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Title: How Does Income Inequality Affect Community Economic Resilience?

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The Great Recession, which resulted from the burst of housing bubble and officially lasted from December 2007 to June 2009, started as a national recession in the U.S. and then affected countries across the world. Economies reacted differently to this recession and those systems that lost fewer jobs and/or recovered more quickly are considered to be resilient. Rising income inequality might pose an explanation for what is behind the Great Recession and why regions react differently, as it has been considered one of the structural causes of the crisis. In this research, I explore the relationship between income inequality and economic resilience for U.S. counties. Specifically, I examine the relationship between three measures of inequality and income distribution – the Gini coefficient, poverty rate, share of aggregate income held by households earning $200,000 or more – and economic resilience measures developed by Han and Goetz (2015). Results show that, controlling for county-level capital stocks and economic structure variables, income inequality does not significantly predict drop, rebound or economic resilience.

How Does Income Inequality Affect Community Economic Resilience?

By

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In understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorized release of my thesis to any reader upon request.

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Chapter 1 Introduction

The Great Recession, which officially lasted from December 2007 to June 2009, started as a national recession in the U.S. and then spread to affect countries across the world. The Great Recession resulted from the burst of housing bubble which hobbled the mortgage and banking system and spread to other sectors. Hout, Levanon, and Cumberworth (2011) summarized the subsequent crisis as follows,

> "The 'housing bubble' burst, Wall Street stumbled, banks stopped lending, construction workers lost their jobs, sales of building materials and appliances plummeted, truckers and dockers lost their jobs, shops and restaurants suffered, tax revenues fell, governments furloughed police and teachers, and the downward spiral spun even lower.".

Data from Bureau of Labor Statistics (2016) show that during the eighteen-month recession the U.S. experienced a much sharper increase in unemployment rate than before, from 5.0% in December 2007 to 9.5% in June 2009. The previous recessions had a change range from 2.0% to 4.2%. That the unemployment rate stayed above 9.0% until August 2011 also indicated a much slower recovery than in previous recessions (see Figure 1 and Figure 2). The Great Recession has been considered as the most severe economic downturn ever since the Great Depression in the 1930s and it broadly affected the economy of United States: escalated unemployment, higher poverty and reduced well-being of individuals and households in the United States (Iceland, 2013). Bosworth (2012) stated the nation experienced a decline of 8 percent in GDP from the fourth quarter of 2007 to mid-2009 and a loss of 8.5 million jobs from the peak 138.1 million in December 2007 to the trough 129.6 million in February 2010. Updated total employment data (Bureau of Labor Statistics, 2016c) show an 11.2 million of job loss between the peak 138.1 million in February 2008 and the trough 126.9 million in February 2010[1]. Unemployment almost doubled and peaked 10.0% in October in 2009 (Bureau of Labor Statistics, 2016). Bosworth (2012) also mentioned households lost one-quarter of their wealth during the two-year period

[1] Data are seasonally adjusted using X-13 ARIMA SEATS.

and a third of this loss was in home equity (declining home values). People experienced extended hardship in reentering the labor market due to the slow recovery after the official end of the recession. The poverty rate increased from 12.5% in 2007 to 15.1% in 2010 (U.S. Bureau of Census, 2016a).

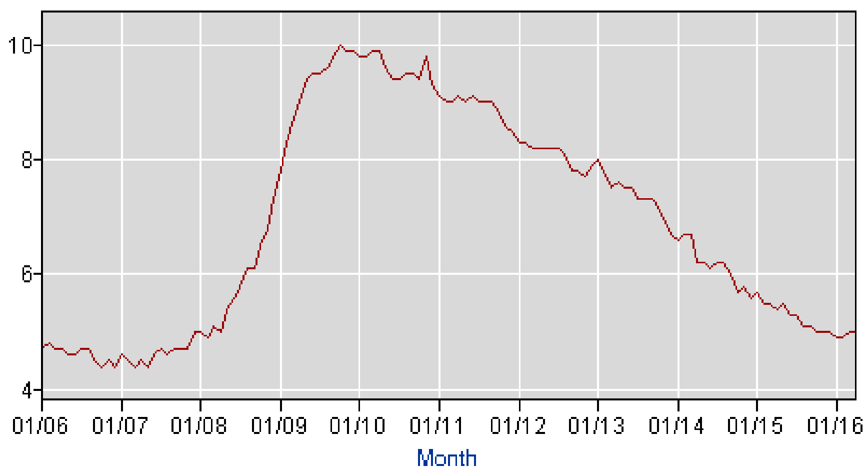

Figure 1 Unemployment rate from 2006-2016, population of 16 years and over. Source: Data from Bureau of Labor Statistics 2016a

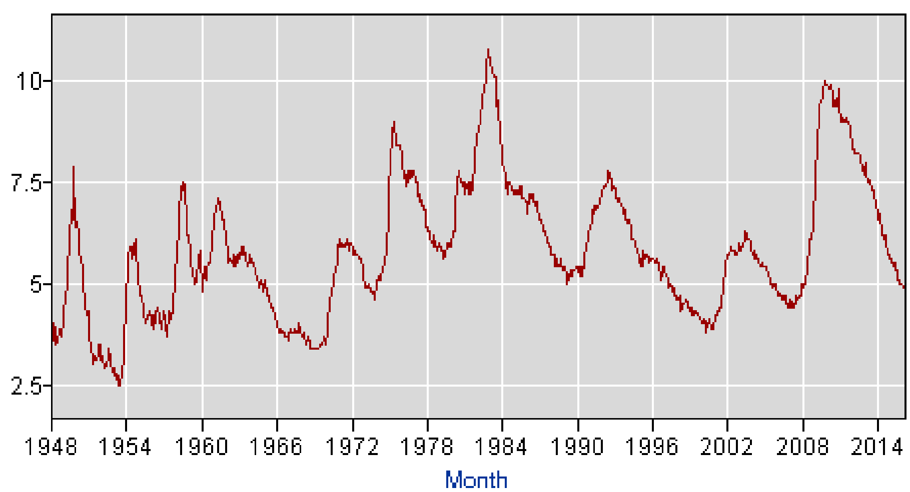

Figure 2 Unemployment rate from 1948-2016, population of 16 years and over. Source: Data from Bureau of Labor Statistics 2016b

As the nation got worse during the recession, individual counties reacted uniquely. Some counties lost fewer jobs during the recession and/or recovered quickly afterwards. One indicator of this is unemployment. Figure 3 and Figure 4 shows how unemployment rates in 2008 and 2011 varied across the counties in the U.S. There were more counties that experienced high unemployment (red regions) in 2011, which indicates the recession lasted much past 2009. However, there were several counties that recovered from or never entered the recession, as seen in the blue regions in Figure 3 and Figure 4.

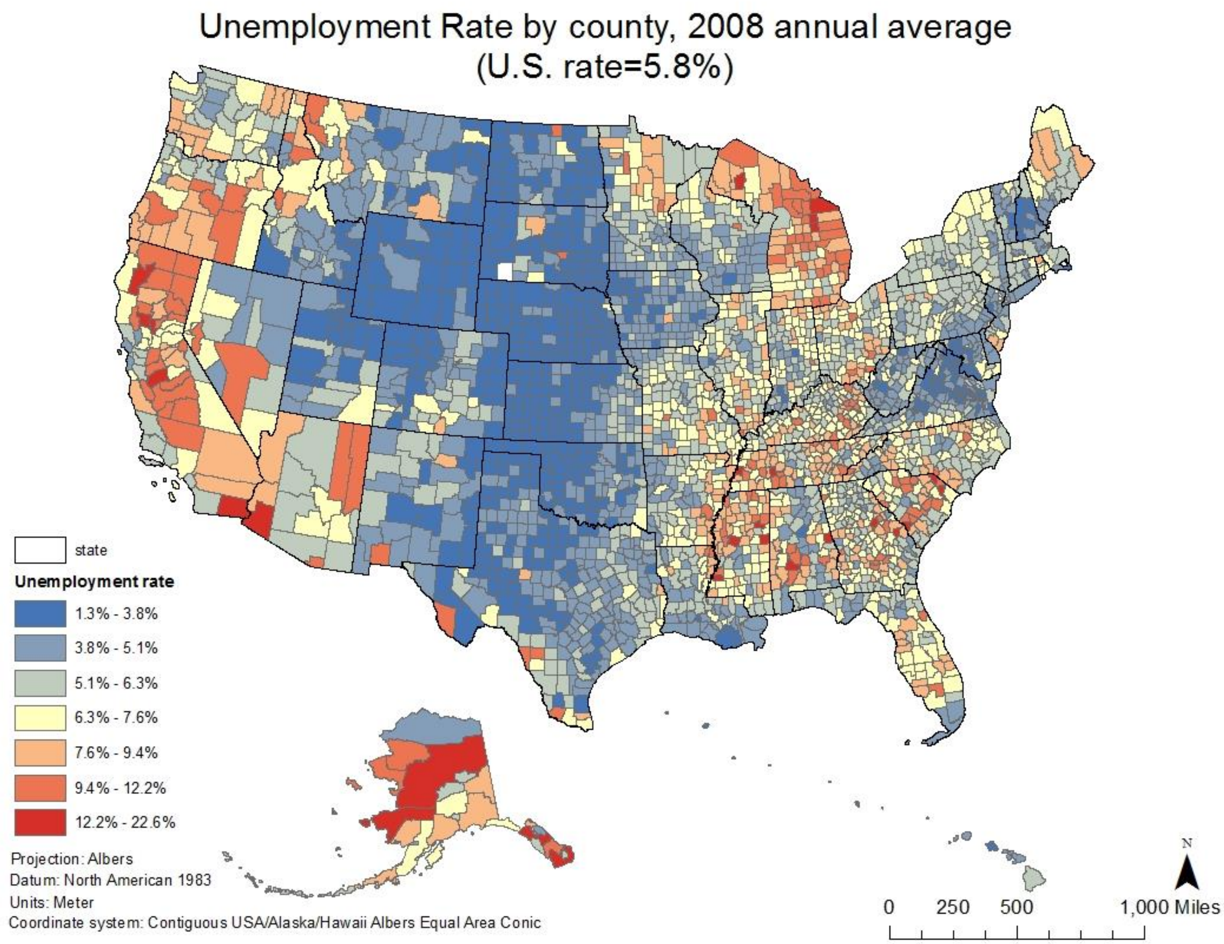

Figure 3 Unemployment rate by county, 2008 annual average. Source: Data from Bureau of Labor Statistics 2008

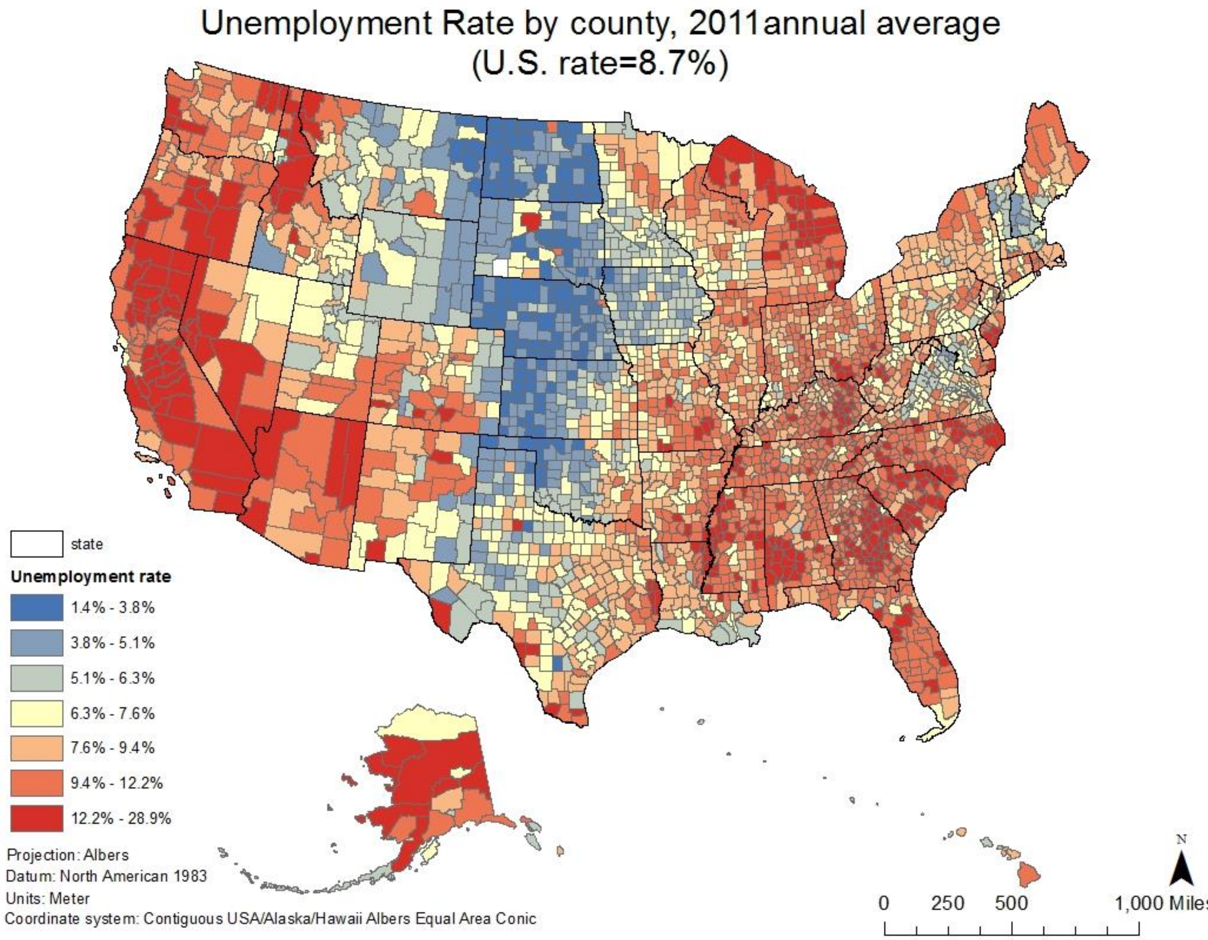

Figure 4 Unemployment rate by county, 2011 annual average. Source: Data from Bureau of Labor Statistics 2011

The capacity of a region to resist, absorb and adjust to an exogenous shock as well as to bounce back is defined as economic resilience (Han and Goetz, 2015), where the exogenous shock could be natural disaster, economic recession, or terrorist attack. Resilience has attracted increasing attention recently, as policy makers want to understand, promote and ensure economic resilience. That the unemployment rate differs in counties in 2008 and 2011 indicates counties behaved differently in and after the recession. This research wants to identify why and how some counties are resilient while others are not.

Rising income inequality is considered as one structural cause of the crisis (Raghuram, 2012). Income inequality refers to the uneven manner of income distribution where income acts as a proxy of economic well-being. A rising trend in income inequality is observed in Figure 5 measured by four income inequality indicators. The Gini coefficient has increased from 0.397 in 1967 to 0.48 in 2014. The income share of America’s highest fifth and top five percent households steadily increased over the years. From Figure 5, the share of aggregate income held by the highest fifth households seems highly correlated with the Gini coefficient. The poverty rate, which measures the percent of households whose incomes place them at or below a poverty threshold for a household of their size and composition, is another indicator of income distribution. The U.S. poverty rate increased from 11.3% in 2000 to 14.8% in 2014. Such imbalances in income distribution would reduce the purchasing power among those in the middle and low income households which drives down the total demand. Inequality may also spur lower productivity, more instability, lower efficiency and lower growth (Stiglitz, 2012). Rising income inequality poses risks on America’s economy and is hypothesized to weaken the ability for the economy to withstand and recover from the Great Recession.

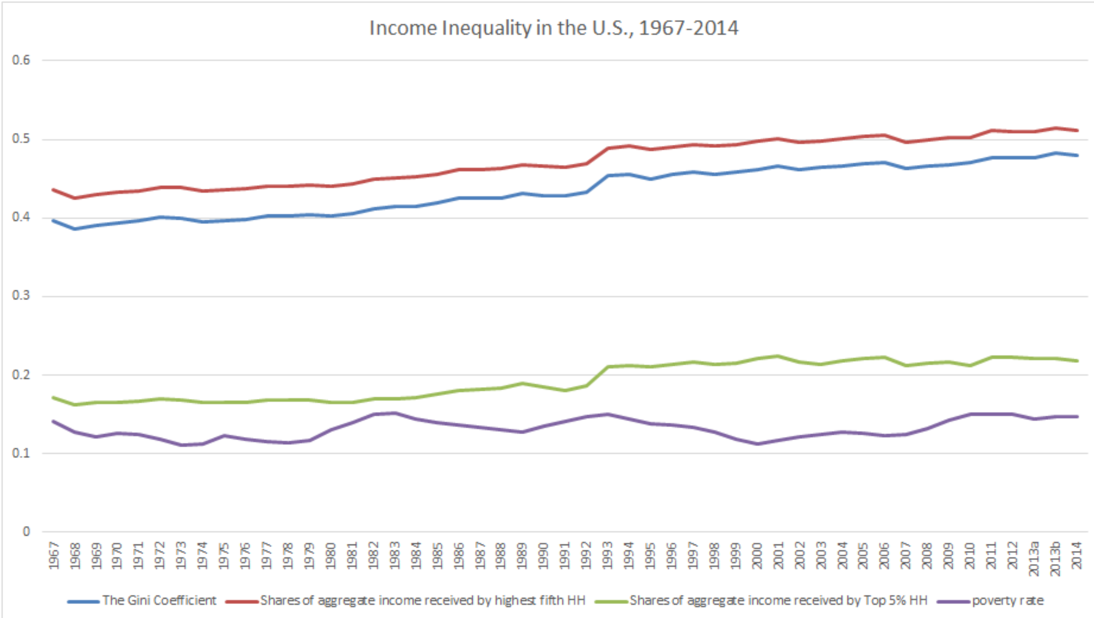

Figure 5 Income distribution for U.S. population from 1967 to 2014. Source: Data from U.S. Census Bureau 2014a, 2014b.

Inequality also varies across counties in the U.S. (see Figure 6). There are more counties with high Gini coefficient in the south while more counties with low Gini coefficient in the north. This research examines the role of income inequality and explores the hypothesis that income inequality is related to economic resilience.

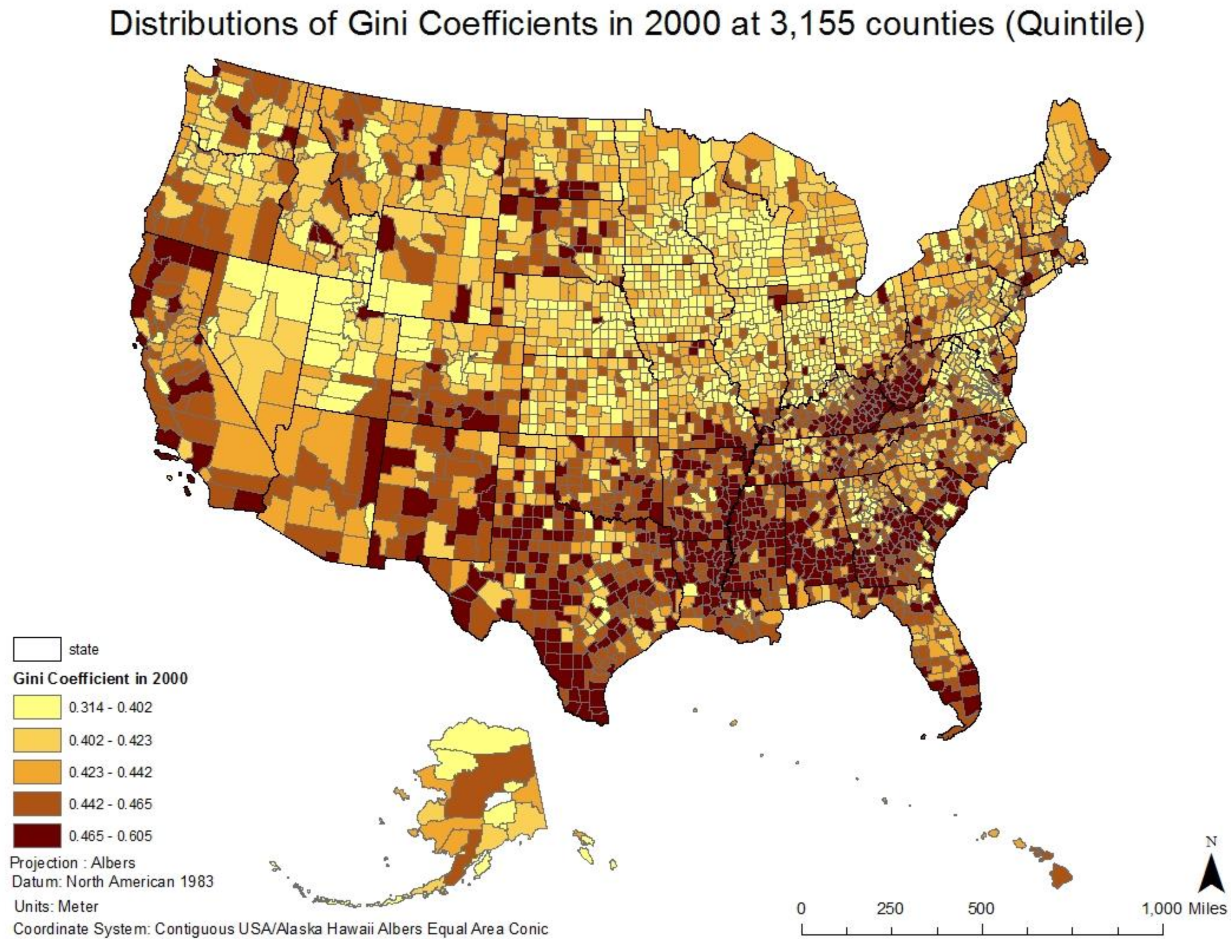

Figure 6 Distribution of the Gini coefficient for the year 2000 for 3155 counties.

