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A Quantile Regression Approach to Examine Changes in County Unemployment Rates in Indiana during the Great Recession*

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Abstract: We take a closer look at changes in county unemployment rates in Indiana during the Great Recession and evaluate how local population and the mix of sectoral employment influence these patterns. Using a quantile regression approach, we specifically observe the impacts on counties on both tails of the changes in unemployment distribution. We find the impact of sectoral composition of a county's workforce depends on its geographical classification. Overall, greater reliance on pro-cyclical industries, most notably manufacturing, magnifies the increases in unemployment during the recession. This effect is further amplified for MSA counties. In contrast, counter-cyclical industries, education in particular, insulates the counties in the top 10th percentile of the distribution of changes in unemployment rates, and a stronger insulation effect is observed for MSA counties. At the bottom 10th percentile, education marginally amplifies changes in unemployment rates for MSA counties, whereas it insulates non-MSA counties from the same distribution.

Keywords: unemployment, Great Recession, quantile regression

JEL Codes: R23, J60, J614

1. INTRODUCTION

High unemployment rates are one of the widely recognized indicators of a recession. During the Great Recession of 2007-2009, the national unemployment rate reached a peak of 9.5 percent, from 5 percent in December of 2007 (U.S. Bureau of Labor Statistics, 2012). Although the Great Recession was a national event, the extent to which unemployment increased varied widely across locations. At the end of the recession in June 2009, state level unemployment rates ranged from a high of 14.6 percent in Michigan to a low of 4.2 percent in North Dakota. Indiana was one among several states posting a double-digit unemployment

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rate at 10.6 percent. All 92 counties in Indiana experienced an increase in unemployment during this period and a closer examination reveals an uneven distribution. At the start of the recession in October 2007, the average county unemployment rate was 4.1 percent with a high of 6.3 percent in Fayette County and a low of 2.6 percent in Dubois County. By the end of the recession in June 2009, the average county unemployment rate was 11.5 percent with a high of 20.2 percent in Howard County and a low of 6.0 percent in Davies County. The apparent variation in county unemployment rates highlights the need to examine changes in county unemployment across its entire distribution rather than solely the conditional mean.

The objectives of this paper are to analyze the bottom 10th and the top 10th percentiles of the distribution of changes in county unemployment rates in Indiana and to investigate how local structural characteristics and demographic composition influence these changes. We also examine whether the impact of local structural characteristics, i.e., the mix of sectoral employment, is affected by the geographical classification of a county as captured by its Metropolitan Statistical Area (MSA) vs non-MSA status. We use a quantile regression (QR) to achieve our objectives, in addition to ordinary least squares regression (OLS) which captures relationships at the conditional mean for comparison.

2. PREVIOUS LITERATURE

The literature most relevant to this study examines unemployment and job losses during the Great Recession as well as regional and local differences on unemployment outcomes. Walden (2012) finds a higher share of state GDP in manufacturing, larger declines in housing prices, and bigger household in-migration, are associated with greater state labor market deterioration. In addition, higher increases in state unemployment rates during the Great Recession were mostly clustered in the Far West, Southeast, and Midwest. Strong regional differences between states were identified by Connaughton and Madsen (1980), with the New England Census Region exhibiting relatively weaker job performance. Thiede and Monnat (2016) examine differences in recession-related changes in county unemployment rates and find counties that experienced larger increases in unemployment during the Great Recession are characterized by larger shares of racial and ethnic minority populations, low educational attainment, and economic reliance on pro-cyclical industries.

The regional and local disparities on the predictors of the Great Recession in general, and unemployment rates in particular, have been investigated in a few studies. Shoag and Veuger (2016) argue that increased cross-sectional economic and policy uncertainty added to the severity of the Great Recession. Mian and Sufi (2014) show that through the Great Recession, larger declines in employment in industries that are not tradeable outside the local areas (i.e. restaurants and retail shops) was typical in counties that had severe declines in housing net worth.

These studies indicate local industry and population characteristics may have a bearing on how much a county is susceptible or insulated to adverse economic shocks. In fact, past recessions provide evidence that differences in industrial structure causes some states to be more sensitive to aggregate economic performance (Connaughton and Madsen, 1980). We contribute to the literature by taking a closer examination of changes in county unemployment during the Great Recession in two ways. First, we analyze changes in county

unemployment at both tails of the changes in unemployment distribution using the quantile regression approach (QR). QR allows us to gain insights on the impact of our regressors along the entire conditional distribution of changes in unemployment, and not limit attention to the conditional mean. To our knowledge, QR has not been utilized in previous studies that examine changes in county unemployment rates. The literature on cross-sectional variation in unemployment rates focus on the conditional mean estimates, yet there is no a priori reason to assume the estimated relationships hold true for areas/locations not represented by the conditional mean. For instance, the impact of the manufacturing sector on unemployment during the Great Recession may be different for counties that experienced the lowest increases in unemployment relative to the counties that suffered the highest increases. Second, we explore the impact of geographic classification (MSA vs non-MSA status) on the effect of sectoral employment on changes in county unemployment rates.

