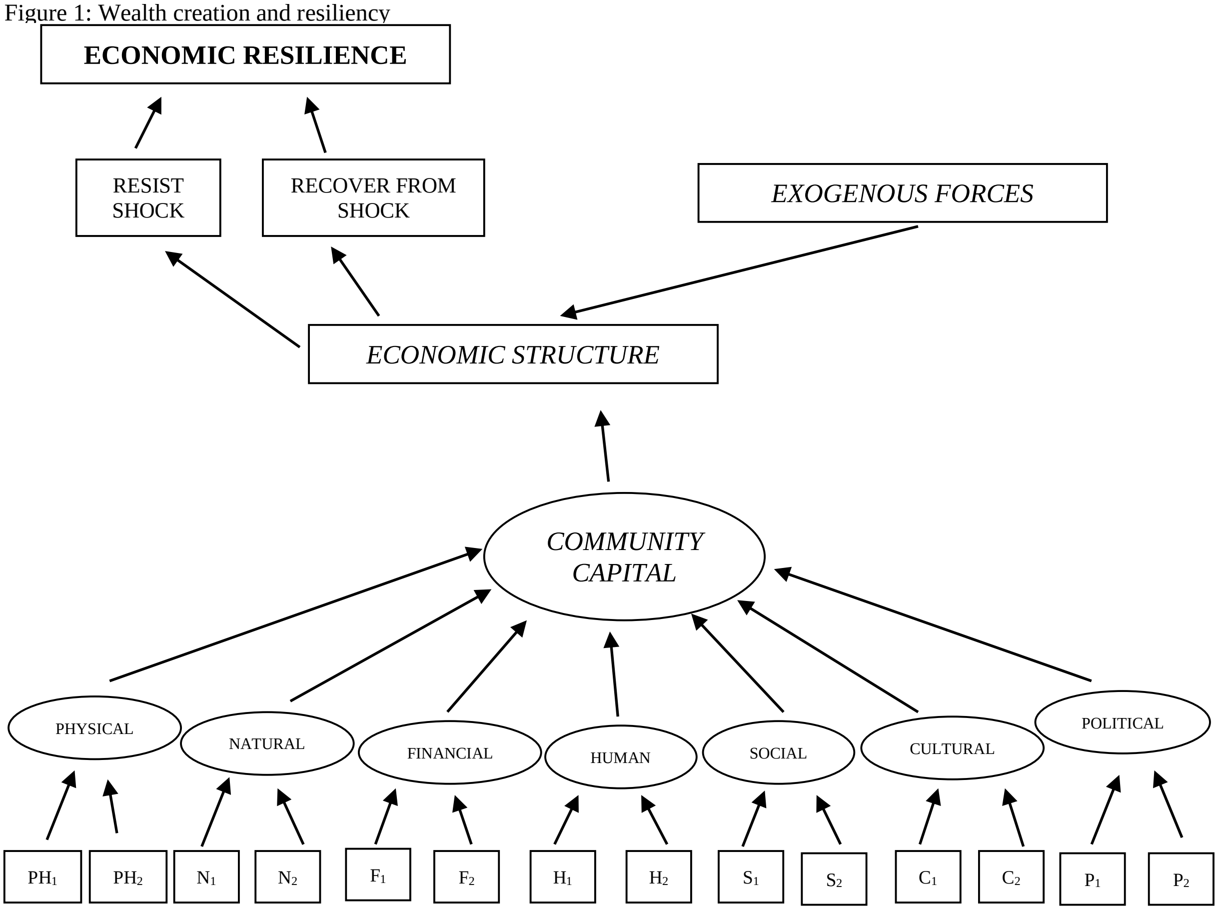
Where *Y* represents regional output, *A* represents technological change, and *K* represents the stock of assets available at a given moment in a region that contributes toward the productivity of a region. The stock can increase through investment, such as through investment in research and development (*A*). Any future stocks depend upon previous levels (Baritto 2008, Arrow et al. 2010). I can divide *K* into several categories, such as natural capital, human capital, physical capital, cultural capital, political capital, financial capital, and social capital. My focus revolves around the stock of *K* in a region and does not factor in the role of technological change *A*.

With stock being defined above as the total quantity of an asset at a given point in time, I differentiate it from flows, which are measured over a period of time. For example, personal income is considered a flow since it represents the amount of money earned in a county during the year. Flows can also be thought of as how they create changes in stock levels over a period of time due to inflows and outflows.

How Does Resilience Relate to Community Wealth?

I have now defined resilience, economic growth theory, and a region's production function leading to wealth creation. Figure 1 provides a schematic through a capitals framework for how these relate to each other in measuring a region's resilience to a recession.[3]

Figure 1: Wealth creation and resiliency



This figure depicts a schematic of community influences on resilience. I start with the region's base of stocks of capital – physical capital, natural capital, financial capital, human capital, social capital, cultural capital, and political capital. These form the aggregated stock of community capital available in a region, which create the regional economic structure such as industry mix. Exogenous forces, such as inflows of federal resources, influence the economic structure by adding to resources not otherwise in the region. Note that exogenous

[3] The capital framework stems from ongoing research by Dr. Philip Watson and Dr. Paul Lewin from the University of Idaho.

forces do not always add to a region. They can also be negative shocks, for example a national financial crisis, which test a region's ability to withstand and recover from a recession. Combined, the economic structure and exogenous forces lead to a region's resilience given the resulting resistance and recovery from recessionary shocks.

The stocks of capital lead to wealth creation and its subsequent growth path over time. The growth path is known as the first moment, or the expected value of a region's output across years. Each year's expected output is conditional on the level of output (based on stock accumulation) from previous years (Simon and Blume 1994). An external shock will throw a region's expected output off of its growth path. This variance from the growth path is considered the second moment, or dispersion around the expected value (Simon and Blume 1994). The length and depth of deviation from the growth path following a negative external shock reflects a region's resilience. I am therefore primarily interested in the second moment condition, or variance, of a region's economic growth. As I will discuss later, I can analyze a region's resilience by looking at a combination of stocks of capital, or by economic structure which reflects the outcome of the stock accumulation.

Measuring an Economic Recession

The time period for the analysis spans from 2005 to 2012. I use annual data at the county-level for all 3,145 counties and county-equivalents in the United States. I recognize there is interdependence between county economies, meaning regional clusters should be taken into account through spatial analysis. Building a comprehensive spatial component into my model is outside the scope of this analysis, although I do control for fixed effects within states.

I use personal income in my dependent variable to indicate economic resilience, or when a county entered recession. Personal income can be seen as a proxy for regional wealth as it represents what was earned in the county. Personal income is similar to gross domestic product (GDP) except it represents what was earned in the county rather than what was spent.[4] The personal income data was collected from the Bureau of Economic Analysis (BEA) and adjusted for inflation to real terms.

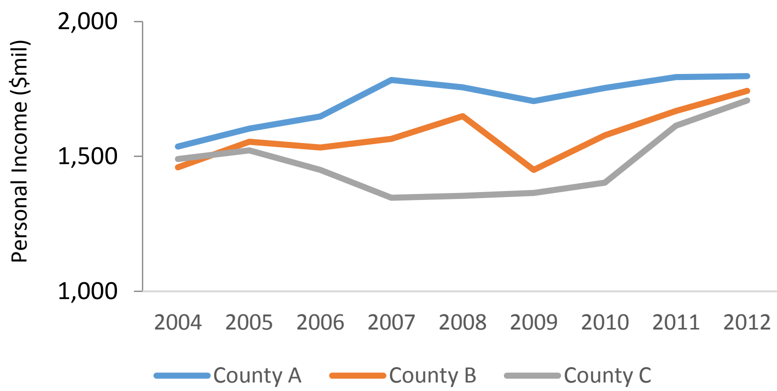
Keep in mind I am analyzing a county's resilience to a recession, or how it strays from its growth path. Decreasing personal income levels indicate the county's entrance to recession. This means I do not use monetary amounts of personal income as the dependent variable, but use personal income to indicate the time when a county enters into a recession.

I defined recession as the first year a county experienced decreases in personal income, even if it was not the lowest point over the time period. The reason I chose this definition was to capture when a county faltered in its growth path (developed a "fever"), not when it was at its bottom (officially "sick"). This aligns with the definition from the National Bureau of Economic Research (NBER) of recession, which is a significant decline in economic activity lasting more than a few months. Declines seen on an annual basis are therefore sufficient in indicating whether a county is entering recession. This scenario is demonstrated by County A in Figure 2, where, according to my definition, it enters recession in 2008 even though its lowest point is in 2009.

[4] Per capita personal income is the total compensation received by a person. It includes: salaries, wages, bonuses, dividends, distributions from investments, rental receipts, profit-sharing, etc. Personal income determines an individual's consumption and investment capacity. Personal income is equal to GDP less: the consumption of fixed capital (i.e. depreciation); corporate profits with inventory valuation and capital consumption adjustments; contributions for government social insurance; domestic net interest and miscellaneous payments on assets; net business current transfer payments; current surplus of government enterprises; undistributed wage accruals; and personal income receipts on assets from outside the country.

Emphasis was placed on declines post 2007 since this was when the United States was officially in a recession. For example, although County B first experienced declining growth in 2006, it recovered for a couple of time periods before officially entering recession in 2009. However, if a county began declining before 2007 without immediate positive growth, I considered its recession to begin before 2008. County C demonstrates this scenario, where it began declining in 2006 and did not recover until 2010, well after the official recession dates. According to my definition, it entered recession in 2006.

Figure 2: Recession definition scenarios



Geographical Recession Patterns

Although I have not specifically accounted for spatial patterns within this analysis, I find it interesting and useful to look at how recession spread across the United States. Figures 3 through 10 present maps of when counties entered recession. The maps show a county's survival against entrance to recession. Counties shaded in dark red are those that entered recession in a respective year. Note that once a county enters recession, it remains red throughout subsequent years. In other words, I only capture entrance into recession and not recovery. So for the map in 2012, it can be seen that the majority of counties entered into recession at some point between 2005 and 2012. Keep in mind, however, not all of these counties were actually in recession in 2012; when they recovered is just not shown on the maps.