The study of economic resilience and income inequality is not a new area. Martin (2012) and Han and Goetz (2015) summarize definitions and develop measures for economic resilience. Studies also explore the measurement (Atkinson, 1970; Allison, 1978) and the dynamics behind income inequality (Snower, 1999; Levernier and Rickman, 1998a; Levernier and Rickman, 1998b; Peters, 2011; Peters, 2012; Peters, 2013). However, few studies explore the relationship between income inequality and economic resilience (Augustine et al., 2013; Tsai, Wilson and Rahman, 2015). This research contributes to this gap in the literature by specifically examining the links between income inequality and economic resilience. This understanding would be central to help craft policies to build, promote and ensure systemic resilience and a steady economic growth.

Framework

In the framework underlying this analysis, economic resilience is determined by a region's capital assets or wealth and by its economic structure. Capital stocks include eight capitals posited in earlier studies (Emery and Flora, 2006; Pender, Marre and Reeder, 2012; Pender and Ratner, 2014): human capital, intellectual capital, cultural capital, built capital, natural capital, social capital, financial capital and political capital. Economic structure is characterized by a region's sector composition, size and urbanization of the economy. Capital assets and economic structure contribute to economic resilience through two dimensions summarized by Martin (2012), resistance and recovery.

I would like to fit income inequality into the framework, and re-conceptualize some of the capital stock variables (see Figure 7). Political capital is removed from the community capital stocks due to inadequate data at county level. However, the social capital index (Rupasingha, Goetz and Freshwater, 2006), the measure of social capital, partially includes political capital as the index is calculated based on the number of political organizations and voter turnouts rates. Cultural capital and intellectual capital are also not included in the model due to unavailability of a proper measure. Race and ethnicity variables and per capita income are included as control variables. Economic structure is represented by Herfindahl-Hirschman index, total population, percentage of urban population, and the Euclidean distance between the mean center of population within each county and its nearest urban areas with population greater than or equal to 50,000. This framework considers the hypothesis that pre-recession income inequality affects economic resilience. Exogenous forces include natural disasters, terrorist attacks, economic recession, pandemic disease, civil wars, human error, climate change and new public polices, etc. Here the general external force is the Great Recession and this research looks at how each county responded to the Great Recession that affected them all.

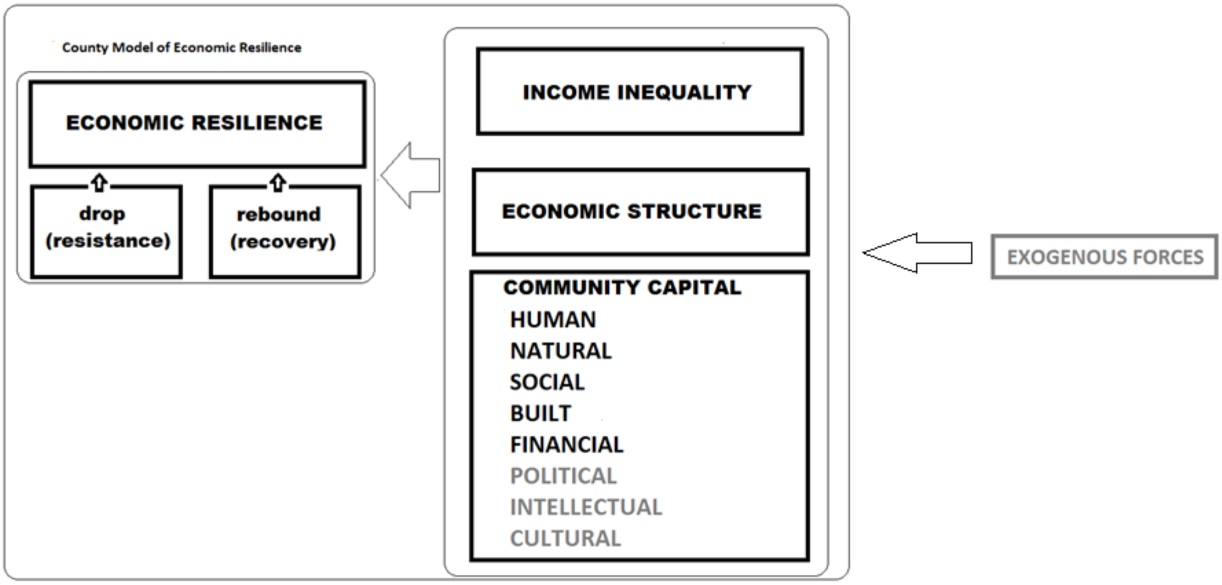

Figure 7 A framework for understanding county-level economic resilience and income inequality

In this research resilience is measured by changes in total employment and resilience is separated into two components *drop* and *rebound*. Income inequality might affect a county's total employment through four paths: 1) Job loss, 2) consumption affected by income loss, 3) investment affected by income loss, 4) government transfers and spending. One challenge to understanding the impact of income inequality on either *drop* or *rebound* is that measures of income inequality alone indicate something about the relative concentration or lack of concentration of income but nothing about the level at which income is concentrated. Mathematically, counties could attain a similar low measure of income inequality with different income distributions. Empirically there have been too few studies that test the relationship between these concepts to develop hypotheses so instead possible explanations are outlined below.

For income inequality to affect *drop*, *rebound* and *resilience*, the first path to be considered is job loss. How the likelihood of losing a job during a recession varies across the income distribution is unknown a priori. Therefore, the impact of income inequality on resilience through job loss is ambiguous in expectation because it depends on who lost jobs, which needs empirical studies.

Local consumption during a recession, however, is expected to be systematically related to the distribution of income. Wealthy households are expected to spend a much smaller proportion of their income locally for basic consumption and a higher percentage on luxury goods or services outside the local economy. On the contrary, low-income people spend a higher percentage of their income on basic consumption such as groceries and gas, which usually take place locally. During periods of economic contraction, individuals cut back on discretionary spending such as charitable donations, dinners at fine restaurants, movies and concerts. The service industry – a growing share of the U.S. economy – is driven by consumer spending; therefore less consumer spending will result in employment loss. So high income inequality that concentrates a higher proportion of total income into discretionary spending categories is hypothesized to heighten *drop* and slow *rebound*, and therefore decrease *resilience*. These effects are stronger in counties with a larger share of total employment in the service industry.

Considering the third path, investment during a recession is also expected to be related to the distribution of income. If income decreases during the Recession, rich people, who are those most able to invest, will slow their investments. So through investment, higher income inequality that concentrates more income with the rich will also increase *drop*, decrease *rebound* and lead to a lower *resilience*.

Regarding the effects of government transfers and spending, higher income inequality that results from a larger share of people with low incomes might decrease *drop*, increase *rebound* and therefore increase *resilience.* Government transfers increase income and consumption for qualifying low income households. As more individuals qualify for government assistance in a recession, government transfers are designed to reduce the effects of additional employment loss depending on the size of the transfer programs and will affect economies regardless of pre-recession income inequality levels. These four paths are offsetting, so the overall impact of income inequality on *drop*, *rebound* and *resilience* is indeterminate.

This research is structured into the following chapters. Chapter Two reviews the existing literature on economic resilience. Chapter Three talks about methodology and the measures used for economic resilience, income inequality and the explanatory variables for economic structure and capital stocks. Hypotheses about how each variable affects economic resilience are also included. Chapter Four covers the regression results and analysis. Conclusions, limitations and next steps appear in Chapter Five.

Chapter 2 Literature Review

This chapter focuses on the literature about resilience. It starts with a section of defining and measuring resilience. Then it describes factors affecting resilience discussed in current studies. The contribution of the thesis to the literature is talked about at the end of this chapter.

Framework for Considering Economic Resilience

Definitions and Measurements of Economic Resilience

The idea of ‘resilience’ has been introduced to economics recently. However, there is much ambiguity in the definition of ‘resilience’. Martin (2012) has summarized three interpretations of ‘resilience’ (see Table 1). Martin (2012) also summarized dimensions of economic resilience that offer guidance for measuring economic resilience (see Table 2).

Table 1 Definitions of resilience

Type of resilience	Main focus
Engineering Resilience (in physical sciences)	Ability to return to or resume (resistance to shocks) assumed stable equilibrium and growth trend (stability around equilibrium).
Ecological Resilience (in ecological sciences)/ Adaptive Resilience (in complex adaptive systems)	The system can absorb or adapt to a shock/disturbance and move to a new stable state. The system can either maintain its previous growth path or shift to a new growth path.

Table 2 Dimensions of resilience

Dimensions of economic resilience	Meaning
Resistance	Degree of sensitivity or depth of reaction of a regional economy to a recessionary shock
Recovery	Speed and degree of recovery
Reorientation and Renewal	Ability of a region to adapt to the shock and renew its growth path

In empirical studies, Martin (2012) uses four quadrants of regional resistance and regional recovery. Augustine et al. (2013) determine economic resilience by whether the employment growth rate returns to its previous path in any of the next four years. Han and Goetz (2015) define *resilience* as the ability to resist the recession and bounce back, calculated as the standard score of logarithm of ratio of $rebound$ and $drop$ using monthly employment. Faggian, Gemmiti and Santini ((2014) treat ecological resilience[2] as the ability to absorb a shock and lift to a new equilibrium or growth path. Table 3 shows the definition, measurement, and time and geography frame used in several empirical papers.

Table 3 Measurements of resilience

Citation	Definition of Economic Resilience	Measurement	Methodology	Time and Geography units
Martin, Ron (2012)	Engineering, Ecological and Adaptive Resilience combined. Four dimensions: resistance, recovery renewal, and structural re-orientation and adaptation (touched on only briefly).	4 Quadrants of regional resistance and regional recovery using employment. 1. Regional resistance is measured by a 'sensitivity index' β_r[1], If β_r for a given region is greater than unity, we say that the region in question has a low (relative) resistance (high sensitivity) to a recessionary shock. 2. Regional recovery is measured by average growth rate. Structural re-orientation and regional adaptive resilience[2] is measured by employment change.	-	The British standard Government Office regions (NUTS1 level, using the European Commission nomenclature) for 3 recessions: 1979-1983, 1990-1993, and 2008-2010;
Han and Goetz, (2015)	'Ecological/Adaptive' Resilience: A region's capacity to absorb and resist shocks as well as to recover from them. A new growth path is established.	Regional *economic resilience*[3] is the standard score of logarithm of ratio of $rebound$ and $drop$ using employment. *Drop*[4] and *rebound*[5] are measured using employment in the peak and trough months of each county, respectively.	-	N=3138 U.S. counties from 2000 to 2014
Augustine et al. (2013)	'Engineering' Resilience. Regional economic resilience: ability to recover from an economic downturn (get back to its previous growth trajectory) within a relatively short period time.	If the downturn[6] ends and the employment growth rate returns to its previous path in any of the next four years, we say the region was resilient. If at the end of four years it has not returned to its previous growth path (the average employment growth over the previous eight years), then we say that it is non-resilient.	Comparison of explanatory variables between resilient and nonresilient /Logit regression	361 metropolitan areas in the U.S. between 1978 and 2007 (1067 downturns)

[2] They consider ecological resilience the same as adaptive resilience in the slides.

Table 3 (Continued)

Citation	Definition of Economic Resilience	Measurement	Methodology	Time and Geography units
Faggian, Gemmiti and Santini (2014)	'Ecological and Adaptive' Resilience resistance and recovery, following Martin (2012)	4 groups defined by two measures of regional resistance and recovery (employment is used for the calculation) following Martin (2012). The speed of recovery is proxied by the percentage change in employment in 2011 as the post-recession period.	Multinomial logit model	Pre-recessionary period: 2007-2008, recession 2009-2010 and recovery 2011(definition by the Italian Statistical Institute ISTAT) 686 Italian 'local labor systems'
Brown (2015)	The capacity of a region to resist external shocks and to continue to develop (Han and Goetz, 2013). Narrowed down to how a region mitigates its entrance into recession.	Recession is defined as the first year a county experienced decreases in personal income.	Cox Proportional Hazards Model	3145 counties and county-equivalents in the United States (2005 to 2012).
Tsai and Wilson, 2015	Vulnerability refers to the permanent characteristics more prone to external shocks; Resilience is the ability to recover or adjust to shocks.	Four quadrants Vulnerability Index and Resilience Index. Vulnerability is measured by distance, population density, public land, natural amenity scale. Resilience is measured by educational attainment, health insurance, right to work, Gini coefficient, Herfindahl-Hirschman Index, Oil wealth	OLS, Multivariate Index Model	225 rural counties in the West (AZ, CA, CO, ID, MT, NV, NM, OR, UT, WA, and WY)

Note: [1] The ratio of decline in employment or output in a region to the respective decline in the country as a whole, that is $\Delta E_r/E_r = \beta_r(\Delta E_N/E_N)$, or $\beta_r = (\Delta E_r/E_r)/(\Delta E_N/E_N)$ where ΔE/E is the percentage change in employment, and β_r is a 'sensitivity index'.
[2] Martin mentioned he would identify regional renewal earlier but later examined structural reorientation and adaptation.
[3] $Resilience = \frac{ratio - ave(ratio)}{stdev(ratio)}, ratio = \ln(\frac{Rebound - \min(Rebound)+s}{Drop - \min(Drop)+s})$.$\mathrm{ave}()$:the average; $\mathrm{stdev}()$: the standard deviation; $\min()$: the smallest value among all regions' values; $s = 0.0001$
[4] The ability to absorb is measured by how much a region's employment *drop*s below the expected employment after a shock, referred as a *drop*.
[5] *Rebound* is defined as the employment increase during six months following the trough. *Rebound* represents the velocity or elasticity of recovery from recession.
[6] A downturn is defined as "a single-year, two percentage point drop in the rate of employment growth, relative to the average employment growth rate for the preceding eight years"(Augustine et al. 2013).

Factors Affecting Economic Resilience

Table 4 shows the independent variables used in Augustine et al. (2013), Faggian, Gemmiti and Santini (2014) and Brown (2015). Han and Goetz (2015) suggest that future research should examine effects of independent variables including income, population density, land area population age, education attainment, social capital stocks, industrial structure, etc. Brown et al. (2014) suggest factors correlating with greater resilience include increased human capital like skilled laborers (Chapple and Lester, 2007), college education (Christopher, Michie and Tyler, 2010), organizations with high-skilled laborers, regional systemic flexibility and diversity (Ficene, 2010), pre-shock levels of economic resources (the pre-shock development, wealth in the region and its equitable distribution and technological developments), quality of physical infrastructure (improving water, power and other critical facilities (Bruneau et. Al 2003) and the presence of good plans and governance structures.

Table 4 Independent variables to predict economic resilience

Variables	Augustine et al. 2013[1]	Faggian, Gemmiti and Santini 2014	Brown 2015
Size of local labor systems (SLL)		Up to 10,000 inhabitants (reference group), 10,001-50,000, 50,001-100,000, 100,001-500,000, above 500,000	
Urban areas		Urban areas highly specialized Urban areas moderately specialized Urban areas non specialized Urban ports (Urban without specialization as the base group)	
Vocation/Industrial structure	Share of employment in four key export industries: durable manufacturing, nondurable manufacturing, healthcare and social assistance, tourism	Touristic vocation and agricultural vocation	Number of jobs broken out by NAICS code at 2 or 3-digit levels[4].

Table 4 (Continued)

Variables	Augustine et al. 2013[1]	Faggian, Gemmiti and Santini 2014	Brown 2015
Districts		Leather, Shoes, Textile***, Clothing, Furniture, Glasses, Machinery, Food **, Metals, Transportation, Construction, Chemical and Oil	
Innovative capacity of SLL		Number of patents (added in Model 2)	
Regional Economic Capacity Index (RECI) by Foster (2012)	80/20 ratio[2]; Herfindahl index, number of major export industries; the cost of housing compared to the level of income; right-to- work[3]		
The existence of potential sources of economic activity	Research institutions; % adult population that has least a high school education (25+)		
Pre-shock economic condition	Eight-year growth rate prior to the downturn; employment in the previous year; wages per employee, adjusted to 2005 dollars;		
Other control variables	% metro population living in central city; age of metropolitan area		Rural status: rural and metro[5]
Capital stocks			Natural; Human; Social; Cultural; Physical; Financial; Political[6].
Exogenous Forces			Federal funds

Note: [1] The explanatory variables are observed in the year prior to the onset of the downturn. The potential variables to cause resilience are lagged (besides the control variable: pre-shock economic condition and other control variables).

[2] The 80/20 ratio is the ratio of the income of the person at the 80th percentile of the income distribution to the income of the person at the 20th percentile.

[3] Right-to-work is "whether the state has laws that prohibit employment agreements between employers and labor unions from requiring participation in a union" (Augustine et al., 2013). This is used to describe the business environment/ climate

[4] Certain manufacturing and government industries are identified at the three-digit level.

Table 4 (Continued)

[5] U.S. Department of Agriculture Economic Research Service ERS 2003 rural-urban county classification range from Code 1 Metropolitan areas of 1 million population or more to Code 9 Completely rural area of less than 2,500 population and not adjacent to a metro area. Here Code 1-3 is defined as metro and rural for Code 4-9.
[6] Natural capital: topography: plains, plains with hills, open hills, mountains and tablelands; water coverage; indication of weather patterns: mean temperatures/mean hours of sunlight for Jan., mean temperature for July and mean relative humidity for July; land square miles
Human Capital: educational attainment of population aged 25+, number of people in labor force and population by age group
Social Capital: number of social capital organizations and associations
Cultural Capital: race and ethnicity
Physical Capital: median value of specified owner-occupied housing units
Financial Capital: total deposits in commercial banks and saving institutions
Political Capital: number of political organizations in 2005 and the number of votes cast for the president during the 2008 presidential election

Conclusions are included in Table 5. There are few papers try to empirically explain economic resilience.

Table 5 Conclusions on economic resilience

Author and Title	Conclusion
Augustine et al., 2013 Regional Economic Capacity, Economic Shocks	Regional Economic Capacity Index (RECI) is not associated with actual resilience. Possible reasons: 1) there is no relationship between economic capacity and actual resilience.2) the measurements of economic capacity may not be valid.3) the resilience is measured incorrectly.
Faggian, Gemmiti and Santini, 2014, Regional resilience: Lessons learned from the Italian local labor systems and urban areas	Medium size cities (50,001-100,000 and 100,001-500,000) are the most resilient (QI: high resistance and Fast recovery). Innovative capacity promotes resilience.
Brown, 2015, Measuring United States County-Level Economic Resilience to a Recession	Mountains and hills, residents with bachelor’s degrees, within 30-49 age group, local government jobs and federal funding for defense and space functions mitigates the county’s entrance to recession (makes county resilient). Transportation equipment manufacturing and finance will reduce the resistance of a county.
Tsai and Wilson, 2015 Economic Resilience and Vulnerability in the Rural West	In rural counties: poor environmental quality (topography, climate, etc.) would inhibit human settlement and increase vulnerability towards exogenous shock. Higher education levels, health care, absence of right to work law, and oil wealth reduce unemployment. Income inequality improves resilience to economics shocks.