3. DATA AND METHODS

3.1. Data

Our analyses draw upon annual data for county unemployment rate estimates from the Bureau of Labor Statistic's Local Area Unemployment Statistics (LAUS), county sectoral employment data from Quarterly Census of Employment and Wages (QCEW), and county population characteristics data from STATS Indiana. We focus our analysis on unemployment during the Great Recession and thus examine changes in county unemployment rates capturing the overall difference between 2006 and 2009. We use 2006 as the pre-recession baseline and our time frame captures this baseline through the bottom of the Great Recession. Thiede and Monnat (2016) utilize the same time frame to study the geography of unemployment during the Great Recession.

3.2. Empirical Model

The impact of aggregate economic downturns on local outcomes vary across areas and are shaped by location-specific characteristics. We develop a framework for examining changes in county unemployment by drawing upon results of related studies as presented in our literature section. To investigate the exposure of counties to the recession's effects, we group our regressors into two sets: (1) structural characteristics and (2) demographic composition.

Structural characteristics of local areas have an impact on the severity of unemployment experienced during the Great Recession. One of the key outcomes of the recession was the non-random impact across industries. We include a vector of variables capturing sectoral employment to control for local industrial structure and specialization. Sectoral employment is specified as the percentage of a county's employment in a specific sector relative to total county employment. As an empirical strategy, we only include relevant sectoral employment rates and define as those whose mean percentage of the county employment in a particular sector is greater than the overall mean percentage of the county employment for all sectors. Data from the QCEW comprise a total of 20 sectors and we include 8 relevant sectors in our

analyses.¹

In addition to the sectoral composition of employment, we also explore the vulnerability of counties to economic downturns based on their geographical classification. We include a dummy variable to capture counties within an MSA.² A metro area is defined to include central counties with one or more urbanized area of 50,000 people or more, and outlying counties with 25 percent or more of labor force employed and commuting from the central city. This variable also captures commuting patterns and labor force mobility. Ransom et al. (2014) contend that disadvantaged labor markets through low educational attainment, an aging population, and structural changes are found in many rural areas. In addition, Slack (2014) indicates that the said outcomes occur in areas that were experiencing declines in manufacturing activities before the recession. On the other hand, Mattingly et al. (2011) argue that since rural areas are already at a disadvantage prior to the recession, they have less room to even go further down as evidenced by the fact that average increase in unemployment in rural areas were lower than urban areas. Similarly, the likely impact of the composition of sectoral employment differs between MSA and non-MSA counties. If workers skills are substitutable, workers can commute across neighboring counties when labor markets are tight especially during a recession. The extent of these movements is limited to the relative substitutability of skills required across sectors and the relative mobility of workers between adjacent counties.

The second set of regressors capture local demographic composition. Previous research suggests large increases in unemployment during the Great Recession are experienced by areas with relatively large proportions of at-risk and vulnerable workers as indicated by race and level of education (Thiede and Monnat, 2016). We include the following county-level variables: percentage of Black population, percentage of Hispanic population, total population, per capita income, and percentage of population with a Bachelors' degree.³ Total county population is included to capture potential economies/diseconomies of scale. It is likely that the larger a county's population is, the more at-risk workers there are during a recession due to dwindling work opportunities. On the other hand, a larger population may provide a better cross-section of workers who can switch jobs during an economic downturn, which could put downward pressure on the overall unemployment rate. We use per capita income both as a proxy for the overall level of human capital and the strength of the local economy which could potentially shield counties from higher unemployment during the recession. Lastly, we control for pre-recession unemployment rates by including 2006 county unemployment rates in the model.

¹This strategy likewise avoids the problem of singularity. The overall average percentage of county employment across all sectors in Indiana is 5.00 percent. Manufacturing employs the largest at 24.61 percent, followed by retail trade (11.95 percent), health care & social services (11.54 percent), accommodation & food services (8.54 percent), educational services (8.23 percent), public administration (6.80 percent), and construction (5.10 percent). In addition, we also include the agriculture sector (1.07 percent) given its historical significance to the state. In 2017, Indiana was the 8th largest agricultural exporter in the nation.

²We considered alternative measures of relative location including Indiana County Classification System from Purdue University which classifies counties into urban vs rural and a continuous measure called rurality index. The MSA vs non-MSA classification worked best given the demographic variables already included in our models.

