Predicting the Economic Resilience of US Counties from Industry Input-Output Accounts

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Abstract

Resilience is defined as the capacity of a system to recover its functions and structure after an internal or external shock. Any natural, economic or other shock to a system can be represented by two stages: a drop (economic decline) and rebound (recovery), and these stages are affected by the inherent properties of system components. Regional economic recovery after a recession or other external shock is often a key policy objective. In this paper we estimate the economic complexity of all US counties using network measures based on the centrality and entropy properties of the local economy; these measures are derived from the national industry input-output table and the number of employees in each industry. Then we apply our measures to predict local economic resilience during the 2007-2009 Great Recession. The results suggest that higher economic complexity is associated with more economic resilience. We conclude that our measures of resilience and complexity give us a framework for planning local development strategy and designing policy to enhance post-shock recovery.

Introduction

Economic growth and stability are key goals of regional development policy. Growth includes expansion of population, jobs and income while stability suggests smaller deviations from the steady-state growth path, or a smaller decline and faster recovery from an internal or external shock. Ideally, development involves continuous growth under stable conditions. However, many rural areas may be economically unstable because they lack their own economic growth engines and have relatively fewer economic sectors and activities compared with larger cities. Thus even minor shocks can cause an economic recession in rural areas. For example, a rural county dependent on agriculture may shrink following a natural disaster or crop failure. Until now, research has primarily focused on local economic development and growth, and only to a lesser degree on local economic stability.

Although no common definition is agreed upon and each field has its own interpretations, it is widely accepted that resilience is the capacity of a system to maintain or recover its functions and structure following an internal or external shock (Allenby and Fink, 2005). Thus, the notion of resilience can be used to motivate an index of economic stability. In economics, regional resilience is explained as a region's ability "to withstand change or to retain its core function despite external upheaval" (Davies, 2011:370), and then "to remain on or return to a long run developmental path" (371). While recovery from a recession or other external shock is often an important goal of national and local policy makers, our understanding of regional resilience and applications of the concept to regional development policy are limited by two basic unanswered questions: how to measure regional economic resilience and why different regions respond differently to the same shock.

Regional economic growth has been shown to depend strongly to regional economic complexity (Arthur, 1999; Durlauf, 2005; Hidalgo *et al.*, 2007; Eagle *et al*., 2010). Economic complexity depends on the diversity of knowledge within an economy and on the ability of economic agents or firms to synthesize and use this knowledge in complex webs of economic transactions. Further, complexity has been linked to the composition of a region's output and the structures that emerge to hold and combine knowledge (Hidalgo *et al*., 2009; Hausman *et al*., 2011). We hypothesize that economic complexity affects not only economic growth but also resilience, because higher complexity implies more diverse economic activities, sources of growth, and flexible responses against shocks. Even though portfolio approaches based on managing a number of different risks are known to be the most efficient strategy (Allenby and Fink, 2005), the relationship between regional economic complexity and resilience has to date not been quantified. A regional economy consists of firms and industries that are connected with each other by exchanges of products or other transactions, and each industry has different scale, characteristics and demand-supply chains. For example, agriculturally-based regions and financial sector-based regions would be expected to differ in terms of local economic complexity because the interconnections between agriculture and finance with the rest of the economy are not same. Thus regional economic complexity needs to reflect the relative influence of local industries, as measured by interconnectedness as well as industrial structure.

The influence of an industry on the economy can be measured using industry Input-Output (IO) accounts (Hewings *et al*., 2005; Lian and Haimes, 2006). All industries are connected in varying degrees through demand and supply chains: IO accounts represent quantitative buying and selling transactions between economic sectors. An industry has greater "influence" or importance if it enters into more transactions with a greater variety of other industries. A more influential industry acts as a key sector in the economy and its failure or removal causes a greater shock to the entire economy. Xu *et al*. (2011) measured economic resilience by the responses of economic systems to failures of different sectors through input-output transactions.

Not surprisingly, more developed countries have more complex transactions. A highly developed region has redundant economic systems guarding against failure of any one industry, because it has alternative routes to (re-)connect industries without significant loss. But in the case of a region with a simple economic structure, a shock emanating from any one industry spreads quickly to others and causes a crisis for the entire local economy because no options exist in terms of switching to alternative supply chains.

