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Income Inequality and County Economic Resistance to Job Loss during the Great Recession*

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Abstract: This paper examines the effects of income inequality on short-run changes in growth in the context of the most recent U.S. recession in both urban and rural counties. Resistance to job loss in the Great Recession is modeled as a function of local income inequality, controlling for community capital assets, and the size and structure of the local population and economy. Regression results suggest that the effect of local inequality on resilience depends on the size of a county's population. High inequality increases the recessionary employment drop in counties with large populations but reduces the employment drop in the smallest counties.

Keywords: Great Recession, income inequality, economic resilience, economic growth

JEL Codes: D3, E32, R11

1. INTRODUCTION

The depth of the U.S. recession dating December 2007 to June 2009 and the subsequent slow and uneven recovery across the U.S. has prompted substantial empirical inquiry into causal and coincident factors while renewing theoretical interest into economic resistance to external shocks. This paper was motivated by the work of Rajan (2010) who points to cumulative instabilities created by rising income inequality in the U.S., in what has been termed the 'Rajan hypothesis.' This paper explores the 'local Rajan hypothesis' that local income inequality may have been a factor explaining the depth of job loss during the Great Recession. Inequality in the distribution of income and wealth in the U.S. has increased

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substantially over the past several decades (Piketty, 2013; Stiglitz, 2012). The considerable variation in income inequality that exists across U.S. counties Peters (2013) has generated interest in whether local inequality may be related to local economic responses to the Great Recession.

To date, little work has been done to explore if income inequality affects resistance to economic decline, or short-term changes in the growth rate, the same way it affects long-run growth. Lewin et al. (2018) point to this sizable gap in the empirical examination of the Great Recession. Changes in the growth rate, they argue, can be understood as a second moment condition of economic growth. The literature on stability, also a second moment condition of 'the absence of variation in economic activity' (Malizia and Ke, 1993), contains some work examining the role of income inequality (Deller and Watson, 2016).

The recession has renewed interest in economic performance during business cycles; but rather than building on past literature (Martin, 2012), recent studies have focused on defining and measuring resilience. In this paper, we focus on examining how inequality levels affected the depth of a local recession, which is closer to economic stability and is only a partial understanding of resilience. Rising income inequality is increasing the need to better understand the role of income inequality on both long-term growth and short-term economic resistance to job loss and to identify policy implications (Partridge and Weinstein, 2013).

Income inequality may have different effects in the short-term compared to the long-term and in the specific context of national economic fragility. In a study of U.S. urban counties, counties with higher rates of income inequality entered the recession earlier (Lewin et al., 2018). These short-term results contradict previous fixed effects model results of a positive relationship between income inequality and growth (Li and Zou, 1998; Forbes, 2000), suggesting that income inequality can produce different results depending on macroeconomic conditions.

This paper contributes to the understanding of inequality and stability during a recession by extending the analysis in Lewin et al. (2018) for urban counties to the full U.S. and by choosing a different measure of resistance to job loss. Our results focus on the degree of job loss a county experienced entering the recession: its drop in employment. We do not examine the role of inequality in how a county recovers from a recession, nor do we address long-term effects of inequality on growth.

Examining all U.S. counties, we find that the effect of inequality on the depth of a local recession depends on the county's population size. Our results support the findings of Lewin et al. (2018): in urban areas higher income inequality worsens a county's experience during a recession. We also find support for the work of Fallah and Partridge (2007), as our results suggest that income inequality has a different and opposite effect in small population counties.

In the next section, we discuss how inequality might affect employment stability and review previous literature. We then present our measures of inequality and employment stability, describe the data, and outline the empirical model. This is followed by our results and a conclusion.

2. HOW INEQUALITY MIGHT AFFECT THE DEPTH OF JOB LOSS

The Rajan hypothesis proposes rising income inequality as one structural cause of the most recent recession. Inequality has been posited previously as a contributor to the Great Depression (Eccles, 1951; Galbraith, 1954). The Rajan hypothesis observes that income in the U.S. has become increasingly concentrated among the highest income groups, leading low- and middle-income households to finance consumption by taking on more credit.

As the amount of capital U.S. consumers borrowed increased to maintain consumption levels, capital markets became unstable. As much of the debt-financed consumption was for imported goods and services, the productive capacity of the domestic economy was not stretched, limiting the upward pressure on prices that would have triggered increases in interest rates and dampened the debt-financed consumption (van Treeck and Sturn, 2012). Therefore, rising income inequality created excess demand for borrowed capital. When the housing market turned down and the subprime mortgage crisis began in 2007, debt-financed consumer spending declined and triggered a larger economic downturn in the U.S. that spread to affect economies around the globe (Rajan, 2010).

Both government policies and changes in social norms led to the increased debt-financing of consumption prior to the recession. Government policies encouraged the subsidization of low-income households and deregulated the financial sector to allow new financial instruments and arrangements, private credit markets that make capital accessible. Furthermore, social norms among the population reacted to declining income by borrowing instead of saving and prioritized consumption levels over debt levels. In the U.S. case, the policies and changes in norms coincided in a way that amplified these effects (van Treeck and Sturn, 2012). Rajan (2010), by examining how increasing income inequality was simultaneously encouraging growth and weakening an economy's ability to resist economic downturns, merges both classic understandings of the long term positive relationship between inequality and growth and the imperfect capital markets hypothesis as expounded by Fallah and Partridge (2007).