³Values for population and per capita income vary widely across counties and specified in the empirical models in natural log form for a better fit.

Our empirical model of changes in county unemployment rates is:

$$\Delta UR_i = \beta_0 + \beta_k Structure_{ik} + \beta_j Demog_{ij} + \epsilon_i \quad (1)$$

where, ΔUR_i is the change in county i unemployment rate between 2006 and 2009. Since all counties experienced an increase in their unemployment rate during the Great Recession, the dependent variable, ΔUR_i is positive. $Structure_{ik}$ represents k set of structural characteristics in county i ; and $Demog_{ij}$ is a vector of j demographic variables in county i . All regressors are measured at the pre-recession baseline year of 2006.⁴ As previously indicated, it is possible for the impact of sectoral employment to differ between MSA and non-MSA counties. To demonstrate this difference, we estimate a second model with interaction terms between the MSA and relevant sectoral employment variables.

We estimate the empirical model using QR and OLS. The OLS approach summarizes the average relationship between a set of regressors and the regressand based on the conditional mean. The QR approach summarizes the impact at different points in the conditional distribution. OLS minimizes the sum of squared errors, whereas QR weights differently the distances between predicted and actual dependent variables and minimizes the weighted distances. QR utilizes all observations in fitting a series of regressions for different quantiles, but weights different portions of the sample to generate parameter estimates, thus increasing the power of the test to detect differences in upper and lower tails where data is sparser. Additional benefits of the QR methodology include its robustness to outliers. QR is robust to non-normal errors and outliers. Extreme observations can lead to a loss in efficiency and biased estimates in an OLS regression since the corresponding residuals will be large and squaring these residuals gives these extreme observations greater weight. Least Absolute Deviations (LAD) regression minimizes the absolute deviations from the predicted dependent variable and is a well-known estimation technique robust to extreme observations. LAD, however, is a special case of QR. For brevity we refer the reader to Koenker and Hallock (2001) and Koenker (2005) for a detailed description of QR and its many applications. The most recent applications of QR have been to simply gain more insights about points in the distribution of the dependent variable other than the conditional mean (Buchinsky, 1994, 1995; Eide and Showalter, 1998; Arano et al., 2018). This is our main motivation for utilizing the QR approach, in addition to the observed uneven distribution of the changes in county unemployment rates across Indiana.

We specifically focus on counties at the bottom 10th (10th quantile) and top 10th (90th quantile) percentiles of the ΔUR_i distribution. The bottom 10th percentile regressions represent counties that experienced less than a 3.7 percentage point increase in unemployment. The top 10th percentile regressions relates to counties that experienced greater than 8.0 percentage point increase in unemployment during the Great Recession. The results from the OLS are used as a baseline for comparisons.⁵

⁴Except for the percentage of the population with a Bachelors' degree which was measured using 2000 Census data due to data availability. The inclusion of per capita income in 2006 can be considered a proxy to the education variable in terms of capturing human capital. Thiede and Monnat (2016) use county variables from 2000 Census data in their examination of unemployment between 2006 and 2009.

⁵QR at the 50th percentile is median regression, i.e., LAD regression. We also estimated the 25th, the 50th, and the 75th percentile regressions and those results are available upon request. We report and discuss the

Figure 1: Frequency Distribution of Changes in County Unemployment Rates

4. RESULTS AND DISCUSSION

4.1. Changes in County Unemployment Rates

Figures 1 and 2 represent the distribution of changes in unemployment rates, ΔUR_i , between 2006 and 2009 for all 92 counties in Indiana. All counties experienced an increase in unemployment, averaging 5.8 percent, with a high of 13.3 percent and a low of 2.2 percent. The frequency distribution (Figure 1) shows an uneven distribution, skewed to the right. Four counties suffered more than a 10 percentage point increase in the unemployment rate during this period. Elkhart County endured the largest increase with 13.3 percentage point increase in the unemployment rate. Monroe County experienced the lowest change (2.2 percentage points) in the unemployment rate (Figure 2a). In Figure 2b, counties at the bottom 10th percentile of changes in unemployment rates are shaded lighter. In these 10 counties, changes in unemployment rates were less than a 3.7 percentage point increase between 2006 and 2009. In the same map, counties at the top 10th percentile of changes in the unemployment rates are shaded orange. These 11 counties experienced greater than an 8 percentage point increase in the unemployment rate. All other counties (in white) experienced anywhere between a 3.7 and 8.0 percentage point increase in the unemployment rate.

OLS results as opposed to the median results to highlight the insights gained from using QR, particularly at lower and upper quantiles.