Figure 3: Counties in recession in 2005

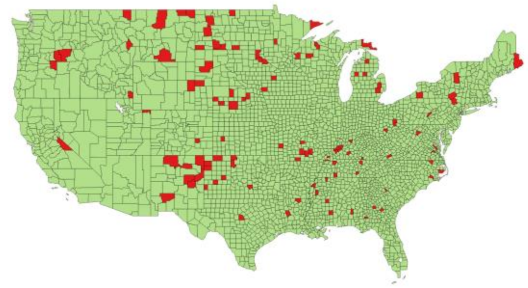


Figure 4: Counties in recession in 2006

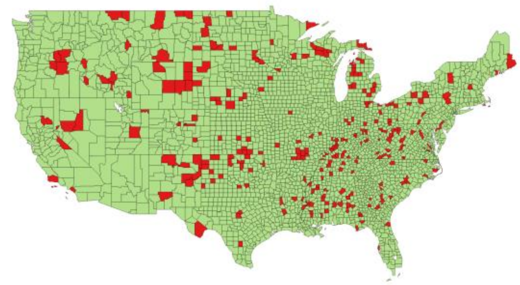


Figure 5: Counties in recession in 2007

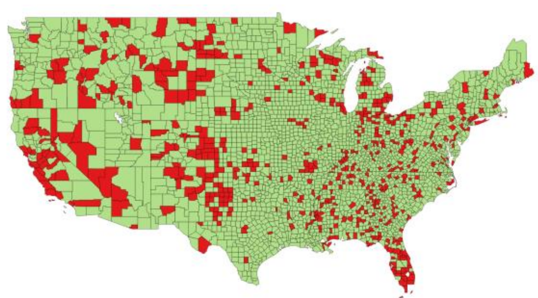


Figure 6: Counties in recession in 2008

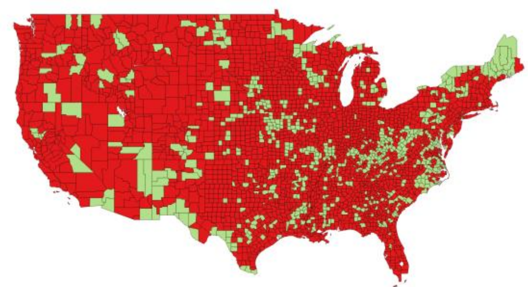


Figure 7: Counties in recession in 2009

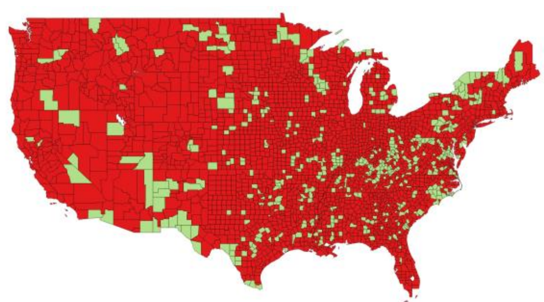


Figure 8: Counties in recession in 2010

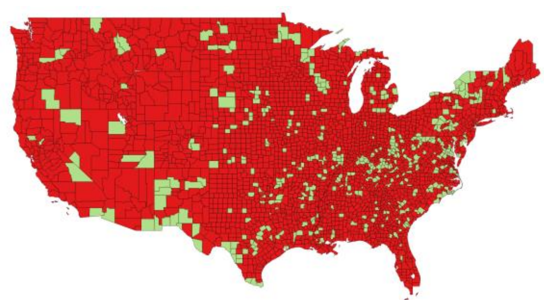


Figure 9: Counties in recession in 2011

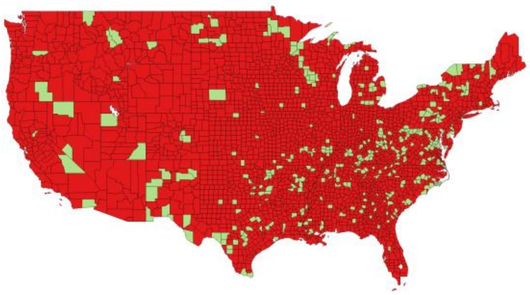
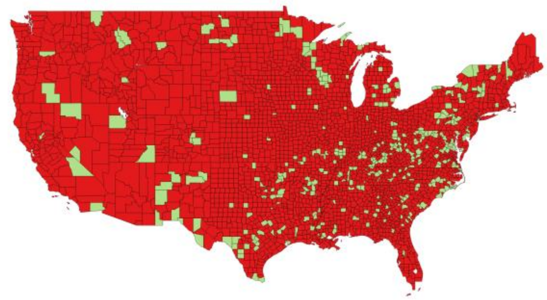


Figure 10: Counties in recession in 2012



In looking at these maps, I see clustering did occur. In other words, certain regions were hit by the recession around the same time. For example, I see that the recession initially began in counties in Michigan in 2006, demonstrating signs of the fall of the automobile industry. I see spatterings of counties entering recession in 2007, especially in the rust belt of the Midwest and in the West. I see the vast majority of counties enter recession in 2008 and 2009, with the exception of certain counties in the Dakotas and Nebraska (perhaps due to hydraulic fracturing), the Southwest, and the Northeast. By 2012, I can see several counties never entered recession during this time period, several of which are located in the Appalachian region.

Use of the Cox Model to Measure Resilience

Now that I have determined how to identify when a county entered into recession, I turn to the empirical model used to estimate results. I use the Cox model (Cox 1972) to estimate the factors contributing toward economic resiliency. Generally used in medical research, the Cox model is a statistical survival analysis model for analyzing the relationship between patient survival and explanatory variables. I use stocks of capital and economic structure to indicate regional health (explanatory variables) and their effect on regional recession patterns (survival).

The Cox model features a survival function, or the probability that a county will enter recession at some time later than a specified time. This is represented generally by the following equation:

$$S(t) = Pr(T > t) \qquad [3]$$

where t is a given time, T represents the time when a county entered recession, Pr stands for probability, and $S(t)$ represents the survival function at a given time.

The Cox model regresses the hazard function, or in this case the probability that a county will enter a recession, within a specified time interval. The hazard function can be represented generally as:

$$\mathrm{h}(t) = \frac{\text{number of counties experiencing a recession beginning at } t}{(\text{number of counties surviving recession at } t) * (\text{length of time period})} \qquad [4]$$

The hazard function is used as the dependent variable at a given time. The coefficients for each of the explanatory variables, estimated based on maximum likelihood, represent the proportional change of h(t) for each respective change in the explanatory variables.

The general Cox model is a semiparametric model, meaning no assumptions are made about the form of the baseline hazard function. This provides an advantage since there is no need to make assumptions, which could produce misleading results, about the shape of the hazard. However, the Cox model does make assumptions of the parametric form of the effect of the explanatory variables on the hazard. This means the parameter estimates can be interpreted in the usual way when dealing with parametric models.

The Cox model assumes the baseline hazard function is the same for everyone. If there is reason to believe the hazard function will vary across groups, stratification can be used whereby the identical baseline hazard assumption is relaxed in return for assuming the hazard function will be the same within groups but different across groups.

Recall from Figure 1 that I can measure economic resilience based on stocks of capital or on the economic structure resulting from stocks of capital. Exogenous forces combined with these contribute toward a county's resilience. This means I have two models to work with, represented as follows:

$$\mathrm{h_i}(t) = \mathrm{h_0}(t) * \exp\{\beta_1 PhysCap_{\mathrm{i1}} + \beta_2 NatCap_{\mathrm{i2}} + \beta_3 FinCap_{\mathrm{i3}} + \beta_4 HumCap_{\mathrm{i4}} + \beta_5 SocCap_{\mathrm{i5}} + \beta_6 CulCap_{\mathrm{i6}} + \beta_7 PolCap_{\mathrm{i7}} + \beta_8 ExogForc_{\mathrm{i8}}\} \quad [5]$$

$$\mathrm{h_i}(t) = \mathrm{h_0}(t) * \exp\{\beta_1 EconStruc_{\mathrm{i1}} + \beta_2 ExogForc_{\mathrm{i2}}\} \quad [6]$$

Where Equation 5 represents the model with stocks of capital and Equation 6 the economic structure model. In terms of explanatory variables, $\mathrm{h_i}$ is the hazard function for county *i*, *t* is a nonnegative random variable denoting the time to an event (in this case entering a recession), $\mathrm{h_0}$ is the baseline hazard function, β_x is a vector of regression coefficients to be estimated from data, $PhysCap_i$ represents stocks of physical capital in the county, $NatCap_i$ represents stocks of natural capital in the county, $FinCap_i$ represents stocks of financial capital in the county, $HumCap_i$ represents stocks of human capital in the county, $SocCap_i$ represents stocks of social capital in the county, $CulCap_i$ represents stocks of cultural capital in the county, $PolCap_i$ represents stocks of political capital in the county, $EconStruc_i$ represents the economic structure of the county, and $ExogForc_i$ represents injections of exogenous forces into the county.

An explanatory variable with a positive regression coefficient indicates that the hazard is higher for regions with large values of the variable. Taking the exponent of the regression coefficient gives us the hazard ratio. The "hazard" I mean here is entering into a recession in year *t*, having not entered into a recession in year *t-1*. An explanatory variable with a hazard ratio below 1 can be seen as an asset to a region since it helps a county mitigate the effects of a recession. Each of the hazard ratios are tested for their level of statistical significance before concluding their importance in regional recession patterns.

I censor the data in the event that a county does not enter an economic downturn. To account for censoring, a dummy variable is added to the hazard function where 1 indicates censored data and 0 indicates that I observed exact entrance times.

Recall that the coefficients for each of the explanatory variables are estimated based on maximum likelihood. This means it is important to consider the ordering of the failures since the Cox model estimates the risk set, or the subjects at risk of failure, at each failure time and maximizes the conditional probability of failure. This can be expressed generally as:

$$L(\beta_x) = \prod_{j=1}^{k} \left\{ \frac{\exp(x_j \beta_x)}{\sum_{i \epsilon R_j} \exp(x_i \beta_x)} \right\} \qquad [7]$$

where *L(β)* signifies the likelihood function, *k* represents distinct observed failure times, R_j provides the risk set, and *x* represents multiple variables. The model technically considers partial likelihood since it looks only at individual failure times and does not make an assumption about the baseline hazard when there are no failures. In this way, the Cox model treats the partial likelihood model as an ordinary likelihood model when finding the maximum likelihood estimates of the coefficients (Cleves et al. 2010).