Relationship Between Income Inequality and Economic Resilience

There are few studies exploring the relationship between income inequality and economic resilience, while none focus on income inequality. Augustine et al. (2013) includes income inequality in the Regional Economic Capacity Index (RECI). However, RECI is not associated with actual resilience in the results. Tsai, Wilson and Rahman (2015) use the Gini Coefficient to predict resilience (here resilience is defined as the ability to bounce back from the economic shock of the Great Recession). Results show that counties with more unequal income distribution are more capable to recover from economic recession. This limited empirical evidence finds no consistent relationship between income inequality and economic resilience.

Several studies examine the role of income inequality in economic growth. Stiglitz (2012) concludes income inequality leads to lower productivity, more instability, lower efficiency and lower growth (Stiglitz, 2012, Chapter 4). Barro (2000) finds higher inequality retards growth in poor countries and encourages growth in richer places while Fallah and Partridge (2007) conclude positive inequality-growth link in the urban sample with the opposite in nonmetropolitan case. Based on these studies, income inequality might negatively affect *rebound*. Moreover, the conclusion of Fallah and Partridge (2007) suggests that future research should consider if the relationship between income inequality and economic resilience differs between metropolitan and nonmetropolitan places.

This research aims to fill in the gap in the literature by exploring the inequality-resilience link. Measurements of resilience and income inequality discussed or used in literature will be compared and used to test the relationship. The effect of counties' internal properties on regional economic resilience will also be tested by looking at regional capital stocks and economic structure. Data and methodology will be discussed in the next chapter.

Chapter 3 Data and Methods

Introduction

This chapter first describes the process of selecting and measuring the two primary variables of interest, income inequality and economic resilience. Secondly, the study's other variables of interest – including three control variables (for population growth, race and ethnicity), variables for economic structure, and variables for the five capital stocks – are also defined. Following this description of variables is a description of the study's methodology. This research primarily uses OLS regressions and the results of these findings are presented in Chapter 4.

Selecting Measures of Income Inequality

Measuring Income Inequality

There are several measures of income inequality, such as the Gini coefficient, the variance of the log of income, and Theil's T index. Among scholars of income inequality measures, there is consensus on the desirable properties inferred by the five axioms (Ray, 1998): Income Scale Invariance, Dalton Population Principle (Dalton, 1920), the Pigou-Dalton Transfer Principle (Dalton, 1920; Pigou, 1912), Anonymity, and Decomposability.

The first property is Income Scale Invariance, which requires that inequality remain unchanged by equal proportional increases in all incomes (Ray, 1998). For example, a change in currency units does not constitute any real change in the income distribution, therefore income inequality should not be affected by currency conversions or inflation adjustments. This principle states that only relative income matters, not absolute income.

Dalton (1920) introduced the Dalton Population Principle and the Pigou-Dalton Transfer Principle. The Dalton Population Principle holds that merging two identical distributions does not change the level of inequality. As long as the composition of income classes doesn't change, income inequality won't be affected by the size of the population.

The transfer from a higher income person to a lower income person is defined as a Pigou-Dalton transfer or a progressive transfer. The progressive transfer must reduce inequality regardless of the size of the transfer or the relative level of income of either person. On the other hand, a regressive transfer from a lower income person to a higher income person worsens inequality (Atkinson, 1970, 1983,; Cowell, 1985).

For those inequality measures that satisfy the Pigou-Dalton principle of transfer, they might be different in their relative sensitivity of income. Relative sensitivity to transfers is the characteristic of a measure indicating that the precise size of the inequality reduction from the transfer depends on the income level of the recipient and the donor. For example, there are two pairs of individuals that each have the same absolute difference in income, and one pair is relatively rich and the other relatively poor. One case would be that the first pair includes a person earning $50,000 and a person earning $51,000 while the second pair includes two persons earning $5,000 and $6,000 separately. Then the progressive transfer (from richer person to poorer person) should reduce inequality more for the second pair than for the first pair. That is, a $100 transfer in the second pair from the person earning $ 6,000 to the person earning $5,000 should reduce inequality more than a transfer of $100 in the first pair from the person earning $51,000 to the person earning $50,000 (Allison, 1978; Salverda, Nolan and Smeeding, 2009). Inequality measures satisfying this are called "transfer sensitive" (Shorrocks and Foster, 1987).

Inequality measures with different transfer sensitivities will show different rankings of income inequality. For example, Atkinson (1970) argues the measures that are more sensitive to changes among the lower income levels tend to show relatively lower inequality in developing nations and higher inequality in developed nations. This occurs because the distribution of income in the developing counties is more equal at the bottom while less equal at the top compared to developed countries.

Table 6 compares eight separate income inequality measures that were considered in this research. Based on data availability and properties inferred by the five axioms, this research will use four measures of income inequality: the Gini Coefficient, Coefficient of Variation, Theil's T index and Atkinson Index (Salverda, Nolan and Smeeding, 2009, 50-52). The Coefficient of Variation, Theil's T index and the Atkinson Index are either ordinally equivalent[3] or belong to the Generalized Entropy class and satisfy all five axioms (Cowell, 1995). For example, Generalized Entropy inequality indices can be decomposed by population subgroup (Jenkins, 1995). Even though the Gini coefficient cannot be decomposed, it is included because it is the most population income inequality measure. Together these measures offer complementary insights into income inequality.

For the other measures of income inequality, half the relative mean deviation is also defined as Pietra ratio/Ricci-Schutz index/ Robin Hood Index. Allison (1978) argues the variance of logarithms responds appropriately to transfers at lower income levels but not at high income levels. It decreases with a transfer from relatively poorer to a richer individual. Greedy (1977) argues the extent to which the variance of logarithms violates the Principle of Transfers is very minor. Salverda, Nolan and Smeeding (2009) say the variance of logs doesn't satisfy the Principle of Transfers. Atkinson (1970) states the standard deviation of logs is sensitive to transfers at all income levels, more sensitive to transfers to lower level of income. Relative Mean Deviation is completely insensitive to transfers between people of the same side of the mean (Atkinson 1970).

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[3] For every value ε of Atkinson index, there is a Generalized Entropy index with that ranks a pair of income distribution in the same way as the Atkinson Index. A more negative value of reflects the index which is more sensitive to differences among the poorest incomes. The index with a more positive of is more sensitive to differences in income shares among the rich. Higher values for the weight ε, called a measure of inequality aversion, reflect greater sensitivity to incomes at the lower end of the distribution (Salverda, Nolan and Smeeding, 2009).

Table 6 Income inequality measures

Income Inequality Measure	Income Scale Invari-ance	Dalton Population Principle	Pigou-Dalton Transfer Principle	Anonymity	Decomposability	Years Available and Data source
Coefficient of Variation[1,2,3]	Y	Y	Y	Y	Y	
The Gini Coefficient[1,2,3]	Y	Y	Y	Y	N	
Generalized Entropy class[102,3]	Y	Y	Y	Y	Y	Census 1990, Census 2000, ACS 2007-2011
Atkinson Index[1,3]	Y	Y	Y	Y	Y	
Variance/SD[1,3]	N					
Variance of the log[23,]	Y		N		Y	
Standard deviation of logarithms[1]	Y		Y			
Percentile ratios (P90:P10 ratio etc.) [3]	Y		N			ACS 2007-2011
Relative Mean Deviation[1,2,3]	Y		N			unknown
Generalized Gini[3]	Y		N			

Note: [1] This measure is discussed in Atkinson (1970
[2] This measure is discussed in Allison (1978).
[3] This measure is discussed in Salverda, Nolan and Smeeding (2009).

The four income inequality measures complement each other, because they are different in upper and lower bounds as well as relative sensitivity to transfers. CV and Theil's T index vary from zero and infinity. Zero shows perfect equality in income and higher values represents a higher level of inequality. The Atkinson Index and the Gini coefficient range between zero and one. Zero is perfect equality and one is perfect inequality. For the Atkinson Index, the inequality aversion parameter ε is larger than zero[4].

[4] Typically, $\varepsilon \sim [0,2]$. But any positive value can be used. Higher values for the measure of inequality aversion, reflect greater sensitivity to incomes at the lower end of the distribution.

The coefficient of variance is equally sensitive to transfers at all income levels (Atkinson, 1970; Allison, 1978; Salverda, Nolan and Smeeding, 2009). The Gini coefficient is most sensitive to transfers around the middle of the distribution, and least sensitive at the extremes. Allison (1978) originally wrote about the desirability of this property as the Gini coefficient is the best measure to use to understand changes in the middle of the income distribution. However, DeNavas-Walt and Proctor (2015) show that over time the incomes of the middle of the distribution, or the middle class, change far less than the incomes of the wealthy and poor, which weakens the Gini coefficient's ability to accurately reflect change. Theil's T index is more sensitive to transfers among people with lower levels of income. As mentioned in the calculation of income inequality measures, the Atkinson Index will attach more weight to the lower end of the income distribution when the degree of inequality-aversion measured by ε increases (Atkinson, 1970). Here $\varepsilon = 0.5$, then the Atkinson Index is more sensitive to the higher end of the income distribution. Therefore, when income or other social safety net payments are assumed to have diminishing marginal utility, Theil's measure works better. For the flat marginal utility case (for example to measure inequality of age, city size, years of schooling, etc.), the coefficient of variation is preferable. As mentioned above, the Gini coefficient is also not decomposable, so to examine relationships between or within different income levels this research will use the CV, Theil's T index and the Atkinson Index in addition to the widely used the Gini coefficient.

The measures are calculated in the following ways (Haughton and Khandker, 2009): The Gini coefficient is calculated as $Gini = 1 - \sum_{i=1}^{N}(x_i - x_{i-1})(y_i + y_{i-1})$[5]. Using unordered data, the Gini coefficient is calculated as the relative mean difference between incomes for all pairs of households

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[5] x_i is a point on the X-axis (households), and y_i a point on the Y-axis (income).

divided by twice the mean income. (Allison 1978). $Gini = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|x_i - x_j\right|}{2N^2\bar{x}}$ [6]. Coefficient of variation is defined as the ratio of the standard deviation of income, $SD(Y)$, to mean income $\bar{Y}$, $CV = \frac{SD(Y)}{\bar{Y}}$.

The Atkinson Index is $A_{\varepsilon} = 1 - [\frac{1}{N}\sum_{i=1}^{N}(\frac{y_i}{\bar{y}})^{1-\varepsilon}]^{1/(1-\varepsilon)}, \varepsilon \neq 1$ and $A_{\varepsilon} = 1 - \frac{\prod_{i=1}^{N}(y_i^{(1/N)})}{\bar{y}}$, $\varepsilon = 1$. Higher values for the weight ε, called a measure of inequality aversion, reflect greater sensitivity to incomes at the lower end of the distribution. Generalized Entropy measures are calculated as $GE(\alpha) = \frac{1}{\alpha(\alpha-1)}[\frac{1}{N}\sum_{i=1}^{N}(\frac{y_i}{\bar{y}})^{\alpha} - 1]$, where $\bar{y}$ is the mean income (or expenditure per capita). α is the weight given to distances between incomes at different parts of the income distribution. $\mathrm{GE}(1)$ is the Theil's T index, that is $GE(1) = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}}\ln(\frac{y_i}{\bar{y}})$. Each of the measures were initially calculated across three time periods using data from the Decennial Census for 1990 and 2000, and the 2007-2011 American Community Survey (ACS) for 2007-2011. The included results primarily use the 2000 Gini coefficient to predict economic resilience.

Examining the Quality of Midpoint Data to Estimate Aggregate Income

Income inequality measures must be calculated using estimated midpoints of the provided household income categories instead of the actual income data for each household. This reduces the accuracy of all calculated income inequality measures, and affects each county differently depending on how well a calculated midpoint reflects household incomes within each category. Total household

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[6] N: The total number of households, i and j index each household, x is household income, $\bar{x}$ is mean income over the sample.

income in the 2000 Decennial Census and ACS 2007-2011 five-year estimates[7] are used to calculate income inequality. The income data for 2000 census and ACS 2007-2011 report 17 income classes. This research assumes that each household in the income class is at the midpoint of its income class, and that no one can have a negative income. For the open-ended category, each household is assumed at the mean income of the category. For the highest income level - households earning $200, 000 or more, the mean income is calculated using the aggregate income held by households earning $200,000 or more divided by the number of household in that category.

A comparison of estimated aggregate income using these midpoint estimates to a separately provided estimate of county aggregate income provides a limited understanding of how using the midpoint could affect a calculation of income inequality. Here for 2000 census data, the summed total income for all income categories earning less than $200,000 (midpoint*numbers of household in this category) is compared with aggregate income for household earning less than $200,000 provided by the census. For the Census 2000, calculating the aggregate income held by households earning less than $200,000 using midpoints and comparing this to a separately provided estimate of aggregate income in the Census 2000 shows only one county's aggregate income being overestimated by more than 5%, 46017 Buffalo County, South Dakota with the difference as 6.85%. The aggregate income held by households earning less than $200,000 calculated using midpoints estimates is overestimated by less than 1% for 467 counties, underestimated by less than 1% for 2 counties; overestimated by larger than 1% but less than 2% for 2589 counties, overestimated by more than 2% but less than 3% for 76 counties., overestimated by more than 3% for 1 county (Buffalo County, South Dakota). For ACS 2007-2011 data[8],

[7] American Community Survey (ACS) first published the Gini coefficient calculated using individual data from 2006. The Gini coefficient is calculated using ACS 2007-2011 aggregate income data for comparison with the published Gini coefficient based on individual data shown in the next section.

[8] There are missing values in ACS 2007-2011 B19081 Mean Household Income of Quintiles for 6 counties for ACS 2007-2011, 15005 Kalawao County, Hawaii, 16033 Clark County, Idaho, 48261 Kenedy County, Texas, 48269 King County Texas, 48301 Loving County, Texas, 48443 Terrell County, Texas. Among the 6 counties in ACS, King County, Texas that the two aggregate HH income differ more than 10%. It is underestimated.

total income for all income categories is summed up to compare with aggregate income for household income. For the ACS data, the 90 counties are overestimated for more than 5%. The mean value is 14.57% while the range is 5.09% to 49.90%. 121 counties are underestimated for more than 5% with the mean -6.67%, and range from -16.53% to -5.003%. For the 50 counties overestimated for more than 10%, the mean for overestimation is 20.45% with the range 10.52% to 49.90% while for the 6 underestimated counties for more than 10%, the mean is -12.53% with the range -16.53% to -10.35%. For the majority of counties, the calculated sum of the aggregate income is larger, or overestimated, relative to the actual provided aggregate income total from the census. The number and the degree of overestimate of affected counties in 2000 is lower than in ACS 2007-2011, yet since the aggregate level income ignores within-group income difference (Kuhn, 2015), the Gini coefficient computed using midpoint estimates would likely underestimate the Gini coefficient based on individual data for both years.

Comparing Gini Coefficients Calculated from Mid-point Data and Individual data

As a second point of comparison, this research compares the level of accuracy for one data point, the Gini coefficient using ACS 2007-2011 5 year estimates. The U.S. Census Bureau calculated and released the Gini coefficient using actual household income data for the 2007-2011 ACS. By replicating the method of calculating the Gini coefficient in 2000 using household midpoints, the calculated Gini coefficient is found to be smaller than the Gini coefficient provided by ACS (see Table 7). This implies that calculating the Gini coefficient based on midpoint estimates underestimates the true level of income inequality among households for the 07-11 data and possibly the earlier data as well. The mean difference in percentage of the two Gini coefficients is 2.7%. The mean difference in absolute value of 0.012 may be significant given that Levernier, Partridge and Rickman (1998) believed the metropolitan-nonmetropolitan differential in Gini at 0.0105 is nontrivial and an increase in the family income Gini of 0.0301 during the 1980s is considered dramatic. The calculated Gini coefficient is lower than Gini coefficient provided by the ACS, which suggests that using the midpoints for grouped data will underestimate the actual dispersion in income (see Figure 8).

Table 7 Comparison of Gini calculated and Gini offered by American Community Survey (ACS):2007-2011

# of counties	Gini calculated-ACS 2007 2011				Gini-ACS 2007-2011				Difference	
	Mean	Std.Dev	Min	Max	Mean	Std.Dev	Min	Max	Mean	%
3135	0.421	0.036	0.193	0.666	0.433	0.035	0.200	0.671	-0.012	-2.7%

Note: All the numbers are rounded to 3 significant digits.

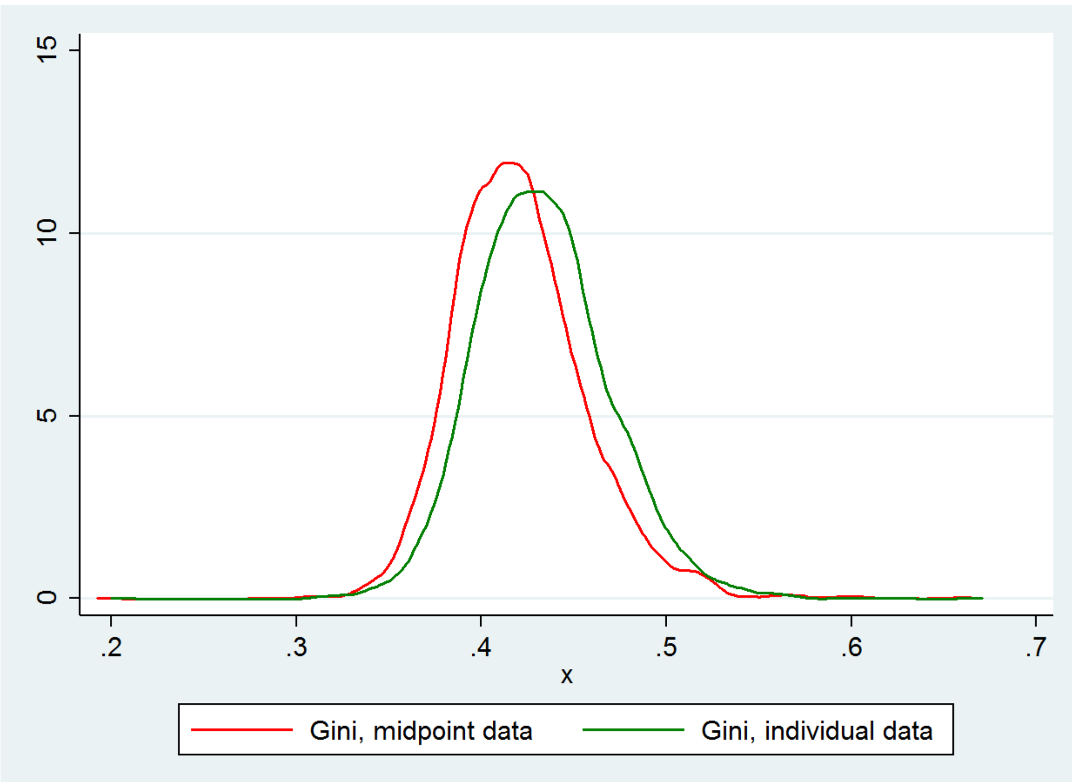

Figure 8 Kernel density of the Gini coefficient calculated using midpoint data and individual data.

Limitations to the Inequality Measures and Income Data

After considering tradeoffs between different measures of income inequality, there are additional limitations to the quality of estimates that can be constructed based on the underlying source data. The U.S. Census Bureau's income is defined as the total pre-tax cash income and includes five primary sources. The census excludes capital gains, or income earned from investments in the stock market, and noncash benefits for the poor including food stamps, health benefits, and subsidized housing (U.S. Census, 2015). Therefore, the census underestimates income for both the upper and lower ends of the income distribution. In addition, household income data is different than individual income data. In an analysis of the Annual Social and Economic Supplement (ASEC) data of 2002, approximately 50 percent of the data is proxy reporting by other household member rather than directly from each eligible person. This may introduce non-sampling error because information on other members provided by the respondent may be less accurate than that of themselves (Ruser, Pilot and Nelson, 2004). Moreover, knowing only the income and not the size of the household limits an understanding of each household's standard of living. Given these limitations in the type of incomes counted in the census data, the way the data is released to the public also diminishes the accuracy of calculated income inequality measures.

Selecting Measures of Economic Resilience

The idea of 'resilience' has been introduced to economics recently. However, there is much ambiguity in the definition of 'resilience'. In empirical studies, Martin (2012) uses four quadrants of regional resistance and regional recovery. Augustine et al. (2013) defined regional resilience as the ability to recover from an economic downturn. If the employment growth rate of the county returned to its previous path within four years, the region was resilient to that downturn. If at the end of four years it has not returned to its previous growth path, then it is non-resilient. Han and Goetz (2015) define resilience as the regional capacity "to absorb and resist shocks as well as to recover from them". It is calculated as the standard score of logarithm of ratio of $\boldsymbol{rebound}$ **and** $\boldsymbol{drop}$ using monthly employment (see Figure 9). This paper will use the measure *resilience* following Han and Goetz (2015) as it offers two dimension of resilience as well as a one-number score.