(a) Changes in County Unemployment Rates

(b) Bottom and Top 10th Percentiles of Changes in County Unemployment Rates

Figure 2: Changes in County Unemployment Rates

The summary statistics for the independent variables used in the models are presented in Table 1. In column 1, we present the data for all 92 counties of Indiana in 2006. The pre-recession average unemployment rate was 5.16 percent. The manufacturing (MFT) sector nearly employed a quarter of the labor force in Indiana, followed by retail trade (RT) with 11.95 percent, and health care and social services (HCSS) with 11.53 percent. Accommodation and food services (AFS) and educational services (ES) employed 8.54 percent and 8.23 percent, respectively. The construction (CONS) sector employed 5.1 percent of Indiana's labor force. With regards to demographic composition, on average 2.96 percent of the county population were Hispanic, whereas Blacks accounted for 2.52 percent of the county population. Lastly, the average per capital income was \$30,274 in 2006.

The second and third columns in Table 1 pertain to the bottom and top 10th percentiles of counties in the changes in county unemployment rates ΔUR_i distribution. There are 10 counties that fall in the bottom 10th percentile, 6 of which are MSA counties and 11 counties that fall in the top 10th percentile, 4 of which are MSA counties. We find the average pre-recession unemployment rate (in 2006) in the bottom 10th percentile was 9.84 percent, while it is 6.95 percent in the top 10th percentile. The manufacturing (MFT) sector had the highest proportion of county employment, while the agricultural (AG) sector had the lowest proportion of workers at both the top and bottom 10th percentiles of the distribution. Counties in the bottom 10th percentile of the ΔUR_i distribution employed a larger proportion of their labor force in AFS, CON, HCSS, RT, and PA compared to counties in the top 10th percentile. On the other hand, counties that experienced the largest ΔUR_i (i.e. top 10th percentile) employed a larger proportion of their workers in the MFT and AG

Table 1: Descriptive Statistics for All, Bottom Tenth, and Top Tenth Percentile of Counties in Indiana in 2006

Variables	Average	Bottom Tenth Percentile	Top Tenth Percentile
Unemployment Rate 2006	5.16	4.72	5.3
	-0.92	-1.08	-0.83
% Workers in Accommodation & Food Services (ACFS)	8.54	9.84	6.95
	-3.91	-5.1	-1.85
% Workers in Agriculture, Forestry, Fishing & Hunting (AG)	1.07	0.7	0.86
	-1.58	-0.82	-0.57
% Workers in Construction (CONS)	5.1	6.75	3.45
	-2.39	-2.64	-0.89
% Workers in Educational Services (ES)	8.23	9.32	8.06
	-5.06	-5.99	-2.22
% Workers in Health Care & Social Sciences (HCSS)	11.53	13.06	8.22
	-3.74	-5.26	-1.76
% Workers in Manufacturing (MFT)	24.61	14.8	39.73
	-12.13	-6.4	-7.28
% Workers in Public Administration (PA)	6.8	8.14	4.71
	-5.71	-12.04	-4.03
% Workers in Retail Trade (RT)	11.95	11.58	10.59
	-2.68	-3.07	-1.95
% Black	2.52	2.56	1.82
	-4.5	-2.74	-2.52
% Hispanic	2.96	1.8	4.43
	-2.78	-0.99	-3.75
% Population with a bachelor's degree ⁶	5.77	7.71	5.01
	-2.63	-5.51	-1.31
Per Capita Income	30274	32789	28414
	-4645.9	-7032.02	-3203.22
Population	68496.7	81206.9	53669.09
	-113018	-79175	-50426
MSA Counties	46	6	4
N	92	10	11

Note: Values in parenthesis are standard deviation.

sectors compared to the bottom 10th percentile counties. There is a larger percentage of Black population in the bottom 10th percentile of counties relative to top 10th, while the opposite is true for the percentage of Hispanic population. As expected, the percentage of population with a Bachelor's degree and per capita income are higher in counties that suffered the lowest ΔUR_i (i.e. the bottom 10th percentile).

4.2. Determinants of Changes in County Unemployment Rates

The impact of the Great Recession on an average-performing county, as captured by OLS regressions, may mask valuable insights. Our QR models explicitly analyze outcomes for counties that suffered the lowest increases in unemployment (i.e. bottom 10th percentile of ΔUR_i distribution) and the outcomes for counties that experienced the largest increases in unemployment (i.e. top 10th percentile of ΔUR_i distribution). By estimating the models for these three conditional distributions, we can see a more comprehensive view of the impact of the explanatory variables to changes in county unemployment rates during the Great Recession.

