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Economic Downturn, Change in Unemployment, and the Midwest:A Quantile Regression Approach*

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Abstract: Although every area of the U.S. was hit by the Great Recession, the change in unemployment rates varied widely across locations. We use a quantile regression approach to examine the tails of the distribution of change in unemployment rates between 2006 and 2009 across all counties in the Midwest. We find consistent evidence that manufacturing was the largest contributor to the change in unemployment across the three conditional distributions examined, with the impact increasing as we move from the 25$^{\text{th}}$ quantile to the mean (OLS) and 75$^{\text{th}}$ quantile. Likewise, local labor mobility has amplifying effects on the change in unemployment rates, while educational attainment has a moderating effect. Our results suggest that human capital and location-and industry-targeted policies are important in promoting recession-resilient local economies.

Keywords: unemployment rate, local labor mobility, sectoral composition, manufacturing
JEL Codes: R1, R11, R2, R23, J6, J61

1. INTRODUCTION

All corners of the U.S. were hit by the Great Recession, but the extent of the impact varied across localities and regions. Data from the U.S. Bureau of Labor Statistics (BLS) indicate the Western region was hardest hit among the four U.S. census regions, posting a 5.3 percentage-point increase between December 2007 and June 2009, followed by the Midwest with a 4.6 percentage-point increase during the same period. Meanwhile, the least hit region of the Northeast experienced a 3.8 percentage-point increase. The differences in the impact of an economic downturn can be attributed to the industry or sectoral makeup of these regions (among states or counties within a state), making them either more susceptible or resilient to the shocks. Economies (states and counties) that rely heavily on counter-cyclical industries, for example, the education sector, are likely more resilient during these shocks relative to economies that are dependent on pro-cyclical industries, such as manufacturing

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and construction sectors. In addition, location and local labor mobility between neighboring and/or adjacent counties will influence an area's ability to endure these downturns. This regional disparity in the change in unemployment rates underscores the importance of investigating the issue on a smaller geographical scale that allows for easier control of unmeasurable sources of heterogeneity. Our objective is to investigate the impact of an economic downturn on the change in unemployment rates by looking at the sectoral composition of local employment and location/local labor mobility in the Midwest region of the U.S. using a quantile regression approach along the conditional distribution.

The Midwest region provides an excellent opportunity, a natural experiment, to empirically investigate how unemployment responds to a significant adverse economic shock. The region includes states that were at both ends of the change in the unemployment spectrum during the Great Recession. In fact, the Midwest—the Great Plains, in particular, has been considered a shining spot in the U.S.'s otherwise bleak economy during this period (Fiegerman, 2011). At the height of the national unemployment in October 2009, several states in the Midwest, including North Dakota, South Dakota, and Nebraska, had unemployment rates of 5 percent or less. On the other hand, Michigan and Illinois had unemployment rates of 14.10 and 11 percent, respectively. The agriculturally based economies of the Great Plains in the Midwest may be the reason why this area experienced relatively small increases in unemployment, although they may also be susceptible to commodity price volatility. This is in contrast to the more economic shock-prone manufacturing industries in the East-North-Central areas of the Midwest. This wide disparity in the change in unemployment rates across the Midwest during the Great Recession suggests we employ quantile regression (QR) analysis which considers the distribution of the dependent variable at the tails, overlooked by classical regression. Quantile regression (QR) allows us to characterize our data better, gaining insights about specific points in the distribution of the change in unemployment rates other than the conditional mean. Additionally, this approach provides specific information to policymakers to revive affected sectors in an area rather than implementing a common policy across all areas and sectors for economic recovery.

To summarize our goals for this paper, we attempt to understand how prior levels (i.e., pre-recession) of the sectoral composition of local employment and location/local labor mobility contribute to the change in county unemployment rates in the Midwest as it entered the Great Recession while controlling for economic structure and demographic characteristics. We allow for these impacts to vary at different points, in particular the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the change in unemployment rates distribution.

2. LITERATURE REVIEW

Previous studies have examined the impact of an economic downturn on multiple aspects of an economy. Connaughton and Madsen (1980) have shown that disparities in the industrial structure make some states more sensitive to aggregate economic performance during an economic downturn. Watson and Deller (2017) provide an extensive review of the literature and theoretical framework for the generally inverse relationship between economic diversity and unemployment. Brown and Greenbaum (2017) examine the impact of industrial diversity and concentration on unemployment in Ohio counties between 1977 and 2011, and find evidence of lower unemployment on more concentrated counties when times were good. During times of national or local employment shocks, however, counties with more diverse industry structures fared better. Tan et al. (2020) find a positive effect of industrial diversification while specialization tends to have a negative effect on economic resilience in mining cities in China.

Fogli et al. (2013) and Ribant (2012) show the importance of local geographic factors in investigating unemployment dynamics during the Great Recession. Watson and Deller (2017) found spatial spillover effects, that in times of economic downturns, a neighbor's economic diversity can provide a buffer to one's unemployment.

Generally, regression models estimate the impact at the mean, while the distribution of the dependent variable at the tails (lower and higher ends) are often ignored. The literature on regional and local predictors of change in unemployment rates during the Great Recession examines conditional mean estimates (Connaughton and Madsen, 2012; Walden, 2012; Mian and Sufi, 2014; Shoag and Veuger, 2016). In contrast, we employ quantile regression (QR) which allows for the effects of our predictor variables to vary at different points of the conditional distribution of the change in unemployment rates. To our knowledge, only one other study has utilized such framework (Srinivasan and Arano, 2019) in examining unemployment in Indiana during the Great Recession. Although a spatial modeling framework has been utilized in recent literature on unemployment given the potential for spatial dependence, we attempt to control for these with the explicit inclusion of location-specific predictor variables in our model. We fully explore the effects of the sectoral composition of local employment by looking at the impacts for counties that experienced the most, the average, and the least change in unemployment, with the use of quantile regression.