The current understanding of income inequality is incomplete and largely derived from the economic growth literature (Kuznets, 1955; Kaldor, 1956). The results of this work have produced conflicting results (Partridge, 2005), often at a cross-national scale (Alesian and Rodrik, 1994; Barro, 2000; Bleaney and Nishiyama, 2004). Fallah and Partridge (2007) argue that the conflicting results on the relationship between inequality and growth are an indication that income inequality operates differently depending on context and time horizon. In a cross-sectional long-run effects model of U.S. counties, they find that higher rates of income inequality in 1990, perhaps through traditional economic incentive conditions, promote income growth from 1990 to 2000 in urban areas. However, increased income inequality has an opposite effect in rural areas, perhaps due to the detrimental effects of social tension produced by income inequality on income growth (Fallah and Partridge, 2007). These results suggest the importance of accounting for other forms of capital when examining income inequality. An analysis of the 2000 Gini ratio by metropolitan statistical areas finds increased inequality reduces employment and income growth between 2000 and 2009 (Partridge and Weinstein, 2013).

Research on the links between income inequality and economic contraction has been conducted primarily at the national level. The pathways of influence between local inequality and local economic downturns are certainly affected by national policies and institutions, but may also operate through the local consumption of all income groups and perhaps also the asset management and investment decisions of higher income groups. These relationships may operate differently in urban and rural places.

With an analysis of U.S. counties, we look for evidence of a local Rajan hypothesis. First, the propensity to consume locally is lower for those with higher incomes (Hanson and Golan, 2002), so it may be reasonable to focus more on the local consumption effect of low-income households. At the national level, the Consumer Expenditure Survey reports that, for households with $150,000 or more in pre-tax income, average expenditures represented 54 percent of total income, whereas for all households, expenditures represented 80 percent of income. For households with incomes of less than $40,000, average expenditures totaled more than pre-tax income (U.S. Department of Labor, 2008).

Two countervailing effects suggest that the percent of income held by low-income individuals could either stabilize or further reduce local employment, depending on consumer spending. Higher rates of local consumption by low-income individuals may mean that more consumption is fueled by credit, which would be curtailed by the onset of a recession generating employment losses. Alternatively, to the extent that low-income consumption was supported by an increase in social safety net programs, the higher propensity to consume of low-income populations could stabilize job losses in a recession.

Empirically, Deller and Watson (2016) find higher Gini ratios decrease economic stability through higher unemployment rates from 2005-2012 and the inequality of neighboring counties strengthens this relationship. They also test a second inequality variable, the percent of households earning more than $150,000, and find higher levels of high earning households in neighboring counties decreases economic stability of a county. The degree of wealth concentration may adversely affect employment through consumption or asset management.

Furthermore, the effect of agglomeration economies and dense labor markets combined with relative anonymity and more consumer based economic activities may lead to faster job loss in urban areas with high income inequality as owners of capital have more options to reorganize (Fallah and Partridge, 2007). In rural areas, higher social capital may serve as a mediating factor, buffering economic loss as employers are more reluctant to fire workers or close operations and are less able to relocate assets. Deller et al. (2017) find that regions with higher shares of women owned businesses had greater job and wage stability regardless of geographic location during the Great Recession. Strong bonds across various capital owners in an area help accommodate industrial restructuring (Safford, 2009) and create economic opportunities for lower income individuals (Duncan, 1999).

This paper measures employment stability as the difference between actual employment and expected employment at a county's trough (Han and Goetz, 2015). Our ordinary least squares (OLS) regression uses a simplified community capitals framework while controlling for other important factors which influence employment stability. Explanatory variables are measured for the year 2000, at least six years before the Great Recession began. We look for an indication that prior local levels of income inequality, measured in two ways, explain variations in employment changes as counties entered the recession.

2.1. EMPIRICAL MODEL AND DATA

This section presents the empirical model and data used to examine whether income inequality influenced the reaction of U.S. counties to the recessionary shock of the Great Recession. Following Han and Goetz (2015), we measure employment stability as *drop*, the percent change difference between a county's expected employment and actual employment during the month the county reaches its lowest total employment, or trough, between February 2006 and June 2014. Expected employment assumes the county maintains its previous growth path based on the previous 36 months of employment growth prior to the county reaching its peak or maximum total full and part time jobs.

Drop, d, is defined as in Equation (1) below:

$$d = (\hat{y}_{t_2} - y_{t_2})/\hat{y}_{t_2} \tag{1}$$

where y_{t_2} is the county's lowest post-shock employment occurring at time t_2 ($t_2 > t_1$) and $\hat{y}_{t_2}$ is expected employment if the county had continued on its previous three year growth path (i.e. in the absence of the shock). The value of drop for each county reflects the degree of employment change as the percentage of expected employment, allowing counties to reach employment troughs within the context of their own business cycle. There are some controls to isolate a business cycle's peaks and troughs to the Great Recession as explained below.

The empirical model relates county-level drop d to income inequality and other factors that theory and empirical evidence suggest as influential to regional economic outcomes as in Equation (2) below:

$$d = \alpha_0 + \alpha_1 i + \alpha_2 p + \alpha_3 i * p + \alpha_4 X + \alpha_5 K + \alpha_6 E + \alpha_7 R + \epsilon. \tag{2}$$

Here i is income inequality; p is the natural logarithm of population; X is a vector of demographic characteristics expected to influence a communitys capacity to withstand economic shocks; K represents the four capital stocks (human, financial, natural, and social capital); E denotes economic structure; and R is a set of eight regional binary variables. All variables are measured at the county level. Table 1 provides information on the model variables, time periods, and descriptive statistics.