Given the importance of failure time ordering, I considered any ties in the data or, in other words, whether two or more subjects had the same event time of when they entered into recession. In the case of tied events, the Cox model needs to determine an ordering of failed event times. There are four common ways to account for ties. The first is the marginal calculation, which assumes that subjects did not actually fail at the same time, the data is just limited in showing the actual failure time. This method takes the probability of the subjects with the apparently same event times, and observes them to fail in any order. The second method is the partial calculation, which assumes the events did fail at the same time and uses multinomial calculations to calculate event times. Note that although the first and second methods tend to be more accurate, they can also be problematic in practice given the length of time to compute the calculations (Cleves et al. 2010).

One of the other methods is the Breslow approximation, which makes an estimation based on the exact method. The risk pools for the events with same event times are not adjusted for previous failures. This method works best when there are few subjects with the same event times. The last method, and the method I used, is the Efron approximation:

$$L(\beta_x) = \prod_{i=1}^{k} \frac{\exp[(\sum_{j \in D_i} z_j)\beta]}{\prod_{l=1}^{d_i} [\sum_{j \in R_i} \exp(z_j\beta - \frac{l-1}{d_i} \sum_{j \in D_i} \exp(z_j\beta)]} \qquad [8]$$

where z_j are vectors of covariate values for the jth individual, D_i is a set of d_i individuals who failed at time t_i, and R_i is the risk set at time t_i, meaning R_i consists of those that have not yet failed at time t_i (Xin 2011).

As seen in equation 8, this method uses weighted probability weights to approximate the marginal ordering of event times so multiple events cannot occur at the same time. It is generally recognized as being the preferred method of accounting for ties especially when there is a high number of tied event times (Cleves et al. 2010).

Cox Model Descriptive Outputs

Before beginning my analysis, I find it helpful to look at the number of counties that entered into recession in a given year and the resulting survival function. Table 1 displays the survival function table of counties entering recession from 2005 to 2012. I start with 3,145 counties. Not shown in the table is 2005, or Time 0. I see we start 2006 with 2,995 counties.

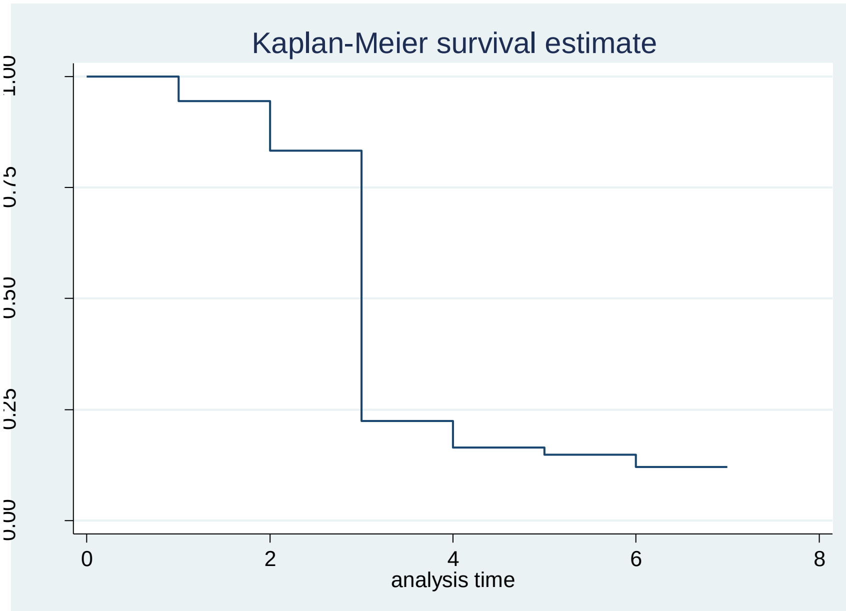
This implies 150 counties (the difference between the full number of 3,145 counties and 2,995) were already in recession prior to 2006. These 150 counties are censored from the analysis so I can analyze "healthy" counties. In other words, I do not include counties "sick" at the beginning of our analysis. I then see 166 counties "fail", or enter into recession, in 2006, which creates a survival of 94.5% (see Survival Function column). Put another way, 94.5% of counties were successful in withstanding against a recession in 2006. This continues until 2012, with the majority of counties entering recession in 2008. By the end of our analysis, I find 361 counties never enter into recession and are censored from the analysis.

Table 1: Survival function table of entering recession

Beginning Time	# of Counties	Fail	Net Lost	Survival Function	Standard error	95% Confidence Interval	
2006	2,995	166	0	94.5%	0.0042	93.6%	95.2%
2007	2,829	332	0	83.4%	0.0068	82.0%	84.7%
2008	2,497	1,826	0	22.4%	0.0076	20.9%	23.9%
2009	671	179	0	16.4%	0.0068	15.1%	17.8%
2010	492	48	0	14.8%	0.0065	13.6%	16.1%
2011	444	83	0	12.1%	0.0059	10.9%	13.3%
2012	361	0	361	12.1%	0.0059	10.9%	13.3%

Table 1 shows the overall trend of when counties enter into a recession. Nonparametric procedures and their associated figures, such as the Kaplan-Meier survival function, provide a way to visualize these patterns for descriptive purposes. This often proves beneficial prior to running a regression to see the shape of the survival function. The Kaplan-Meier survival function is a decreasing step function with each step signifying one unit of time, or one year in my analysis, across the horizontal axis. The vertical axis shows the probability of a county surviving in a given time period. Again, keep in mind that in my analysis "survival" refers to a county overcoming the probability of entering recession. As seen in Figure 11, the probability of counties withstanding against a recession dropped significantly in 2008.

Figure 11: Kaplan-Meier survival function



Variables

In an ideal setting, I would be able to measure actual levels of capital stocks to determine their effect on output, or, more specifically, deviations from a county's growth path. Realistically, such data is difficult to collect and distinguish between specific capitals, particularly at the county-level across several years. What I find instead is that one indicator may represent several capitals, or the outcome from the availability of capital. For example, while the percentage of jobs in industries requiring high-skilled labor may seem to provide an indication of human capital, it intrinsically also reflects other capitals, such as amenities (natural capital) and infrastructure (physical capital) available in a region to attract and retain highly skilled workers.

Therefore I collected two sets of variables. One set reflects stocks of capital available in a county. The other set represents the economic structure of a county through its industrial composition. This second set can be seen as outcomes from stocks of capital since the industries would not be present if not for the availability of capital resources. These relate back to Figure 1, with the first set representing community capital and the second set economic structure. I also include a third set of data reflecting exogenous forces, which can be added to both the community capital data and the economic structure data. I discuss the variables used in each of these data sets below. In order to remain consistent, I use only stocks, not flows, as independent variables where possible.

Variables for Capital Stocks

Natural Capital (N_n)

I accounted for the availability of natural capital through several variables. The first variable captures the topography of a county. Topography affects connectivity and natural amenities. This can relate to agglomeration effects discussed under the theoretical background section. For example, a mountainous county may be more isolated from external markets, which could be positive in that it may not be as affected by a recession, or negative given lack of economic options. Several topographical classifications were available at the county-level. I focused on whether the county was classified as plains, plains with hills, open with hills, tablelands, or mountainous. This allowed me to aggregate similar topographical classifications by indicating through a dummy variable which of these groups best represented a county's topography.

I also looked into the percentage of county water coverage and several variables providing indications of weather patterns – the mean temperature for January, mean hours of sunlight for January, mean temperature for July, and mean relative humidity for July from 1941-1970. To test the significance and underlying interpretation of each of these variables, I ran the analysis using the variables comprising the natural amenity scale rather than the natural amenity scale itself. All natural capital data were available from the United States Department of Agriculture, Economic Research Service.

County size can also play a large role in a county's level of natural capital, with larger counties possibly holding larger stocks of natural capital. County size can also vary widely, with some counties a mere fraction of the size of other counties. I therefore use the total area in square miles of each county. This was released by the U.S. Census Bureau in 1990.

Human Capital (H_n)

I collected several different measures on the availability of human capital. The standard measurement of skilled labor is the number of residents age 25 and older with less than a high school diploma, just a high school diploma, some college, and a bachelor's degree and above. This data is published by the United States Census American FactFinder. I used the American Community Survey five-year estimates from 2006-2010. A county with a high number of residents with a bachelor's degree and above serves as a proxy of higher levels of human capital.

I also looked at the breakdown of county population by age group. This data was available from the United States Census American FactFinder. I used the 2010 demographic profile data. Age groups were initially reported in five year increments. I aggregated these to calculate age bands that fit within the working life cycle. For example, I grouped those age 20-29 years old together since these residents are at the beginning of their working life, age 30-49 years old together which takes workers through their peak performance, age 50-64 years old together to represent workers easing out of their career and into retirement, and then age 65 years old and over to represent retirees.

Social Capital (S_n)

The Penn State University Northeast Regional Center for Rural Development collects data on a variety of measures that could be used to indicate the level of social networks within a county. These data have been collected for 1990, 1997, and 2005. I use the 2005 data since it fits within my analysis timeframe. These are bowling centers, civic and social associations, physical fitness facilities, public golf courses, religious organizations, sports clubs, professional organizations, business associations, labor organizations, and not-for-profit organizations. I combine these to measure the total number of organizations and associations in a county that, through their work, promote communication, cooperation, and trust between citizens (Rupasingha et al. 2000).

Cultural Capital (C_n)

I used the breakdown of the county population classified by race as Caucasian, African American, Native American, and Asian. This data was available for 2010 from the United States Census American FactFinder. I also used the number of county residents classified as Hispanic, which is considered an ethnicity and differs from the race categories.

I use race and ethnicity as a proxy for cultural capital since they can help determine how people think of the world, their traditions, spirituality, and language (Flint 2010). Note that race and ethnic diversity might also be considered social capital. Some researchers state race and ethnic homogeneity promotes social capital given enhanced social networks; there may be higher levels of trust between community members sharing similar customs and norms (Shaffer, Deller, and Marcouiller 2004). Other researchers argue race and ethnic diversity promotes social capital through increased tolerance of other cultures (Florida, Mellander, and Stolarick 2008). With this literature, I recognize the lack of certainty in defining race and ethnic diversity as a cultural capital rather than a social capital. However, I keep with the definitions by Flora and Flora (2004), Flint (2010), and Pender et al. (2012) and classify it as a cultural capital.