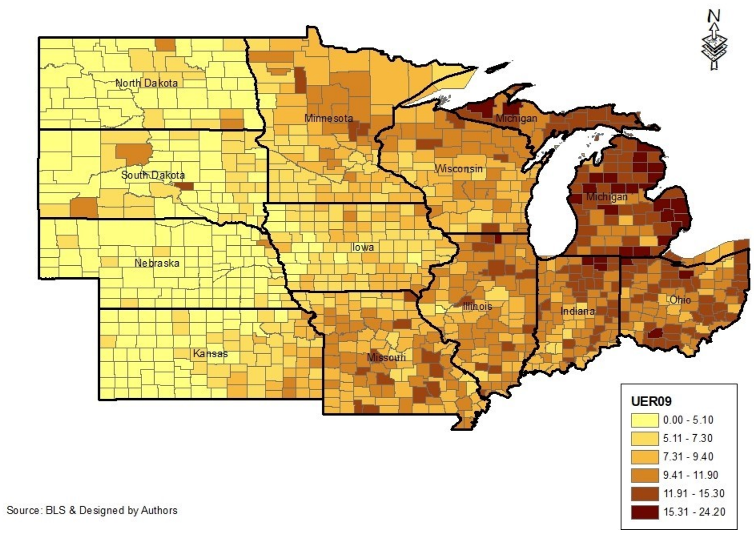
Our contribution to the literature on unemployment during an economic downturn, particularly during the Great Recession, is in four ways. First, we examine an exhaustive list of the sectoral composition of local employment and identify sectors that contributed the most to the rise in unemployment in the local area during a severe economic downturn (e.g., the Great Recession). Previous studies primarily examined economic diversity and concentration using aggregated measures such as Herfindahl indexes and location quotients (e.g., Deller and Watson (2016); Mizuno et al. (2006)). Second, we explore the location aspect of the rise in unemployment by including predictor variables in our model that capture local labor mobility and local area geographic classification. Third, we tackle our questions by employing a methodology that has not been widely utilized in the literature when examining unemployment during the Great Recession. Our modeling approach is quantile regression (QR), focusing on the tails of the conditional distribution—the 25$^{\text{th}}$ and the 75$^{\text{th}}$ percentiles. And finally, we provide insights to pursuing target-specific policies, including both area-specific and sector-specific policies.

3. DATA AND EMPIRICAL MODEL

3.1. Data

We examine the change in county unemployment rates in the Midwest between 2006 and 2009. The data for our principal variable, the unemployment rate, is from the Bureau of

Figure 1: 2009 County Unemployment Rates in the Midwest



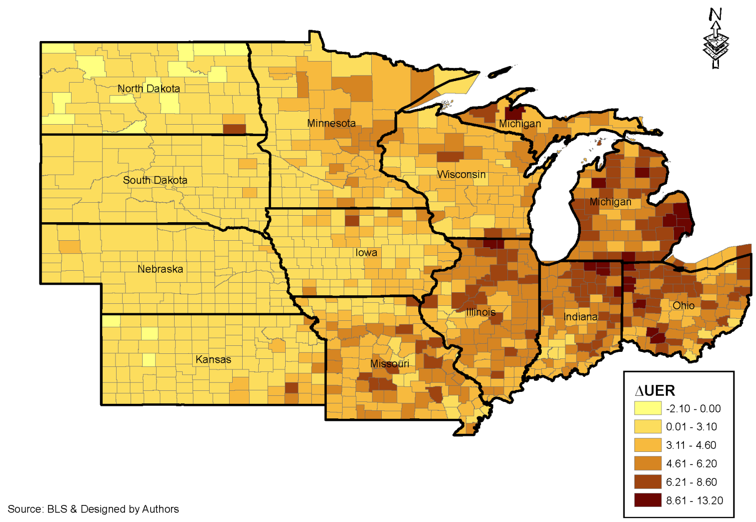
Labor Statistics' Local Area Unemployment Statistics (LAUS). We use 2006 as the baseline year to capture pre-recession employment and 2009 as the closing year to capture the end of the recession, consistent with Thiede and Monnat (2016) who utilized the same period to investigate the geography of unemployment during the Great Recession. Our dependent variable is, therefore, the change in unemployment rates between 2006 and 2009 (ΔUER) for all counties in the Midwest. The set of explanatory variables, which is fully discussed in the next section, include sectoral employment using data from the Quarterly Census of Employment and Wages (QCEW); labor mobility and geographic classification of counties using data from the Economic Research Service of the U.S. Department of Agriculture (ERS, USDA); and economic and demographic factors using data from the Bureau of Economic Analysis (BEA) and Census Bureau, respectively, and are collected for the year 2006.

3.2. Distribution of Change in Unemployment Rates (ΔUER)

In 2006, the average rate of unemployment across all counties in the Midwest was 4.72 percent, and by 2009, it was up at 8.48 percent. Figure 1 shows pockets of double-digit unemployment rates mostly in Michigan, Ohio, and Indiana in 2009. The highest unemployment rate of 24.2% was in a county in Michigan, while the lowest unemployment rate at 2.1% was in a county in North Dakota. Among the 12 states in the Midwest, Michigan had the biggest average change in county unemployment between 2006 and 2009 at a 6.16 percentage-points increase.