Measuring Resilience Following Han and Goetz (2015)

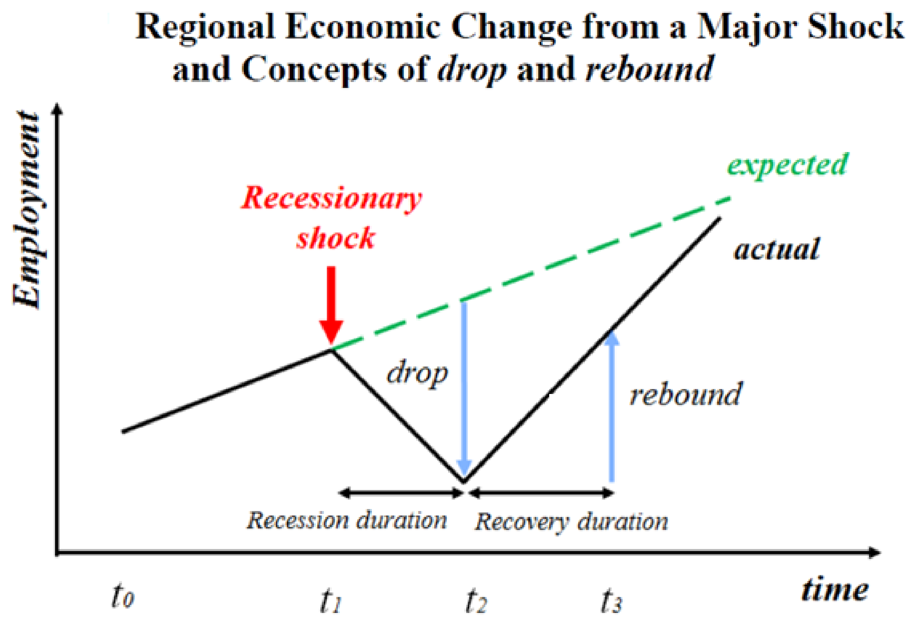

Figure 9 Regional economic change from a major shock and concepts of drop and rebound, diagram from Han and Goetz (2015).

There are peak month t_1 and trough month t_2 for employment within each county. $\boldsymbol{Drop}$ measures the amount of impulse that a county experiences from a shock.

$$\boldsymbol{drop} = \frac{\widehat{y_{t_2}} - y_{t_2}}{\widehat{y_{t_2}}}$$

$\boldsymbol{Rebound}$ measures the recovery velocity after the recession.

$$\boldsymbol{rebound} = \frac{y_{t_3} - y_{t_2}}{y_{t_2}} \cdot \frac{1}{t_3 - t_2}.$$

A resilient system might experiences a smaller $\boldsymbol{drop}$ and allows a greater $\boldsymbol{rebound}$.Then $\boldsymbol{resilience}$ is defined as the standard score of logarithm of a ratio of $\boldsymbol{drop}$ and $\boldsymbol{rebound}$.

$$\boldsymbol{Resilience} = \frac{\boldsymbol{ratio} - \boldsymbol{ave}(\boldsymbol{ratio})}{\boldsymbol{stdev}(\boldsymbol{ratio})}, \boldsymbol{ratio} = \ln\left(\frac{\boldsymbol{Rebound} - \min(\boldsymbol{Rebound}) + \boldsymbol{s}}{\boldsymbol{Drop} - \min(\boldsymbol{Drop}) + \boldsymbol{s}}\right).$$

$$\textbf{Ave ( ) i s the average, stdev( ) is the standard deviation.} \ \boldsymbol{s} = \boldsymbol{0.0001}$$

$\boldsymbol{t_1}$: peak (when the shock happens)

$\boldsymbol{t_2}$: trough

$\boldsymbol{y_{t_2}}$: the region's lowest post-shock employment occurring at $\boldsymbol{t_2}$ (trough),

$\widehat{\boldsymbol{y_{t_2}}}$: the expected employment at time $\boldsymbol{t_2}$. Expected employment is "the region's employment based on the long-run growth path in the absence of a shock" (Han and Goetz, 2015).

$\widehat{\boldsymbol{y}}_{\boldsymbol{t}}$: expected employment. $\widehat{\boldsymbol{y}}_{\boldsymbol{t}} = \mathbf{y}_{\boldsymbol{t_1}}(\mathbf{1}+\boldsymbol{r})^{\boldsymbol{t}-\boldsymbol{t_1}}$, $\boldsymbol{t} > \boldsymbol{t_1}$. $\boldsymbol{r}$ is compound growth rate, $\boldsymbol{r} = (\boldsymbol{y_{t_1}}/\boldsymbol{y_{t_2}})^{\mathbf{1}/\boldsymbol{t_1}-\boldsymbol{t_0}} - \mathbf{1}$.

$\boldsymbol{t_0} = \boldsymbol{t_1} - \mathbf{36}$, as the compound growth rate for the long-run path is estimated over three years before the peak employment $\boldsymbol{t_1}$.

$\boldsymbol{t_3} = \boldsymbol{t_2} + \mathbf{6}$, as *rebound* is defined as the employment increase during six months following the trough $\boldsymbol{t_2}$,

$\boldsymbol{y_{t_0}}$and $\boldsymbol{y_{t_1}}$: the region's actual employment at time $\boldsymbol{t_0}$ and $\boldsymbol{t_1}$.

$\boldsymbol{y_{t_3}}$: **recovered employment**.

These three measures are constructed using county-level monthly data for total employment from U.S. Bureau of Labor Statistics for 3,138 U.S. counties[9]. Han and Goetz (2015) adjusted the seasonal effect using data monthly employment data from 2000-2014 for the 2000-2014 time period and then used the adjusted data from 2003-2014 to measure resilience[10]. In the thesis, data are seasonally adjusted using Census X-13 ARIMA-SEATS[11] instead of X-12 ARIMA because X-12 has known bugs that have been fixed in X-13. Seasonally adjusting employment data smooths out predictable or seasonal fluctuations to emphasize actual change (see Figure 10). In Figure 10, the national peak for total

[9] Following Han and Goetz (2015), Skagway Municipality (FIPS = 02230) and Hoonah-Angoon Census Area (FIPS code = 02105) are merged into Skagway-Hoonah-Angoon Census Area, AK (FIPS code = 02232) which were split on June 20, 2007. Wrangell City and Borough (FIPS code = 02275) and Petersburg Census Area (FIPS code = 02195) are merged into Wrangell-Petersburg Census Area (FIPS code = 02280) which were split on June 1, 2008. Greenlee County, Arizona (FIPS=04011) with missing data for 2003 April-Dec, 2004 July-Dec. Bedford City, Virginia (FIPS=51515) are merged in Bedford County, Virginia (FIPS=51019) as it rejoined the Bedford County on July 1, 2013. Out of 3141 counties and county-equivalents in the 2014 BLS data, 3138 counties remain.

[10] Han and Goetz didn't mention the detail about how they do the seasonal adjustment, the time period, and the data. But I confirmed with Han in May 2016 that they used the data from 2000-2014 and time period 2000-14 for the seasonal adjustment and then use the adjusted data from 2003 to 2014 for analysis.

[11] Data are seasonally adjusted using x11 with auto transformation (log transformation or none). Trading days, Easter and Hard-code AIC results are checked as the regression variables in ARIMA model.

employment happens in Jan 2008 and the trough happens in Jan 2010 which is consistent to Han and Goetz (2015)[12].

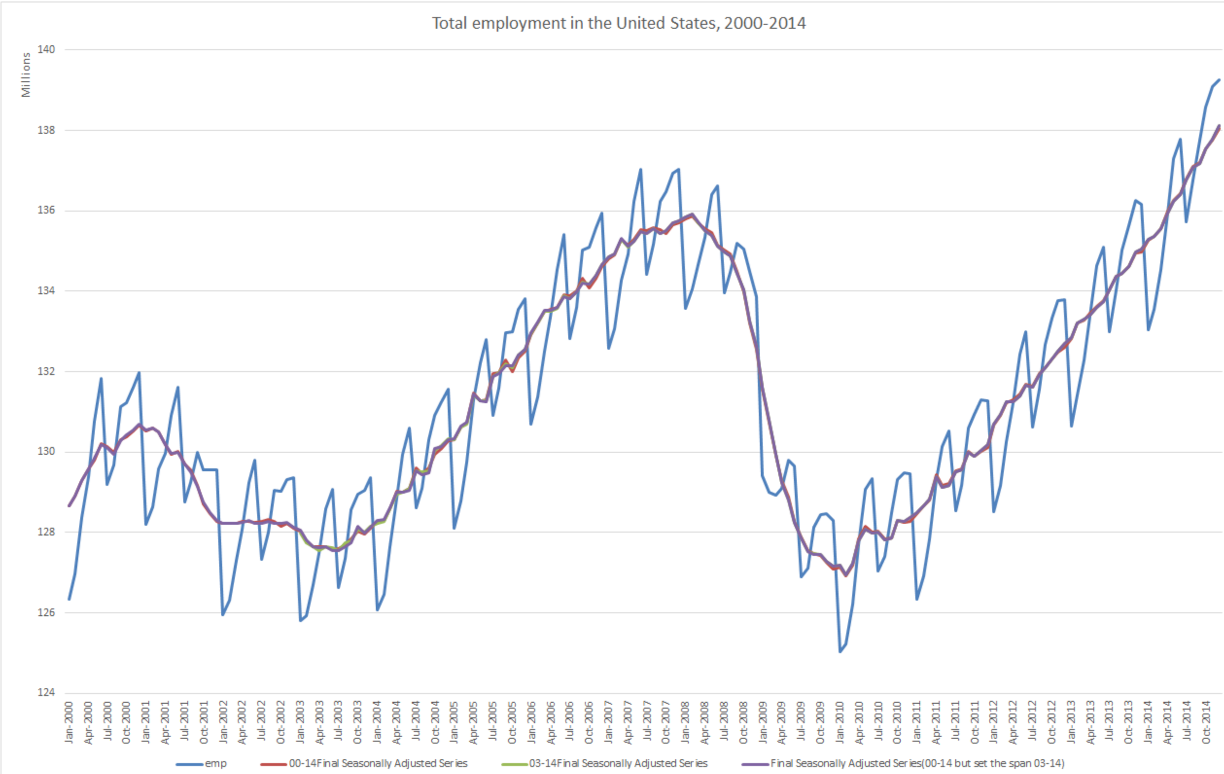

Figure 10 Seasonal adjustment of monthly employment data for the U.S., using X-13 ARIMA-SEATS. Source: Bureau of Labor Statistics (2016c)

Peak, Trough and Duration

Each county has a peak month t_1 and a trough month t_2 for employment[13]. The duration of recession is the gap between a county's peak and trough months in employment. Table 8 provides a comparison between the calculated estimates (called Wu estimates) and results from Han and Goetz (2015). A large difference appears in the percentage of counties with a trough in 2012-2014. Particularly, 14 percent of counties experienced a trough in employment in 2014 in Wu estimates compared to 5.3 percent in Han and Goetz (2015).

[12] However, in their paper, the data values for U.S. total employment are 4 million lower. The possible reason might be an update of the data. The data was accessed in February 2016, around a year later than Han and Goetz (2015).

Table 8 Comparison for the peak, trough, duration of recession

	Wu estimates	Han and Goetz estimates
Counties recorded peak employment in %t	February 2008 (4.24%) and March 2006 (4.17%) August 2008 (3.82% - 4th highest)	February 2008 (4.5%) and August 2008 (4.0%)
Entire year:		
Peak in 2006	29.9%	30.90%
Peak in 2007	28.60%	27.30%
Peak in 2008	32.00%	32.20%
Peak in 2009	8.30%	7.50%
Peak in 2010	1.20%	2.00%
Counties experienced trough employment %	February 2010 (6.0%) and January 2010 (4.0%)	February 2010 (7.0%) and January 2010 (4.7%)
Entire year:		
Trough in 2006	0.1%	0.20%
Trough in 2007	0.70%	0.70%
Trough in 2008	1.90%	1.80%
Trough in 2009	25.10%	27.20%
Trough in 2010	24.80%	27.80%
Trough in 2011	14.30%	15.40%
Trough in 2012	8.70%	10.00%
Trough in 2013	10.40%	11.70%
Trough in 2014	14.00%	5.30%
Average recession duration in years (all counties)	3.7	
2006 peak-year counties	4.9	4.6
2007 peak-year counties	3.8	3.5
2008 peak-year counties	2.8	2.5
2009 peak-year counties	2.3	2.0
2010 peak-year counties	2.3	1.8
Counties with continuously rising employment[1]	15	12
Counties with continuously declining employment [2]	19	20
Counties with employment recovering in July 2014 or later[3]	260	270
Counties remaining in analysis	2844(90.6%)	2836 (90.4%)

Note: [1] These counties are captured when the global minimum of employment happen in Feb. 2006 while the maximum happen in Feb. 2010.

[2] Counties which recorded maximum employment (Han and Goetz(2015) use peak) in Feb. 2006 and trough in or after July 2014

[3] Counties which recorded trough in or after July 2014 but the maximum employment was not in Feb. 2006

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[13] First find the local maximum (minimum) and then find the global maximum (minimum), which is the peak (trough).

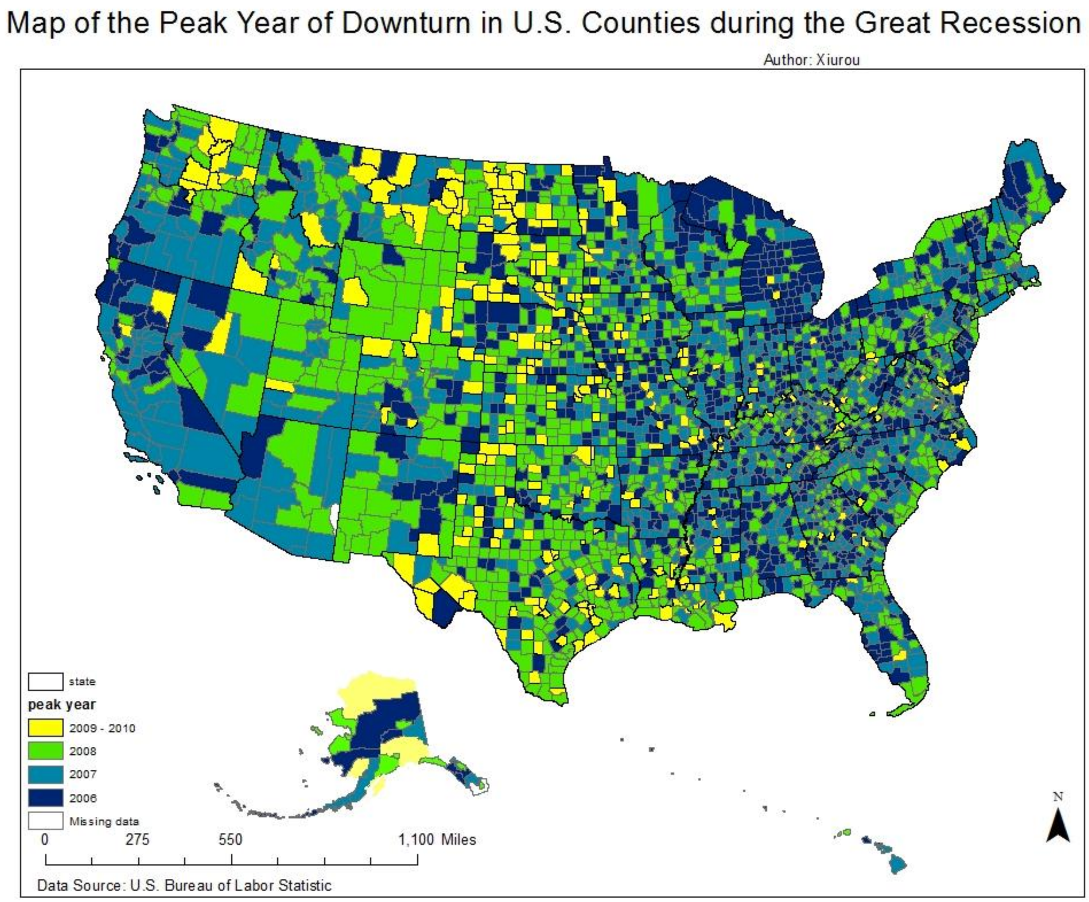

Figure 11 Map of the peak year of downturn using Wu Estimates

Figure 11 shows the distribution of the year of counties recorded their peak employment months. More counties entered the Recession before year 2008. For those 294 counties whose employment rose continuously, declined continually or didn't recover before July 2014, it is not possible to measure *rebound* as *rebound* is defined as the employment increase during six months following the trough $\boldsymbol{t_2}$. Therefore they are removed from the sample. Four counties[14] are also removed from the sample due to undisclosed data. The resulting 2840 counties are used to calculate $\boldsymbol{drop}$, $\boldsymbol{rebound}$ and

[14] 19003 Adams County, Iowa, 19159 Ringgold County, Iowa, 42113 Sullivan County, Pennsylvania, 48301 Loving County, Texas have undisclosed data recorded as 0 for total employment from 2012-2013. After seasonal adjustment, these counties have negative employment which bring noise to the calculation of *rebound*. 49009 Daggett County, Utah, 49301 Piute County, Utah, 56027 Niobrara County, Wyoming also have undisclosed data in 2001 or 2005 which turns to be negative employment after seasonal adjustment. However, since 2001 and 2005 are out of the period to capture peak (Feb. 2006 to Feb. 2010), these counties are not deleted. Those counties

$\boldsymbol{resilience}$ following formulas in Han and Goetz (2015). The calculated results are compared in Table 9. The Wu estimates capture most of the information shown in Han and Goetz estimates: *drop* is quite similar but *rebound* is different. The difference might result from 1) updated data, 2) X-13 ARIMA-SEATS are used instead of X-12 ARIMA, 3) not fully disclosed methodology of calculation in the original paper.

Table 9 Comparison of drop, rebound, and resilience

Variable	Wu estimates					Han and Goetz estimates (2015)				
	Obs.	Avg.	St. dev.	Min.	Max.	Obs.	Avg.	St. dev.	Min.	Max.
drop	2,839	0.186	0.116	-0.236	0.895	2,836	0.188	0.117	-0.329	0.902
rebound	2,840	0.006	0.009	0.000[1]	0.303	2,836	0.035	0.055	0.000	2.199
resilience	2,839	0.000[2]	1.000	-4.787	10.857	2,836	0.000	1.000	-5.215	9.680

Note: All numbers are rounded to three digits.
[1] 2.14E-06
[2] -7.29E-13

The difference might be influenced by the updated data. When BLS updates the monthly employment data in each quarter, the most recent monthly employment data are modified slightly. Many counties might fall into “double-dip” after 2014, and employment of the second half of 2014 may be modified to smaller values[15]. Thus more counties may have peaked in 2014 in Wu estimates. Moreover, the seasonal adjusted values are affected by updated data for year 2014. The x11 seasonal adjustment method uses symmetric moving average filters when possible. The most common seasonal filters are 3X3 (a five year filter, 2 years on each side of the value being adjusted), 3X5 (7 year filter, 3 years on each side) and 3X9 (11 year filter, 5 years on each side). Take 3x3 for example, the seasonal filter applied to December 2014 data needs data for December 2012, December 2013, December 2014, December 2015 and December 2016. If the data contains December 2016, the symmetric filter can fit the data and the adjustment for December 2014 is close to the “final” value. If the data ends in December 2014, the program will either use an asymmetric filter or forecast two years of data and use

whose employment stay positive after seasonal adjustment undisclosed data are kept as well. Such counties are not mentioned in Han and Goetz (2015).

[15] Personal communication with Yicheol Han, Pennsylvania State University.

the forecasts for the adjustment. Either option will result in a revision to the December 2014 adjusted value when new data points are added. The change will also happen if the current data points are updated because they are used in the seasonal and trend filters[16].

Maps of Drop, Rebound and Resilience

The level of economic resilience differs across regions (see Figure 12, Figure 13, Figure 14, Figure 15). Figure 12 shows there are 33 counties with a negative *drop*, where actual employment is larger than the expected employment. Most of these counties experienced a continuous decline or a sharp decline before the peak employment month which was constrained between Feb 2006 and Feb 2010. Therefore, the expected employment calculated using the compound growth rate over three years before the peak employment month would be much lower than the actual employment. These counties might fall into the Great Recession after a short recovery from their last recession, however, they didn't fall worse than before. Only 30083 Richland County, Montana had an overall increasing trend in employment. The employment grew faster after the peak, therefore the actual employment at trough month is larger than the expected employment. The negative *drop* values in these counties indicate these counties behaved better than expected during the Great Recession[17]. *Drop* shows a different distribution from *rebound* indicating counties behaved differently in and after the recession, which contributes to the difference in *economic resilience*. There is variation within every region and no specific patterns are noticed in *drop*, *rebound* and *resilience*. However, the distribution of *resilience* seems to follows the pattern of *rebound*.