Also, I decided to use the amount of cultural capital available in a county through the number of people in the labor force employed in art occupations. I chose this based on research by Florida, Mellander, and Stolarick (2008) that suggests those in the labor force in culturally creative occupations play a positive role in regional development. Artistic occupations range from artists to dancers to musicians. The data was originally based on Florida's research and later refined using Census Bureau 2007-2011 American Community Survey pooled data. I used the latter data set which was available through the United States Department of Agriculture, Economic Research Service.

Political Capital (P_n)

I again use data collected by the Penn State University Northeast Regional Center for Rural Development, but this time to measure the extent of political participation within a county. The variables used are the number of political organizations within a county in 2005 and the number of votes cast for the president during the 2008 presidential election. The data was originally considered by Rupasingha et al. (2000) in developing a social capital index, but I felt they more accurately represented political capital.

Physical Capital (Ph_n)

I found physical capital to be difficult to measure given it often reflects other types of community capitals or economic structure. The variable I chose to represent physical capital was the median value of specified owner-occupied housing units, available from the Census Bureau 2007-2011 American Community Survey five-year estimates. Wu and Gopinath (2008) find households locate in a region due to housing prices that maximize their utility for a region, and firms locate in a region given easy access to labor and input markets. Therefore I find the median value of housing units intrinsically reflects physical capital since households and firms would not locate in a region without a given level of physical capital.

Financial Capital (F_n)

I used total deposits in commercial banks and savings institutions from the Federal Deposit Insurance Corporation (FDIC) to reflect financial capital. The data was available from 2005 to 2010, and I calculated estimates for 2011 and 2012 based on averages of previous years. Since it represents the total amount of deposits, it is considered a stock variable. I find total deposits useful in determining the amount of money county residents have liquid and readily available. This can help provide a buffer when hit by an economic downturn, for example if workers lose their jobs as a result of economic contraction.

Variables for the Economic Structure

I used the number of jobs broken out by NAICS code[5] on an annual basis from 2005 to 2012 to determine the industrial composition, or economic structure, of each county. I

[5] NAICS stands for North American Industry Classification System (http://www.census.gov/eos/www/naics/). It is a product of Census and classifies each industry according to its primary activities.

aggregated the industries according to their respective two- or three-digit NAICS code levels. Economic Modeling Specialists International (EMSI)[6] provided the data for each year.

Table 2 provides the NAICS code and description for easier identification and discussion when I present the results. Given broad two-digit categorization, I split certain manufacturing and government industries to the three-digit level to capture nuances on their effects in county resilience. For example, machinery manufacturing and electrical manufacturing require vastly different types of workers and inputs. They have different markets that could be more or less affected by external shocks than the other. Therefore I feel including them under the same two-digit NAICS code could be misleading.

[6] EMSI collects data from the Census and a variety of other sources, removing suppressions and providing a more complete dataset. For a list of EMSI data sources, please visit http://www.economicmodeling.com/2014/10/15/emsi-faq-where-does-emsi-data-come-from/

Table 2: Industry classification

NAICS Code	Industry Description
11	Crop and Animal Production
21	Mining, Quarrying, and Oil and Gas Extraction
22	Utilities
23	Construction
311-312	Mfg: Food, Beverage & Tobacco
313-316	Mfg: Textile, Fiber & Printing
324-327	Mfg: Chemicals, Energy, Plastics, Rubber
331-332	Mfg: Metals- & Mining-Based
333	Mfg: Machinery
334-335	Mfg: Electronic & Electrical
336	Mfg: Transportation Equipment
321-323, 337, 339	Mfg: Furniture & Misc.
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Admin., Support, Waste Mgmt, and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
901	Federal Government
902	State Government
903	Local Government

Variables for Exogenous Forces

I captured exogenous forces through federal funds data available through the United States Department of Agriculture, Economic Research Service. The data was initially reported for 2005 through 2010, and I calculated values for 2011 and 2012 based on averages of previous years. The federal funds data reflects federal payments for functions such as income security. The classifications are demonstrated in Table 3. Note that each of these classifications includes subcategories specifying payments at a more detailed level. For the purposes of this analysis I focus on the high-level categories. Also, keep in mind that the original data represents flows since it is a measurement of money over time. Since the federal funds are not a measure of county wealth, or stocks of capital, I keep them as a flow and do not convert them to a stock.

Table 3: Federal fund categories

Federal Funds Code	Federal Funds Description
100	Agriculture and natural resources functions
200	Community resources functions
300	Defense and space functions
400	Human resources functions
500	Income security functions
600	National functions

Control Variable

Rural Status

The control variable I used was whether counties were classified as rural to see if the rural nature affected results. Recall the agglomeration effects from Kaldor (1970) and Krugman (1991) and the challenge rural communities face in terms of centrifugal and centripetal forces. For example, rural status can provide an indication for commuting patterns since those in rural regions may commute to neighboring metro areas. It also reflects population density – the more rural the county the less residents per square mile. This means rural regions tend to have different means of coping with economic changes compared to metro areas. They are generally dependent on a smaller and spread out population with limited industrial diversity.

I used the 2003 rural-urban county classification provided by the United States Department of Agriculture Economic Research Service (ERS). There are nine different classification types ranging from metropolitan areas of 1 million population or more (Code 1) to a completely rural area of less than 2,500 population and not adjacent to a metro area (Code 9). I ran model iterations using the nine classification types. I also simplified the model in other iterations by collapsing the nine categories into two categories – rural and metro. A county received a dummy variable of 0 for rural status if it was classified in Code 4-9 and a dummy variable of 1 for metro status if it was classified in Code 1-3. According to my classification, 2,054 counties are classified as rural, with the remaining 1,091 counties classified as metro.

Summary Statistics

Table 4 provides summary statistics for the various explanatory variable possibilities. They have been broken out according to whether they are considered a capital, economic structure, or exogenous force.

Table 4: Explanatory variable summary statistics

Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Natural Capital (N_n)				
% of water area	5	11	0	75
Temperatures - January	33	12	1	67
Hours of sunlight - January	152	33	48	266
Temperatures - July	76	5	56	94
Humidity - July	56	15	14	80
Plains	0.5	0.5	0.0	1.0
Plains with hills	0.1	0.3	0.0	1.0
Open hills	0.2	0.4	0.0	1.0
Mountains	0.1	0.4	0.0	1.0
Land square miles	924	1,199	2	20,062
Human Capital (H_n)				

# of pop. < high school diploma	9,577	38,786	3	1,511,061
# of pop. high school diploma	18,506	48,486	15	1,332,186
# of pop. bachelor's degree +	17,802	64,723	7	1,816,606
# people in labor force	48,813	156,464	0	4,936,378
# residents 20-29 years old	12,803	46,573	7	1,512,065
# residents 30-49 years old	25,179	87,921	16	2,857,214
# residents 50-64 years old	17,725	54,140	29	1,669,163
# residents 65 years old and above	12,152	35,557	12	1,070,228
Social Capital (S_n)				
# social capital organizations	541	1,566	2	42,636
Cultural Capital (C_n)				
# African American residents	10,969	50,076	0	1,288,279
# Asian residents	4,305	35,330	0	1,345,149
# Native American residents	896	3,642	0	80,159
# Hispanic residents	15,079	112,483	0	4,683,475
# of artistic labor force	517	2,853	0	121,620
Political Capital (P_n)				
# political organizations	1	4	0	149
# 2008 presidential voters	41,935	119,826	79	3,318,248
Physical Capital (Ph_n)				
median value house prices ($000s)	$128	$88	$29	$1,000
Financial Capital (F_n)				
Total deposits ($000s)	$2,229	$12,688	$0	$481,168
Industrial Composition				
# jobs in NAICS 11	1,105	2,254	0	57,097
# jobs in NAICS 21	348	2,027	0	106,443
# jobs in NAICS 22	184	583	0	14,975
# jobs in NAICS 23	3,166	9,873	0	252,773
# jobs in NAICS 311-312	2,409	8,589	0	279,764
# jobs in NAICS 313-316	825	7,678	0	426,427
# jobs in NAICS 324-327	3,139	11,187	0	284,437
# jobs in NAICS 331-332	2,783	11,291	0	315,928
# jobs in NAICS 333	1,670	6,717	0	283,134
# jobs in NAICS 334-335	2,511	15,935	0	532,857
# jobs in NAICS336	2,130	10,904	0	276,562
# jobs in NAICS 321-323,337,339	3,988	14,340	0	476,918
# jobs in NAICS 42	1,859	7,912	0	260,442
# jobs in NAICS 44	3,497	11,335	0	349,163
# jobs in NAICS 45	2,247	6,543	0	191,778

# jobs in NAICS 48	1,306	5,423	0	154,950
# jobs in NAICS 49	489	1,942	0	52,848
# jobs in NAICS 51	1,070	6,280	0	248,364
# jobs in NAICS 52	2,868	12,811	0	374,732
# jobs in NAICS 53	2,435	10,206	0	356,105
# jobs in NAICS 54	3,644	17,004	0	457,479
# jobs in NAICS 55	629	3,009	0	72,541
# jobs in NAICS 56	3,240	13,283	0	385,119
# jobs in NAICS 61	1,263	5,861	0	161,057
# jobs in NAICS 62	5,832	19,696	0	553,734
# jobs in NAICS 71	1,175	5,272	0	203,427
# jobs in NAICS 72	3,809	13,510	0	380,980
# jobs in NAICS 81	3,148	12,446	0	509,274
# jobs in NAICS 901	6,778	28,524	0	719,619
# jobs in NAICS 902	7,107	25,549	0	446,632
# jobs in NAICS 903	21,993	87,188	0	2,567,228
Exogenous Forces				
Federal Funds Category 100 ($000s)	$33,000	$58,700	($3,259)	$2,050,000
Federal Funds Category 200 ($000s)	$120,000	$448,000	($34,500)	$12,300,000
Federal Funds Category 300 ($000s)	$133,000	$704,000	($375,000)	$26,500,000
Federal Funds Category 400 ($000s)	$34,600	$212,000	($675)	$11,500,000
Federal Funds Category 500 ($000s)	$853,000	$3,850,000	$256	$102,000,000
Federal Funds Category 600 ($000s)	$139,000	$879,000	($153,000)	$43,300,000

Results

The tables in the next section present the results split by whether the variables are within the capital stock model or the economic structure model. I present three different scenarios within each model based on how the model was controlled for rural status. The first scenario is a stratified analysis based on the rural-urban classification code of a county. Here I relaxed the assumption that each county faces the same baseline hazard despite their rural-urban classification. Instead, the baseline hazard is unique to each of the nine rural-urban classification codes. The coefficients remain equal across the strata. All counties are considered within the stratified analysis. The second scenario reflects just metro counties

(counties classified as rural are excluded), and the third scenario focuses on rural counties (counties classified as metro are excluded). Given these scenarios, I can analyze how rural status affects the significance of factors contributing toward the probability of entering into recession.