Focusing on the robustness of complex economic networks may provide a new perspective on economic resilience (Janssen *et al*., 2006). In particular, an IO account can be regarded as a network. Once we recognize this, a suite of tools and analyses is available to examine how an economy functions. Industries and economic transactions between industries in IO accounts are represented by *nodes* and directed *edges* in the network. The influence of an industry in the economy can be measured by the centrality of the node in the IO table (Freeman, 1978/79; Wasserman and Faust, 1994; Borgatti, 2005; Tutzauer, 2007). In turn, regional economic complexity depends on local industrial diversity and relative size or scale. Thus, we can calculate local economic complexity based on the industrial organization of an area and centrality of each industry.

Network structures range from random to scale-free, depending on the connecting rule. In a random network, nodes have an average number of connections (edges) with other nodes, and no particular node stands out as being most important or most central (Watts and Strogatz, 1998). Random networks are less efficient in transmitting knowledge and information but at the same time they also are less vulnerable to targeted attacks. Scale-free networks are characterized by a few nodes having most connections and most nodes having very few connections; they follow a power law distribution (Barabási and Albert, 1999). These kinds of networks, well-illustrated by the hub-and-spoke system used by airlines, are highly vulnerable to targeted attacks of the most central nodes or hubs but they are otherwise robust. The entire network continues to function if a few hubs survive even though numerous less important nodes may fail (Albert *et al*., 2000).

An analysis of the 2002 US national input-output accounts and 2008 employment per industry reveals that industry output or industrial *strength* follows a power-law distribution (Fig. 1). The power-law distribution of IO accounts means that most transactions between industries occur between just a few industries, namely hubs or key sectors. Retail trade, wholesale trade and real estate represent the backbone of the US economy. Thus a few core industries dominate economic transactions, and the economy is especially vulnerable to downtowns in these core sectors, as was clear in the real estate collapse starting late in 2007.

In this paper we propose that economic resilience can serve as an index of local economic stability, and then propose a quantitative measure based on local economic complexity. To do this, we calculate centrality scores for all industries from the national IO table and then step these measures down to the county-level using the number of employees in each industry in a county.

Then we use regression analysis to examine local economic resilience during the 2007-2009 downturn.

Measurement of Local Economic Resilience

Resilience is generally defined as the capacity of a system to recover its functions and structure following internal or external shocks (Allenby and Fink, 2005). The recovery process involves reorganization of a system to cope with the shocks and bouncing back to the pre-shock state. Depending on their properties, different systems have different recovery patterns in terms of rebound, hysteresis and realignment (Simmie and Martin, 2010; Martin, 2011). Thus a definition of resilience needs to consider not just the recovery phase during which a system reorganizes in response to a shock, but also the initial decline. As noted, Davies (2011) explains economic resilience as a region's ability to resist change or to maintain its basic functions after an external shock, and then also to stay on or move back onto its steady-state path of development. We focus here especially on the concepts of 'ability to withstand' and 'steady-state development path'. 'Withstand' refers to the capacity of a system to resist changes while the 'steady-state development path' refers to a system's expected position in the absence of a shock.

We define three dependent variables to operationalize our measure of resilience (Fig. 2). First is the *Drop*, which measures how much a system's output changes after a shock at *t1*. This is calculated as the deviation of actual from expected (based on the trend) output at time *t2*:

$$Drop = \frac{expected_{t2} - actual_{t2}}{expected_{t2}} \times 100 \tag{1}$$

Even though a system's output may bounce back to the pre-shock level, the system reorganizes due to the shock. In a local economy, this may be reflected in firm bankruptcies, salary reductions and unemployment. A smaller *Drop* suggests more resilience. Next is the *Rebound,* which captures the extent to which a system's output recovers by time *t3*. This is calculated from:

$$Rebound = \frac{actual_{t3} - expected_{t3}}{expected_{t3}} \times 100 \tag{2}$$

Rebound is the ability to overcome a shock and follow a new growth path. A system may not return exactly to the pre-shock state, because the reorganization changes its structure. A greater rebound implies a more sound system (or economic) structure and greater resilience. Minimizing the effect of a crisis and maximizing the benefits of reorganizing are basic components of resilience. We calculate system *Resilience* as the ratio between *Drop* and *Rebound*:

$$Resilience = \log\left(\frac{Rebound - \min(Rebound) + 1}{Drop - \min(Drop) + 1}\right) \quad (3)$$

If a system experiences a smaller decline and more recovery against the same scaled shock, that system is more resilient than others. Our resilience measure captures these concepts and the extent of impact on a system by comparing actual and expected output. Assume two regions have the same output in time *t2* and *t3*, but one has been growing and the other declining. In the growing region we expect a greater output in *t3* than in the declining region, but the outputs are actually identical because output in the growing region falls in *t3* to that of the declining region, because of the shock. In this case, the shock affects the growing region more than the declining region. We can detect this difference only by considering the long-run growth path.