Figure 2 shows the change in unemployment rates between 2006 and 2009 across all counties in the Midwest. They range from -2.1 percentage points (a drop in unemployment) from a county in North Dakota to 13.2 percentage points (increase in unemployment) from a county in Indiana. Among the 1,054 counties in the Midwest, 16 counties experienced

Figure 2: Change in County Unemployment Rates between 2006 and 2009 in the Midwest



either no change or a drop in unemployment between 2006 and 2009 (3 counties in Kansas and 13 counties in North Dakota). We can also observe from Figure 2 that the change in unemployment rates increases as we move from West to East. In Michigan, Indiana, and Ohio, a greater percentage of counties experienced a bigger change in unemployment relative to the other nine states across the Midwest. The Northeastern and Northwestern counties in Indiana and Ohio, respectively, along with Southeastern counties in Michigan, have higher concentrations of counties with loss of employment. The change in the unemployment rate is much smaller (between 0 and 3 percentage-points increase) in most of the Western areas of the Midwestern states.

3.3. Empirical Model

To examine the basis for such wide differences in the change of unemployment rates across the counties in the Midwest during the Great Recession, we utilize cross-sectional data to develop a model that incorporates sectoral employment composition, location-related variables, economic factors, and demographic factors which theory and empirical evidence suggest as influential to local economic outcomes in a region. This is summarized in equation (1):

$$\begin{aligned} \Delta UER_i &= \beta_0 + \beta_1 SECTOR_i + \beta_2 LOCATION_i + \beta_3 ECONOMIC_i \\ &\quad + \beta_4 DEMOGRAPHIC_i + \beta_5 DIVISION_i + \epsilon_i \end{aligned} \tag{1}$$

where $SECTOR$ is a vector of sectoral employment variables; $LOCATION$ is a vector of location-related variables expected to influence a local area's capacity to withstand adverse economic shocks; $ECONOMIC$ is a vector of variables controlling for economic environment; $DEMOGRAPHIC$ is a vector of demographic variables; and $DIVISION$ is a vector of dummy variables controlling for divisions within the Midwest region.

All explanatory variables are measured at the county level at the beginning of the period (i.e., pre-recession baseline year 2006[1]) to avoid endogeneity issues. We look for an indication of how prior levels of local sectoral employment as well as location-related characteristics, explain variations in the change in unemployment rates as counties in the Midwest entered the Great Recession. We likewise control for local economic and demographic factors. We describe each set of explanatory variables below.

The industrial makeup of a local economy (i.e., county) influences the degree to which it is vulnerable to changes in unemployment during an adverse economic shock. Connaughton and Madsen (1980) show that variation in industrial structure causes some states to be more sensitive to aggregate economic changes. Rather than utilizing an aggregate measure of industrial structure that captures industry diversity and/or specialization, we use sector employment data from 9 super-sectors available from the QCEW. The vector of $SECTOR$ variables is one of the two primary sets of explanatory variables that we wish to investigate in this study. We define the vector of variables SECTOR as sectoral local employment, calculated as the percentage of a county's employment in a specific sector to the total county employment. As an empirical strategy to avoid the issue of singularity in the empirical model, we only include the top 8 super-sector employers. These include construction, education & health, financial activities, leisure & hospitality, manufacturing, natural resources & mining, professional & business services, and trade, transportation & utilities. We drop the information sector from the empirical model (i.e., the least super-sector employer). In general, we hypothesize that counter-cyclical industries and non-cyclical industries, like education & health services will contribute less to the change in unemployment during a recession. The demand for products and services from these industries continue or remain stable even in an economic downturn. On the other hand, we expect cyclical industries which are sensitive to the business cycle, for example, construction and leisure & hospitality, will contribute more to the change in local unemployment.

The second set of explanatory variables of primary interest in this study are those included in $LOCATION$. The ability of a county to withstand adverse economic shocks is also influenced by location-related variables as they affect the ability of the local area and local labor to adjust to such shocks. Bailey et al. (2014) argue that rural areas may be more disadvantaged during economic downturns due to low educational attainment, aging population, and structural changes. On the other hand, Mattingly et al. (2011) contend that rural areas may have less room to go further down as they are already at a disadvantage prior to the recession. To capture the impact of relative location and proximity to urban areas, we include Metro Area, a dummy variable for Metro counties using the Census Bureau's 2003 definition, i.e., a core area containing a large population nucleus, together with adjacent communities that have a high degree of economic and social integration with that core.[2] This variable allows us to capture the impact of market size and source of labor force. It can also proxy for agglomeration economies (i.e., benefits of clustering of economic activities),

[1]Except for the education variable under $DEMOGRAPHIC$ which uses 2000 Census data due to data availability.

[2]At least 50,000 in a city, or contain a Census Bureau-defined urbanized area (UA) or have a total population of more than 50,000 (at least 100,000).

thereby decreasing unemployment. Local labor mobility can be geographic or occupational. The ability of workers to work within adjacent and neighboring counties, in addition to job skills across industries being potentially substitutable, can help workers better handle labor markets during an economic downturn, helping manage the increase in unemployment. On the other hand, the ability of counties to attract laborers can lead to a larger fluctuation in local unemployment. Feasel and Rodini (2002) show that labor mobility is important to achieve labor market equilibrium. We include the variable Percent Commute, which is the percentage of workers in non-metro counties commuting to central counties of adjacent metro areas, to capture the impact of local labor mobility.[3] These two variables, Metro Area and Percent Commute, allow us to control for the potential spatial correlation, which was visually observed in Figure 2, or the possibility of geographical spillover effects.

The third set of explanatory variables included in the model are to control for economic and demographic characteristics of a county. They include per capita income[4] to indicate the level of economic development, unemployment rate to control for labor market condition and a set of demographic variables including the percentage of female, Black, Hispanic, Asians in total county population, and percentage of the adult population (25 years and older) with a bachelor's degree. In general, factors that increase the stock of human capital in counties will make them less susceptible to economic downturns, helping to manage increases in local unemployment (Partridge and Rickman, 1995) while counties with a larger population of historically racially disadvantaged groups make them more susceptible (Thiede and Monnat, 2016).