I also considered a fourth scenario which can be considered a base scenario where I did not control for rural status; in other words, it treats counties the same regardless of their rural-urban classification. However, I exclude the results from the base scenario in this analysis given the lack of significant findings compared to the stratified model for both the capital stocks and the economic structure. I find the stratified model to be more robust in that it at least considers a detailed level of rural-urban classification.

In each model, I use the White's estimator to remove potential heteroscedasticity. I also consider fixed effects based on the state a county is located in. This helps account for some spatial effects in that I assume all counties share the same baseline hazard function, but the sign of the state coefficient will multiply the baseline hazard function up or down (Cleves 2010). I also considered a shared frailty model, or a model with a latent random effect that enters multiplicatively on the hazard function (Cleves 2010). However, after running the Hausmann test for orthogonality conditions imposed by the random effect, the results showed the state-level individual effects appear correlated with the regressors. I therefore determine the fixed effects model to be a more accurate measure.

Before finalizing my model, I analyzed the functional form of the variables through histograms to ensure I was estimating models with an accurate goodness of fit. This led me to transform a few variables, particularly those relating to monetary values and people as they tended to be skewed. Not transforming the data could create large standard errors in my model. I chose to use an inverse hyperbolic sine transformation for the variables with skewed distributions. I could have also used a log transformation, but opted for the inverse hyperbolic sine transformation given I am working with wealth data and cases with no reported data.[7]

Results from the Capital Stocks Model

Table 5 lists results from the capital stocks model in terms of hazard ratios and based on rural status. I excluded the coefficients to reduce redundancy since the hazard ratio is the exponent of the coefficient. Also shown are the standard errors next to the hazard ratios.

The hazard ratio represents the probability that the region will enter recession in time *t* conditional on it not yet in a recession in time *t*. A hazard ratio greater than 1 means the explanatory variable shortens the time to the event. For example, a hazard ratio of 1.001 for hours of sunlight in January in the stratified model means that a one unit increase in January hours of sunlight causes the hazard ratio, or probability of entering into a recession, to increase by 0.01%. Conversely, a hazard ratio of less than 1 means the explanatory variable lengthens the time until a county enters recession. I see this in the temperatures in July in the stratified model with a hazard ratio of 0.983. This means a one unit increase in July temperatures reduces the probability of entering recession by 1.7%.

Since I have used inverse hyperbolic sine transformations (represented in the table with a “log” prefix) for some variables, the interpretation differs slightly from above for those variables. The inverse hyperbolic sine transformation can be interpreted the same as a standard log transformation. For example, a hazard ratio of 1.393 (such as for the log number of social capital organizations in the stratified model) means a log unit increase in the number

[7] Note within Tables 5 and 6 I have prefaced those variables under the inverse hyperbolic sine transformation as “log” for reporting simplicity.

of social capital organizations causes the probability of entering into recession to increase by 39.3%.

Table 5: Results from capitals model

	Stratified Model			Metro Model			Rural Model		
	Hazard Ratio		SE	Hazard Ratio		SE	Hazard Ratio		SE
Natural Capital (N_n)									
log water area	1.013		(0.023)	0.982		(0.037)	1.039		(0.029)
log land sqr miles	0.984		(0.033)	1.064		(0.057)	0.950		(0.041)
temps - Jan	0.995		(0.006)	0.980		(0.014)	0.999		(0.007)
hrs of sun - Jan	1.001		(0.001)	0.996		(0.003)	1.001		(0.002)
temps - July	0.983		(0.009)	0.993		(0.018)	0.988		(0.011)
humidity - July	0.996		(0.004)	1.000		(0.007)	0.996		(0.005)
plains	0.940		(0.095)	1.071		(0.175)	0.876		(0.111)
plains with hills	0.932		(0.117)	1.254		(0.216)	0.797		(0.136)
open hills	0.840		(0.098)	1.023		(0.177)	0.736	**	(0.115)
mountains	0.847		(0.110)	0.973		(0.193)	0.762	*	(0.135)
Human Capital (H_n)									
log # < high school dipl	0.985		(0.098)	1.446		(0.169)	0.850		(0.118)
log # high school dipl	1.028		(0.175)	0.988		(0.383)	1.090		(0.198)
log # bach degree +	0.734	*	(0.130)	0.854		(0.292)	0.743	*	(0.145)
log # 20-29 yrs old	0.875		(0.105)	0.780		(0.185)	0.811		(0.137)
log # 30-49 yrs old	0.515	**	(0.256)	0.105	***	(0.497)	1.017		(0.313)
log # 50-64 yrs old	1.787		(0.346)	8.557	**	(0.689)	1.161		(0.425)
log # 65 yrs old +	1.003		(0.211)	1.026		(0.375)	0.810		(0.257)
Social Capital (S_n)									
log # soc cap orgs	1.393	**	(0.108)	1.389		(0.171)	1.277	*	(0.117)
Cultural Capital (C_n)									
log # African American	1.006		(0.021)	0.977		(0.044)	0.991		(0.024)
log # Asian	0.973		(0.036)	1.003		(0.081)	1.008		(0.042)
log # Native American	0.914	***	(0.025)	0.878	*	(0.062)	0.947	*	(0.028)
log # Hispanic	1.131	***	(0.032)	1.163	*	(0.065)	1.097	*	(0.037)
log # of artistic labor force	1.028		(0.020)	1.024		(0.042)	1.029		(0.022)
Political Capital (P_n)									
log #pol orgs	1.066		(0.038)	1.051		(0.056)	1.022		(0.071)
log # 2008 presidential voters	0.944		(0.248)	0.755		(0.466)	1.139		(0.304)
Financial Capital (F_n)									
log total deposits ($000s)	1.294	***	(0.055)	1.428	***	(0.091)	1.221	**	(0.064)

Physical Capital (Ph_n)								
log house prices ($000s)	1.206		(0.111)	1.466		(0.220)	1.154		(0.134)
Exogenous Forces									
log FF Cat 100 ($000s)	0.991		(0.012)	0.957	*	(0.017)	1.012		(0.016)
log FF Cat 200 ($000s)	0.995		(0.009)	0.985		(0.009)	1.007		(0.012)
log FF Cat 300 ($000s)	0.994		(0.004)	1.013		(0.009)	0.991	*	(0.004)
log FF Cat 400 ($000s)	0.982		(0.034)	1.025		(0.056)	0.923		(0.051)
log FF Cat 500 ($000s)	1.070		(0.061)	0.916		(0.091)	1.118		(0.089)
log FF Cat 600 ($000s)	0.999		(0.015)	0.964		(0.033)	0.995		(0.016)
State Fixed Effects									
Alabama	1.000		(.)	1.000		(.)	1.000		(.)
Arizona	0.828		(0.340)	1.373		(0.568)	0.727		(0.404)
Arkansas	0.843		(0.184)	0.913		(0.384)	0.785		(0.208)
California	0.752		(0.272)	1.086		(0.458)	0.624		(0.377)
Colorado	0.568	*	(0.281)	0.599		(0.563)	0.570		(0.339)
Connecticut	0.514		(0.384)	0.720		(0.420)	0.158		(1.073)
Delaware	0.302		(0.716)	0.387		(1.406)	0.373	**	(0.309)
Florida	1.627	*	(0.226)	3.822	***	(0.365)	1.115		(0.287)
Georgia	1.079		(0.168)	1.410		(0.302)	1.021		(0.201)
Idaho	0.958		(0.286)	1.251		(0.543)	0.790		(0.346)
Illinois	0.577	**	(0.189)	0.894		(0.346)	0.418	***	(0.225)
Indiana	0.881		(0.191)	1.147		(0.339)	0.715		(0.243)
Iowa	0.556	**	(0.210)	0.530		(0.423)	0.518	**	(0.238)
Kansas	0.683		(0.201)	0.891		(0.367)	0.548	*	(0.237)
Kentucky	0.542	***	(0.184)	0.913		(0.329)	0.410	***	(0.219)
Louisiana	0.856		(0.185)	1.548		(0.296)	0.615	*	(0.242)
Maine	0.356	***	(0.270)	0.367	*	(0.479)	0.328	***	(0.325)
Maryland	0.287	***	(0.323)	0.317	*	(0.451)	0.323	*	(0.566)
Massachusetts	0.586	*	(0.237)	0.342	**	(0.372)	6.138	***	(0.371)
Michigan	0.535	*	(0.254)	0.678		(0.459)	0.425	**	(0.306)
Minnesota	0.578	*	(0.241)	0.732		(0.490)	0.483	**	(0.278)
Mississippi	1.188		(0.179)	2.140	*	(0.327)	0.941		(0.209)
Missouri	0.587	**	(0.180)	1.002		(0.327)	0.463	***	(0.210)
Montana	0.691		(0.276)	0.859		(0.478)	0.613		(0.316)
Nebraska	0.497	***	(0.210)	0.636		(0.435)	0.411	***	(0.238)
Nevada	1.012		(0.442)	3.674	*	(0.620)	0.709		(0.506)
New Hampshire	0.801		(0.330)	0.749		(0.543)	0.805		(0.398)
New Jersey	0.394	**	(0.292)	0.353	*	(0.412)	N/A		N/A
New Mexico	0.317	**	(0.355)	0.724		(0.621)	0.288	**	(0.405)
New York	0.333	***	(0.241)	0.206	***	(0.412)	0.357	**	(0.328)