To measure the economic resilience of US counties in the 2007-2009 downturn we use county level per capita personal income data over the years 2005-2011. We calculate each county's long-run development path as an average trend over 2005-2008, and then obtain *Drop*, *Rebound* and *Resilience* measures using 2005, 2008, 2009, and 2011 as *t0*, *t1*, *t2*, and *t3*, respectively, as shown in Fig. 2. These three measures are mapped in Figures 3-5. The 2007-2009 downturn originated in large part from subprime mortgages and homeowners who lost their jobs and could not pay back their mortgages, which affected the financial and real estate industries. Thus we expect that counties depending on financing and real estate industries experienced a bigger drop.

The yellow shaded areas in Fig. 3 had the smallest drops and these were found primarily in the eastern non-coastal part of the country. Proportionally larger drops occurred in the nation's center, including southwest of Chicago, as well as the coastal counties. With some notable exceptions, the pattern for rebounds in Fig. 4 is opposite to that of the drops, with greater rebounds in places where drops were less pronounced. Resilience was greatest along the Appalachian counties, the non-coastal northeast, Michigan, Minnesota and Wisconsin, as well as some of the Plains states (Fig. 5).

Measurement of Local Economic Complexity

Local economic complexity is reflected in the composition of a county's products (Hidalgo *et al*., 2009; Hausman *et al*., 2011 show this for nations). Greater product diversity in a region implies more economic complexity, which increases economic resilience. The scale and variety of products are proportional to the amount of employment across industries. Each industry connects to other industries and has different scales, properties, and demand-supply chains as captured in the IO table. We calculate local economic complexity based on the scale and variety of employment and industry transactions in counties while considering the importance of each industry. As noted, industries and transactions between them in the IO accounts are represented by heterogeneous nodes and directed edges in the network. The importance of an industry in the economy can be measured by the centrality of nodes in the IO network or table.

We calculate the first industrial centrality measure, Industry Strength (*IS*) as eq. (4):

$$IS_s = \frac{\sum_t^n IO_{st}}{N} \tag{4}$$

Here *IO* is the input-output table or account, ***N*** the number of industrial sectors, and *s* and *t* are sectors. Strength centrality in a network is the most basic index of centrality and measures an actor's degree of activity (Freeman, 1978/79; Wasserman and Faust, 1994; Borgatti, 2005). A high *IS* means the industry sells more commodities to other industries and represents a key sector in the economic system. The highest *IS* are obtained for wholesale, retail and real estate sectors.

Our second centrality measure, Industry Entropy (*IE*) is calculated as shown in eq. (5):

$$IE_s = \frac{-\sum_t^n p_{st} \log_2 p_{st}}{\log_2 N}, \; p_{st} = \frac{IO_{st}}{\sum_u^n IO_{su}} \tag{5}$$

Entropy reflects the diversity of an actor or system (Tutzauer, 2007; Goetz *et al*., 2010). Thus IE_S refers to the diversity of industry *s*. A high *IE* means that the industry sells commodities to a greater variety of consumers. Even if one particular consumer fails or collapses during a downturn, the industry has other customers to whom it can sell.

To convert our two national industry centralities into a local economic complexity measure we use industry employment data from the US Commerce Department's County Business Patterns.

$$LI_{ij} = \frac{EMP_{ij}}{\sum_k^m EMP_{ik}} \tag{6}$$

Here *EMP* is the number of employees per industry in the county. Subscript *i* indicates the county and *m* the number of industries. *LI* is normalized by total employment *EMP* and measures the industrial composition of employment (or employment share). From this we calculate a local industrial strength and entropy for each county, represented as *LIS* and *LIE*, respectively.

$$LIS_i = \sum_j^m LI_{ij} \cdot IS_j \quad LIE_i = \sum_j^m LI_{ij} \cdot IE_j \tag{7}$$

A high *LIS* means a county sells more commodities and the county has an important position within the economy. The failure of that county will have significant negative effects on other counties but the county itself may or may not be vulnerable to a shock because of its size. *LIE* measures the economic diversity of a county. A high *LIE* indicates that the county sells its output to a greater *diversity* of markets (i.e., other counties). Thus that county will be less vulnerable to an economic downturn because even if some of its client counties enter into a recession, the county can replace that market or consumer by selling to others.