Inclusion of the interaction term i*p enables us to investigate whether inequality has a differential impact in counties with larger versus smaller population. In the absence of the interaction term, α_1 would be interpreted as the marginal effect of income inequality on drop, i.e. the effect on drop of a one-unit change in income inequality. With the interaction term, the interpretation of α_1 is the effect of income inequality on drop when natural log population is zero, which is not meaningful.

Two approaches are used to aid in interpretation of the results related to income inequality in the presence of the interaction term. First, we mean-center the income inequality and log population variables, before calculating the interaction terms. The coefficient α_1 is then interpreted as the effect of income inequality at the average natural log population. Second, we calculate the marginal effect of income inequality on drop *conditional* on the value of natural log population (Friedrich, 1982). The conditional nature of the marginal effect in

Table 1: Description of the Empirical Model Variables (n = 2,741)

Labels		Variable name (2000 data unless noted)	Mean	SD	Min	Max
d	Drop	Drop (varies)	0.187	0.115	-0.329	0.905
i	Gini	Gini ratio (1999)	0.433	0.037	0.333	0.586
i	Top share	Share of income by hh earn ≥$200K (1999)	0.091	0.050	0.000	0.456
p	Pop (Ln)	Natural log of population	10.281	1.427	4.205	16.069
p	Pop density	Population density (÷ by 1,000)	0.227	1.633	0.0001	66.940
X	Pop growth	Population growth rate (2001-2005)	0.022	0.056	-0.203	0.428
X	Black	Black population	0.084	0.139	0.000	0.865
X	Asian	Share Asian population	0.008	0.016	0.000	0.308
X	Other	Share Other minority population	0.056	0.083	0.002	0.883
X	Latino	Share Latino population	0.064	0.124	0.001	0.975
X	< 20 years	Population ¡ 20 years of age	0.284	0.033	0.165	0.459
X	20-64 years	Population 20-64 years	0.568	0.037	0.440	0.771
K	Hschool	≥ 25 years high school degree	0.347	0.066	0.109	0.532
K	Associates	≥ 25 years associates' degree	0.057	0.020	0.004	0.156
K	Scollege	≥ 25 years some college	0.206	0.044	0.087	0.373
K	Bachelors	≥ 25 years bachelor's degree	0.167	0.077	0.049	0.603
K	Amenities	Natural amenity scale (1999)	0.089	2.335	-6.400	11.17
K	SocialK	Social capital index (2005)	0.003	1.389	-3.904	14.379
K	DIR	Dividends, interest, rent in personal income (1999)	0.189	0.054	0.081	0.561
E	PC income	Per capita income ($000s) (1999)	17.611	3.925	5.213	44.962
E	Poverty	Share below poverty (1999)	0.139	0.063	0.000	0.569
E	HHI	Herfindahl-Hirschman index	4.166	1.421	2.906	33.333
E	Manu	Share manufacturing employment (2001)	0.114	0.092	0.000	0.629
E	Gov	Share government employment (2001)	0.166	0.070	0.026	0.888
E	Urban	Share urban population	0.406	0.306	0.000	1.000
E	PE ratio	Population-employment ratio	2.040	0.575	0.367	7.818
E	Urban dist	Distance (km) to urban area pop ≥ 50,000	56.823	60.310	0.000	393.288
R	NewEng	New England division	0.145	0.352	0.000	1.000
R	MidAtlantic	Middle Atlantic division	0.204	0.403	0.000	1.000
R	East-North	East North Central division	0.169	0.375	0.000	1.000
R	West-North	West North Central division	0.115	0.319	0.000	1.000
R	South	South Atlantic division	0.157	0.364	0.000	1.000
R	East-South	East South Central division	0.090	0.286	0.000	1.000
R	West-South	West South Central division	0.048	0.213	0.000	1.000
R	Mountain	Mountain division	0.145	0.352	0.000	1.000
R	Pacific	Pacific division	0.204	0.403	0.000	1.000

Note: The time period for the drop variable varies by county. Han and Goetz used monthly data for 2003-2014 from the U.S. Department of Labor Statistics to measure county-level drop and rebound during the Great Recession.

the presence of an interaction term is evident when we take the partial derivative of drop with respect to income inequality as shown in Equation (3) below:

$$\delta d/\delta i = \alpha_1 + \alpha_3 p. \tag{3}$$

When reporting results in section 3 of the paper, these marginal effects will be reported for different percentiles of the population distribution for ease of interpretation. Before turning to the empirical model results, however, we first describe the empirical model variables.

2.2. Model Variables

2.2.1. Drop

The estimates of drop used in this paper are the Han-Goetz estimates available on the Northeast Regional Center for Rural Development website. Han and Goetz (2015) used county-level monthly data for total employment from the U.S. Bureau of Labor Statistics for

3,138 U.S. counties. They seasonally adjusted monthly employment data from 2000-2014 and then used the adjusted data from 2003-2014 to measure resilience.[1] Their analysis included a total of 2,836 counties after removing 294 counties whose employment rose continuously, declined continually or counties that failed to start adding jobs before July 2014 (which precluded observing a six month recovery). Four counties are also removed from the sample due to undisclosed data.