[16] Personal communication with Demetra Lytras, Mathematical Statistician, Economic Statistical Methods Division, U. S. Census Bureau

[17] However, it needs further thoughts if there exist flaws in the measurement calculating methods.

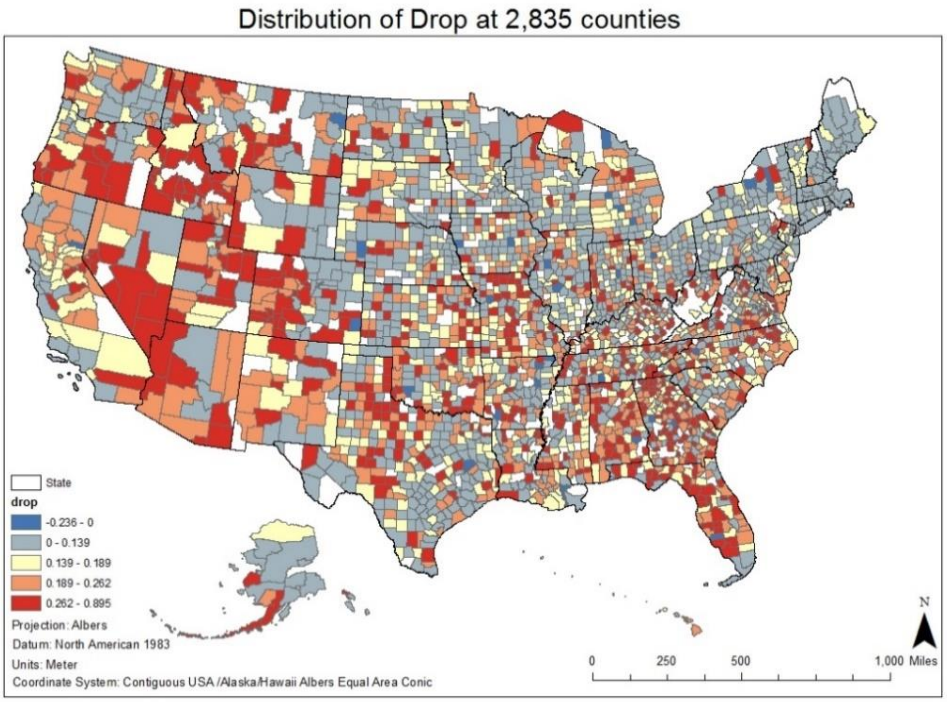

Figure 12 Distribution of Drop at 2,835 U.S. counties, the first category shows negative drop

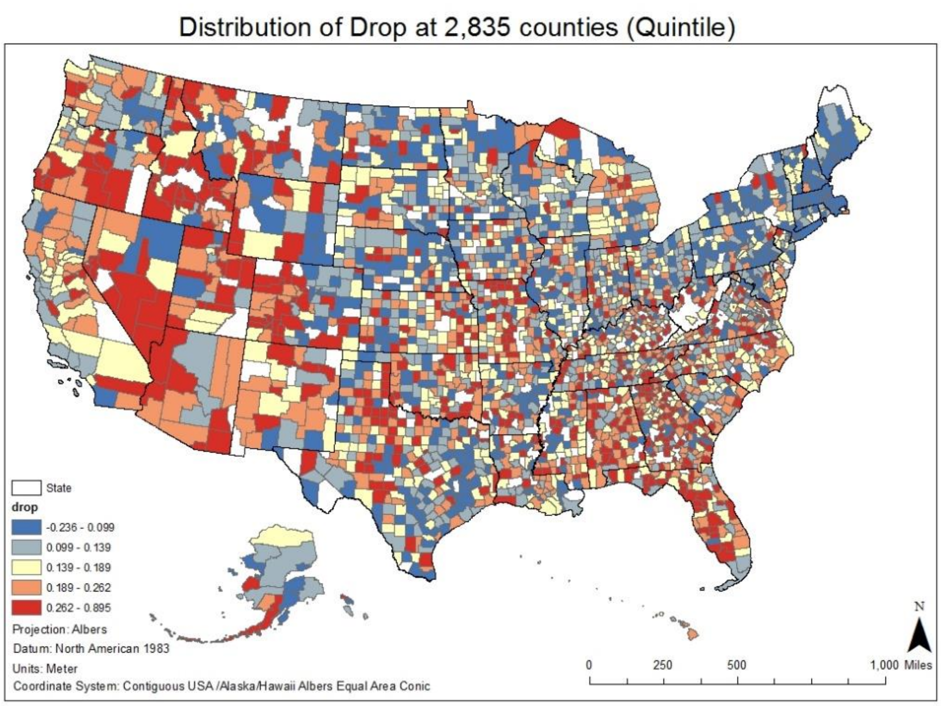

Figure 13 Distribution of Drop at 2,835 U.S. counties (Quintile)

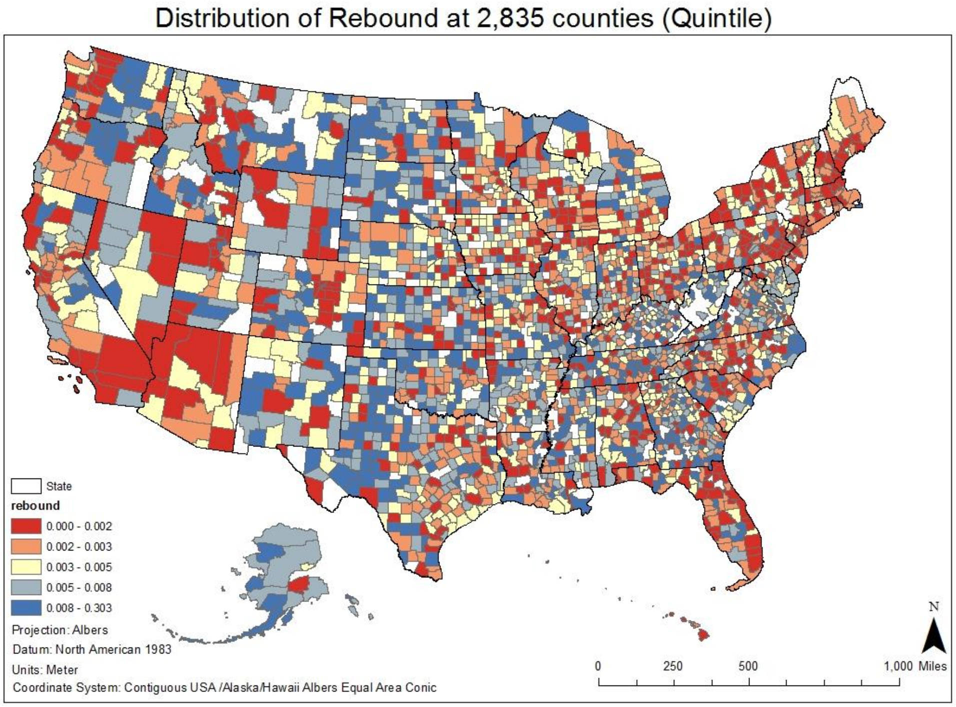

Figure 14 Distribution of Rebound at 2,835 U.S. counties (Quintile)

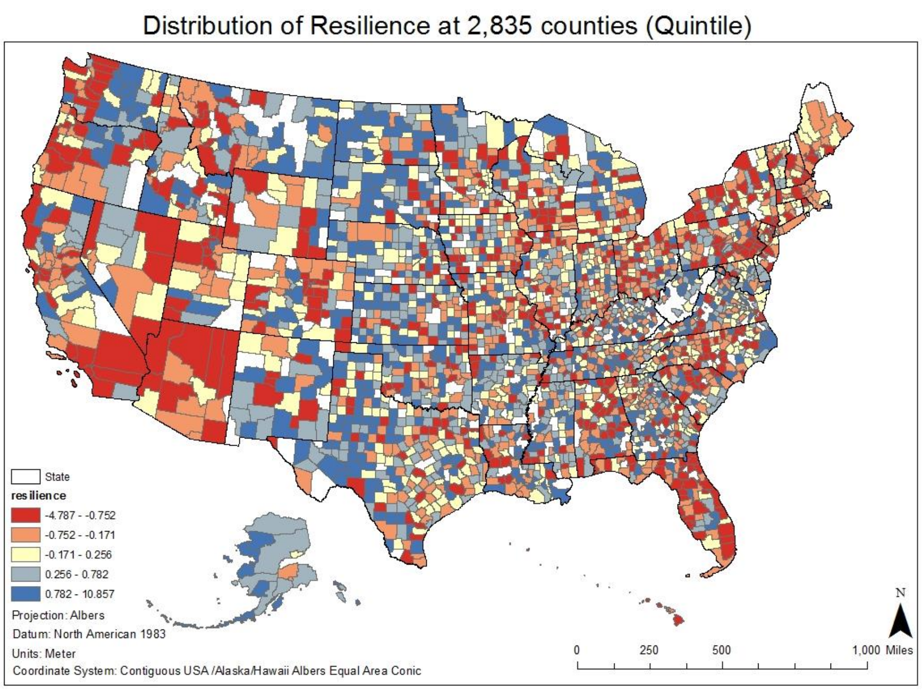

Figure 15 Distribution of Resilience at 2,835 U.S. counties (Quintile)

Explanatory Variables

There are multiple factors in addition to income inequality that may determine the resilience of a region to economic shocks. Drawing upon previous literature, the poverty rate, share of aggregate income held by households earning $200,000 or more, capital stocks and variables representing economic structure in a county are used – in addition to inequality measures – to capture the variation of *economic resilience* and its two components, *drop* and *rebound*. The capital stocks model contains estimates for the following forms of capital: human, natural, social, built and financial capitals. Inadequate data at a county level precluded estimating cultural capital, political capital, and intellectual capital although political capital is partially embedded in the measure of social capital. Economic structure here refers to sector composition (as measured by the Herfindahl-Hirschman index) and the size and urbanization of the economy, indicated by total population, percentage of urban population and the Euclidean distance between the mean center of population within each county and its nearest urban areas with population greater than or equal to 50,000. The hypothesized effect of each variable to *drop*, *rebound* and *resilience* is summarized in Table 10. The population growth rate, race and ethnicity, and per capita income are included as the control variables. Table 11 shows summary statistics.

Income Inequality and Income Distribution

The Gini coefficient, as a measure of overall relative inequality, doesn't tell the absolute income level in each income bracket. A county could have a similar Gini coefficient if everyone is rich or everyone is poor. Two variables, poverty rate and the percentage of wealth held by households in the highest income category, are also included to provide more information about the poor and the rich. These two variables complement the overall income inequality measures to represent income distribution. There is no theoretical expectation about the expected direction of impact for the Gini coefficient, poverty rate, and share of aggregate income held by households earning $200,000 or more because, as discussed in Chapter 1, the result depends on how the three variables work out empirically.

Control Variables

The population growth rate, percentage of Black or African American, percentage of Hispanic or Latino people, and per capita income are chosen as the control variables. These control variables are hypothesized to affect *drop*, *rebound* and *resilience,* and also may be correlated with other independent variables. Omitted variables bias might rise if these variables are not included since the estimates of the impact of inequality on drop, rebound and resilience could be biased, incorporating the impact of population growth, race or income. Data on these variables come from 2000 U.S. Decennial Census.

Human Capital

Human capital is defined as the stock of education, skills, physical and mental health embedded in people (Becker, 1962; Pender and Ratner, 2014). Several variables are collected to reflect human capital. The first is educational attainment, measured by the percentage of people age 25 and over with bachelor's degree or higher. The proportion with higher educational attainment is associated with higher-level employment and increased income (Irwin et al., 2002). Therefore a county with higher percentage of higher education is hypothesized to lose less employment and/or recover faster. The breakdown of population by age group acts as the second variable. Two age groups are considered percent of the population ages 20 to 29 and ages 30 to 49 in the year 2000. People who are in the age group of 20 to 29 in 2000 and stayed in the county would be 26 to 35 in 2006.[18] This portion of the population is likely to be early in their career, therefore they are more adaptable in a company and willing to accept inferior jobs to support family because there is no saving to depend on. Counties with higher percentage of people in this age group are hypothesized to experience a smaller employment loss and a quicker recovery. People aged 30 to 49 at year 2000 who stayed in the county and became 36 to 55 in 2006 are hypothesized to positively contribute to resiliency, assuming they don't easily lose their job and could find a job if fired because they are experienced and have seniority in their career.

However, it could also go in the opposite direction if there is age discrimination and firms don't want to pay for experience. Therefore the hypothesized effect of people in this age group is ambiguous on *drop*, *rebound* and *resilience*. Female civilian labor force participation rate is the third human capital variable. Females tend to be employed in low-paying industries such as retail trade, health care, and low-paying occupations such as secretary and elementary school teacher; at the household level, it is resistant. Counties with higher female civilian labor force participation rate are hypothesized to experience a large *drop* in the recession followed by a possibly large recovery. All data come from Decennial Census 2000.

Natural Capital

Natural capital is the stock of healthy environmental assets in a region such as air, water, land, etc. which will yield a flow of goods and services (Costanza and Daly, 1992; Pender and Ratner, 2014). The natural amenities scale (McGranahan, 1999), which ranges from negative two to three, is used to measure natural capital. The composite score is based on six measures of environmental quality: warm winter, winter sun, temperate summer, summer humidity, topographic variation and water area. Natural amenities are positively related to rural economic performance. Climate and water appear to influence population growth, but have a weak influence on per capita income growth and no role in employment growth. Positive relationship between land amenities and employment and population growth rates reflect that there exist tourist economies. Winter recreational activities are positively related to growth rates in population, employment and per capita income (Deller et al., 2001). Open hills and mountains delays the time of a county to enter recession (Brown, 2015). A county's level of natural amenities is hypothesized to be positively related to employment loss and employment recovery. This is because industries depending on environmental quality are more likely to be vacation and recreation, which would be negatively affected due to decreased discretionary consumption in the Great Recession. During the recovery time, better environmental quality will encourage people to choose to relocate in

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[18] The first county entered the recession in September, 2006.

these areas while industries of vacation and recreation will also recover faster with better environmental quality.

Social Capital

Social capital captures the features of social organization such as networks, norms and trust (Putnam, 1993). The Northeast Regional Center for Rural Development at Pennsylvania State University developed an index to measure county level stock of social capital for years 1990, 1997, and 2005 (Rupasingha, Goetz and Freshwater, 2006). The social capital index is calculated using principal component analysis on variables relating to business establishments thought to encourage social networks, voter turnout rate, census response rate and numbers of non-profit organizations. Businesses hypothesized to build social networks include religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, and sport clubs. Social capital is hypothesized to weakly decrease *drop* and increase recovery and *resilience*. Data for the year 2005 are used.

Built Capital

Built capital includes the stock of infrastructure that contributes to other forms of wealth, such as buildings and equipment used by the firms; roads, bridges and telecommunication networks to reduce costs of commerce; durable goods such as houses and vehicles used by households (Flora et al., 2004; Pender and Ratner, 2014). Median value of all owner-occupied housing units is used to reflect built capital. The hypothesized effect of higher median housing value on *drop*, *rebound* and *resilience* is ambiguous. Counties with higher median housing value may experience less employment loss because people who can afford the housing are expected to be more resistant where high price probably comes from the shortage of housing supply. It might be related with less recovery because high housing price might discourage people from living in an area, negatively impacting the local labor force. However, high median housing value in 2000 might signal the area experienced a housing bubble which burst during the recession where people lost jobs and their spending in and after the recession were reduced. Nevertheless, wealthy counties with higher built capital are hypothesized to recover faster than poor counties. Data come from 2000 Decennial Census.

Financial Capital

Financial capital refers to the stock of money and other financial resources such as stocks, bonds, etc. The share of dividends, interest and rent in personal income is used to represent financial capital. Data from CA25N Bureau of Economic Analysis for the year 2005 are used. Places with a higher proportion of investment income would be volatile in recession and weak in recovery because investment income possibly decreased during the recession and recovered slowly afterwards.

Economic Structure

Economic structure refers to the industry composition, size and urbanization of the regional economy in this research. The Herfindahl-Hirschman index (HHI) is used to reflect diverse industrial structure $\mathbf{HHI} = \sum_{i=1}^{N} s_i^2$, where $\mathbf{s}_i$ is the employment share of industry i, and $\mathbf{N}$ is the number of industries. An HHI below 0.01 indicates a highly diversified industrial composition while an HHI above 0.25 indicates high concentration. The diversity of industry is also considered as Jacobs externalities because Jacobs (1969) concluded industrial diversity is key in employment growth. Augustine et al. (2013) include economic diversification measured by Herfindahl-Hirschman index in the regional economic capacity index, and expect counties with more concentrated economic activity will be more vulnerable. Therefore a high HHI representing low industrial diversity is hypothesized to increase *drop* and decrease *rebound*.

Total population, percentage of urban population and the Euclidean distance between the mean center of population within each county and its nearest urban areas with population greater than or equal to 50,000 are used to measure urbanization of the county. Urbanization is key in the process of development (Bairoch and Braider, 1991). Lucas (1988) and Romer (1986) showed human capital is important in economic development. Bertinelli and Black (2004) conclude urbanization encourages human capital accumulation and therefore becomes the engine of growth. However, a highly urbanized place might be vulnerable during the recession because of negative externalities of urbanization called congestion costs such as urban poverty, noise, and crime due to increased population and population densities. Congestion costs reduce productivity in urban areas (Broersma and van Dijk, 2008; Saito and Wu, 2016). Therefore the impact of all three urbanization variables, total population, percentage of urban population and distance to urban areas to *drop* and *rebound* is indeterminate. Table 10 summarizes the hypothesized effect of variables on *drop* and *rebound*. Hypothesized effect on *resilience* is not listed because *drop* and *rebound* can be affected differently by the same variables, it is unknown how the effect will combine.

Table 10 Variables and corresponding hypotheses

Variables	Description	Hypothesized signs	
		Drop	*Rebound*
Income distribution			
Gini coefficient in 2000		?	?
Poverty rate		?	?
% Aggregate income held by HH earning 200K or more		?	?
Capital stocks			
% persons with Bachelor's degree or higher	Human capital	-	+
%Total: 20 to 29 years		-	+
%Total: 30 to 49 years		?	?
%Female Civilian Labor Force Participation		+	+
Natural amenity scale	Natural capital	+	+
Social capital index 2005	Social capital	-	+
Median value All owner-occupied housing units	Built capital	-	?
Share of dividend, interest and rent	Financial capital	+	?
Economic Structure			
Herfindahl-Hirschman index		+	-
Total population		?	?
% urban population		?	?
Euclidian distance to the nearest urban areas with population >=50,000		?	?

Table 11 shows the summary statistics of the dependent variables and explanatory variables[19].