Fig. 6 shows a pattern of local industrial strength, as measured here, in the central part of the nation as well as in selected counties along the West Coast, portions of Texas, the Gulf Coast, Florida and only a few Northeast counties. The traditional manufacturing belt of Michigan, Indiana, Ohio and Pennsylvania, especially, is characterized by relatively low industrial strength. The local industrial entropy map in Fig. 7 on the other hand shows high entropy values in Michigan, Illinois, Wisconsin, Indiana, Ohio and Pennsylvania, as well as in many counties in the Southeastern States, Colorado and Denver. These counties are heavily diversified in terms of the industries represented in the national input-output accounts.

Regression Framework and Results

We start with a conventional economic growth model and modify it to capture explicitly the economic bust and subsequent recovery as well as our county-level measures of resilience described in the previous section (Table 1). In particular, following Goetz *et al*. (2010) our basic model includes initial income, population density and land area, age of the population along with educational attainment, social capital stocks and regions of the country as controls. For the most part these variables are from the US Census and measured in 2008 with the exception of social capital in 2005, which is from Rupasingha *et al*. (2006). In addition, we add the *LIE* and *LIS* measures as regressors to examine how they affected counties' performance during the recession.

Table 2 shows key regression results with the alternative dependent variables. Looking across the columns it is apparent that counties with greater population density experienced a smaller drop in average per capita income during the Great Recession and a greater rebound; in addition they demonstrated greater resilience, all else equal. Counties with larger shares of younger (24-44 year olds) working age adults saw smaller drops and smaller rebounds but this variable had no effect on resilience. The counties with larger shares of older workers saw smaller drops and bigger rebounds -- perhaps because the workers were more experienced -- and also exhibited greater resilience. Counties with more post-65 year olds suffered both a greater drop and a lesser rebound, and they were statistically less resilient.

Counties with higher shares of population holding bachelor's degrees or more saw a smaller decline during the recession, and they rebounded more in the subsequent recovery and also showed higher resilience overall. Thus education to some extent shielded a county's economy from the recession. In fact, after initial income per capita, education clearly had the highest standardized coefficient estimate in the resilience equation. Social capital, on the other hand had a mixed effect: while it failed to protect counties during the drop, it increased the rebound but overall had no effect on our resilience measure.

The Northeast and Northcentral regions both experienced a smaller drop, but also a stronger rebound and overall greater resilience than the South (the excluded region). As a region, the West overall experienced a greater drop, a smaller rebound and overall lower resilience than the south. Counties with proportionately more employment in the real estate sector experienced a greater drop, smaller rebound and overall less resilience but these effects were not statistically significant at the 1% percent level or lower.

Turning last to our key measures of interest, counties with greater industrial strength experienced a smaller drop, enjoyed a greater rebound and also were more resilient. Counties with greater industry diversity, as measured here, benefited in the same way during the Great Depression, as hypothesized. Thus, at least one of our network-based measures of economic complexity, calculated for each industry from the national input-output table, performs as hypothesized.

Conclusion

While the notion of keystone sectors within an input-output framework is not new, we submit that the idea of examining input-output accounts using concepts and tools from the emerging science of networks is relatively novel, and fruitful. While previous studies have looked at this issue at the national level, to date no other work has to our knowledge attempted to "step down" these measures to the county-level, and this framework has not been applied to study resilience or recovery from a disaster. The results of our analysis suggest that the measures we develop here offer some promise in continuing this line of work. More specifically, we believe there are strong benefits to applying concepts related to robustness and resilience from networks occurring in nature to social and economic networks within the field of regional science.