Han and Goetz (2015) show the enormous variation across counties in employment loss during the Great Recession. The drop score ranges from -0.329, indicating that the lowest employment during the recession was still higher than what was expected due to negative growth rates before peak employment, to 0.905, indicating a county failed to attain 90.5 percent of expected jobs at its minimum employment. The average drop score of 0.187 indicates on average, and not weighting for population, U.S. counties experienced actual employment numbers that were 18.7 percent below their expected employment during their month of lowest employment in the recession. The Northeast and North Central regions generally had smaller job losses than the South and the West, but there are strong and weak performers in all regions.

Drawing on the Rajan hypothesis outlined above and on previous literature explaining regional economic growth and well-being (Fallah and Partridge, 2007; Partridge and Rickman, 2007), we hypothesize that cross-county variation in economic employment stability during the recession, as measured by drop, can be explained by cross-county variation in income inequality, demographics, community capitals, and economic structure.

2.2.2. Income Inequality

Income inequality has limited measures at the county level. Measures which capture inequality across the distribution are common, including the Theil index, the Atkinsons index, and especially the Gini ratio. Measuring income inequality as the concentration of income is more challenging. Current data prevent the calculation of income held by the top 90$^{\text{th}}$ or 99$^{\text{th}}$ percentile.

In this paper, we use two measures of pre-recession inequality: the Gini ratio and the share of income received by households earning more than \$200,000 per year in 1999. The Gini ratio has a value ranging from 0 (indicating perfect equality in the distribution) to 1 (indicating that one household has all income). See Allison (1977) for a fuller discussion of the Gini ratio and alternative measures. The Gini ratio is calculated as in Equation (4) below:

$$Gini = 1 - \sum_{i=1}^{N} (x_i - x_{i-1})(y_i - y_{i-1}). \tag{4}$$

Given that data for individual households are not available at the county level, income inequality measures must be calculated using estimated midpoints of the provided household

[1]Han and Goetz (2015) do not provide detailed steps for constructing the resiliency measure. Attempts to recreate their original measure produced different results, perhaps because the BLS revises past data on subsequent data releases. This paper uses the published estimates for consistency.

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.

The income data for the 2000 Decennial Census are reported in 17 income classes. We assume that each household receives the midpoint income of the class and that no one can have a negative income. 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 households in that category. The average Gini ratio for 1999 was 0.433 and the Gini ratio value ranged from 0.333 to 0.586.

Our second indicator of income inequality, a measure of income concentration, is the share of income received by the highest income group identified in the Census: households earning \$200,000 or more in income in 1999. Across all counties, the average share of all household income received by this group was just over 9 percent (see Table 1). This variable ranges from 0 percent (counties with no households in this income group) to 45.6 percent. In contrast to the Gini ratio, which measures the overall income distribution in a county and is most sensitive to variations in the middle income range, the income share of the highest income group reveals concentration at the top of the income range and is easier to interpret.

Our model draws on two related theoretical strands of the regional economics literature to identify factors other than income inequality which may determine a region's employment stability to shocks. We begin with reduced form models of regional economic growth based on location decisions of profit-maximizing firms and utility-maximizing households developed by Partridge et al. (2008). We augment this specification with measures of community capital assets developed by Pender and Ratner (2014). We include variables for four of the eight forms of capital identified in this rural wealth creation framework: human, natural, social, and financial capitals. Our model specification is similar to other empirical studies of regional economic growth, especially Fallah and Partridge (2007) and Watson and Deller (2017). We now describe the control variables.

2.2.3. Community Capitals

Human capital is defined as the stock of education, skills, physical health, and mental health embedded in people (Pender and Ratner, 2014). Educational attainment, measured by the share of people age 25 and over with a high school degree, an associate's degree, some college education, or a bachelor's degree or higher, measures human capital. Higher educational attainment is associated with higher-level employment and increased income (Becker and Chiswick, 1966). Therefore, a county with a larger share of adults with higher education is hypothesized to lose less employment in a recession.

Natural capital is the stock of healthy environmental assets in a region, such as air, water, and land, which yields 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.

Industries depending on environmental quality are more likely to be vacation and recreation based, which would be negatively affected due to decreased discretionary consumption in the Great Recession. Positive relationships between land amenities and employment and population growth rates may reflect tourist economies. Climate and water appear to influence population growth, but have a weak influence on per capita income growth and no role in employment growth. Winter recreational activities are positively related to growth rates in population, employment, and per capita income (Deller et al., 2001). Open hills and mountains have been found to delay the time of a county to enter recession (Lewin et al., 2018). A county's level of natural amenities is hypothesized to be positively related to employment loss.

Social capital includes social ties and networks, social norms, and levels of trust (Putnam, 1993). The Northeast Regional Center for Rural Development at Pennsylvania State University developed an index to measure the county level stock of social capital (Rupasingha et al., 2006). The social capital index is calculated using principal component analysis on variables relating to business establishments thought to encourage social ties and networks, voter turnout rate, census response rate, and the number of non-profit organizations. Social capital is expected to weakly decrease drop. Data for the year 2005 are used.

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. Places with a higher proportion of investment income would be volatile in a recession due to potential volatility in the stock markets.