Table 11 Summary statistics

Variables	Obs	Mean	Std. Dev.	Min	Max	Unit	Data source
Drop, *rebound* and *resilience*							
Drop	2,771	0.186	0.115	-0.236	0.895		Wu estimates
rebound	2,771	0.006	0.009	0.000	0.303		based on 2003-
resilience	2,771	-0.005	0.997	-4.787	10.857		2014 BLS QCEW
Drop	2,742	0.187	0.115	-0.329	0.905		Han and Goetz
Rebound	2,742	0.035	0.055	0	2.199		(2015) estimates
Resilience	2,742	-0.004	0.998	-3.697	7.789		
Income Distribution							
Gini coefficient	2,771	0.433	0.037	0.333	0.586		Census 2000 P052
Atkinson's Index	2,771	0.163	0.027	0.099	0.303		
Theil's T index	2,771	0.351	0.074	0.194	0.835		
Coefficient of Variation	2,771	1.025	0.189	0.606	2.396		
Poverty rate	2,771	0.139	0.063	0.021	0.569	%	Census 2000 P087
% Aggregate income held by HH earning 200K or more	2,771	0.091	0.050	0.000	0.456	%	Census 2000 P054
Gini Coefficient using midpoint data	3,055	0.421	0.036	0.193	0.666		ACS 07-11 B19001
Gini Coefficient using individual data	3,143	0.433	0.036	0.200	0.671		ACS 07-11 B19083
Control Variables							
Population growth rate 2001 -2005	2,771	0.022	0.055	-0.203	0.428	%	BEA 2001-2005 CA5N
%Black or African American	2,771	0.084	0.139	0.000	0.865	%	Census 2000 SF1 QT-P3
%Hispanic or Latino	2,771	0.064	0.123	0.001	0.950	%	
Per capita income ($000)	2,771	17.606	3.919	5.213	44.962		Census 2000 SF3 P082
Capital Stocks							

[19] The following counties are deleted according to NBER so that there is a comprehensive and consistent data points across the three time periods: 02068 Denali Borough, Alaska, 02105 Hoonah-Angoon Census Area, Alaska, 02195 Petersburg Census Area, Alaska, 02198 Prince of Wales-Hyder Census Area, Alaska, 02201 Prince of Wales-Outer Ketchikan Census Area, Alaska, 02230 Skagway Municipality, Alaska, 02231 Skagway-Yakutat-Angoon Census Area, Alaska, 02232 Skagway-Hoonah-Angoon Census Area, Alaska, 02275 Wrangell City and Borough, Alaska, 02280 Wrangell-Petersburg Census Area, Alaska, 02282 Yakutat City and Borough, Alaska, 08014 Broomfield County, Colorado, 30113 Yellowstone National Park, Montana, 51780 South Boston city, Virginia, 51560 Clifton Forge, VA. 12025 Dade County, Florida is changed to 12086 Miami-Dade County, Florida

Table 11 (Continued)

Variables	Obs	Mean	Std. Dev.	Min	Max	Unit	Data source
% persons with Bachelor's degree or higher	2,771	0.167	0.077	0.049	0.602	%	Census 2000 SF3 P037
%Total: 20 to 29 years	2,771	0.118	0.034	0.042	0.346	%	Census 2000 P012
%Total: 30 to 49 years	2,771	0.288	0.026	0.158	0.412	%	
%Female Civilian Labor Force Participation	2,771	0.550	0.064	0.346	0.809	%	Census 2000 SF3 QT-P24
Natural amenity scale	2,771	0.084	2.329	-6.400	11.170		1999 USDA- ERS Natural Amenity Index
Social capital index 2005	2,771	-0.001	1.374	-3.784	14.379		Rupasingha, Goetz and Freshwater, 2006
Median value All owner-occupied housing units	2,771	82.036	42.630	22.500	583.500	$	Census 2000 H085
Share of dividend, interest and rent	2,771	0.189	0.053	0.081	0.561	%	2000 BEA CA5
Economic Structure							
Herfindahl-Hirschman index	2,771	0.107	0.044	0.022	0.789		BEA 2001 CA25N
Total population	2,771	0.096	0.306	0.000	9.519		Census 2000 SF1 P001
% urban population	2,771	0.406	0.307	0.000	1.000		Census 2000 SF1, P002
Euclidian distance of the mean center of population to the nearest urban areas with pop >=50,000	2,771	0.592	0.652	0.000	4.122		Calculated using total population at block group level in GIS

Note: ACS- American Community Survey, BEA- Bureau of Economic Analysis, BLS- Bureau of Labor Statistics, ERS-Economic Research Service, QCEW-Quarterly Census of Employment and Wages.

Methodology

Differences in *drop*, *rebound* and *resilience* are expected to be related to the variation of the regional characteristics represented by income distribution, control variables, capital stocks and economic structure. To examine the sources of difference, ordinary least square regression will be used, especially to test the role of income distribution. The Great Recession officially lasted from December 2007 to July 2009, so the pre-recession Gini coefficient, poverty rate, and share of aggregate income held by households earning $200,000 or more at year 2000 will be used. Since *drop* and *rebound* are two components of *economic resilience* which represent *resistance* and *rebound* of an economy separately, they might be impacted differently, while there also might be different factors affecting them both. So I will run the regression to see how income distribution and other explanatory variables contribute to *drop*, *rebound* and *resilience*. To separate the effect of capital stocks from the effect of economic structure on *drop*, *rebound* and *resilience*, besides running the full model (see Equation (3)), the capital stocks model and the economic structure model are developed (see Equation (1) and Equation (2)). In Equation (1) (2) and (3), *drop*, *rebound* and *resilience* for the U.S counties are written in general form for county i:

$$(\mathbf{1})\boldsymbol{y_i} = \boldsymbol{f}(\boldsymbol{Income\ distribution_i}, \boldsymbol{Control_i}, \boldsymbol{Capital\ Stocks_i}) + \boldsymbol{\varepsilon_{1,i}}$$

$$(\mathbf{2})\boldsymbol{y_i} = \boldsymbol{f}(\boldsymbol{Income\ distribution_i}, \boldsymbol{Control_i}, \boldsymbol{Economic\ Structure_i}) + \boldsymbol{\varepsilon_{2,i}}$$

$$(\mathbf{3})\boldsymbol{y_i} = \boldsymbol{f}(\boldsymbol{Income\ distribution_i}, \boldsymbol{Control_i}, \boldsymbol{Capital\ Stocks_i}, \boldsymbol{Economic\ Structure_i}) + \boldsymbol{\varepsilon_{3,i}}$$

where $\boldsymbol{f}(\cdot)$ is a linear function. $\boldsymbol{y}_{\,i}$ could be $\boldsymbol{drop_i}/\boldsymbol{rebound_i}/\boldsymbol{resilience_i}$.

$\boldsymbol{Income\ distribution}$ includes the Gini coefficient, poverty rate, and share of aggregate income held by households earning $200,000 or more. $\boldsymbol{Control}$ is a vector of population growth rate, percentage of Black or African American population and percentage of Hispanic or Latino population. $\boldsymbol{Capital\ Stocks}$ is a vector of variables representing the five capital stocks (human capital, natural capital, social capital, built capital and financial capital) within county i. $\boldsymbol{Economic\ Structure}$ vector includes four measures of sector composition and agglomeration economies. The error term $\boldsymbol{\varepsilon}$ represents the effect of variables omitted from the model.

Chapter 4 Results

Introduction

This chapter examines how income inequality may affect economic resilience in a model that includes capital stocks and economic structure. This study aims to understand a county's resilience during the Great Recession, considering both employment loss and recovery. Adopting Han and Goetz (2015) measures, $drop$ is the ability to resist and absorb a recessionary shock and is calculated as the percentage of difference between a county's actual employment and expected employment at the lowest level of employment during a recession, or the trough. $Rebound$ is the ability to bounce back from the shock and reorient to a new growth path after the recession. It is calculated as the velocity of change of employment during the six months after the lowest employment. Combining $drop$ and $rebound$, a standard score of logarithm of ratio of $rebound$ and $drop$ is developed to measure $economic\ resilience$. Although $drop$ and $rebound$ are two different dimensions of regional *economic resilience* and are hypothesized to be affected by different factors, there might be some variables that affect both $drop$ and $rebound.$ A county can achieve *economic resilience* in a number of ways. A county with either a low *drop* or a high *rebound*, holding other factors unchanged, could be considered resilient. A county whose positive *rebound* is larger than the negative *drop* can also be resilient. Therefore, besides running models with $drop$ and $rebound$ separately, the full concept, $economic\ resilience$, is also used as a dependent variable.

Three variables, the Gini coefficient, poverty rate and share of aggregate income held by households earning $200,000 or more are used as measures of income inequality and income distribution. I test how these income distribution variables contribute to *economic resilience*. A simple bivariate ordinary least squares regression between all three income distribution variables and the *drop*, *rebound* and *economic resilience* measures reveals shared covariance. This analysis is followed by three simple OLS regressions that trace the covariance between each component of resiliency with all three income distribution variables to identify the extent to which different segments of the income distribution independently vary with the concept and components of resiliency.

The Relationship between Income Inequality and Economic Resilience

Table 12 Relationship between economic resilience, drop, rebound and distributional variables (individual)

	(1) *Drop*	(2) *Rebound*	(3) *resilience*	(4) *drop*	(5) *rebound*	(6) *resilience*	(7) *drop*	(8) *rebound*	(9) *resilience*
Gini coefficient in 2000	0.225** (3.23)	0.0159** (2.83)	1.093* (1.98)						
Poverty Rate				0.255*** (6.85)	0.0178*** (8.23)	2.336*** (7.53)			
% Aggregate income held by HH earning 200K or more							-0.127** (-2.59)	-0.0105 (-1.64)	-2.752*** (-6.17)
Intercept	0.0883** (2.94)	-0.00109 (-0.45)	-0.479* (-2.02)	0.150*** (29.12)	0.00334*** (10.85)	-0.330*** (-7.30)	0.198*** (38.56)	0.00682*** (10.76)	0.251*** (5.88)
N	2771	2771	2771	2771	2771	2771	2838	2838	2838
R^2	0.005	0.004	0.002	0.019	0.016	0.022	0.003	0.003	0.019

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12 contains the results of the bivariate OLS regressions. The Gini coefficient and poverty rate are significant and positively related with *drop*, *rebound* and *economic resilience.* Results suggest that income inequality and low income people would increase employment loss, and increase employment recovery. The share of aggregate income held by households earning $200,000 or more is significant and negatively related with *drop* and *economic resilience, indicating* wealth concentrated among the rich people would decrease employment loss but decrease the overall *economic resilience* at the same time. This needs further investigation. The economic resiliency results show the contributions of Gini coefficient and poverty rate to recovery overcome their negative effect on employment loss, leading to a higher economic *resilience*. Moreover, the Gini coefficient has a 0.721 correlation with the poverty rate and 0.520 with share of aggregate income held by households earning $200,000 or more across all US counties in the year 2000. The same signs of the Gini coefficient and the poverty rate for *drop*, *rebound* and *resilience* in Table 12 confirm the high correlation between the two income distribution variables. Each variable alone accounts for a small percentage in the variation of how many jobs a particular county lost, how quickly a particular county recovered and the overall *economic resilience* during the recession.

Table 13 Relationship between economic resilience, drop, rebound and income distribution variables (combined)

	(1) *drop*	(2) *rebound*	(3) *resilience*
Gini coefficient in 2000	-0.0149	0.00193	0.782
	(-0.09)	(0.16)	(0.64)
Poverty Rate	0.255**	0.0164**	1.835**
	(3.10)	(2.59)	(2.90)
% Aggregate income held by HH earning 200K or more	-0.0966	-0.00831	-2.718***
	(-1.23)	(-0.84)	(-4.01)
Intercept	0.166**	0.00345	-0.352
	(3.02)	(0.97)	(-0.86)
N	2771	2771	2771
R^2	0.021	0.018	0.036

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When the variables are combined in a regression, Table 13 shows only poverty rate remains significant and positive for *drop*, *rebound* and *economic resilience*. The share of aggregate income held by households earning $200,000 or more is significantly and negatively related to economic *resilience*. These results are consistent with the idea that it is the vulnerability of low-income people in a recession that explains the variation across counties in drop in jobs (the percentage of difference between the actual employment and expected employment at trough). The results are also consistent with the notion that the rigidity of basic consumption and support from government spending and private transfer payments could explain the most of the rate of employment change during six months after the trough. For the overall *economic resilience*, the positive sign of poverty rate shows its positive effect towards *drop* is smaller than the positive effect towards *rebound*, consistent with the hypothesis that the positive effect of basic consumption and government transfer incomes of low income people in local economy for employment recovery, outweighs the negative effect of their vulnerability to job losses. The rich contribute negatively to a county's overall *economic resilience*, and have a bigger effect than the percentage of people living in poverty, when looking at the magnitude and significance of the coefficients. This suggests that the local economy is more affected by less discretionary consumption and investment made by high-income people than the consumption and government transfer and spending of low income people.

In models including all the three income distribution variables, the interpretation of the Gini coefficient is complicated by the inclusion of the other variables and no longer simply represents an overall income inequality. The Gini coefficient may be capturing the importance of the size of middle class when poverty rate and share of aggregate income held by households earning $200,000 or more are controlled. But the significance of Gini coefficient is gone for *drop*, *rebound* and *resilience* when the two distributional variables are added, indicating it's more of the specific income bracket such as the poor or the rich or both, rather than the middle class, which explains county's employment loss, recovery and general *resilience*. Models in Tables 13 show higher adjusted R-squared compared to the models in Table 12, showing the Gini coefficient and share of aggregate income held by households earning $200,000 captures some variation although they are insignificant. Therefore, the two variables are still included in the following analysis. However, the R-squared are still low, 0.021 for *drop*, 0.018 for *rebound* and 0.036 for *resilience*, indicating there is a lot of variation left unexplained. Starting with this preliminary understanding of income inequality and resiliency I turn to a more complete set of OLS regression equations which examine the relationships between both a county's capital stocks and industry structure alone and combined with resiliency and its two dimensions.

Modeling Resilience as a Function of Income Inequality, Capital Stocks and Economic Structure

Table 13 has confirmed that a county's income distribution, primarily the poverty rate but also the share of aggregate income held by households earning $200,000 or more is related with *drop*, *rebound* and *economic resilience*. To figure out the role of income inequality, if any, in explaining *economic resilience*, and possible pathways through which inequality affects economic resilience (for example through the comprehensive assets of a county) I first run the ordinary least square model including the three distributional variables, four control variables and eight capital stock variables. *Drop*, *rebound* and *economic resilience* work as the dependent variables separately. Results show almost all three distributional variables are significant in explaining *drop*, *rebound* and *economic resilience* when controlling for capital stocks. The share of aggregate income held by households earning $200,000 or more is insignificant in explaining *rebound*.

Besides wealth accumulation among the forms of capital assets, economic structure via sector composition and urbanization is also expected to affect the regional resilience to the recession. The next set of regressions examines how income distribution together with economic structure contribute to economic resilience. Economic structure models in Table 14, 15 and 16 show only poverty rate is significant to predict *drop*. The significance of almost all the income distributional variables is absorbed by economic structure variables. The economic structure model has more explanatory power towards *drop*, *rebound* and *resilience* than the capital stock model.

Although economic structure variables explain a county's economic resilience better than the capital stocks model, variables in both models have significant explanatory power. Therefore all of the variables are included in a final full model. Full models in Table 14, 15 and 16 shows that, several capital stock variables remain significant although some of the variation explained by the capital stocks is captured by economic structure when all of the variables are combined. Therefore both capital stocks and economic structure are important to comprehend a county's economic resiliency. This research was motivated to understand the role of accumulation across the capital stocks. The exploration of the relationship between capital stocks and economic growth and development is a growing but limited area of research because of a lack of good measures for these concepts of additional forms of wealth. Some variation in capital stocks is captured by economic structure variables but the full model provides the best explanatory power. Therefore the discussion of results of the components of resiliency below will focus on the complete model. Partial models will be mentioned if variables change sign or lose significance.

Drop

Drop is the percent difference between the actual employment and expected employment at the trough during the Great Recession. The expected employment is calculated using a compound growth rate over three years before the peak employment month. Data for *drop* are available for 2,771 counties, where 33 counties have a negative *drop* indicating actual employment is larger than expected employment at trough. As the results in Table 13 discussed previously, when considering the relationships between *drop* and the three income distribution variables, only the poverty rate is positively related to *drop*. A county with more low-income people will have a larger deviation of actual employment from its original growth path during the recession. Since a lot of variation in *drop* is left unexplained, other explanatory variables such as control variables, regional capital stocks and economic structure are included in the regression.

Capital Stocks Model of Drop

Adding control variables and the capital stocks changes the relationship between *drop* and the three distributional variables (see Table 14). Now all three variables are significant when capital stocks

Table 14 Models for drop

Drop	Capital Stocks	Economic Structure	Full Model
	(1)	(2)	(3)
Gini coefficient in 2000	-0.562**	-0.0696	-0.356
	(-2.71)	(-0.38)	(-1.68)
Poverty rate	0.232*	0.0902	0.148
	(2.47)	(1.00)	(1.49)
% Aggregate income held by HH earning 200K or more	0.417**	0.124	0.178
	(3.14)	(0.98)	(1.34)
Population growth rate 2001 -2005	0.223***	0.329***	0.211***
	(4.08)	(6.62)	(3.79)
%Black or African American	0.0459*	0.0686**	0.0772***
	(2.02)	(3.21)	(3.48)
%Hispanic or Latino	-0.120***	0.0363	-0.0251
	(-5.62)	(1.73)	(-1.17)
Per capita income ($000)	-0.00556*	-0.000902	0.00174
	(-2.51)	(-0.64)	(0.78)
% persons with Bachelor's degree or higher	-0.232***		-0.182**
	(-3.39)		(-2.78)
%Total: 20 to 29 years	-0.341**		-0.0161
	(-3.15)		(-0.14)
%Total: 30 to 49 years	0.124		-0.0471
	(0.93)		(-0.36)
%Female Civilian Labor Force Participation	-0.0695		-0.0265
	(-1.01)		(-0.40)
Natural amenity scale	0.00825***		0.00887***
	(6.35)		(7.12)
Social capital index 2005	-0.00138		-0.00437
	(-0.47)		(-1.53)
Median value All owner-occupied housing units ($000)	0.0000377		-0.0000447
	(0.38)		(-0.44)
Share of dividend, interest and rent	0.168**		0.112
	(2.65)		(1.77)
Herfindahl-Hirschman index		0.197*	0.189*
		(2.19)	(2.01)
Total population (million)		-0.00794	-0.0134**
		(-1.68)	(-2.93)
% urban population		-0.132***	-0.119***
		(-13.78)	(-11.01)
Euclidian distance to the nearest urban areas with population >=50,000		-0.00369	-0.00300
		(-0.92)	(-0.67)
Intercept	0.501***	0.228**	0.336**
	(4.61)	(2.87)	(3.12)
N	2771	2771	2771
R^2	0.116	0.143	0.177

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

are controlled, the Gini coefficient is negative and poverty rate is positive while the share of aggregate income held by top earning households has reversed from negative to positive. Counties with a higher Gini coefficient and lower poverty rate will have less change between expected employment and actual employment at the trough month. The same relationships were present in Table 13 but not significant. A higher Gini coefficient may mean a larger size of middle class when poverty rate and share of aggregate income held by households earning $200,000 or more are controlled. Counties with a larger middle class may be more stable and equal in income distribution and may experience less employment loss during the Recession. This might explain the sign for the Gini coefficient changes from positive in Table 12 to negative in Table 14 for *drop*. When capital stocks are controlled, the Gini coefficient is significant and has the largest coefficient, probably showing the size of middle class is the most important to resist employment loss. This relationship goes away in the economic structure model and the full model. The share of income held by top earning households is positively related to the *drop* variable. It originally had a statistically significant and negative relationship with a county's total employment loss when considered alone, the significance disappeared but the sign remained negative when the Gini coefficient and poverty rate were added. Adding capital stock variables reverses the relationship, which is now statistically significant and positive. This positive sign suggests that actual employment would largely deviate from its original growth path in a county with more wealth concentrated in the wealthy due to negatively affected consumption and investment by decreased income.

Besides the distribution variables, the control variable and several capital stock variables have a statistically significant relationship with a county's ability to resist and absorb a recessionary shock measured by the *drop* variable. For the control variables, population growth rate, with the coefficient of 0.223, shows that a county with high population growth would suffer more employment loss, perhaps because there are many vulnerable jobs in an expanding economy. The percentage of Black or African American population with the coefficient of 0.0459, and the percentage of Hispanic or Latino population with the coefficient of -0.120, suggest that counties with higher share of Black or African American population will suffer more employment loss while counties with higher share of Hispanic or Latino population will lose fewer jobs. A possible interpretation could be that due to lingering racism in the American workforce, African American people might be more likely to be fired before Hispanic or Latino people. The negative coefficient of per capita income (in thousands of dollars), -0.00556, suggests that counties with higher per capita income would lose less employment during the recession. For capital stocks variables, the percentage of people between the ages of 20 to 29 in 2000 has the largest coefficient -0.341 among all the capital stock variables. The earliest trough employment month was September in 2006, then the people of this age group who stayed in the county were 26 to 35 in year 2006. The coefficient confirms the hypothesis that county with more people of age 26 to 35, will have less employment loss from expected employment. This may be because they are more adaptable in a company and willing to accept inferior jobs to support family because there is no saving to depend on. The second biggest factor is the percentage of population with a bachelor's degree of higher with a coefficient -0.232. This is consistent with the hypothesis that more education is related with more job opportunity and people with higher educational attainment are more likely employed with essential and stable jobs during the recession. The significant coefficient 0.168 of share of dividends, interest and rent confirms the previous hypothesized positive effect of decreased investment income on employment loss. People whose income is comprised with a larger share of investment income, which is likely decreased during the Great Recession, cut back on the discretionary spending and investment both local and external due to a tightened budget. Industries including services are therefore negatively impacted. Natural amenity scale positively contributes to the employment loss with the coefficient as 0.008 which confirms the hypothesis as well. There might be more recreation and vacation industries in counties with better environment quality. These counties may suffer more employment loss due to less discretionary spending. The R-squared increased from 0.021 to 0.116 in the capital stocks model. Capital stocks explain a relatively low percent of the total variation in the difference between expected employment and actual employment at the trough, therefore, the next regression examines the relationship between *drop*, income distributional variables and economic structure variables.