Lastly, we also control for other sources of state-level heterogeneity by grouping the 12 states into three divisions for parsimony in modeling. The region dummies are: Eastern which includes Illinois, Indiana, Ohio, Michigan, and Wisconsin; Middle which includes Iowa, Minnesota, and Missouri; and Western which includes Kansas, Nebraska, North Dakota, and South Dakota. We use Middle as the reference category. These regions are consistent with the observed disparity in the change in unemployment rates from Figure 2. The Eastern region experienced the largest change in county unemployment rates during the Great Recession, while the Western region faced a relatively modest change in county unemployment rates.

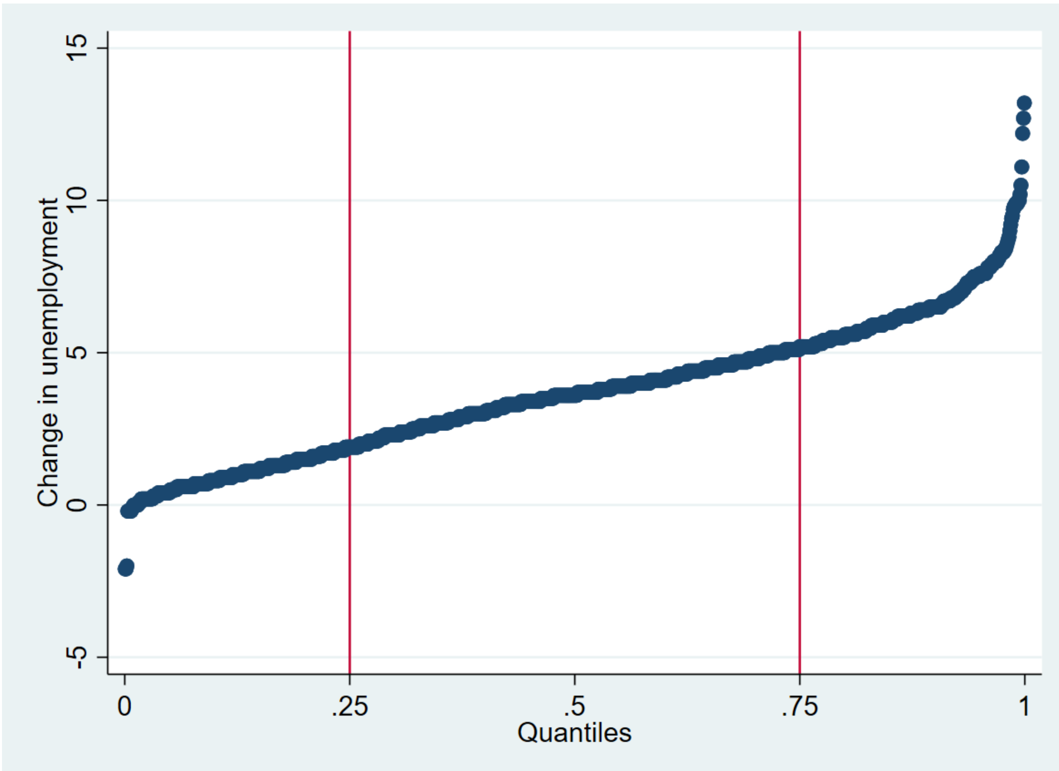
3.4. Estimation Approach

The wide disparity in the change in county unemployment rates (as noted in Figure 2) leads us to further examine the distribution of our dependent variable ΔUER. We plot the distribution by quantiles (Figure 3) and determine that it is not normally distributed but slightly skewed to the right, with a few counties posting relatively large increases in unemployment. This sets the stage for the application of quantile regression (QR) in our

[3] Data is from the 2003 Rural-Urban Continuum Codes from Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). Data distinguishes metropolitan counties by population size of their metro area and non-metro counties by their degree of urbanization and adjacency to a metro area. The data is updated each decennial. We use data from 2003 to match our baseline year of 2006. For more details about methodology, refer to https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/#Methodology.

[4] Per capita income is specified in equation 1 in natural log for a better fit as values vary widely across counties.

Figure 3: Distribution of Change in County Unemployment Rates between 2006 and 2009 in the Midwest by Quantiles



empirical model.

Given the uneven distribution of the change in county unemployment rates in the Midwest during the Great Recession, a methodology that allows for a richer characterization of the data is needed, particularly at the tails of the distribution. Classical linear regression estimates a conditional mean function, while quantile regression (QR) estimates a conditional quantile function. We, therefore, estimate equation 1 using QR. The QR approach examines the impact of predictor variables at different points in the conditional distribution of the dependent variable. It fits a series of regressions at different quantiles, using all observations, but weights different portions of the sample, increasing the power of the test to detect differences in the upper and lower tails of the distribution where data is sparse. QR is robust to outliers and non-normal error terms. Koenker and Hallock (2001) and Koenker (2005) provide an extensive discussion of the QR methodology and its many applications. For comparison, we also estimate equation 1 using Ordinary Least Squares Regression (OLS) which represents the relationship of the explanatory variables to the change in unemployment rates at the conditional mean. This allows us to highlight the insights gained from using QR.