2.2.4. Economic Structure

Economic structure here refers to the level of development of the county (as measured by per capita income) and to sector diversification (as measured by the Herfindahl-Hirschman index for three digit NAICS codes and the share of county employment in government and manufacturing), as well as the size and urbanization of the economy. Literature examining diversification and economic stability finds the relationship is context dependent (Dissart, 2003). Typically, diversification is thought to reduce the risk to external shocks. Yet specialization, dependent on the industry, can lead to stronger growth and stability. Or sometimes the degree of diversification within a dominant industry is more important than the level of diversification across industries (Noseleit, 2015).

We expect diversification and specialization in government employment will promote short-term job stability, while specialization in manufacturing will lead to higher job losses. Size and urbanization are measured by the natural log of the total population, share of the population living in urbanized areas, and the Euclidean distance measured in kilometers between the mean center of population within each county and its nearest urban area of 50,000 people or more.

In summary, we attempt to understand cross-county variation in drop during the Great Recession as explained by variations in levels of pre-recession income inequality, demographics, four forms of local capital, economic structure, and other variables that affect the economic capacity of a county. Towards this end, we use ordinary least squares regression.

3. RESULTS

3.1. Base Model Results

Table 2 reports OLS regression results for four models. Model 1 includes all of the control variables and measures income inequality using the Gini ratio. Model 2 adds to Model 1 an interaction term equal to the Gini ratio multiplied by the natural logarithm of population. Model 3 is identical to Model 1, except that income inequality is measured as the share of aggregate income held by the top earning households, those with $200,000 or more in annual income. Model 4 adds to the Model 3 specification an interaction term between natural log population and the share of income received by the top-earning households. Inclusion of an interaction term in Models 2 and 4 allows us to explore the possibility that the relationship between income inequality and employment stability depends on the population of the county, with large counties having a different inequality-drop relationship than small counties. A larger drop indicates a county had far fewer jobs than expected, so positive coefficients increase drop and negative coefficients decrease drop.

Before turning to a description of empirical results we discuss some potential issues with the empirical model and data and our approach to addressing them. To account for possible heteroskedasticity, which is common for cross-sectional data, statistical significance of the coefficients in Table 2 are based on heteroskedasticity-robust standard errors (White, 1980). Endogeneity is another common concern in cross-sectional analysis. For example, variables that affect a county's employment stability in the 2006-2013 period could also affect its income inequality in 1999. We attempted to mitigate this concern by specifying the control variables for characteristics for the year 2000 or later.[2] There are almost certainly omitted variables but our inclusion of a comprehensive set of social and economic controls should mitigate this problem.

Another possible concern is that counties that had declining population going into the Great Recession could drive the empirical results for drop. This is mitigated as the (Han and Goetz, 2015) measure of drop leaves out 290 counties that declined continuously throughout the period February 2006 to July 2014.

We tested for multicollinearity by computing each independent variable's variance inflation factor (VIF), an estimate of how much the variance of a coefficient is "inflated" due to linear dependence with other predictors (Allison, 2012). The VIF test indicated multicollinearity only for the models that include interaction terms (i.e., Models 2 and 4) and

[2]Population growth may also be endogeneous to drop, but our efforts to use instrumental variables (IV) to control for endogeneity related to either income inequality or population growth were unsuccessful. We tried to use a Durbin-Wu-Hausman test for endogeneity of income inequality and population growth. We were unable to identify theoretically or empirically defensible instruments for income inequality. For population growth, following the county-level analysis of Deller et al. (2001), we chose mean January temperature and natural log of water area as a proportion of total county area as instruments, but these were found to be weak based on Stock and Yogo (2005)'s critical values of a first-stage F-statistic. Furthermore, a Sargan-Hansen test of overidentifying restrictions rejected the null hypothesis that the instruments are uncorrelated with the error term of the drop equation, casting doubt on the validity of the chosen instruments. We opted not to use an IV estimation approach because invalid instruments lead to biased and inconsistent IV estimates that can be even more severe than the corresponding OLS estimates (Murray, 2006).

Table 2: Ordinary Least Squares Regression Results for County-Level Employment Drop