North Carolina	0.609	**	(0.181)	0.653		(0.328)	0.562	**	(0.224)
North Dakota	0.517	*	(0.288)	0.255		(0.938)	0.505	*	(0.323)
Ohio	0.826		(0.203)	0.952		(0.371)	0.666		(0.243)
Oklahoma	0.793		(0.226)	1.687		(0.428)	0.578	*	(0.259)
Oregon	0.622		(0.289)	0.739		(0.480)	0.565		(0.367)
Pennsylvania	0.371	***	(0.234)	0.309	**	(0.386)	0.377	**	(0.311)
Rhode Island	0.525	*	(0.303)	0.455		(0.465)	N/A		N/A
South Carolina	0.769		(0.217)	0.879		(0.338)	0.811		(0.277)
South Dakota	0.715		(0.236)	0.480		(0.494)	0.604		(0.264)
Tennessee	0.630	*	(0.197)	0.785		(0.313)	0.492	**	(0.258)
Texas	0.688	*	(0.183)	0.931		(0.340)	0.655		(0.221)
Utah	0.777		(0.279)	0.933		(0.543)	0.616		(0.346)
Vermont	0.472	*	(0.353)	0.361		(0.722)	0.512		(0.413)
Virginia	0.451	***	(0.193)	0.558		(0.312)	0.450	**	(0.249)
Washington	0.586	*	(0.265)	0.519		(0.453)	0.523		(0.346)
West Virginia	0.330	***	(0.255)	0.270	**	(0.446)	0.339	***	(0.317)
Wisconsin	0.433	***	(0.251)	0.449		(0.463)	0.392	**	(0.300)
Wyoming	1.000		(0.284)	1.683		(0.802)	0.892		(0.318)

Marginal effects; Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Breaking down the results in Table 5 by types of capital, I find that natural capital is largely insignificant across the models. The exception is the rural model, in which I find that open hills and mountains mitigate a county's entrance into recession. I posit open hills promote connectivity within a rural region, allowing it to grow while still offering amenities to attract workers. Mountains, on the other hand, may mitigate entrance to recession since mountainous communities are likely more remote to external market forces. This means mountainous communities may have been sheltered from the types of economic activities that spurred the Great Recession. In addition, mountainous communities may hold the types of amenities that attract wealthy people, which in and of itself could have provided a buffer from a recession.

As for human capital, I find that increases in the number of residents with bachelor's degrees and those in the 30-49 year old age group significantly mitigate a county's entrance to recession. In other words, higher skilled workers are assets to a county in both the stratified and rural models. The same can be said for workers within the 30-49 year old age group, which is when workers are typically their most productive, within the stratified and metro models.

I am surprised by the social capital results. According to the stratified and rural models, increases in the number of social capital organizations significantly increases the probability of a county entering into recession. I expected the opposite, in that more social capital organizations would promote networking which could help communities respond to negative external forces. My guess is that social capital will better promote recovery to a recession rather than mitigation against entrance to a recession, although I do not test this theory within this analysis.

For cultural capital, I find Native American residents significantly reduce the probability a county will enter into a recession across each model. On the other hand, increases in Hispanic population increase a county's chance of entering into recession. These each demonstrate cultural identity do affect a county's resilience.

In terms of financial capital, the more deposits in local banks the more likely counties are to enter into recession. This occurs across each model. I find this somewhat surprising because I figured the amount of deposits would serve as a buffer to recession since residents would have liquid sources of income to depend upon in the case of, for example, unemployment. However, this could also be a side effect of the financial crisis, in that the

Great Recession did hit the banking industry fairly hard. Neither political capital nor physical capital provided significant results.

Exogenous forces were largely insignificant with the exception of two cases. The amount of external funds in Category 100 (Agriculture and Natural Resources) in the metro model and funds in Category 300 (Defense and Space) in the rural model both significantly mitigate a county's entrance into recession. The latter finding is likely due to the fact that defense spending, such as for military bases, national laboratories, and so forth tend to be placed in remote locations given the need for plenty of space and security. In this way, rural counties may become dependent upon injections of federal funding as an economic base.

I performed a couple of diagnostics to ensure my model was correctly specified and I did not have an omitted variable issue. The main test was the link test, which looks to see whether adding variables will add explanatory value. This also helps test the proportional hazards assumption. The test rebuilds the model using the linear predicted values (_hat) and the linear predicted values squared (_hatsq). The goal is for _hat to be significant since it should reflect the estimated model, and for _hatsq to be insignificant. If the model passes this test, it tells us that it has accurately specified the predictors, and that adding other variables will not add significance unless by chance.

Upon running the linktest across all scenarios, I find _hat is significant and _hatsq is not in the metro and rural models. Therefore these models seem to be properly specified. In the stratification model, both _hat and _hatsq are insignificant. This leads me to believe that while the model is significant, it may omit potentially useful information once stratified.

Another diagnostic I performed was to check for outliers and influential data points. This way I could see whether any data points have a disproportionate influence on my estimates. I first looked into likelihood displacement, which looks at the influence of observations across all coefficients. This was useful considering I have a large number of explanatory variables. I found that Cumberland County (Tennessee) looked to be an outlier.

However, this information was limited since I did not know where it was an outlier. Therefore I also ran a DFBETA test, which compares estimated parameters from the full model to one using a reduced model. Outliers were provided for each explanatory variable. Using this diagnostic, I found Cumberland County to be an outlier in terms of federal funds category 600. I looked at the raw data files for this observation, and to the extent possible it seems the data is accurate. I therefore kept it as it was since I did not have reasoning to support its removal from the analysis.

The following figures represent the baseline cumulative hazard function, baseline survivor function, and estimated baseline hazard function, respectively, for the capital stock model. These were created after running the model from estimates of coefficients from the model. The baseline cumulative hazard function confirms the hazard of entering recession increases over time. With the exception of 2008, the hazard seems to be increasing at a steady rate over time. Figure 13 shows the survivor function decreasing over time. Again, 2008 demonstrates a large drop in the number of counties surviving against entrance into recession. Finally, Figure 14 shows a smoothed hazard curve across the analysis timeframe. It is shaped like an upside down U, meaning the baseline hazard was low at the beginning and end of the timeframe, and high in the middle.

Figure 12: Capital stock baseline cumulative hazard function

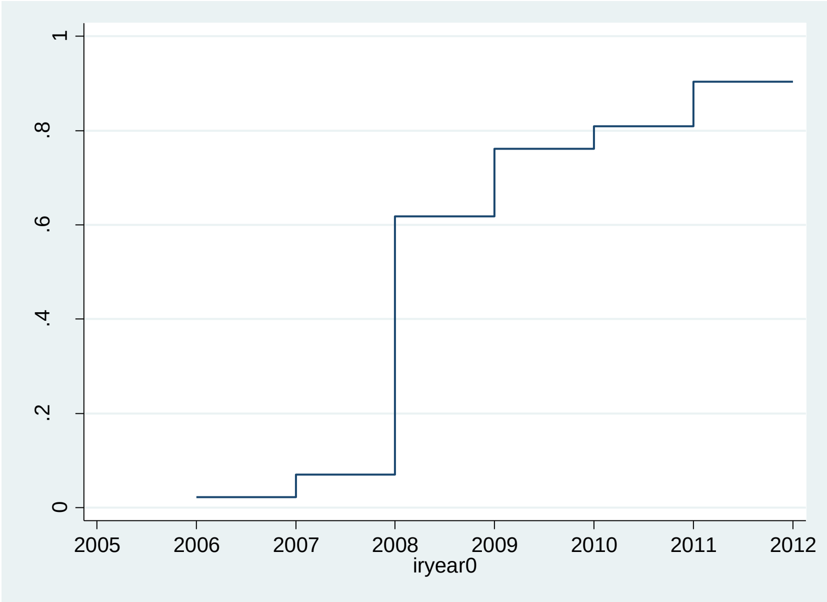


Figure 13: Capital stock baseline survivor function

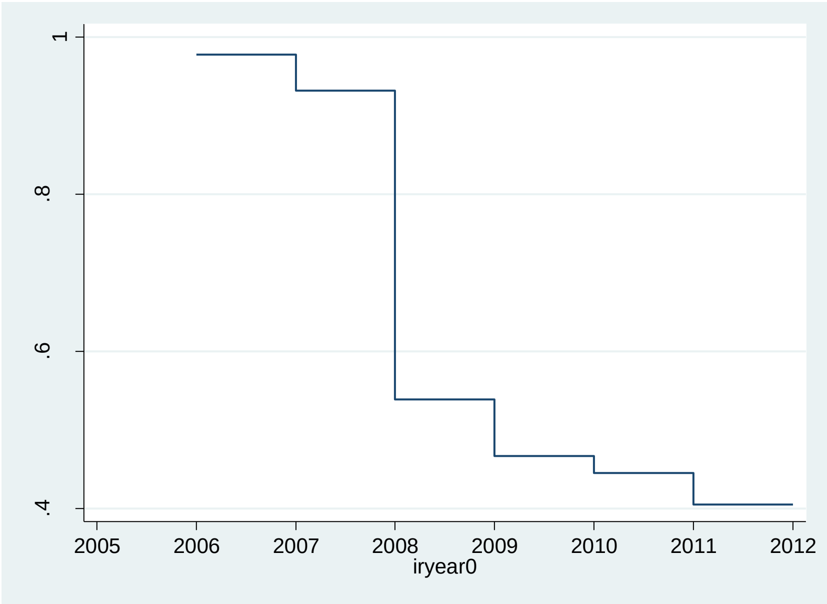
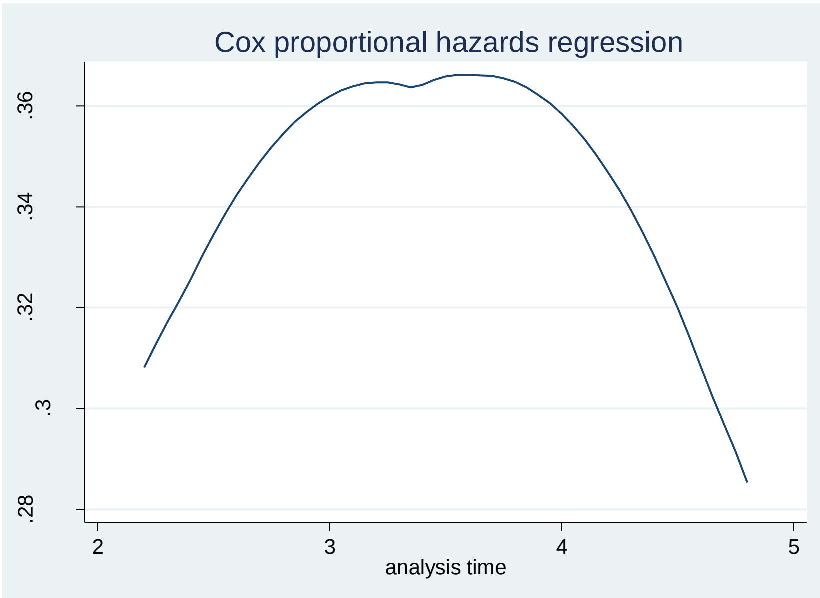


Figure 14: Capital stock estimated baseline hazard function



Results from the Economic Structure Model

Table 6 presents results from the economic structure models. The above scenarios, transformations, and interpretations apply to the economic structure model as the capital stocks model.