Before turning to a description of our empirical results, we discuss some modeling considerations. First, we report robust standard errors for the OLS results since the OLS model has heteroskedastic errors.[5] This further justifies the use of QR as it provides greater flexibility in modeling with heteroskedastic errors. Second, there is a possibility of spatial auto-correlation given that the data are composed of geographical locations (i.e., counties).[6] Our modeling approach to address this is with the inclusion of two location-specific variables, Metro Area and Percent Commute. The main motivation for our study is to examine the change in unemployment rates for counties that suffered the most versus counties that suffered the least during the Great Recession. Therefore, we use QR as it allows us to accomplish such an objective. An alternative approach would be to employ a spatial autoregressive model to account for spatial autocorrelation, but this would only look at the conditional mean of the ΔUER distribution. To maintain the validity of our results, we also use robust standard errors for the QR results since spatial auto-correlation will invalidate the i.i.d assumption of errors. Lastly, there were a few missing observations for industrial employment from either undisclosed or unreported data. Therefore, the sample size for the regression models is 1,020.

We are specifically interested in examining relationships at the tails of the ΔUER distribution that are not necessarily captured with OLS. Thus, we investigate counties at the bottom 25$^{\text{th}}$ (Q25; least-hit counties) and top 25$^{\text{th}}$ (Q75; hardest-hit counties) percentiles of the ΔUER distribution. As can be gleaned from Figure 3, the Q25 regression characterizes counties that experienced less than 1.9 percentage-points increase in unemployment. These are mostly in the Middle and West divisions of the Midwest. The Q75 regression describes counties that experienced greater than 5.2 percentage-points increase in unemployment during the Great Recession, mostly counties in the East division. A total of 258 counties are in Q25 experiencing an average rise in unemployment of 0.92 percentage points, while 246 counties are in Q75 with an average 6.74 percentage-points increase in unemployment. The average increase in the unemployment rate across all the 1,054 counties in the Midwest was 3.69 percentage points.

4. RESULTS

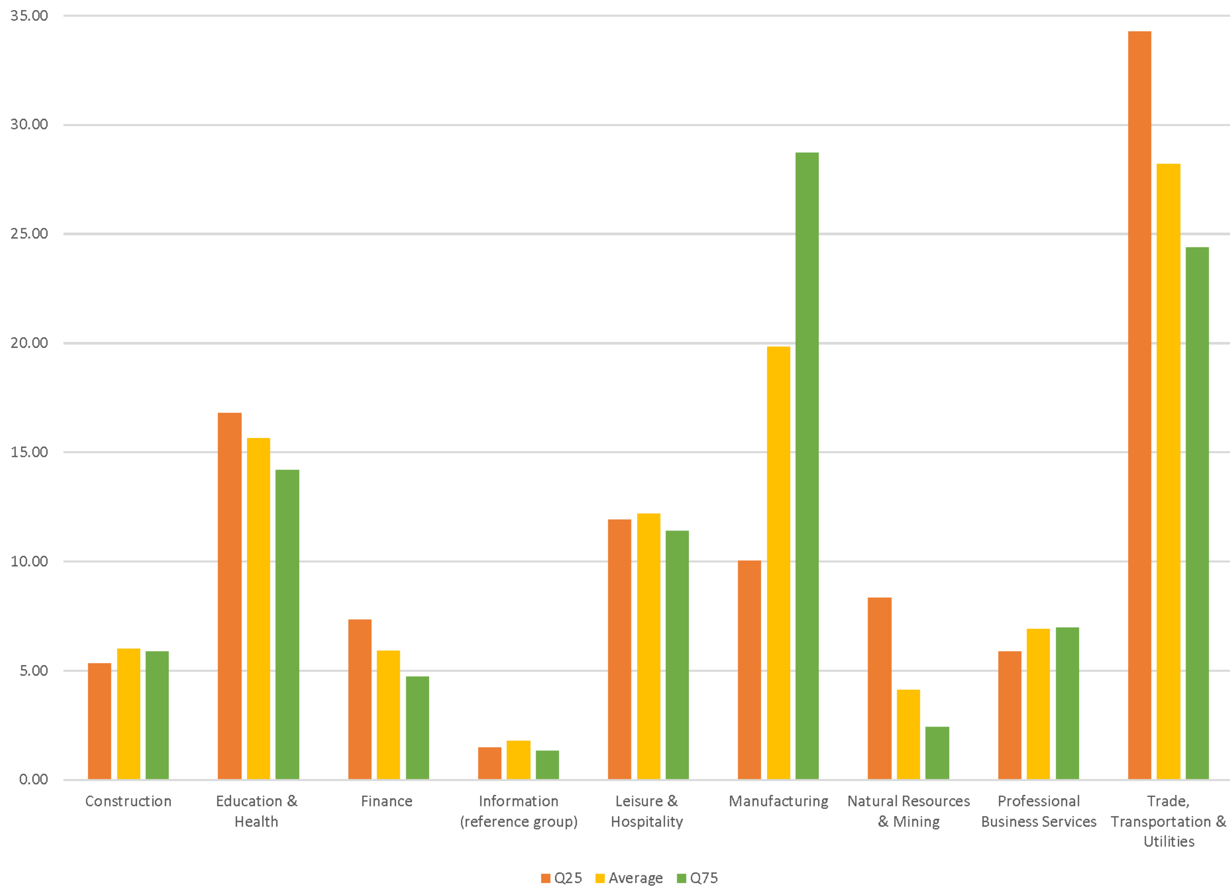
4.1. Summary Statistics of Explanatory Variables

We briefly present the overall profile of counties by the conditional distribution of the dependent variable (ΔUER) before proceeding to report on the results of the regression models. Figure 4 presents 2006 sectoral local employment by relevant quantiles including the average (i.e., 50$^{\text{th}}$ quantile). The summary measures of sectoral local employment as shown in Figure 4, along with all the explanatory variables in equation 1 are also presented in Table 1. Across all counties in the Midwest, only four sectors accounted for nearly 76 percent of total employment. Trade, transportation & utilities employed the highest proportion of the workforce with 28.22 percent, followed by the manufacturing sector with 19.85 percent, education & health sector with 15.65 percent, and leisure & hospitality with 12.20 percent.