Variable (n=2,735)	Model 1 Coeff.	Std. Error	Model 2 Coeff.	Std. Error	Model 3 Coeff.	St. Error	Model 4 Coeff.	Std Error
Constant	0.1430	0.0873	0.1360	0.0863	0.1658*	0.0824	0.1403	0.0824
Gini	0.0604	0.0938	0.0981	0.0892	-	-	-	-
Top share	-	-	-	-	-0.0442	0.0711	0.0243	0.0677
Pop (Ln)	-0.0355***	0.0036	-0.0370***	0.0036	-0.0354***	0.0035	-0.0371***	0.0036
Interaction	-	-	0.1010*	0.0439	-	-	0.0828***	0.0243
Pop growth	0.1950**	0.0618	0.2077***	0.0621	0.1870**	0.0614	0.2052***	0.0611
Black	0.0509	0.0269	0.0459	0.0274	0.0572*	0.0266	0.0521	0.0267
Asian	0.3352**	0.1254	0.3057*	0.1290	0.3187*	0.1238	0.1504	0.1225
Other	0.0573	0.0379	0.0550	0.0381	0.0608	0.0377	0.0526	0.0382
Latino	-0.0638*	0.0261	-0.0666*	0.0262	-0.0657*	0.0260	-0.0610*	0.0260
< 20 years	-0.0013	0.1101	0.0139	0.1101	-0.0194	0.1084	-0.0161	0.1080
20-64 years	-0.0140	0.0977	-0.0122	0.0972	-0.0314	0.0971	0.0237	0.0995
Hschool	-0.0195	0.0726	-0.0224	0.0724	-0.0454	0.0706	-0.0226	0.0706
Associates	-0.4187**	0.1570	-0.4089**	0.1555	-0.4472**	0.1553	-0.4000**	0.1535
Scollege	0.2449**	0.0887	0.2443**	0.0884	0.2092*	0.0868	0.2550**	0.0880
Bachelors	-0.1397*	0.0682	-0.1484*	0.0683	-0.1428*	0.0685	-0.1371*	0.0684
Amenities	0.0058***	0.0014	0.0058***	0.0014	0.0059***	0.0014	0.0058***	0.0014
SocialK	-0.0119***	0.0030	-0.0118***	0.0030	-0.0124***	0.0031	-0.0120***	0.0030
DIR	0.0401	0.0649	0.0186	0.0651	0.0502	0.0654	0.0388	0.0650
Pc income	0.0018	0.0010	0.0021*	0.0010	0.0022	0.0012	0.0007	0.0013
HHI	0.0065*	0.0033	0.0070*	0.0032	0.0066*	0.0032	0.0067*	0.0031
Manu	0.0979**	0.0349	0.1016**	0.0348	0.0950**	0.0346	0.1040**	0.0344
Gov	-0.1341**	0.0448	-0.1314**	0.0449	-0.1360**	0.0448	-0.1382**	0.0448
Urban	-0.0357**	0.0122	-0.0333**	0.0122	-0.0358**	0.0122	-0.0330**	0.0122
Urban dist	-0.0002***	0.0001	-0.0002***	0.0001	-0.0002***	0.0001	-0.0002***	0.0001
MidAtlantic	0.0201	0.0102	0.0203*	0.0102	0.0202*	0.0102	0.0201*	0.0101
East North	0.0158	0.0103	0.0160	0.0102	0.0164	0.0103	0.0158	0.0102
West North	0.0163	0.0115	0.0151	0.0114	0.0176	0.0115	0.0152	0.0115
South	0.0313**	0.0114	0.0310**	0.0113	0.0315**	0.0114	0.0306**	0.0114
East South	0.0186	0.0124	0.0172	0.0123	0.0204	0.0124	0.0179	0.0123
West South	-0.0123	0.0127	-0.0124	0.0126	-0.0102	0.0127	-0.0111	0.0126
Mountain	0.0493***	0.0132	0.0482***	0.0132	0.0509***	0.0133	0.0480***	0.0132
Pacific	0.0136	0.0139	0.0131	0.0138	0.0155	0.0139	0.0152	0.0138

Note: Adjusted R^2 for Model 1 =.260, Model 2 = .262, Model 3 = .260, Model 4 = .264. * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$.

revealed five problematic variables having VIF > 10: log population, the two income inequality measures, and the two interaction terms.[3] Multicollinearity can be safely ignored when it is caused by the inclusion of products of other variables; it has no adverse consequences for standard errors or model goodness of fit (Friedrich, 1982; Allison, 2012).

We begin our discussion of the results on Table 2 by focusing on the control variables that are statistically and substantively significant and then turn to the results of primary

[3]Multicollinearity is common when regression models include transformed variables, such as squared or interaction terms (Aiken and West, 1991). It arises because the interaction term is a product, and income inequality and natural log population are of course highly correlated with their product (Friedrich, 1982).

interest, i.e. those related to the local Rajan hypothesis. Population size, population growth, racial and ethnic composition, urbanization, and some community capitals, are important predictors of drop. The natural log of total population has the largest standardized coefficient, which is not shown but ranges from -0.449 to -0.496, with smaller drops predicted for counties with a larger population. Faster growing counties, by contrast, saw greater job losses.

Counties with more natural capital also experienced larger drops in the recession, perhaps because many of these counties have businesses that depend on discretionary recreation-based spending which could be expected to decline during a recession. Counties with more human capital and more social capital, on the other hand, experienced smaller expected job loss, as might be anticipated. Both urbanization (higher share urban population) and remoteness (increased distance from a large urban center) reduce expected job loss in a recession. A high share of Asian Americans is predictive of greater job loss, while a high share of Latino population is associated with less job loss.

As expected, industrial structure is influential: counties with higher shares of manufacturing jobs experience higher levels of drop, while counties with higher shares of government jobs experience lower levels of drop. Our measure of economic diversification has a positive coefficient and is significant at the 10 percent level, greater diversity led to higher job loss in the Great Recession. This is perhaps explained by sensitivity to the degree of sectoral disaggregation (Frenken et al., 2007). Or, it may reflect that the diversity we are capturing does not imply modularity, unrelated businesses could still be linked through buyer-supplier relationships, reducing the containment effect diversity is supposed to imply in the face of an external shock (Martin and Sunley, 2015). Surprisingly, perhaps, the returns from financial and property assets (dividend, interest and rent share) are not related to the size of recessionary job drop. During the Great Recession counties located in the Middle Atlantic, South Atlantic, and Mountain divisions experienced greater job loss than counties in the New England division.

Turning to the results of primary interest, in Table 2 we mean-centered the income inequality and log population before calculating the interaction terms. This can improve interpretation of the main effects and the constant term. As shown in the table, neither measure of income inequality has a statistically significant direct linear relationship with drop. More revealing is that the interaction term is positive and statistically significant in Models 2 and 4.