Table 6: Results from economic structure model

	Stratified Model			Metro Model			Rural Model		
	Hazard Ratio		SE	Hazard Ratio		SE	Hazard Ratio		SE
Industrial Composition									
log # jobs NAICS 11	0.983		(0.036)	1.103		(0.056)	0.938		(0.050)
log # jobs NAICS 21	1.019		(0.013)	1.083	**	(0.027)	1.007		(0.015)
log # jobs NAICS 22	1.016		(0.016)	1.003		(0.029)	1.010		(0.019)
log # jobs NAICS 23	0.914		(0.062)	0.972		(0.135)	0.928		(0.070)
log # jobs NAICS 311-312	1.004		(0.011)	0.999		(0.025)	1.002		(0.013)
log # jobs NAICS 313-316	0.996		(0.011)	1.015		(0.023)	0.990		(0.012)
log # jobs NAICS 324-327	1.014		(0.013)	0.996		(0.028)	1.015		(0.014)
log # jobs NAICS 331-332	1.000		(0.012)	0.982		(0.031)	1.004		(0.014)
log # jobs NAICS 333	1.010		(0.009)	0.996		(0.022)	1.009		(0.010)
log # jobs NAICS 334-335	1.010		(0.008)	1.004		(0.018)	1.009		(0.010)
log # jobs NAICS 336	1.018	*	(0.008)	1.053	**	(0.018)	1.007		(0.009)

log # jobs NAICS 321-323, 337, 339	0.997		(0.016)	1.037		(0.041)	1.010		(0.017)
log # jobs NAICS 42	1.096	**	(0.035)	1.272	**	(0.077)	1.025		(0.040)
log # jobs NAICS 44	0.996		(0.081)	0.782		(0.192)	1.083		(0.092)
log # jobs NAICS 45	0.845	**	(0.064)	0.623	***	(0.139)	1.007		(0.076)
log # jobs NAICS 48	0.987		(0.039)	0.909		(0.077)	0.993		(0.046)
log # jobs NAICS 49	0.992		(0.019)	0.953		(0.043)	1.002		(0.021)
log # jobs NAICS 51	1.032		(0.032)	1.036		(0.062)	1.030		(0.035)
log # jobs NAICS 52	1.249	***	(0.055)	1.234		(0.108)	1.162	*	(0.069)
log # jobs NAICS 53	1.013		(0.055)	1.081		(0.139)	0.990		(0.064)
log # jobs NAICS 54	0.976		(0.064)	0.892		(0.123)	1.018		(0.080)
log # jobs NAICS 55	1.039	**	(0.012)	1.029		(0.025)	1.035	*	(0.014)
log # jobs NAICS 56	1.013		(0.051)	1.213		(0.117)	0.930		(0.056)
log # jobs NAICS 61	0.993		(0.020)	1.023		(0.047)	0.994		(0.023)
log # jobs NAICS 62	0.922		(0.048)	1.300	*	(0.104)	0.883	*	(0.053)
log # jobs NAICS 71	1.050		(0.038)	1.061		(0.071)	1.049		(0.045)
log # jobs NAICS 72	1.097		(0.059)	1.187		(0.123)	1.036		(0.069)
log # jobs NAICS 81	1.120		(0.082)	0.982		(0.195)	1.141		(0.092)
log # jobs NAICS 901	0.864	***	(0.038)	0.858	*	(0.062)	0.838	***	(0.052)
log # jobs NAICS 902	0.984		(0.016)	0.948	*	(0.025)	0.978		(0.021)
log # jobs NAICS 903	0.838	**	(0.067)	0.751	*	(0.127)	0.916		(0.081)
Exogenous Forces									
log FF Cat 100 ($000s)	0.991		(0.012)	0.949	**	(0.018)	1.027		(0.017)
log FF Cat 200 ($000s)	0.988		(0.007)	0.974		(0.015)	1.004		(0.011)
log FF Cat 300 ($000s)	0.991	*	(0.004)	1.001		(0.009)	0.990	*	(0.004)
log FF Cat 400 ($000s)	0.953		(0.025)	1.026		(0.052)	0.863	***	(0.045)
log FF Cat 500 ($000s)	1.082		(0.042)	1.071		(0.067)	1.091		(0.065)
log FF Cat 600 ($000s)	1.002		(0.015)	0.989		(0.040)	0.995		(0.015)
State Fixed Effects									
Alabama	1.000		(.)	1.000		(.)	1.000		(.)
Arizona	1.521		(0.229)	1.488		(0.373)	1.347		(0.301)
Arkansas	0.883		(0.176)	0.733		(0.356)	0.872		(0.210)
California	1.545	*	(0.206)	1.755		(0.302)	1.258		(0.314)
Colorado	1.235		(0.203)	0.922		(0.402)	1.145		(0.245)
Connecticut	0.795		(0.389)	1.234		(0.343)	0.223		(1.082)
Delaware	0.711		(0.836)	0.649		(1.429)	1.008		(0.210)
Washington DC	0.840		(0.306)	0.766		(0.545)			
Florida	2.114	***	(0.193)	2.772	***	(0.297)	1.521		(0.272)
Georgia	1.102		(0.150)	1.057		(0.254)	1.182		(0.185)
Idaho	1.611	*	(0.199)	1.919		(0.371)	1.282		(0.240)

Illinois	0.749		(0.175)	1.430		(0.269)	0.463	***	(0.230)
Indiana	1.170		(0.151)	1.805	*	(0.232)	0.855		(0.206)
Iowa	0.861		(0.161)	0.872		(0.314)	0.720		(0.196)
Kansas	1.029		(0.153)	1.128		(0.250)	0.810		(0.197)
Kentucky	0.570	***	(0.166)	0.890		(0.285)	0.449	***	(0.204)
Louisiana	0.807		(0.179)	0.859		(0.275)	0.702		(0.239)
Maine	0.660	*	(0.206)	0.792		(0.288)	0.536	*	(0.275)
Maryland	0.518	*	(0.304)	0.502		(0.426)	0.604		(0.555)
Massachusetts	1.315		(0.203)	1.146		(0.267)	30.945	***	(0.314)
Michigan	0.764		(0.200)	0.892		(0.369)	0.587	*	(0.247)
Minnesota	0.982		(0.157)	1.087		(0.272)	0.786		(0.201)
Mississippi	1.120		(0.171)	1.726		(0.319)	0.977		(0.206)
Missouri	0.737	*	(0.149)	1.174		(0.252)	0.554	**	(0.189)
Montana	1.367		(0.205)	1.879		(0.374)	1.066		(0.244)
Nebraska	0.801		(0.164)	1.177		(0.304)	0.604	*	(0.203)
Nevada	1.434		(0.415)	9.390	***	(0.381)	0.887		(0.460)
New Hampshire	1.260		(0.272)	1.555		(0.411)	1.179		(0.357)
New Jersey	0.736		(0.279)	0.778		(0.364)			
New Mexico	0.662		(0.265)	0.792		(0.580)	0.547		(0.309)
New York	0.526	**	(0.206)	0.520	*	(0.322)	0.453	**	(0.304)
North Carolina	0.703	*	(0.164)	0.585		(0.275)	0.701		(0.212)
North Dakota	0.926		(0.220)	0.384		(0.798)	0.881		(0.244)
Ohio	1.044		(0.177)	1.397		(0.288)	0.782		(0.222)
Oklahoma	0.788		(0.194)	0.964		(0.327)	0.730		(0.231)
Oregon	1.279		(0.184)	1.099		(0.271)	1.142		(0.261)
Pennsylvania	0.581	**	(0.195)	0.719		(0.288)	0.445	**	(0.281)
Rhode Island	1.074		(0.235)	1.038		(0.314)			
South Carolina	0.883		(0.187)	0.863		(0.277)	0.905		(0.268)
South Dakota	0.975		(0.178)	0.493		(0.481)	0.837		(0.216)
Tennessee	0.677	*	(0.185)	0.912		(0.274)	0.512	**	(0.253)
Texas	0.919		(0.146)	0.707		(0.256)	0.926		(0.185)
Utah	1.003		(0.196)	1.000		(0.293)	0.934		(0.249)
Vermont	0.782		(0.350)	0.783		(0.760)	0.779		(0.408)
Virginia	0.683	*	(0.170)	0.920		(0.261)	0.563	*	(0.233)
Washington	1.172		(0.169)	1.209		(0.241)	0.944		(0.243)
West Virginia	0.474	**	(0.227)	0.510		(0.381)	0.424	**	(0.292)
Wisconsin	0.639	*	(0.196)	0.691		(0.302)	0.539	*	(0.263)
Wyoming	2.355	***	(0.210)	5.138	*	(0.670)	1.892	**	(0.239)

Marginal effects; Standard errors in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

I find several industries, namely mining (NAICS 21), transportation equipment manufacturing (NAICS 336), wholesale trade (NACS 42), finance and insurance (NAICS 52), and management of companies and enterprises (NAICS 55) significantly increase the time until a county enters recession. Of these, I find the transportation equipment manufacturing industry and the finance and insurance industry the most interesting since they correspond with the commonly known culprits of the recession, which were the decline in automotive manufacturing and a banking crisis. Transportation equipment manufacturing applies to the stratified and metro models, which makes sense given it tends to be based in more urbanized areas with clusters of related supply chain industries. I see finance and insurance is significant in the stratified and rural models, which I take to mean that rural regions were more adversely affected by the banking crisis. This is likely because rural regions do not have as diverse of a banking or economic structure.