The results from Model 1 (without MSA interactions) are presented in Table 2. In terms of structural characteristics as captured by sectoral employment, the manufacturing sector (MFT) is the only consistently significant predictor of ΔUR_i across the three conditional distributions (i.e. at the mean (OLS), bottom 10th, and top 10th percentiles). Higher local employment in MFT magnifies the increase in the county unemployment rate during the Great Recession. The magnitude appears to be highest for a county in the top 10th percentile of the conditional distribution (counties with relatively large ΔUR_i). However, further examination of the 95 percent confidence intervals of the estimated coefficients of the bottom and top 10th percentiles show that they are not significantly different relative to the OLS coefficient.⁷ Local employment in agriculture (AG) significantly heightens the increase in unemployment during the Great Recession for counties in the top and bottom 10th percentiles, but not apparent on average-performing counties (OLS). A one percentage point increase in local retail trade (RT) employment magnifies the increase in unemployment by 0.13 percentage points for a county in the bottom 10th percentile of the conditional distribution, but does not add to unemployment of counties that experience either the average or relatively larger increase in the unemployment rate. On the other hand, local employment in the education sector (ES) lessens the increase in unemployment for a county in the top 10th percentile but have no impact at the mean and bottom 10th percentile of the conditional distributions. Lastly, a higher pre-recession unemployment rate (i.e. 2006) amplifies the increase in unemployment across all three conditional distributions. More specifically, the impact on counties that experiences lesser ΔUR_i (bottom 10th percentile) is significantly higher relative to counties that experiences larger ΔUR_i (top 10th percentile).

In terms of demographic composition, the percentage of county Hispanic population consistently amplifies the increases in county unemployment across the three conditional distributions. The magnitude of the impact at the mean (OLS) is not different relative to the specifications for bottom and top 10th percentiles. However, counties in the top 10th percentile (larger ΔUR_i) experienced a larger increase in unemployment (rate) compared to counties in the bottom 10th percentile. These results are consistent with results from previous studies which show racial minorities are disadvantaged by macroeconomic change (Orrenius and Zavodny, 2009). On the other hand, for counties in the top 10th percentile of the conditional distribution, we find a larger percentage of the Black population is associated with lower increases in unemployment. One explanation for this finding is that this minority group is already at a disadvantage prior to the recession, and therefore there is less room for them to be further disadvantaged. Lastly, a larger percentage of population with a Bachelor's degree is associated with greater changes in unemployment for a county with a relatively low ΔUR_i but no significant impact is observed on average (OLS) and on a county with relatively high ΔUR_i (top 10th percentile).

In Model 2 (Table 3), we provide a new set of results which include interactions between the MSA and sectoral employment variables, allowing for the impact of local industry struc-

⁷We use the 95 percent confidence interval of the OLS estimates to determine if quantile estimates are statistically significantly different (i.e. if the quantile coefficient is outside the OLS confidence interval, then we have significant differences between the quantile/s and OLS coefficients) We also use the 95 percent confidence interval of the estimates for the top 10th percentile to determine if bottom 10th percentile estimates are statistically significantly different (Leeds, 2014).

Table 2: Model 1 Regression Results

Variables	Model 1		
	OLS	Q10 (bottom 10th percentile)	Q90 (top 10th percentile)
% Workers in Accommodation & Food Services (ACFS)	-0.0299	-0.0437	-0.0232
	-0.0549	-0.039	-0.0562
% Workers in Agriculture, Forestry, Fishing & Hunting (AG)	0.1578	0.3757***	0.2552*
	-0.1147	-0.0935	-0.1347
% Workers in Construction (CONS)	-0.0087	-0.0023	0.0401
	-0.0942	-0.0649	-0.0935
% Workers in Educational Services (ES)	-0.052	0.0069	-0.0883**
	-0.0359	-0.0311	-0.0448
% Workers in Health Care & Social Services (HCSS)	-0.0606	0.0147	-0.0417
	-0.0497	-0.041	-0.059
% Workers in Manufacturing (MFT)	0.0800***	0.0981***	0.1362***
	-0.0247	-0.0207	-0.0299
% Workers in Public Administration (PA)	-0.0221	0.0277	0.0637
	-0.0513	-0.0361	-0.0521
% Workers in Retail Trade (RT)	0.0778	0.1260**	0.1341
	-0.0922	-0.0624	-0.0899
Unemployment rate 2006	0.5265**	0.7484***#	0.2674
	-0.2337	-0.1628	-0.2345
% Black	-0.0846	0.0399	-0.1406**
	-0.0611	-0.0498	-0.0717
% Hispanic	0.1468*	0.0925*#	0.2682***
	-0.1022	-0.0558	-0.0803
% Bachelors	0.0199	0.1823***#	-0.109
	-0.1016	-0.0866	-0.1247
Ln Population	0.4359	-0.2682	0.7662
	-0.4441	-0.3446	-0.4964
Ln Per capita income	-2.0606	0.8662	-1.8429
	-2.4702	-1.4899	-2.1465
MSA	-0.3898	-0.3887	0.1171
	-0.532	-0.3052	-0.4398
N	92	92	92