Table 3 presents marginal effects and standard errors, where the marginal effects are calculated as in Equation (3) for different percentiles of the population distribution. The effects show how predicted drop changes for small changes in income inequality, holding natural log population constant. For the Gini ratio, marginal effects are statistically significant at the five percent level for more populous counties, those at the $75th$ percentile or higher. In large population counties, increasing income inequality leads to increased job loss. When income inequality is measured by the degree of income concentration, marginal effects are statistically significant at the five percent level for the $1st$ population percentile, with a negative coefficient, and at the $90th$ percentile and higher with a positive coefficient. Income concentration reduces job loss for very small counties and increases job loss for large counties, those with a population of 190,365 people or more.

Table 3: Marginal Effects and Percentage Change in Drop of OLS Results

Percentiles of county population	County population	Gini Ratio Marginal effect	Gini Ratio Std. error	Income Share of HH earings 200K or more Marginal effect	Income Share of HH earings 200K or more Std. error
1st percentile	991	-0.244	0.186	-0.256*	0.107
5th percentile	3,165	-0.126	0.143	-0.160	0.087
10th percentile	5,463	-0.071	0.125	-0.114	0.080
25th percentile	11,756	0.006	0.104	-0.051	0.072
Median	26,453	0.088	0.090	0.016	0.068
75th percentile	66,533	0.181*	0.091	0.092	0.070
90th percentile	190,365	0.288**	0.111	0.179*	0.081
95th percentile	404,119	0.364**	0.134	0.242**	0.092
99th percentile	1,194,156	0.473**	0.173	0.331**	0.112

Notes: * $p < 0.05$, ** $p < 0.01$

3.2. Sensitivity Results

We assess whether these findings are robust to changes in model specification with sensitivity analyses. Although economic theory provides guidance for specifying econometric models, it is not explicit about which explanatory variables to include or how they should be measured, the correct functional form, or how to specify the standard errors. An econometric model can be specified in many ways, estimates might be sensitive to the choices made, and it is unknown which specification is best. Thus, there is model uncertainty (Chatfield, 1995; Brock et al., 2007; Watson and Deller, 2017).

We focus our sensitivity analyses on the explanatory variables related to income, population, and economic structure. We present four alternate specifications for Model 4, which is our preferred specification because the income concentration measure of income inequality is more intuitive than the Gini ratio. We briefly report the sensitivity results for the model with the Gini ratio in the text below, but omit the table for space restrictions. The four alternate specifications for sensitivity analyses are: (1) include state fixed effects instead of Census region fixed effects to better capture variation in geographical and political contributions to employment stability, (2) substitute the percent below poverty for per capita income as a measure of relative consumption, (3) substitute population density for log population while omitting share urban as a measure of population concentration, and (4) substitute the population-to-employment ratio for the share urban population as a measure of density of economic activity.

Table 4 presents the results of the four sensitivity analyses where we have included the Model 4 results for comparative purposes. Inclusion of state fixed effects increases model fit, although only slightly. Several explanatory variables lose significance when state fixed effects are included: the Black population share, Latino population share, several educational attainment binary variables, and the natural amenities scale. These variables are not randomly distributed across states, and we find capturing this variation by variable more useful than by state.

Table 4: Sensitivity Analysis Results for County-Level Employment Drop

Variables (n=2,735)	Model 4	Sensitivity Analysis 1	Sensitivity Analysis 2	Sensitivity Analysis 3	Sensitivity Analysis 4
Constant	0.1403	0.1095	0.1077	0.2266**	0.1390
Top share	0.0243	0.0304	0.0509	-0.0278	0.0423
Pop density	-	-	-	-0.0064**	-
Pop (Ln)	-0.0371***	-0.0394***	-0.0370***	-	-0.0421***
Interaction	0.0828***	0.0810***	0.0879***	0.0191***	0.0868***
Pop growth	0.2052***	0.1535*	.2161***	0.1627*	0.2115***
Black	0.0521	0.0350	0.0441	0.0039	0.0455
Asian	0.1504	0.1975	0.1703	-0.2425*	0.1466
Other	0.0526	0.0467	0.0437	0.0105	0.0611
Latino	-0.0610*	-0.0500	-0.0558*	-0.1064***	-0.0783**
< 20 years	-0.0161	0.0392	-0.0254	-0.0076	-0.0349
20-64 years	0.0237	0.1591	0.0473	-0.0633	0.0172
Hschool	-0.0226	-0.0146	0.0127	-0.0766	-0.0247
Associates	-0.4000**	-0.0571	-0.3630*	-0.8084***	-0.4005**
Scollege	0.2550**	0.2201*	0.3112***	0.0494	0.2442**
Bachelors	-0.1371*	-0.0916	-0.1065	-0.3776***	-0.1419*
Amenities	0.0058***	0.0017	0.0057***	0.0047**	0.0059***
SocialK	-0.0120***	-0.0088**	-0.0113***	-0.0014	-0.0112***
DIR	0.0388	0.0579	0.0334	0.1113	0.0355
Poverty	-	-	0.0607	-	-
PC income	0.0007	-0.0001	-	0.0008	0.0005
HHI	0.0067*	0.0071*	0.0067*	0.0162***	0.0067*
Manu	0.1040**	0.1119**	0.1101**	0.0691	0.1089**
Gov	-0.1382**	-0.1800***	-0.1516***	-0.0495	-0.1476**
PE ratio	-	-	-	-	0.0055
Urban	-0.0330**	-0.0394**	-0.0333**	-	-
Urban dist	-0.0002***	-0.0002***	-0.0003***	0.00002	-0.0002***
State binary	No	Yes	No	No	No
Regional division	Yes	No	Yes	Yes	Yes