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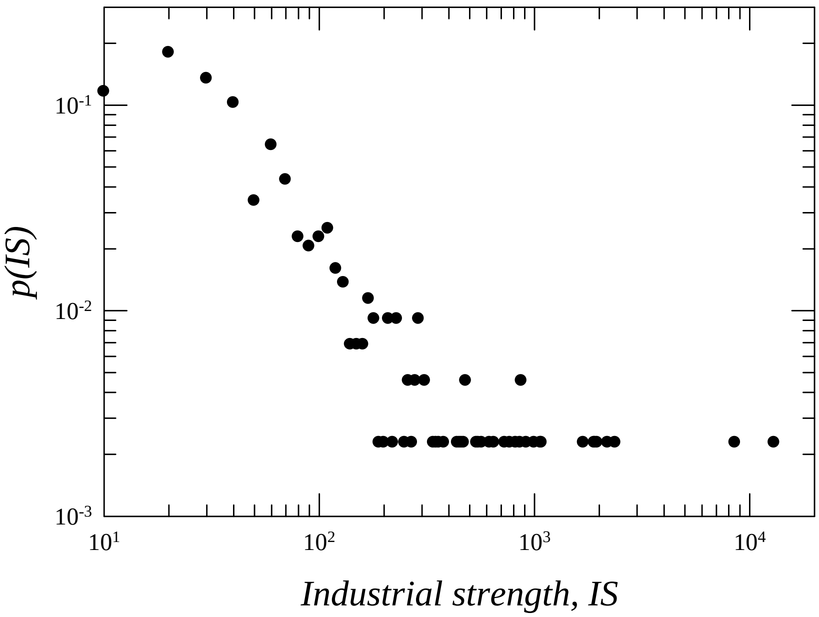

Figure 1: Distribution of industrial strength *IS*

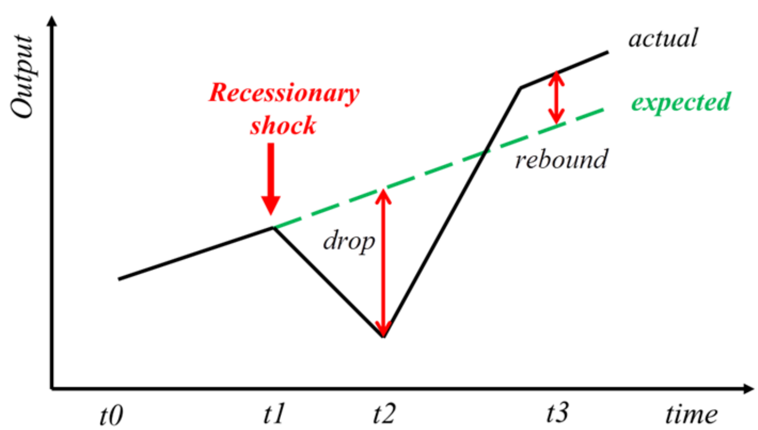

Figure 2 Regional economy changes to a major shock and concept of drop and rebound.