Economic Structure Model of Drop

When considering the economic structure model of *drop*, the introduction of economic structure variables in place of the capital asset variables change the significance of the income distributional variables again. The significance of the Gini coefficient, poverty rate and the share of aggregate income held by households earning $200, 000 or more is absorbed by the economic structure variables. For the control variables, population growth rate from 2001 to 2005, percentage of Black or African American population retain significance and the same signs as in capital stocks model. Higher value in Herfindahl-Hirschman index, measuring sector composition, reflects lower industrial diversity. The coefficient 0.197 confirms the result that counties with less diversified industries represented by higher HHI would be more vulnerable and lost more employment during the recession. The coefficient -0.132 of percentage of urban population suggests that counties with a higher percentage of urban population would lose fewer jobs.

Full Model of Drop

Full model includes both capital stocks and economic structure variables in one model because there might be variation for one set of variables not captured by the other. In the full model, population growth rate, the percentage of Black or African American people, percentage of population with bachelor's degree or higher, the natural amenity scale are still significant and share the same sign in the capital stocks model. The percentage of people in age 20 to 29 and the share of dividend, interest, and rent lose their significance. For economic structure variables, Herfindahl-Hirschman index and percentage of urban population remain significant and retain the same sign as in the economic structure model. Total population in millions gains significance. A negative sign of -0.0134 shows counties with more population will have a smaller drop from the expected growth path. Results show urbanization helps counties to resist and absorb the Great Recession.

None of the distribution variables are significant. Poverty rate, significant in previous models, increased total employment loss probably because low-income people tend to have low pay and temporary jobs, to be minorities, and to have lower education attainment. However, when per capita income, race, and educational attainment are controlled, poverty rate will lose significance because the variation is captured by the other variables. The percentage of people ages in 20 to 29 also loses significance once the type of jobs are controlled. Accounting for race, ethnicity and educational attainment, people are easily fired in a less diversified economy, no matter they are young or old in the Great Recession. The significance decreases of percentage of population with bachelor's degree or higher may partially lie in the industrial composition measured by HHI.

Combining capital stocks and economic structure variables increases the R-squared of the full model to 0.177, higher than either model.

Summary Conclusions for Drop

All the three income distribution variables are significant to explain the deviation of actual employment from expected employment in the capital stocks model. The significance of the three income distribution variables is gone in the economic structure model and full model when economic structure is added. The significant variables such as Herfindahl-Hirschman index measuring sectoral composition, total population and percentage of urban population measuring urbanization absorb the explanatory power of income distribution on employment loss. In the full model, a small part of the variation of a county's employment loss is explained.

Rebound

Rebound is the rate of change of recovered employment in the six months after the lowest employment. It represents the velocity of a county to either bounce back to its original equilibrium or adapt to a new equilibrium. Results in Table 13 show among all the three income distribution variables, only poverty rate is significant to *rebound*. There is a positive relationship between poverty rate and *rebound*, which suggests a county with more low-income people would have a higher velocity of recovery perhaps due to rigidity to basic consumption in local economy. The R-squared is only 0.018, which is relatively low. Therefore explanatory variables such as capital stocks, and economic structure are added to capture the variation of *rebound*. Since full model which includes both capital stocks and economic structure variables provides the best explanatory power, discussion will be focused on the results of the full model.

Full Model of Rebound

Full model includes both capital stock variables and economic structure variables and captures the highest percentage of total variation (see Table 15).

Table 15 Models for rebound

Rebound	Capital Stocks	Economic Structure	Full Model
	(1)	(2)	(3)
Gini coefficient in 2000	-0.0393*	-0.00257	-0.0202
	(-2.41)	(-0.15)	(-1.16)
Poverty rate	0.0256**	0.00882	0.0167
	(2.88)	(1.05)	(1.65)
% Aggregate income held by HH earning 200K or more	0.0283	0.00432	0.0108
	(1.93)	(0.27)	(0.69)
Population growth rate 2001 -2005	-0.00531	-0.00422	-0.00437
	(-1.54)	(-1.57)	(-1.25)
%Black or African American	-0.00124	0.000865	0.000908
	(-0.76)	(0.59)	(0.58)
%Hispanic or Latino	-0.00174	0.00512***	0.00426**
	(-1.09)	(3.32)	(2.66)
Per capita income ($000)	-0.000194	0.000113	0.000274
	(-1.01)	(0.81)	(1.31)

Table 15 (Continued)

rebound	Capital Stocks	Economic Structure	Full Model
% persons with Bachelor's degree or higher	-0.00599		-0.00287
	(-1.17)		(-0.61)
%Total: 20 to 29 years	-0.0111		0.00801
	(-1.23)		(0.97)
%Total: 30 to 49 years	0.0212*		0.00939
	(2.33)		(1.04)
%Female Civilian Labor Force Participation	-0.00505		-0.00284
	(-0.79)		(-0.46)
Natural amenity scale	0.000216		0.000241
	(1.68)		(1.82)
Social capital index 2005	0.000450*		0.000258
	(2.20)		(1.35)
Median value All owner-occupied housing units ($000)	-0.0000188*		-0.0000220**
	(-2.23)		(-2.58)
Share of dividend, interest and rent	0.00950		0.00411
	(1.52)		(0.76)
Herfindahl-Hirschman index		0.0203*	0.0192
		(1.98)	(1.87)
Total population (million)		-0.000661*	-0.000601
		(-1.98)	(-1.79)
% urban population		-0.00748***	-0.00741***
		(-8.58)	(-7.68)
Euclidian distance to the nearest urban areas with population >=50,000		0.000305	0.0000342
		(1.14)	(0.11)
Intercept	0.0191**	0.00375	0.00655
	(2.61)	(0.49)	(0.88)
N	2771	2771	2771
R^2	0.051	0.093	0.098

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the full model, all three income distribution variables are insignificant although the Gini coefficient and poverty rate are significant in the capital stocks model. In the capital stocks model, the Gini coefficient is negatively related to *rebound* while poverty rate is positively related. A higher Gini coefficient when poverty rate and share of aggregated income held by households earning $200, 000 are controlled may decrease *rebound.* If the Gini coefficient captures the size of middle class, a possible explanation may be that the middle class has less employment loss during the recession (coefficient of -0.562 in Table 14) and therefore not much recovery during the next six months after the trough. The positive sign of poverty rate suggests that Low-income people who received expanded benefits under the Unemployment Insurance program and the Supplemental Nutritional Aid Program will stably keep their non-discretionary spending on groceries and gas, most likely in local economy and increase the employment recovery. However, all these income distribution variables are not significant when economic structure variables are controlled. Economic structure variables capture the variation in the Gini coefficient and poverty rate.

Among the control variables, the percentage of Hispanic or Latino population is significant. The coefficient of 0.00426 suggests that counties with higher percentage of Hispanic or Latino population would recover faster. Among capital stock variables, median housing value (in thousands of dollars) is significant and negatively related to *rebound*. Counties with higher median housing value will recover less in six months after the trough month. High median housing value makes an area more expensive and less attractive to live in. High median housing value in 2000 may also signal that the area was primed for a housing price boom that busted in the recession, and dampened people's spending in the recovery. The coefficient -0.000022 shows every $1,000,000 increase in the median housing value will decrease *rebound* by 0.022. The percentage of people aged in 30 to 49 in 2000, and social capital index, lose significance compared to capital stocks model. In capital stocks model, the positive coefficient 0.0212 of percentage of people in age group 30 to 49 in 2000 is consistent with its hypothesized positive effect to the velocity of employment. People who were in their 30 to 49 in 2000 and stayed would be 36 to 55 in 2006[20].They are experienced and have seniority in their career, and therefore may have an easier time finding a job. Moreover, they might have savings, which would support both discretionary and non-discretionary spending in local economy. Social capital will weakly increase the employment recovery due to social networks helping to solve unemployment. The majority of the capital stocks have less significant and smaller coefficients than the income distribution variables, showing income

[20] The recovered month is six months after the tough (September 2006 as the earliest), hence 2006 would be the earliest year for counties starting recovery.

distribution variables have a larger effect on employment recovery. All these two capital stock variables, the Gini coefficient and poverty rate lose significance in the full model; the variations of income distribution variables and capital stock variables are absorbed by economic structure variables.

For economic structure variables, only the percentage of urban population is significant in the full model. Its coefficient of -0.00741 shows that counties with higher percentage of urban population would recover less after the recession. Herfindahl-Hirschman index is significant in the economic structure model with a positive coefficient 0.0203. This contradicts the hypothesis that lower industrial diversification represented by a higher HHI will decrease rebound. However, it lost significance in the full model.

Summary for Rebound

In the capital stocks model, the Gini coefficient and poverty rate are significant to explain the velocity of employment recovery during the six months after the trough. The coefficients for income distribution variables are more significant and larger in size than all control variables and the capital stocks. This suggests, the Gini coefficient, and poverty rate have a bigger effect on the rebound variable than capital stocks variables in capital stocks model. The significance of income distribution variables, control variables, and capital stock variables is partially captured by economic structure variables. Moreover, the R-square of the full model is 0.098, higher than 0.051 of the capital stocks model and 0.093 of the economic structure model. This shows economic structure variables explain more of the variation of rebound than capital stock variables. However, the full model of rebound is still capturing a small percentage of total variation and is less powerful than the drop model.

Resilience

Economic resilience, as the concept to combine resistance and recovery, is calculated as the standard score of logarithm of ratio of *rebound* and *drop*. A resilient system would be robust to the shock with a smaller *drop* or able to bounce back with a greater *rebound*. A county that experiences both a smaller *drop* and a greater *rebound* would be larger in *resilience* in the Great Recession.

Full Model of Resilience

Table 13 shows among the income distributional variables, poverty rate and the share of aggregate income held by households earning $200, 000 or more are significant to *resilience*. Poverty rate is positively related with *resilience*, showing its positive effect on *rebound* due to rigidity on basic spending and availability to be hired, outweighs the positive effect on *drop* due to vulnerability in job markets. Therefore a county with more people living in poverty would be more resilient. The share of aggregate income held by households earning $200,000 or more has a negative sign, showing income concentrated among the rich would reduce the county's *resilience*.

When controlling capital stocks, the Gini coefficient and poverty rate are significant. Poverty rate retains the same sign, while the Gini coefficient switches sign (see Table 16). A county with more people in poverty is more resilient. The negative sign of the Gini coefficient shows the negative effect to *rebound* overcomes the negative effect to *drop* therefore a higher Gini coefficient would lead to lower *resilience*. This probably suggests holding education and social capital constant, a larger middle class may indeed be more vulnerable to *drop*, less able to *rebound* and less resilient. Nevertheless, the Gini coefficient and poverty rate lose significance in economic structure model or the full model.

Table 16 Models for resilience

resilience	Capital Stocks	Economic Structure	Full Model
	(1)	(2)	(3)
Gini coefficient in 2000	-3.832^{*}	-2.541^{*}	-2.621
	(-2.41)	(-1.96)	(-1.75)
Poverty rate	2.225^{**}	1.283	1.588
	(2.72)	(1.83)	(1.91)
% Aggregate income held by HH earning 200K or more	3.451^{**}	1.494	1.610
	(3.28)	(1.53)	(1.59)

Table 16 (Continued)

Resilience	Capital Stocks	Economic Structure	Full Model
Population growth rate 2001 -2005	-0.248	-0.885*	-0.386
	(-0.60)	(-2.49)	(-0.99)
%Black or African American	-0.304	0.0664	0.0372
	(-1.65)	(0.39)	(0.20)
%Hispanic or Latino	0.00968	0.613**	0.758***
	(0.05)	(3.23)	(3.75)
Per capita income ($000)	-0.0759***	-0.00941	-0.00728
	(-3.94)	(-0.79)	(-0.38)
% persons with Bachelor's degree or higher	-0.318		-0.0105
	(-0.56)		(-0.02)
%Total: 20 to 29 years	-3.129**		0.161
	(-3.23)		(0.17)
%Total: 30 to 49 years	2.516*		1.187
	(2.34)		(1.13)
%Female Civilian Labor Force Participation	-0.742		-0.652
	(-1.28)		(-1.16)
Natural amenity scale	-0.0274*		-0.0247*
	(-2.16)		(-2.07)
Social capital index 2005	0.0763***		0.0291
	(3.65)		(1.39)
Median value All owner-occupied housing units	0.000154		-0.000317
($000)	(0.16)		(-0.34)
Share of dividend, interest and rent	0.817		0.169
	(1.50)		(0.34)
Herfindahl-Hirschman index		0.308	0.382
		(0.46)	(0.57)
Total population (million)		-0.294***	-0.276***
		(-5.09)	(-4.80)
% urban population		-0.944***	-0.908***
		(-12.18)	(-10.43)
Euclidian distance to the nearest urban areas with		0.125***	0.115**
population >=50,000		(4.02)	(3.28)
Intercept	2.338**	1.225*	1.129
	(2.91)	(2.19)	(1.51)
N	2771	2771	2771
R^2	0.109	0.162	0.166

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Among control variables, percentage of Hispanic or Latino people gains significance. Counties with higher percentage of Hispanic or Latino people are more resilient probably because these counties have a high *rebound* (see Table 16). For capital stocks variables, natural amenity scale gains significance in the full model. Its negative sign to *resilience* might come from its significant positive effect on *drop*. A place with good environmental quality is hypothesized to experience a large employment deviation from expected employment path because of decrease in discretionary consumption on vacation and recreation. The significant variables in capital stocks model such as per capita income (in thousands of dollars), percentage of Black or African American, percentage of people aged 20 to 29 in 2000, percentage of people aged 30 to 49 in 2000, social capital index, lose significance when controlling for economic structure variables. The variation in control variables and capital stock variables appears to be captured by economic structure variables.

For economic structure variables, total population in millions and percentage of urban population are both significant and negatively related to *resilience.* The Euclidean distance between the mean center of population within each county and its nearest urban areas with population greater than or equal to 50,000 is significant and positively related with resilience. These three variables represent urbanization. A possible explanation could be that negative externalities due to increased population and population density retard resilience while integration with urban areas increases resilience. However, total population significantly decreases *drop* while insignificantly explains *rebound*, the negative effect on *economic resilience* is inconsistent with the findings about *drop* and *rebound*. The R-squared for the full model is 0.166, higher than both capital stocks model of 0.109 and economic structure model of 0.162. However, this shows capital stocks add little explanatory power to *economic resilience*.

Summary for Resilience

The Gini coefficient, poverty rate, and the share of aggregate income held by households earning $200,000 or more are not significant in the full model of *resilience*. The control variable, percentage of Hispanic or Latino population is significant. All capital stock variables but natural amenity scale are insignificant in the full model. Variables representing urbanization among economic structure variables, total population, percentage of urban population and distance to nearest urban areas with population no less than 50,000, appear to capture the variation of income distribution variables and capital stock variables to explain *resilience*. Because *economic resilience* can be achieved in several ways, *economic resilience*, combining *rebound* and *drop* by using a standard score of logarithm of ratio e *rebound* and *drop*, makes it difficult to explain what affects the *economic resilience* and how. Analysis of the effects of each variable should depend on previous results of *drop* and *rebound*. *Drop* (resistance) and *rebound* (recovery) should be treated as two different dimensions in attempting to explain the complex concept of *resilience*.

Robustness Check and Sensitivity Test

Robustness Check for Heteroscedasticity and Multicollinearity

I detected that heteroscedasticity of residuals exist in models of *drop* and *rebound* using Breusch-Pagan Test and White's general test. Therefore I use robust standard errors to deal with heteroscedasticity in each model for *drop*, *rebound* and *resilience*. Variance inflation factor (VIF) is used to check for multicollinearity. Tolerance, defined as 1/VIF, is used to check on the degree of collinearity. As a rule of thumb, a variable whose VIF values are greater than 10 are worrisome. A tolerance value smaller than 0.1 is comparable to a VIF larger than 10. The multicollinearity check shows the per capita income (in thousands of dollars) with the VIF as 15.23 and tolerance as 0.0656 in the full model of *drop*, *rebound* and *resilience*, indicating that the per capita income (in thousands of dollars) could be considered as a linear combination of other independent variables. However, other significant variables retain significance[21] and similar coefficients[22] when the per capita income (in thousands of dollars) is

[21] When the per capita income ($000) is removed: share of aggregate income held by households earning $200,000 or more is insignificant in the full model of *drop*; poverty rate is insignificant while share of aggregate income held by households earning $200,000 is significant in the full model of *rebound*. Median housing value is less significant (** to *) in the full model of *rebound.*

[22] Most of the coefficients of significant variables change slightly in magnitude when per capita income ($000) is removed.

removed in the full model of *drop*, *rebound* and *resilience*. Therefore the multicollinearity of the per capita income (in thousands of dollars) doesn't quite affect the results and will be kept in the full models.

Sensitivity Test

This research also tested two relationships using robust standard errors. First, there are several measures of income inequality. According to previous literature, the four income inequality measures are different from each other, especially in the transfer sensitivity. The Gini coefficient is most sensitive to transfers around the middle of distribution and least sensitive at the extremes. Theil's T index attaches more weight to the lower end of income distribution while the Atkinson Index with degree of inequality aversion $\varepsilon = 0.5$.is more sensitive to the higher end. The Coefficient of Variation is equally sensitive to transfers at all income levels. I test whether the measure of income inequality affect the regression results.

Secondly, the measure for *economic resilience*, *drop* and *rebound*, is calculated following the recently published paper by Han and Goetz (2015), but using more recent data, updated ARIMA X-13 SEATS to adjust for seasonal effect. I will test for differences between my calculations (Wu estimates) and the published estimates from the original authors.

Test 1 Gini Coefficient and Other Three Income Inequality Measurements

Robustness tests were performed on the full model to confirm that the results won't change when a different measure of income inequality is used. The full models for *drop*, *rebound* and *resilience*, using Atkinson Index, Theil's T index and Coefficient of Variation separately, report consistent coefficients and P values for significant variables compared to Gini Coefficient 2000. Results show that the other three measure of income inequality behave in a similar way as the Gini coefficient. All the income inequality measures are not significant to predict *drop*, *rebound*, and *economic resilience* in the full model. The other significant variables show the similar coefficients and same significance no matter which measure is used. Hence the regression results are not affected by the measure of income inequality. Table 17 shows the results comparison of full model of *drop*, full model of *rebound* and *resilience* reports similar results.