Note: Adjusted R^2 for Model 4 =.264, Sensitivity Analysis 1 = .283, Sensitivity Analysis 2 = .255, Sensitivity Analysis 3 = .184 and Sensitivity Analysis 4 = .253. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The second sensitivity analysis reveals that the poverty rate is not significantly associated with drop, which is consistent with the general finding for per capita income (Table 2). As shown by the third sensitivity analysis, the relationship between population density and drop is in the same direction as log population, it is negative and statistically significant, which is reassuring. The last sensitivity analysis finds no statistically significant association between drop and the population-employment ratio, suggesting that the degree of economic density is not as important as population size or share of urban population.

Across the various specifications we see that most of the explanatory variables are stable, particularly the variables of key interest, i.e. log population and income inequality. Results for the sensitivity analyses with the Gini ratio measure of income inequality are similar to those shown in Table 4, but a notable difference is the interaction term between log population and the Gini is not statistically significant (p-value = 0.07) when state fixed effects are included.

4. CONCLUSIONS

This paper provides an exploratory examination of the 'local Rajan hypothesis.' We do not have a causal model, but we find relationships that are consistent with the hypothesis that pre-recession income inequality in a county had an impact on the depth of the employment drop the county experienced as it entered the recession. Our initial finding - that the level of income inequality in the county does not appear to affect a county's employment loss in a recession relative to what would be expected given the countys previous growth path - would not allow us to reject the local Rajan hypothesis. When we allow the effect of local inequality to depend on the county's population size, however, income inequality is one of several factors that influences drop.

Notably, the influence of income inequality varies by the size of population, supporting the findings of Fallah and Partridge (2007). High inequality, measured by the Gini ratio or by the degree of income concentration, increases the recessionary employment drop in the most populous counties, supporting the findings of Lewin et al. (2018). This effect is larger and more significant in large populations. In contrast, higher income concentration reduces the employment drop in the smallest counties.

This result is obtained controlling for other local characteristics that affect employment stability. Population size, population growth, urbanization, and certain forms of community capital are important predictors of drop. More populous counties saw smaller employment drops in the recession. Faster growing counties, counties with more natural capital, and counties with higher shares of manufacturing jobs and higher industrial diversification by contrast, saw greater job losses. Counties with more human capital (larger share of population with some college, associate's, and bachelor's degrees), more government jobs, more Latinos, and more social capital, on the other hand, experienced smaller expected job loss. Both more urbanized and more remote counties also had reduced job loss. The returns from financial and property assets, a variable that we expected to influence the depth of the job loss, was not significant. These relationships are robust to two alternative measures of income inequality: the Gini ratio and income concentration measured as the share of county income received by those with household incomes of $200,000 or more.

The Great Recession has expanded interest in economic resilience. This paper's emphasis on employment stability provides a partial understanding of resilience. Resilience involves more than just the capacity to withstand the ravages of a recession by minimizing the depth of job loss. It also involves the region's capacity to recover. 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, using a ratio variable like the Han-Goetz index, two counties with very different drop and recovery paths could end up with the same resilience score. Wu (2016)'s finding that different factors are important in explaining drop and rebound suggest that future research would gain insight by analyzing drop and rebound separately. The current Han and Goetz rebound measure cannot adequately capture adaptation as it uses a six month recovery time and counts the number of full and part time jobs alone. Our understanding of resilience remains limited without improved measures (Faggian et al., 2018).

Our findings suggest that in the short-run, income inequality affects employment change differently than in the long-run, and that inequality operates differently among large and small populations. It is possible that in large populations we are seeing the effect of decreased consumption through local and regional reductions in consumption, an effect compounded in urban areas with larger concentrations of employment tied to consumption. This is consistent with how we might expect Rajan (2010)'s effects of inequality to concentrate locally. Fallah and Partridge (2007) note the important role that social capital, facilitated by lower income inequality, can have in rural areas to aid long-run growth. In the short-run, it is possible a level of income inequality may primarily reflect a concentration of locally owned assets. This could imply a region has local business owners who are physically or emotionally less likely to relocate. This finding could also reflect this particular recession, during which many parts of U.S. agricultural production were countercyclical.

Our results suggest that reducing inequality can increase economic stability in the short-run, especially in areas with large populations. Reducing income inequality requires policy action at the national level, and as our results suggest, the effects of this reduction will be unevenly distributed across areas. Communities can reduce inequality and strengthen economic stability by setting priorities for local investment of staff capacity, financial resources, and policy in the following three areas. First, invest in schools and early education initiatives, particularly for minorities, to facilitate the educational attainment and skill development of the current and future labor force. Second, invest in the formation and maintenance of positive social capital, particularly the ties and networks that link people across incomes and resources and that can bridge people and organizations in the county to regional, state, and national people, organizations and resources. Finally, use public dollars to invest in economic and community development efforts that are likely to reduce income inequality through the creation and maintenance of stable employment with fair wages that will improve the lives of low-paid and underemployed residents.

If income inequality continues to increase, further research into the mechanisms through which we observe these differential effects will be vital.

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