Notes: * Significant at the 10 percent level, ** significant at the 5 percent level, and *** significant at the 1 percent level. Values in parenthesis are robust standard errors. + Significant quantile coefficients from OLS at the 5 percent level. # Significant 10th quantile coefficients from 90th quantile at the 5 percent level.

ture (i.e. sectoral employment) to vary depending on its geographical classification (MSA or non-MSA). Ties to major urban centers, size, labor mobility, and location, as captured by the MSA variable, matter in explaining changes in unemployment. When the related impact of sectoral employment is not incorporated, an MSA county in the bottom 10th percentile (those that experience lesser increases in unemployment) experiences about a 7.1 percentage point lower increase in unemployment compared to a non-MSA county in the same conditional distribution. On the other hand, a MSA county in the top 10th percentile (those that experience larger increases in unemployment) incurs about a 4.3 percentage point greater increase in unemployment compared to a non-MSA county in the same conditional distribution. These results suggest that MSA status insulates a county that is already better off before the recession from further increases in unemployment while the opposite is true for a county that is already worse off before the recession. Moreover, the impact of geographical classification varies depending on the local mix of employment sectors as shown in the results of the interaction terms.

A more wide-ranging impact of local industry is observed when sectoral employment is interacted with a MSA classification. The effect of accommodation and food services is only

Table 3: Model 2 Regression Results

Variables	Model 2		
	OLS	Q10 (bottom 10th percentile)	Q90 (top 10th percentile)
% Workers in Accommodation & Food Services (ACFS)	-0.0571	-0.0345	-0.0009
	-0.0625	-0.0584	-0.0287
% Workers in Agriculture, Forestry, Fishing & Hunting (AG)	0.3769**	0.5800***#	0.3755***
	-0.1482	-0.1297	-0.0638
% Workers in Construction (CONS)	-0.0734	-0.1471#	0.1943***+
	-0.1089	-0.0912	-0.0448
% Workers in Educational Services (ES)	-0.0870**	-0.1417***#	-0.0445**
	-0.0351	-0.0423	-0.0208
% Workers in Health Care & Social Services (HCSS)	-0.0999**	-0.0865#	-0.2002***+
	-0.0496	-0.0545	-0.0268
% Workers in Manufacturing (MFT)	0.0801***	0.0352	0.0619***
	-0.0255	-0.028	-0.0138
% Workers in Public Administration (PA)	-0.0118	0.1023+#	-0.1042***
	-0.0445	-0.044	-0.0216
% Workers in Retail Trade (RT)	0.2271*	0.2306***#	0.1203**
	-0.1173	-0.1029	-0.0506
Unemployment rate 2006	0.5588**	0.9674***#	0.7528***
	-0.2478	-0.1668	-0.082
% Black	-0.1381**	-0.0738#	-0.2018***
	-0.0671	-0.0549	-0.027
% Hispanic	0.1421*	0.1245**	0.1166***
	-0.0981	-0.0579	-0.0284
% Bachelors	-0.0148	0.0805	0.049
	-0.112	-0.0921	-0.0453
Ln Population	0.9284*	0.8079**	1.1167***
	-0.4842	-0.4014	-0.1973
Ln Per capita income	-3.3419	2.0611#	-8.2802***
	-2.8133	-1.622	-0.7972
MSA	1.3288	-7.0558*+#	4.2902**
	-4.0377	-3.7588	-1.8475
MSA*ACFS	0.091	0.1427*#	-0.0646*
	-0.0747	-0.0799	-0.0393
MSA*AG	-0.3781*	-0.2095#	-0.6699***
	-0.2019	-0.1777	-0.0873
MSA*CONS	0.1814	0.2768***#	0.0363
	-0.1809	-0.1353	-0.0665
MSA*ES	0.0399	0.1595***#	-0.1215***
	-0.0813	-0.0626	-0.0308
MSA*HCSS	0.0197	0.0275	-0.0172
	-0.0849	-0.0837	-0.0411
MSA*MFT	-0.0036	0.0852***#	0.0385*
	-0.0515	-0.0434	-0.0213
MSA*PA	0.0796	0.1174	0.1468***
	-0.1125	-0.09	-0.0442
MSA*RT	-0.3304**	-0.0770#	-0.3161***
	-0.1634	-0.137	-0.0673
N	92	92	92

Notes: * Significant at the 10 percent level, ** significant at the 5 percent level, and *** significant at the 1 percent level. Values in parenthesis are robust standard errors. + Significant quantile coefficients from OLS at the 5 percent level. # Significant 10th quantile coefficients from 90th quantile at the 5 percent level.