On the other hand, jobs in retail trade (NAICS 45), local government (NAICS 901), state government (NAICS 902), and federal government (NAICS 903) significantly decrease the time until a county enters recession. In other words, concentration in those industries help mitigate a county's probability of entering recession. I find these results to be in line with expectations. In particular, I would expect the different levels of government to help buffer the risks of recession. This is especially true for local government, which is best able to respond quickly to negative effects through community organizations and programs.

These results more or less hold across the different scenarios. However, of interest is health care and social assistance (NAICS 62). It significantly increases a county's probability of entering recession for metro counties, but the opposite occurs for rural counties.

Similar to the capital stocks model results, I again find federal funds category 300 (defense and space functions) significantly helps a county mitigate its probability of recession in the rural model, as well as the stratified model. I also again find that federal funds category 100 (agriculture and natural resource functions) decrease the risk of entering recession for metro counties. In addition, this model demonstrates that federal funds category 400 (human resources functions) helps rural counties.

I again performed the link test to check my model specification. Similar to the capital stock model, I find _hat is significant and _hatsq is not in the metro and rural models. Therefore these models seem to be properly specified. In the stratification model, both _hat and _hatsq are insignificant. This leads me to believe that while the model is significant, it may omit potentially useful information once stratified.

The following figures represent the baseline cumulative hazard function, baseline survivor function, and estimated baseline hazard function, respectively, for the economic structure model. Figure 15 can be interpreted much the same as Figure 12 for the capital stock model. Figure 16 is also similar, although the survivor function seems to decrease more over time. Figure 17 paints quite a different picture than the estimated baseline hazard function for the capital stock model. Here it increases gradually over time.

Figure 15: Economic structure baseline cumulative hazard function

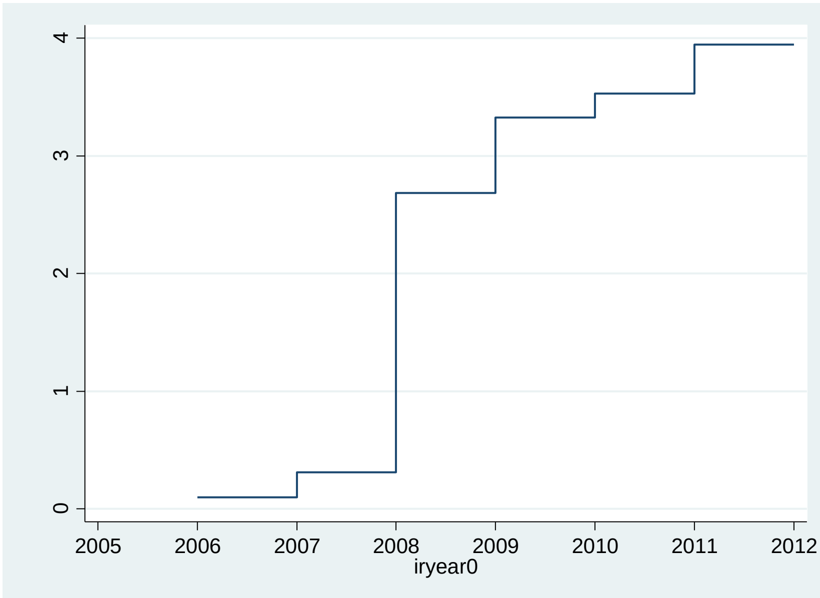


Figure 16: Economic structure baseline survivor function

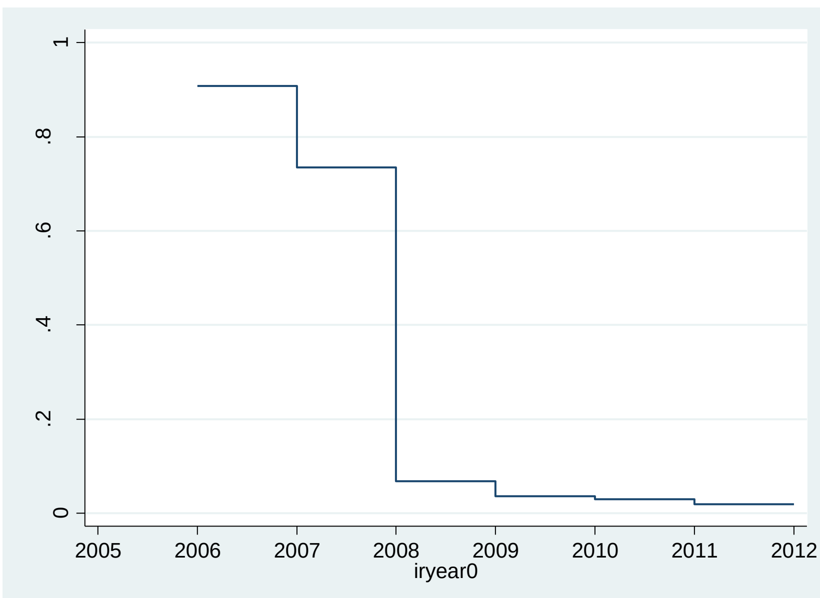
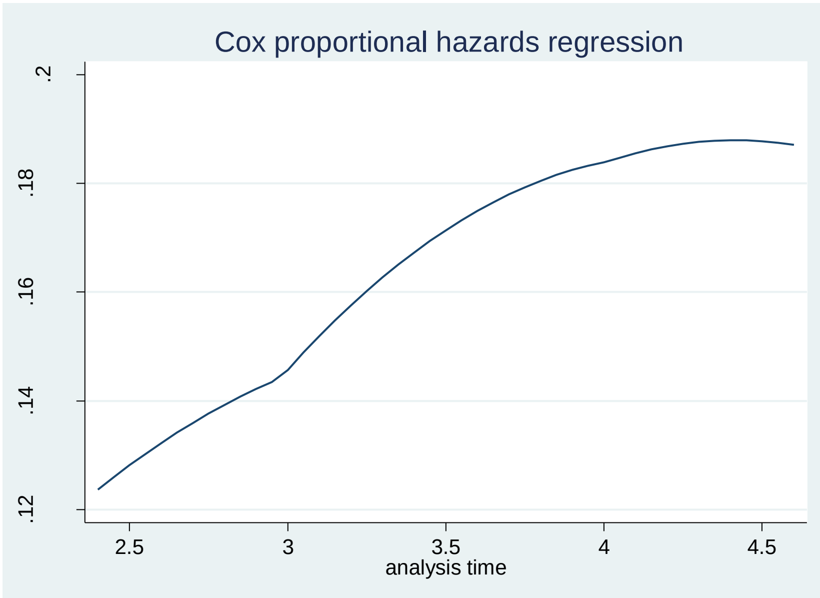


Figure 17: Economic structure estimated baseline hazard function



Conclusion

I have investigated why and how one region may enter into a recession compared to another. Put another way, I looked into factors explaining why some regions are better able to protect against an economic downturn compared to others. This is an important question for communities, especially rural communities, to have an answer to so they can prepare for the inevitable occurrence of another downturn. While I have focused on a recession as the type of downturn or external shock, similar preparedness is necessary for any type whether it be a global financial crisis, a natural disaster, or other unknown phenomena. I used the Cox model and data at the county-level to measure how capital stocks and economic structure lead to a county's resilience to a recession. Emphasis was placed on rural context where feasible.

My Cox model findings test for the significance of explanatory variables. In the capital stock model, I find residents with bachelor's degrees and within the 30-49 year old age band, as well as local government jobs and federal funding for defense and space functions, mitigate a county's entrance to recession. Certain topographical features, namely hills and mountains, also protect against a recession. On the other hand, concentrations in certain industries, such as transportation equipment manufacturing and finance, hinder a county's ability to withstand a recession.

Of these results, I find the differences in human capital effects across scenarios especially interesting since they can be influenced through policy. For example, I demonstrate the positive role skilled labor plays within counties, implying communities should focus on ensuring they have a skilled workforce. The differences between natural capitals really cannot be altered although the role they play in resilience are important to keep in mind.

In terms of the economic structure model, I was not too surprised to see employment concentration in industries such as finance and transportation equipment manufacturing speed a county's entrance into recession given these industries are often blamed for the recession itself. I did find it surprising to see that the agricultural industry did not significantly affect rural counties, although jobs in mining and utilities industries do increase a metro county's probability of entering recession. Also, it seems surprising that injections of federal funds toward agriculture can reduce a metro county's resilience to recession, but is not significant for rural counties, and may even adversely affect rural counties if it was significant. These findings would be interesting to take under further consideration when developing resilience strategies for rural counties.

I recognize my results are limited in terms of factoring in the inevitable occurrence of spatial dependencies. While I did account for them through fixed effects at the state-level, I did not build a comprehensive spatial dependency model wherein I analyze neighboring counties. Further work could better hone in on how geographic proximity to certain regions and amenities comprise a region's response to a recession. Also, this analysis only measures resilience to entrance into recession. Next research can hone in on factors helping a county recover from a recession, or the length and depth of an external shock.

Also, for this analysis I focused on the Cox model given the benefits of its semiparametric form. Future analysis could test the Cox model results against three other fully parametric forms – exponential, Weibull, and Gompertz – to ensure it was a proper fit. While the literature suggests the Cox model generally produces similar results as the fully parametric forms, I would like to include a sensitivity analysis to confirm this is indeed the case for my analysis.

Regardless of the limitations, my analysis not only provides a general overview of regions that have entered into a recession, but also pinpoints certain reasons behind the better protection of some counties over others against an economic downturn. Community economic development leaders can use these results to build strategies for the future.

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