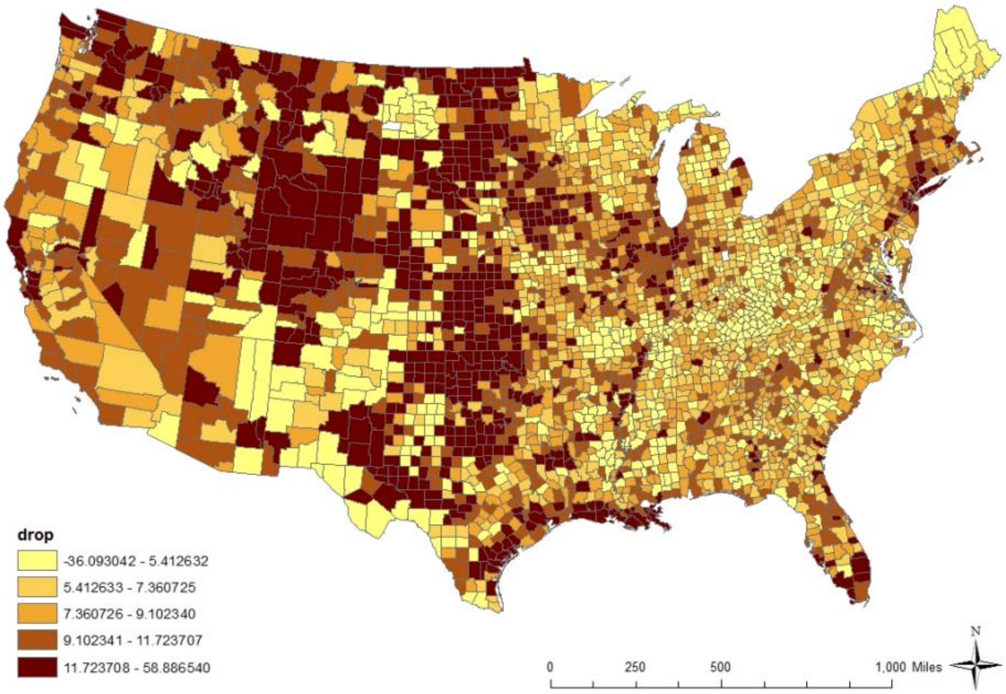

Figure 3 Map of economic *drop* in 2008-2009 recession periods

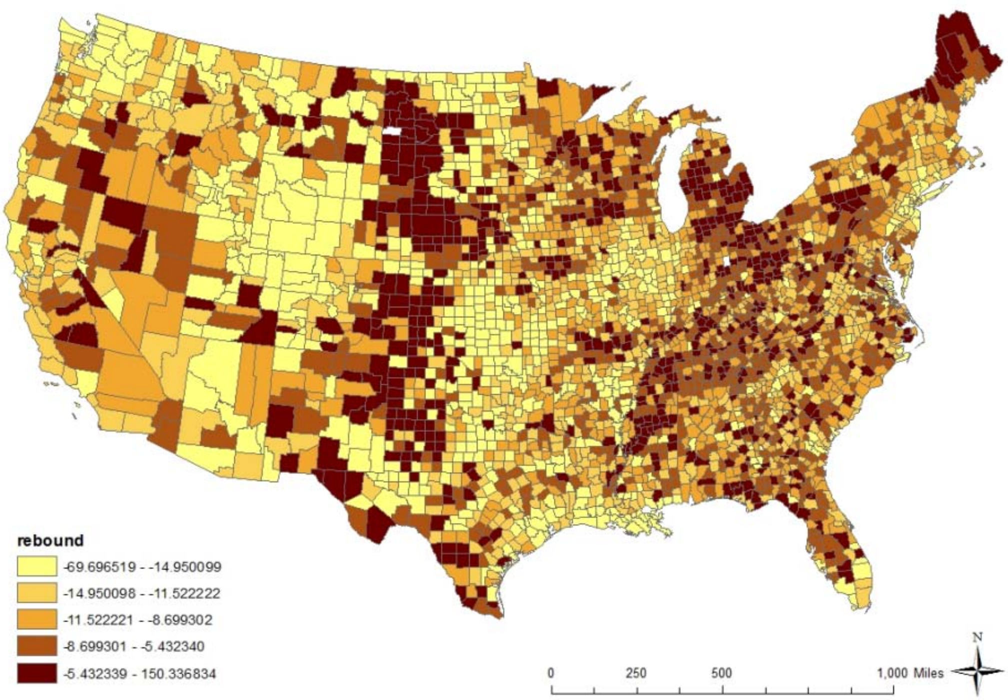

Figure 4 Map of economic *rebound* in 2009-2011 recover periods

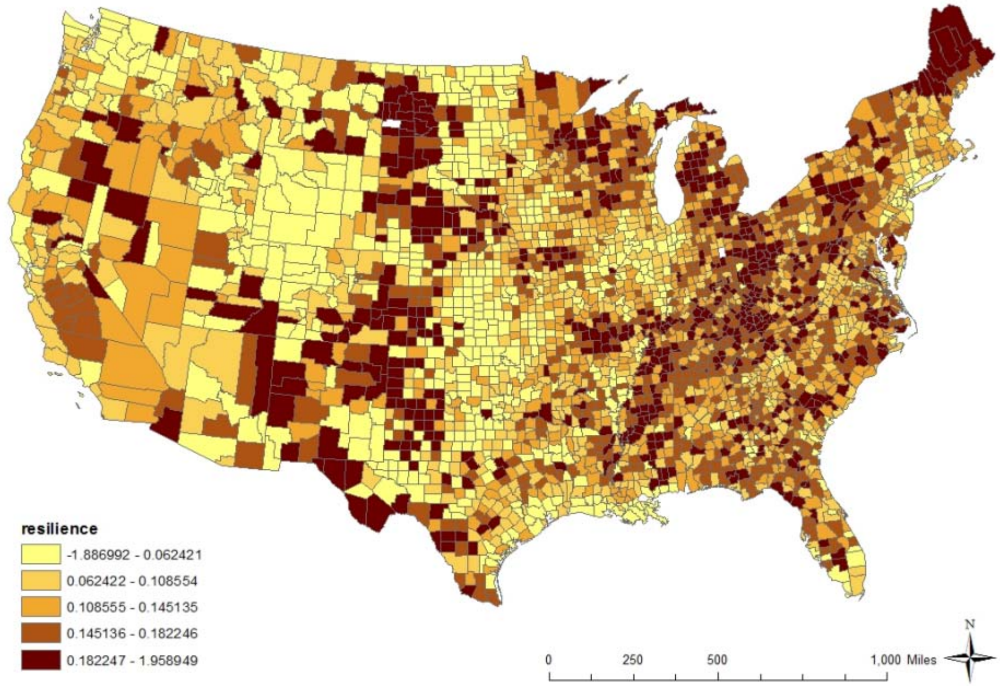

Figure 5 Map of economic *resilience* in 2008-2011 periods

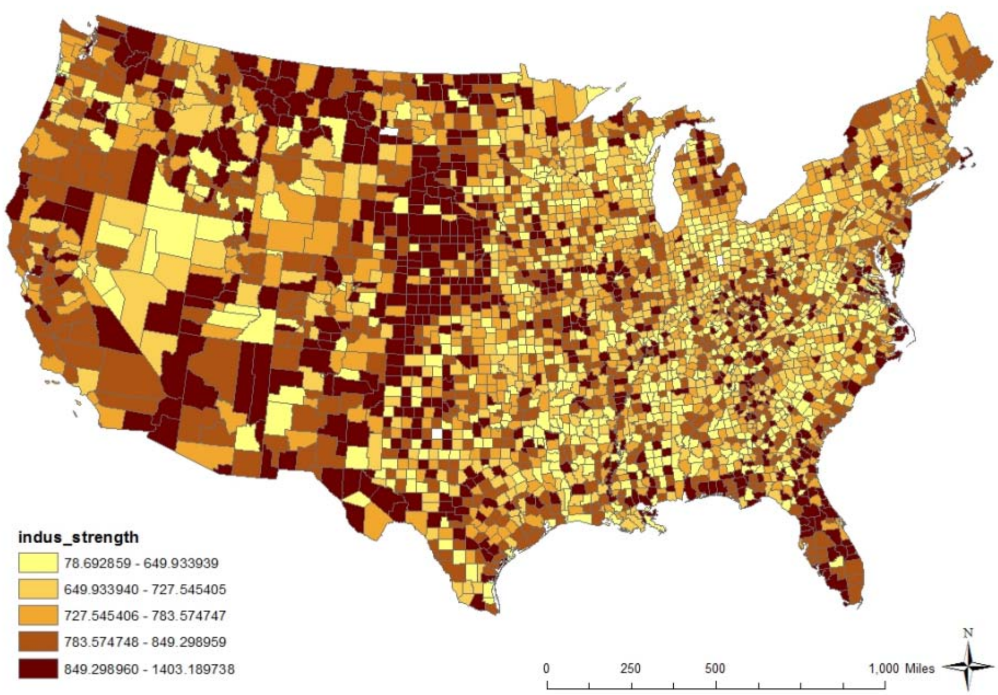

Figure 6 Map of local industrial strength, *LIS*

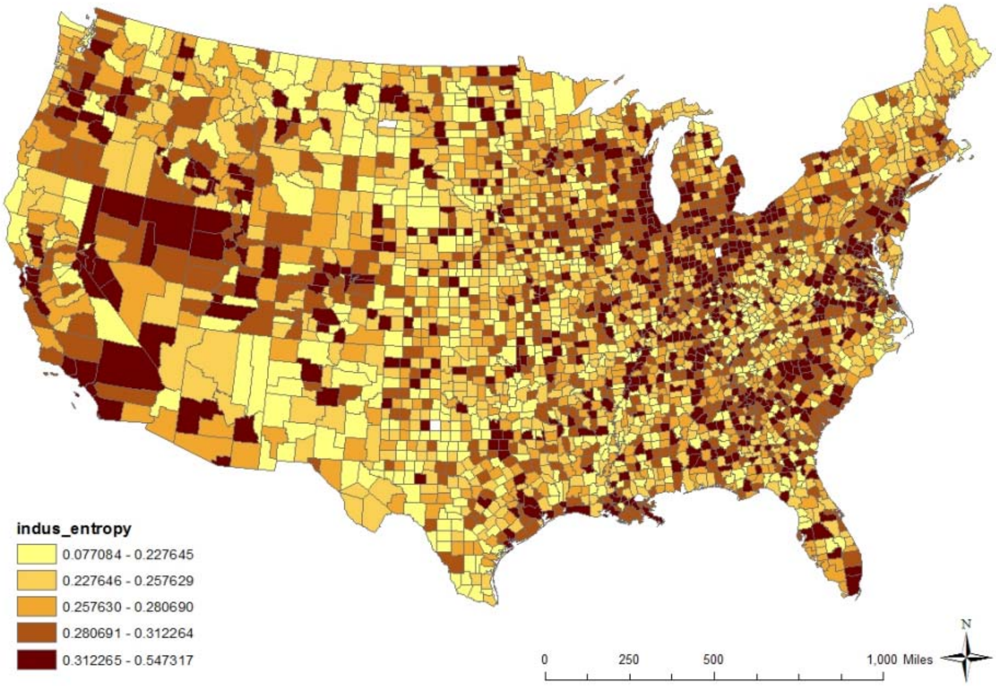

Figure 7 Map of local industrial entropy**,** *LIE*

Table 1 Definition of variables and descriptive statistics

Variable	Definition	No.	Mean	St. Dev.	Min.	Max.
PCPI2008	Per Capita Personal Income 2008	3052	33613	8600	16006	118293
pop_density	Population per square mile 2008	3052	243.1	1767.4	0.1	71467.3
land area	land area of county in square mile 2008	3052	963.3	1310.8	15.0	20056.9
age_25-44	Resident population 25 to 44 years (July 1 - estimate) share	3052	30.7	4.7	17.9	56.2
age_45-64	Resident population 45 to 64 years (July 1 - estimate) share	3052	27.3	3.2	9.2	47.5