Table 17 Results of full model of drop using different income inequality measures

drop	(1)	(2)	(3)	(4)
Gini coefficient in 2000	-0.356			
	(-1.68)			
Atkinson Index in 2000		-0.182		
		(-0.64)		
Theil's T index in 2000			0.0443	
			(0.43)	
Coefficient of Variation in 2000				0.0169
				(0.58)
Poverty rate	0.148	0.0759	0.0197	0.0293
	(1.49)	(0.80)	(0.22)	(0.36)
% Aggregate income held by HH earning 200K or more	0.178 (1.34)	0.0797 (0.57)	-0.0544 (-0.36)	-0.0594 (-0.46)
Population growth rate 2001 -2005	0.211***	0.220***	0.228***	0.228***
	(3.79)	(4.01)	(4.19)	(4.23)
%Black or African American	0.0772***	0.0742***	0.0719**	0.0735***
	(3.48)	(3.33)	(3.27)	(3.34)
%Hispanic or Latino	-0.0251	-0.0198	-0.0147	-0.0143
	(-1.17)	(-0.93)	(-0.69)	(-0.68)
Per capita income ($000)	0.00174	0.00175	0.00209	0.00226
	(0.78)	(0.77)	(0.90)	(0.96)
% persons with Bachelor's degree or higher	-0.182**	-0.187**	-0.182**	-0.180**
	(-2.78)	(-2.87)	(-2.78)	(-2.74)
%Total: 20 to 29 years	-0.0161	-0.0406	-0.0629	-0.0589
	(-0.14)	(-0.35)	(-0.56)	(-0.53)
%Total: 30 to 49 years	-0.0471	-0.0383	-0.0309	-0.0301
	(-0.36)	(-0.29)	(-0.24)	(-0.23)
%Female Civilian Labor Force Participation	-0.0265	-0.00287	0.00926	0.00629
	(-0.40)	(-0.04)	(0.14)	(0.10)
Natural amenity scale	0.00887***	0.00852***	0.00821***	0.00823***
	(7.12)	(6.90)	(6.67)	(6.73)
Social capital index 2005	-0.00437	-0.00465	-0.00499	-0.00496
	(-1.53)	(-1.61)	(-1.73)	(-1.71)
Median value All owner-occupied housing units ($000)	-0.0000447 (-0.44)	-0.00000453 (-0.05)	0.0000376 (0.38)	0.0000370 (0.39)
Share of dividend, interest and rent	0.112	0.106	0.103	0.105
	(1.77)	(1.68)	(1.65)	(1.68)

Table 17 (Continued)

drop	(1)	(2)	(3)	(4)
Herfindahl-Hirschman index	0.189*	0.204*	0.217*	0.216*
	(2.01)	(2.22)	(2.40)	(2.42)
Total population (million)	-0.0134**	-0.0134**	-0.0130**	-0.0129**
	(-2.93)	(-2.94)	(-2.88)	(-2.84)
% urban population	-0.119***	-0.120***	-0.119***	-0.119***
	(-11.01)	(-11.00)	(-10.93)	(-10.94)
Euclidian distance to the nearest urban areas	-0.00300	-0.00278	-0.00243	-0.00243
with population >=50,000	(-0.67)	(-0.62)	(-0.55)	(-0.55)
Intercept	0.336**	0.215**	0.172*	0.166*
	(3.12)	(2.92)	(2.46)	(2.38)
N	2771	2771	2771	2771
R^2	0.177	0.176	0.176	0.176

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Test 2 Resilience Calculated by Han and Goetz

Wu estimates following Han and Goetz (2015) method are different from the original Han/Goetz published estimates. According to Table 9 (Comparison of *drop*, *rebound* and *resilience*) in Chapter 3 and Table 11 (Summary statistics), Wu estimates and Han and Goetz estimates for *drop* are similar in the mean, standard deviation and value range, while the two estimates for *rebound* and *resilience* show much difference.

Using Han and Goetz estimates in the full model of *drop* shows similar results as in the full model using the Wu estimates (see Table 18). Share of dividends, interest and rent gains significance when Han and Goetz estimates are used. Other significant variables are the same in significance but varies in coefficients. For the full model of *rebound* and *resilience*, there are more disagreements, both in significance and the corresponding coefficients.

In the full model of *rebound*, poverty rate and natural amenity scale gains significance using Han and Goetz estimates. Other significant variables are similar in significance but coefficients are larger in size when Han and Goetz estimates are used. This might come from different value ranges of the Wu estimate and Han and Goetz estimate for *rebound*. Han and Goetz estimate for *rebound* for 2,836 counties range from 0.000 to 2.199 with a 0.035 mean and a 0.055 standard deviation, while the Wu estimate for 2,840 counties range from 0.000 to 0.303 with a 0.006 mean and a 0.009 standard deviation. In the regression, Han and Goetz estimate for *rebound* for 2,742 counties and Wu estimates for 2, 771 counties are the same in range, mean and standard deviation rounded to 3 digits. The value range of *rebound* for the Han and Goetz estimates is larger than for Wu estimates, therefore the coefficients of significant variables are larger in size.

In the full model of *resilience*, the Gini coefficient, and poverty rate, gain significance while natural amenity scale loses significance when Han and Goetz estimates are used. The Euclidean distance between the mean center of population within each county and its nearest urban areas with population greater than or equal to 50,000 increase significance from 0.115** to 0.161*** when Han and Goetz estimates are used. Other significant variables are similar in significance but different in size of coefficients because Wu estimates, which range from -4.787 to 10.857, are different from Han and Goetz estimates (range from-5.215 to 9.680 for 2,836 counties while -3.697 to 7.789 for 2,742 counties in the regression[23]) for *resilience* in the value range.

Summary for Robustness Check and Sensitivity Test

Regressions with robust standard errors deal with the heteroscedasticity. Multicollinearity of the Gini coefficient in full models of *drop*, *rebound* and *resilience* does not affect the regression results much. Different income inequality measures do not affect the results, indicating Coefficient of Variation, Atkinson Index, and Theil's T index behave in a similar way with the Gini coefficient. The difference in transfer sensitivity doesn't affect the results, possibly because changes of income inequality over time are not examined here. Sensitivity test using original published estimates of Han and Goetz (2015) show little difference in full model of *drop* but several differences in full model of *rebound* and *resilience*. Full

[23] Han and Goetz estimates for *resilience* are available for 2836 counties with the range of -5.215 to 9.680. When merged with the other explanatory variables, there are only 2742 counties left with the range of -3.697 to 7.789.

model of *rebound* shows the largest difference probably because Wu estimates for *rebound* has a much smaller value range than Han and Goetz estimates, while Wu estimates for *resilience* have a larger value range. Wu estimates for *drop* are almost the same compared to the Han and Goetz estimates. Details about the calculation of measurements in Han and Goetz (2015) are not fully disclosed in their published paper. Calculation for Wu estimates could be refined.

Table 18 Sensitivity test using Wu estimates and Han and Goetz estimates

	drop		*rebound*		*resilience*	
	(1)	(2)	(3)	(4)	(5)	(6)
	Wu estimates	Han and Goetz estimates	Wu estimates	Han and Goetz estimates	Wu estimates	Han and Goetz estimates
Gini coefficient in 2000	-0.356	-0.281	-0.0202	-0.0927	-2.621	-2.964*
	(-1.68)	(-1.32)	(-1.16)	(-0.85)	(-1.75)	(-1.99)
Poverty rate	0.148	0.170	0.0167	0.126*	1.588	2.044*
	(1.49)	(1.68)	(1.65)	(2.28)	(1.91)	(2.56)
% Aggregate income held by HH earning 200K or more	0.178	0.0699	0.0108	-0.00704	1.610	1.394
	(1.34)	(0.51)	(0.69)	(-0.07)	(1.59)	(1.43)
Population growth rate 2001 -2005	0.211***	0.239***	-0.00437	-0.0212	-0.386	-0.740
	(3.79)	(3.93)	(-1.25)	(-0.93)	(-0.99)	(-1.77)
%Black or African American	0.0772***	0.0673**	0.000908	0.00723	0.0372	0.0481
	(3.48)	(3.02)	(0.58)	(0.78)	(0.20)	(0.27)
%Hispanic or Latino	-0.0251	-0.0220	0.00426**	0.0262**	0.758***	0.817***
	(-1.17)	(-0.98)	(2.66)	(2.81)	(3.75)	(4.25)
Per capita income ($000)	0.00174	0.00346	0.000274	0.00271	-0.00728	0.0111
	(0.78)	(1.33)	(1.31)	(1.75)	(-0.38)	(0.59)
% persons with Bachelor's degree or higher	-0.182**	-0.240**	-0.00287	-0.0341	-0.0105	0.316
	(-2.78)	(-2.87)	(-0.61)	(-0.82)	(-0.02)	(0.57)
%Total: 20 to 29 years	-0.0161	-0.0241	0.00801	0.0332	0.161	0.0486
	(-0.14)	(-0.19)	(0.97)	(0.62)	(0.17)	(0.05)
%Total: 30 to 49 years	-0.0471	-0.0125	0.00939	0.0463	1.187	0.477
	(-0.36)	(-0.09)	(1.04)	(0.77)	(1.13)	(0.42)
%Female Civilian Labor Force Participation	-0.0265	0.00971	-0.00284	0.00669	-0.652	-0.452
	(-0.40)	(0.14)	(-0.46)	(0.20)	(-1.16)	(-0.80)
Natural amenity scale	0.00887***	0.00944***	0.000241	0.00186*	-0.0247*	-0.0169
	(7.12)	(6.74)	(1.82)	(2.25)	(-2.07)	(-1.44)
Social capital index 2005	-0.00437	-0.00341	0.000258	0.00232	0.0291	0.00952
	(-1.53)	(-0.89)	(1.35)	(1.17)	(1.39)	(0.41)

Table 18 (Continued)

	drop		*rebound*		*resilience*	
	(1) Wu estimates	(2) Han and Goetz estimates	(3) Wu estimates	(4) Han and Goetz estimates	(5) Wu estimates	(6) Han and Goetz estimates
Median value All owner-occupied housing units ($000)	-0.0000447	-0.0000700	-0.0000220**	-0.000148**	-0.000317	-0.00116
	(-0.44)	(-0.61)	(-2.58)	(-2.68)	(-0.34)	(-1.13)
Share of dividend, interest and rent	0.112	0.159*	0.00411	0.0249	0.169	-0.151
	(1.77)	(2.36)	(0.76)	(0.83)	(0.34)	(-0.30)
Herfindahl-Hirschman index	0.189*	0.222*	0.0192	0.131	0.382	0.719
	(2.01)	(2.28)	(1.87)	(1.85)	(0.57)	(1.12)
Total population (million)	-0.0134**	-0.0109**	-0.000601	-0.00264	-0.276***	-0.281***
	(-2.93)	(-2.61)	(-1.79)	(-1.27)	(-4.80)	(-3.92)
% urban population	-0.119***	-0.121***	-0.00741***	-0.0436***	-0.908***	-1.026***
	(-11.01)	(-11.37)	(-7.68)	(-8.14)	(-10.43)	(-11.87)
Euclidian distance to the nearest urban areas with population >=50,000	-0.00300	-0.00268	0.0000342	0.000659	0.115**	0.161***
	(-0.67)	(-0.56)	(0.11)	(0.36)	(3.28)	(4.53)
Intercept	0.336**	0.252*	0.00655	0.00397	1.129	1.082
	(3.12)	(2.11)	(0.88)	(0.07)	(1.51)	(1.41)
N	2771	2742	2771	2742	2771	2742
R^2	0.177	0.184	0.098	0.093	0.166	0.192

Note: *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

Chapter 5 Conclusions

Summary

U.S. counties reacted differently to the broader macroeconomic events in the Great Recession. *Economic resilience* is a general concept combining the region's capacity to recover and robustness towards the shock, measured through the ratio of the velocity of employment recovery using a "*rebound*" variable and the initial percentage of jobs loss with a "*drop*" variable. There are benefits to having a single measure that captures the overall performance of a county in and after the recession. At the same time, it is complicated to analyze *economic resilience* of a county due to the interaction between the *drop* variable and the *rebound* variable. A resilient county could be a county with a smaller *drop* or a greater *rebound* or both. For a clear insight of what contributes to the *economic resilience*, there is an advantage to treating *drop* and *rebound* as two different parts and analyzed separately. Table 20 summarizes the expected and actual signs of each explanatory variable's effect on *resilience*, combining two different dimensions, and on *drop* and *rebound*, which disentangles the effect of each explanatory variable on *drop* and *rebound* separately.

Table 19 Hypothesized and actual signs of variables to drop, rebound and resilience

	Drop		*Rebound*		*Resilience*
Sign	Expected	Actual	Expected	Actual	Actual
Gini in 2000	?		?		
Poverty rate	?		?		
% Aggregate income held by HH earning 200K or more	?		?		
Control Variables					
Population growth rate 2001 -2005		+			
%Black or African American		+			
%Hispanic or Latino				+	+
Per capita income					
Capital Stocks					
% persons with Bachelor's degree or higher	-	-	+		
%Total: 20 to 29 years	-		+		
%Total: 30 to 49 years	?		?		

Table 19 (Continued)

	Drop		*Rebound*		*Resilience*
Sign	Expected	Actual	Expected	Actual	Expected
%Female Civilian Labor Force Participation	+		+		
Natural amenity scale	+	+	+		-
Social capital index 2005	-		+		
Median value All owner-occupied housing units	-		?	-	
Share of dividend, interest and rent	+		?		
Economic Structure					
Herfindahl-Hirschman index	+	+	-		
Total population	?	-	?		-
% urban population	?	-	?	-	-
Euclidian distance to the nearest urban areas with population >=50,000	?		?		+

Note: The expected effects and the actual effects of income distribution variables are now based on the combined contribution. The Gini coefficient represents the size of middle class income category with the poverty rate and the share of aggregate income held by households earning $200,000 or more.

The three income distribution variables, the Gini coefficient, poverty rate, and the share of aggregate income held by households earning $200,000 or more, are not significant in any full models of *drop*, *rebound* and *resilience*. The variation of income distribution variables appears to be all captured once economic structure variables are added. However, there are several control variables, capital stock variables and economic structure variables significant to predict *drop*, *rebound* or *resilience*. Results in full model of *drop* show that counties with a lower population growth rate from 2001 to 2005, a lower percentage of Black or African American, a higher percentage of people with Bachelor’s degree or higher, a lower natural amenity scale, a lower Herfindahl-Hirschman index, a higher total population and a higher percentage with urban population would be more resistant and experience a low employment deviation from expected growth path during the Great Recession. Meanwhile, counties with a higher percentage of Hispanic or Latino population, a lower median housing value, and a lower percentage of urban population would be more able to recover and have a faster velocity of employment during the next six months after the lowest employment month.

Results show that during the Great Recession, although more variation of *drop*, *rebound* and *economic resilience* is captured by economic structure variables, several capital stock variables and economic structure variables are significant in the three full models. This suggests that educational attainment, total population, percentage of urban population can decrease a county's employment loss while Herfindahl-Hirschman index will increase the employment loss. This might offer some insights that local policies to promote college education, urbanization, and industrial diversification might help to slow future downturns. Counties' recovery velocity negatively depends on median housing value. This indicates that controlling median housing value might help with the recovery. Further investigation is needed for the three variables reflecting urbanization to understand the mechanism of how urbanization affects *drop*, *rebound* and *resilience.* The understanding of these variables could potentially yield lessons to both slow future downturns and boost recovery afterwards. However, all models show a low R-squared, indicating that there are missing key variables.

Limitations and Next Steps

Several important limitations in this research should be noted. The low adjusted R-squared for the models might come from invalid measurement for income inequality and economic resilience, or missing key variables. The Gini coefficient calculated using group midpoints data may underestimate the true level of income inequality for year 2000. Although the Gini coefficient calculated using individual household data is not available for previous decennial censuses, comparison of estimates of the Gini coefficient using individual and group data was shown for 2007-2011 using the American Community Survey (see Table 7 in Chapter 3). The first sensitivity test compares Gini Coefficient with other three income inequality measures (Coefficient of Variation, Theil's T index, and Atkinson's Index) in year 2000. Results show similarity among the measurements. Hence although the calculated income inequality measurements using group means introduce some measurement error, the regression results don't change across the four inequality measurements.

Regarding the economic resilience measures, Wu estimates are calculated following the recently published paper by Han and Goetz (2015) but using updated BLS monthly total employment data, and X-13 ARIMA-SEATS instead of X-12 ARIMA. Results using Wu estimates show differences from the original Han and Goetz estimates. The Gini coefficient become significant in predicting *resilience* and poverty rate become significant in predicting both *rebound* and *resilience* using Han and Goetz estimates but the rest of the significant variable results are similar[24]. Future exploration should refine the calculation methods for Wu estimates. Moreover, using six months used to calculate *rebound*, (the velocity of employment recovery) as Han and Goetz (2015) did due to data availability, might make *rebound* invalidly measured. Table 8 in Chapter 3 shows the average recession duration for all counties were 3.7 years where 4.9 years for 2006 peak-year counties and 2.3 years for 2010 peak-year counties. The average time period between the county's employment trough month and December 2014 is 3.9 years (about 46.7 months). Therefore, six months might be too short to measure recovery for some counties (especially the counties entering recession early) after the Great Recession. This possibly affects *resilience*, which is calculated as the standard score of logarithm of the ratio of *rebound* and *drop*. Future exploration should extend the time period to calculate *rebound*. Moreover, *rebound* is calculated involving the magnitude and time length/velocity of recovery while *drop* only includes the magnitude of loss. Economic resilience, combining the two measures inconsistent in dimensions might not be valid.

The effect of the natural amenity scale on *drop* or *resilience* could provide better information about the pathways for amenity effects if the scale were split into six measures of environmental quality: warm winter, winter sun, temperate summer, summer humidity, topographic variation and water area. Adjusted R-squared is low for *drop*, *rebound* and *economic resilience*, hence key variables should be found to explain the variation. There are some other explanatory variables that could be considered for

[24] When Han/Goetz estimates are used, share of dividends, interest and rent gains significance to predict *drop*. Poverty rate and natural amenity scale become significant in predicting *rebound*. The Gini coefficient, and poverty rate, gain significance while natural amenity scale loses significance to predict *resilience.*

inclusion in the models, such as patents number to represent accumulating knowledge to measure intellectual capital, road density as another measure of built capital, total deposits to measure financial capital. Rural-urban density typology developed by Isserman (2005) of should also be involved to see if the relationship between the explanatory variables and *drop*, *rebound*, and *resilience* will differ between rural, mixed rural, mixed urban and urban counties.

Only the relationship about whether income inequality affects economic resilience is tested here. Other relationships are plausible. Economic resilience might affect later income inequality and there might be a simultaneous relationship between income inequality and economic resilience. These are left untested. Five empirical papers (Levernier, Partridge and Rickman 1998a; Levernier, Partridge and Rickman 1998b; Peters 2011; Peters 2012; Peters 2013) take a labor market approach including individual demographic information and economic structure with spatial context to understand income inequality. The variables used to explain income inequality such as education attainment, civil female labor force participation rate, percentage of people in certain age group, percentage of minority, poverty rate, employment share of several industries, are used to explains *drop*, *rebound* or *resilience* together with the Gini coefficient in this research. This indicates the Gini coefficient might be endogenous, and the simultaneous relationship between income inequality and economic resilience would be the next step to test.

A preliminary spatial analysis not reported here shows evidence of spatial autocorrelation. There is more spatial clustering in income inequality than in *economic resilience* and its two components. However, *drop* is more clustered than *rebound*. Therefore, there is more spatial autocorrelation in income inequality than employment change represented by *drop*, *rebound* and *resilience*. Meanwhile there are more counties where employment loss is related to neighboring counties than counties where employment recovery is related to neighboring counties. To explore the spatial relationships, spatial regressions should be the future step (Fowler, 2011; Murack, 2013). Spatial lag models, which include a spatially lagged predictor, are used when it is expected that the dependent variable (*drop*, *rebound* or *resilience*) is influenced by neighboring values of the same variable. Equation (4) is the full model including spatially lagged dependent variable.

$$(4) y_i = f(Wy_i, Income\ distribution_i, Control_i, Capital\ Stocks_i, Economic\ Structure_i) + \varepsilon_{4,i}$$

where Wy_i is the spatially lagged dependent variable for weights matrix W.

This is used when the dependent variable is expected to be affected by neighboring independent variables. The spatial lag model accounting for spatial autocorrelation in the model with the weights matrix of independent variables is called spatial Durbin model (see Equation (5)).

$$(5) y_i = f(\ X_i + WX_i) + \varepsilon_{5,i}, where\ X$$
$$= (Income\ distribution_i, Control_i, Capital\ Stocks_i, Economic\ Structure_i)$$

When no theoretical reason supports that the dependent variable (*drop*, *rebound* and *resilience*) should be affected by neighboring dependent or independent variables, and spatial heterogeneity problem exists when relationships among the specified variables are stationary, spatial error model should be used. The error term ε_i is assumed to follow a spatially autocorrelated process instead of being independently identically distributed (i.i.d.). The spatial error model accounts for the autocorrelation in the error terms with the weight matrix (See Equation (6)).

$$(6) y_i = f(\ Income\ distribution_i, Control_i, Capital\ Stocks_i, Economic\ Structure_i) + \varepsilon_{3,i},$$

$$where\ \varepsilon_{3,i} = \lambda W \varepsilon_{3,i-1} + \upsilon_i\ (spatially\ autoregressive\ process),$$
$$or\ \varepsilon_{3,i} = \upsilon_i + \lambda W \upsilon_{i-1} (spatially\ moving\ average\ process)$$

Conclusions

My results show pre-recession income inequality and income distribution are not significant factors in explaining *economic resilience* or employment loss or employment recovery during the Great

Recession. Results show it is hard to analyze *economic resilience* when it is treated as a single concept combing *drop* and *rebound*, since *drop* and *rebound* are different processes which should be modeled separately. *Drop*, which refers to the percentage of employment loss during the Great Recession, is significantly explained by prerecession population growth rate, percentage of Black or African American population, educational attainment, natural amenity scale, Herfindahl-Hirschman index and percentage of urban population. Meanwhile, *rebound*, the velocity of employment recovery during six months after the trough month, depends on percentage of Hispanic or Latino population, median housing value and percentage of urban population. Income inequality might be endogenous. More work needs to be done to explore the relationship between income inequality and economic resilience.

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