[5] Breusch-Pagan test for heteroscedasticity yields a $Chi - square = 151.87$ (p-value = 0).

[6] As visually observed in Figure 2, there was some clustering of change in county unemployment rates where a majority of the Q25 counties were in the Western region of the Midwest (North Dakota, South Dakota, Nebraska, and Kansas), while the Q75 counties were mostly in the Eastern region of the Midwest (Illinois, Indiana, Michigan, and Ohio). The Moran's I, which captures spatial correlation for the Q25 counties, was 0.1143 versus 0.1575 for the Q75 counties.

Figure 4: Sectoral Local Employment (percent) in 2006 in the Midwest by Quantiles



These same industries are likewise the top 4 employer industries in Q25 and Q75 counties, but the relative importance of the relevant industries differ. Q25 counties employ a smaller percentage in manufacturing at 10.03 percent but a higher percentage in education & health at 16.81, compared to all counties. In contrast, Q75 counties rely heavily on manufacturing, employing 28.73 percent of its workforce. It is also interesting to note that the natural resources and mining sector (including agriculture) accounted for 8.34 percent in Q25 counties versus 2.41 percent in Q75 and 4.06 percent on average for the Midwest.

In terms of location-related variables, a greater percentage of counties in Q75 is in a Metro area at 31 percent, higher than the Midwest average at 29 percent, and Q25 counties at only 11 percent. There is likewise a higher percentage of workers in non-metro counties who commute to adjacent metro areas for Q75 counties (7.89 percent), compared to the Midwest average (4.42 percent) and Q25 (1.62 percent). With respect to the rest of the control variables, Q75 counties are less educated, have a higher percentage of the Black population, and are mostly in the Eastern section of the region (86 percent), compared to the Midwest average and Q25 counties. On the other hand, Q25 counties have a larger Hispanic population than the Midwest average and Q75 counties, mostly in the Western section of the region (90 percent).

Table 1: Descriptive Statistics

Variables	**Average**	**Q25**	**Q75**
Construction	6.000	5.323	5.867
	(4.142)	(5.212)	(3.022)
Education & Health	15.649	16.810	14.190
	(7.727)	(10.751)	(5.547)
Finance	5.900	7.353	4.727
	(3.258)	(5.616)	(1.785)
Information (dropped group)	1.798	1.491	1.340
	(3.265)	(1.978)	(1.029)
Leisure & Hospitality	12.197	11.905	11.392
	(7.164)	(8.552)	(4.597)
Manufacturing	19.850	10.031	28.734
	(13.310)	(11.225)	(12.479)
Natural Resources & Mining	4.114	8.344	2.406
	(7.109)	(11.828)	(2.854)
Professional Business Services	6.903	5.878	6.967
	(5.764)	(6.466)	(4.300)
Trade, Transportation & Utilities	28.215	34.489	24.382
	(9.708)	(13.114)	(6.401)
Metro Area	0.286	0.112	0.309
	(0.452)	(0.316)	(0.463)
Percent Commute	4.517	1.617	7.891
	(8.550)	(4.560)	(10.973)
Unemployment Rate	4.721	3.458	6.019
	(1.661)	(1.247)	(1.667)
Per Capita Income	30127.810	29831.830	28959.330
	(5440.043)	(5115.593)	(4748.430)
Percent Female	50.167	49.968	50.191
	(1.431)	(1.647)	(1.354)
Percent Hispanic	3.295	4.468	3.074
	(4.807)	(7.682)	(3.655)
Percent Black	2.220	0.710	2.884
	(4.443)	(1.679)	(4.922)
Percent Asians	0.716	0.434	0.605
	(1.053)	(0.584)	(0.799)
Percent of College Graduates	16.084	16.779	13.483
	(6.297)	(4.859)	(4.870)
East Dummy	0.417	0.008	0.862
	(0.493)	(0.088)	(0.346)
Middle Dummy (reference group)	0.285	0.093	0.126
	(0.451)	(0.291)	(0.332)
West Dummy	0.301	0.899	0.012
	(0.459)	(0.302)	(0.110)
N	1054*	258*	246

Note: Values in parenthesis are standard deviations. A few sectoral employment data were undisclosed/unreported so the final n for all observations (Average column) was 1032 and final n for Q25 was 244. All predictor variables are 2006 values except Percent of College Graduates (see footnote 1).

4.2. Regression Results

Table 2 reports regression results for three conditional distributions of the dependent variable (ΔUER)—at the mean using OLS, at the lower tail (Q25) and upper tail (Q75) using QR. Positive coefficients increase ΔUER (i.e., amplify the change in unemployment), and negative coefficients decrease ΔUER (i.e., moderate the change in unemployment).

We begin our discussion of results from Table 2 by focusing on the primary variables of interest—those that relate to sectoral local employment and location, and then turn to the results of the control variables. As expected, the industrial composition of counties had a significant influence on the change in county unemployment rates during the Great Recession. Mostly the same set of industries are significant contributors to the rise in unemployment across the three conditional distributions. These include construction, leisure & hospitality, manufacturing, natural resources & mining, and trade, transportation & utilities—all amplifying the change in county unemployment rates. Moreover, the impact of sectoral employment appears to be consistently stronger at the upper quantile (Q75)—the hardest-hit counties, while the impact at the lower quantile (Q25)—the least-hit counties, was generally weaker compared to OLS results. A formal test using the confidence interval approach at the 95% level, indicates, however, that only leisure & hospitality, manufacturing and trade, transportation & utilities have significantly larger impacts on ΔUER for Q75 versus OLS and Q25 versus OLS.[7] Education & health was only a significant positive predictor of the rise in unemployment for Q75 counties. Across the three conditional distributions, manufacturing is the largest sector contributor to ΔUER as illustrated by the magnitude of the coefficients and confirmed by an F-test of equality in coefficients across all sectors.[8] For Q75 and OLS, construction is the second highest contributor to ΔUER. These results show that the largest local sector employer does not necessarily contribute the most to the change in unemployment rates. Recall that trade, transportation & utilities was the largest sector employer across all counties in the Midwest (OLS) and the Q25 counties (Table 1). Manufacturing was the largest employer in Q75 counties.