age_65+	Resident population 25 to 64 years (July 1 - estimate) share	3052	15.5	4.1	2.6	36.4
edu_bachelor+	Educational attainment - persons 25 years and over - more than bachelor degree 2005-2009	3052	18.5	8.3	4.6	68.8
soccap	Social Capital 2005	3052	0.0	1.6	-3.8	15.2
northeast	counties belong to Northeast region	3052	0.1	0.3	0	1
soutnern	counties belong to Southern region	3052	0.4	0.5	0	1
northcentral	counties belong to Northcentral region	3052	0.3	0.5	0	1
western	counties belong to Western region	3052	0.1	0.3	0	1
%real_estate	Employment in real state share	3052	1.0	1.1	0.0	28.6
indus_strength	local industrial strength (*LIS*)	3052	751.7	138.7	78.7	1403.2
indus_entropy	local industrial entropy (*LIE*)	3052	0.3	0.1	0.1	0.5

Table 2 Regression results of U.S. county economic resilience model estimates, 2007-2009

variables	resilience			drop			rebound		
	standardized coeff.		*t*	standardized coeff.		*t*	standardized coeff.		*t*
const.		***	5.043		***	4.167		**	1.972
PCPI2008	-0.726	***	-30.598	0.780	***	35.872	-0.573	***	-22.432
pop_density	0.102	***	6.207	-0.096	***	-6.337	0.095	***	5.351
land area	-0.001		-0.046	0.032	*	1.873	0.026		1.290
age_25-44	-0.034		-1.039	-0.094	***	-3.110	-0.132	***	-3.721
age_45-66	0.101	***	4.335	-0.205	***	-9.625	0.050	**	2.015
age_65+	-0.077	***	-2.726	0.048	*	1.877	-0.151	***	-5.002
edu_bachelor+	0.277	***	11.214	-0.274	***	-12.093	0.193	***	7.242
soccap	0.015		0.642	0.074	***	3.446	0.112	***	4.471
northeast	0.089	***	5.157	-0.119	***	-7.494	0.050	***	2.672
northcentral	0.068	***	3.353	-0.071	***	-3.807	0.052	**	2.397
western	-0.081	***	-3.858	0.052	***	2.687	-0.115	***	-5.080
%real_estate	-0.031	*	-1.817	0.029	*	1.876	-0.036	**	-1.975
indus_strength	0.053	***	3.140	-0.035	**	-2.256	0.098	***	5.413
indus_entropy	0.053	***	3.154	-0.034	**	-2.196	0.068	***	3.741
adj. R square	0.290			0.404			0.177		

Significant level: different from at *10%, **5%, and *** 1% or lower