significant on counties at the tail end of the unemployment distribution. For a county in the top 10th percentile of the conditional distribution, local employment in accommodation and food service moderates the ΔUR_i whether it is an MSA or non-MSA county. The same impact holds for a non-MSA county in the bottom 10th percentile while an MSA county in the same percentile experiences a larger increase in unemployment. On average (OLS),

larger local employment in agriculture magnifies increases in unemployment for non-MSA counties while moderating the same for MSA counties. A similar direction and magnitude of impact is observed for counties in the top 10th percentile of the ΔUR_i distribution. However, for a county in the bottom 10th percentile of the distribution, higher local employment in agriculture is associated with larger increases in unemployment for both MSA and non-MSA counties, albeit a larger impact is experienced by non-MSA counties.

The construction sector is a significant predictor of changes in unemployment only for counties at both ends of the distribution. Higher local employment in construction is associated with larger ΔUR_i for MSA counties while a non-MSA county in the bottom 10th percentile experiences lesser ΔUR_i . Local employment in the education sector tempers the increase in unemployment on average (OLS) for both MSA and non-MSA counties. This sector is typically considered counter-cyclical, tends to do well in recessions since demand for its products/services continue, and suffers less when the economy declines and can potentially insulate a county during a recession. The same impact holds for non-MSA counties in the bottom and top 10th quantiles. However, for MSA counties in the bottom 10th percentile of the conditional distribution, ES contributes to larger ΔUR_i .

The effect of the health care sector has a similar insulating influence as the education sector. Greater reliance on manufacturing, higher sectoral employment, magnifies the increase in unemployment, and even more so for MSA counties in the top and bottom 10th percentiles of the conditional distribution. On average however (OLS), the increase in unemployment is tempered in MSA counties. Lastly, retail trade contributes to larger increases in unemployment for non-MSA counties across the three conditional distributions. On the other hand, for MSA counties in the top 10th percentile and at the mean (OLS), retail trade moderates increases in unemployment. Employment in retail trade is likely not as severely affected in MSA counties from relatively stable demand for goods and services due to larger markets serviced. Thus, sectoral employment in retail trade in MSA counties can remain relatively stable dampening the ΔUR_i . We also find consistent evidence across the three conditional distributions that counties that started with higher unemployment rates pre-recession also experience larger increases in unemployment during the Great Recession. The impact is amplified for counties at the bottom 10th percentile compared to counties in the top 10th percentile of the distribution.

In terms of the influence of local demographic composition, the impact of racial minority is mixed. Consistent with the existing literature, a greater percentage of a county Hispanic population contributes to larger increases in unemployment regardless of the conditional distributions considered. The opposite is true for the impact of local Black population (i.e. higher Black populations diminish the increase in unemployment). A larger population amplifies ΔUR_i across the three conditional distributions. A higher pre-recession per capita income helps insulate a county in the top 10th percentile of the conditional distribution (counties with larger ΔUR_i) from increases in unemployment during the recession.

4.3. DISCUSSION

Our use of QR and OLS is warranted, both from a statistical methodology standpoint and from a practical and applied perspective. First, we observed an uneven distribution of our

dependent variable (ΔUR_i). The error terms in the OLS models are heteroskedastic⁸ and QR allows for more flexibility in modeling data with heterogeneous conditional distributions. There are also two types of significance that are important for QR coefficients - the more standard test if it is different from zero and the value added from QR if its coefficients are different from OLS. Although we find that a majority of the QR coefficients are not different from OLS, we do find differences in terms of which specific variables are significantly different for each of the conditional distributions. Thus, from an applied and practical standpoint, QR allowed us a richer characterization and description of the data. We can see different effects of a county's structural characteristics and demographic composition on changes in county unemployment rates depending across the spectrum of the changes in the unemployment distribution. More specifically, modelling the tails of the conditional distribution, specifically for counties that were hardest-hit and least-hit during the recession, was insightful.⁹

A comparison of the results across the three conditional distributions using two model specifications reveals a few consistent outcomes, but also more contrasting impacts of the Great Recession on changes in county unemployment rates. Employment in the manufacturing sector, examined at the conditional mean, bottom 10th, and top 10th percentiles of the ΔUR_i distribution and two specifications (with and without interaction), is consistently associated with larger increases in county unemployment rates. In the same manner, higher pre-recession unemployment, larger county population, and larger Hispanic population, are all related with larger increases in unemployment during the Great Recession in Indiana. These results indicate greater reliance on a pro-cyclical industry - an industry sensitive to the economic cycle cycles and moves with them (i.e. manufacturing), a relatively weaker pre-recession local economy (i.e. higher 2006 unemployment), a larger population overall, and a larger racial minority in particular (i.e. Hispanic population), render counties more susceptible to economic downturns by experiencing larger increases in unemployment, regardless of where the county is in the ΔUR_i distribution