[7] Q75 and Q25 coefficients are significantly different from OLS coefficients if they are outside of the OLS confidence interval.

[8] OLS: $F(7, 1000) = 18.87$ (p-value = 0); Q25: $F(7, 1000) = 13.02$ (p-value = 0); and Q75: $F(7, 1000) = 24.72$ (p-value = 0).

Table 2: OLS and Quantile Regression Results

Variables	**Models**		
	OLS	**Q25**	**Q75**
Construction	0.049***	0.030***	0.060***
	(0.013)	(0.011)	(0.025)
Education & Health	0.013	0.006	0.023**
	(0.009)	(0.005)	(0.012)
Finance	0.007	0.010	0.025
	(0.015)	(0.018)	(0.017)
Leisure & Hospitality	0.031***	0.021***	0.056***
	(0.010)	(0.006)	(0.013)
Manufacturing	0.072***	0.048***	0.096***
	(0.009)	(0.006)	(0.012)
Natural Resources & Mining	0.023***	0.022***	0.030**
	(0.010)	(0.006)	(0.012)
Professional Business Services	0.037***	0.011	0.060***
	(0.012)	(0.011)	(0.014)
Trade, Transportation & Utilities	0.026***	0.010**	0.052***
	(0.010)	(0.005)	(0.012)
Metro Area	0.289**	0.343***	0.363***
	(0.122)	(0.126)	(0.142)
Percent Commute	0.017***	0.018***	0.019***
	(0.005)	(0.004)	(0.005)
Unemployment rate	0.332***	0.327***	0.461***
	(0.056)	(0.044)	(0.047)
Per Capita Income (in ln)	(0.175)	(0.253)	0.344
	(0.323)	(0.318)	(0.323)
Percent Female	0.080***	0.076***	0.073*
	(0.030)	(0.025)	(0.038)
Percent Hispanic	(0.001)	−0.015*	0.006
	(0.011)	(0.009)	(0.005)
Percent Black	0.021*	0.023**	0.004
	(0.012)	(0.011)	(0.010)
Percent Asians	0.055	(0.014)	0.107***
	(0.056)	(0.062)	(0.040)
Percent of College Graduates	−0.030***	(0.003)	−0.042***
	(0.010)	(0.010)	(0.009)
East Dummy	1.126***	0.756***	1.035***
	(0.113)	(0.120)	(0.121)
West Dummy	−1.265***	−1.345***	−1.298***
	(0.111)	(0.120)	(0.123)
Constant	(3.320)	(1.884)	−9.972***
	(3.593)	(3.278)	(3.800)
n	1020	1020	1020

Note: Enclosed in the ( ) reports robust standard errors. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Turning onto location-related variables, we find evidence that relative location and market size as captured by Metro Area variable, and local labor mobility as captured by Percent Commute, are relevant in explaining the change in county unemployment rates. The ability of workers from non-metro counties to commute to adjacent metro areas counties (Percent Commute) significantly magnifies the change in unemployment rates across the three conditional distributions. The magnitude of the impact on counties in Q25, OLS and Q75 specifications are comparable. Furthermore, Metro Area counties experience a larger change in unemployment rates, on average 0.2888 percentage points more (OLS). The impact is slightly stronger at the tails of the conditional distributions (0.3427 percentage points for Q25 counties and 0.3632 percentage points for Q75 counties). These results are consistent with the idea that local labor mobility, through location/proximity or occupational mobility, leads to higher job losses during an economic downturn. Labor mobility increases the supply of labor. Unless firms demand more workers which is unlikely during a recession, more workers will be available than jobs, thus increasing the unemployment rate.

Counties with higher pre-recession unemployment rates experience a larger change in unemployment rates during the recession, regardless of where they lie in the conditional distribution. However, while the impact is significantly larger in Q75 counties compared to the conditional mean (0.4605 versus 0.3321 in OLS[9].), there is no significant difference in the impact between Q25 and OLS.

A higher share of female population is predictive of a greater change in the unemployment rate, and this impact is consistent across OLS, Q25 and Q75 specifications. A higher share of the Hispanic population is associated with a lesser change in the unemployment rate in Q25 counties. Rahe et al. (2019) found a similar negative impact of share of Latino on job losses during the Great Recession for all U.S. counties. Meanwhile, a higher share of the Black population is associated with a larger change in the unemployment rate for OLS and Q25 counties. Average-performing counties (OLS) and Q75 counties with more human capital—i.e., a higher share of college graduates—experience lesser change in unemployment rates during a recession. Lastly, we find consistent evidence of division-specific differences in the change in the unemployment rate during the Great Recession, even after controlling for confounding effects of other variables. Counties located in the Eastern division of the Midwest experienced a greater change in the unemployment rate than counties in the Middle division. On the other hand, Western division counties saw a lesser change in the unemployment rate than Middle division counties. These differences hold across the three conditional distributions.