Additionally, our findings suggest that the Great Recession had multifaceted effects across counties and particularly between MSA and non-MSA counties. Changes in county unemployment are not only associated with its workforces' industrial composition, but to an extent affected by geographical classification. Overall, greater dependence on industries that are pro-cyclical, in particular manufacturing and retail trade, lead to greater vulnerability for counties that are both in the lower and upper percentiles of the changes in ΔUR_i . Moreover, manufacturing's impact is further magnified in MSA counties relative to non-MSA counties, while retail trade's impact is quite the opposite, in that it is lessened in MSA counties relative to non-MSA counties. Manufacturing is likely more closely tied with the national trend in aggregate output and economic performance. The construction sector amplifies increases in unemployment for both the hardest-hit and least-hit counties, and relatively more pronounced in MSA counties. Agriculture moderates the increase in unemployment for the hardest-hit MSA counties while it slightly amplifies the increase in unemployment for

⁸Model 1: Breusch-Pagan Test with $\chi^2 = 13.72$ and p-value = 0; Model 2 Breusch-Pagan Test with $\chi^2 = 16.36$ and p-value = 0

⁹One potential limitation of our QR results is the relatively small number of observations. QR utilizes all observations when estimating the coefficients for the quantiles and precision depends on sample size and quantile being modeled. Data is sparser at the extreme quantiles which may lead to lower precision.

the least-hit MSA counties. Greater reliance on education and healthcare help insulate the hardest-hit MSA counties while very minimally amplifying unemployment for the least-hit MSA counties. Overall, we find evidence that greater reliance on pro-cyclical industries (i.e. higher proportion of local employment in industries that move with the economy) make counties more susceptible in economic downturns, experiencing larger increases in unemployment, while reliance on counter-cyclical industries help insulate counties. These are, however, still dependent on county geographical classification (MSA vs non-MSA). Lastly, we find general support to the notion that a county's demographic composition influence changes in unemployment for both group of counties in the top 10th and bottom 10th percentile of the ΔUR_i .

Our analyses and results uncovered common as well as unique characteristics of counties that experienced larger or smaller increases in unemployment during the Great Recession. By identifying key specific predictors to changes in county unemployment rates during a period of economic downturn and how impacts vary across the entire conditional distribution, our results provide policymakers and economic development officials a more precise and targeted set of information. For example, our results provide some evidence that greater reliance in the construction sector is associated with larger increases in unemployment during the Great Recession. As such, local officials can pursue shovel-ready projects to help stimulate the economy. Indiana has the Community Crossings grant program for shovel-ready road construction projects. Using our results, these projects could be targeted more to the hardest-hit MSA counties (top 10th percentile) since the impact of construction employment appeared to be largest for these counties. We also found consistent evidence that the manufacturing sector is related to higher increases in unemployment during the economic downturn. Specific programs and grants to support this sector across the board would be helpful in minimizing severe increases in unemployment. This type of analysis, allowing for more specific information will become increasingly important as resources and funding for development activities become scarce from competing needs.

5. CONCLUSIONS

The severity of unemployment in Indiana during the Great Recession varied across counties. Traditional OLS regression analysis, which examines changes in county unemployment rates at the conditional mean (i.e. for the “average-performing count”) did reveal relevant information. However, quantile regression, which allowed us to examine the “best-performing counties” (bottom 10th percentile of the ΔUR_i distribution) and the “worst-performing counties” (top 10th percentile in the ΔUR_i distribution) yielded additional valuable insights. We do not observe a broad effect of local structural characteristics (i.e. sectoral employment) and local demographic composition on ΔUR_i during the Great Recession by simply looking at the conditional mean. The impact of such determinants become more apparent when examining the extreme percentiles of the ΔUR_i distribution. Even more evident outcomes are uncovered when geographical classification is interacted with local workforce sectoral employment. As revealed in Figures 1 and 2, there is apparent clustering in the ΔUR_i distribution where the top 10th percentile counties were mostly concentrated in the Northeast region of the state while the bottom 10th percentile counties were clustered in the Southwest.

Our use of quantile regression and specifically targeting these two extreme tails of the distribution allowed us to some degree to implicitly capture the spatial aspect of the changes in local unemployment. This, in addition to the fact that our model specification exploits the interaction of structural composition with the MSA vs non-MSA status of counties. This geographical classification capture links to major urban centers, size, labor mobility, and location. Since one of our key findings is the importance of geographical classification, future research can focus on examining unemployment for MSA counties in a regional context.

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