5. DISCUSSION AND CONCLUSIONS

This paper provides an examination of the role of sectoral local employment and location/labor mobility, in addition to other control variables, to the change in county unemployment rates (ΔUER) in the Midwest during an adverse economic shock (e.g., the Great Recession). First, we observed that the change in county unemployment rates (Figure 2) is much higher in the Easternmost areas of the region—Indiana, Michigan, and Ohio relative

[9]Q75 coefficient lies outside the OLS 95% confidence interval

to the Westernmost areas—North Dakota, South Dakota, Nebraska, and Kansas. In fact, a few counties (i.e., eight counties) in North Dakota experienced a decline in unemployment between 2006 and 2009, likely due to more opportunities in the natural resources and mining sector, which coincides with the 2006 to 2009 boom in the shale production in this area. This uneven distribution of ΔUER means modeling the tails of the conditional distribution, in addition to the conditional mean, is both interesting and worthwhile.

The use of quantile regression (QR) enabled us to have a comprehensive description of our data. The ability to model the tails of the conditional distribution—the 25th quantile (Q25, i.e., least-hit counties during the Great Recession) and the 75th quantile (Q75, i.e., the hardest-hit counties) provided additional insights that were not apparent when modeling at the conditional mean (OLS). Our regression results provide evidence that differences in sectoral employment across counties within the Midwest contributed to the variation in the changing unemployment during the Great Recession. Manufacturing was the largest contributor across the three conditional distributions, with the coefficients being significant, positive, and increasing as we move from Q25, to OLS, and Q75. This indicates that greater reliance on manufacturing contributes to a relatively larger change in unemployment during an economic downturn. More importantly, the amplifying effect of manufacturing is strongest for counties that were the hardest hit during the Great Recession. It seems that greater reliance on manufacturing makes a local economy susceptible to larger fluctuations in unemployment during an economic downturn. Construction was the second largest contributor, with impacts increasing as we move up the quantiles. Both the manufacturing and construction industries were hit hard during the Great Recession. Data from the Bureau of Labor Statistics show that of the 8.2 million jobs lost, nearly two million were from construction, while more than 2.1 million jobs were lost in manufacturing. Moreover, the Midwest is in the manufacturing belt. Other than manufacturing and construction, education & health, leisure & hospitality, natural resources & mining, professional business services, and trade, transportation & utilities sectors significantly influence change in unemployment rates for counties in Q75—the hardest-hit counties. The majority of these industries are cyclical.

Generally, the education sector is considered as a counter-cyclical industry, while health care as a non-cyclical sector. But our results for these two sectors indicate they magnify the change in unemployment for Q75 counties during the Great Recession, although it was the weakest contributor across all the relevant industries. There are a few potential reasons for our results. First, the finances for higher education institutions were severely impacted by the financial market crash, which resulted in significant declines both in the value and returns on the endowment. Second, the state appropriation for higher education institutions also declined due to a shortfall in the tax revenue to the state governments. Most of the higher education institutions resorted to increasing the tuition to make up for the lost revenue. In some instances, these institutions had to downsize and/or merge certain departments (in academic and administrative areas) to balance their budget, which would have contributed to the rise of higher unemployment during the Great Recession (Selingo, 2018). In addition, the lag effect and the age group that went back to school during the downturn were also contributing factors for education being pro-cyclical. Barshay (2021) reports that during the Great Recession, although the number of students who enrolled in college jumped nearly 16 percent from fall 2007 to fall 2010, most of the increase was driven by older adults who enrolled in community colleges and for-profit online schools. Further, there was an 18-month lag as laid-off workers likely exhausted their unemployment benefits first before going back to school. The Great Recession likewise took a toll on access to health care, particularly for lower-income households, through losses of employer-linked insurance, financial security, and housing stability (Towne et al., 2017). Health care providers may have likewise suffered during the economic contraction, also contributing to the health industry being pro-cyclical.

The natural resources & mining (includes agriculture) sector, a relatively large source of employment in Q25 counties, did significantly contribute to the change in unemployment rates during the Great Recession, although it was a relatively low contributor compared to other relevant sectors. Hertz et al. (2014) contends that the relatively modest contribution of this sector to the change in unemployment during the recession was likely due to the relatively high employment shares of agriculture in the Great Plains, where domestic demand for agricultural production is not overly sensitive to the business cycle and demand for biofuel during the 2007/09 recession bolstered agricultural prices. In addition, they find that industrial composition, particularly the favorable industrial mix of the Great Plains at the start of the Great Recession, served to moderate the recession-induced increase in unemployment.

Metro counties and links to them through local labor mobility are associated with a larger change in unemployment during the recession. To the extent that the Metro variable captures urbanization, which is typically associated with agglomeration economies, a negative coefficient would be expected. Our results suggest otherwise—perhaps capturing the negative externalities associated with clustering of economic activities (i.e., more dominant agglomeration dis-economies like higher rents and wages, traffic congestion, and other density-related pollution). In addition, the ability of non-metro workers to commute to adjacent metro counties contributes to a larger change in the unemployment rate, consistent with the idea of loose local labor markets (employer's market) during economic downturns. The ability of Metro areas to attract labor can also lead to larger fluctuations in unemployment. In 2009, at the peak of the Great Recession, the Detroit Metropolitan Area had an unemployment rate of 15.1 percent compared to the national average of 9.3 percent (Austin, 2010).

Local demographic characteristics matter most when examining the mean conditional distribution (OLS) and the least-hit counties (Q25). Higher levels of educational attainment have a moderating effect on the change in unemployment rate for the average-performing counties (OLS), and more interestingly, for the hardest-hit counties (Q75). This is consistent with the view of the role human capital plays in promoting growth and curtailing unemployment.

There are a few policy implications that can be drawn from our results. First, the identified variation on the influence of the significant predictors of ΔUER across the three conditional distributions highlights the importance of pursuing target-specific policies, including both location-specific and sector-specific. Our results suggest that dominant industries (i.e., largest sector employer) in an area do not necessarily contribute the most to unemployment during economic downturns. The more relevant factor is the type of industry—whether cyclical or counter-cyclical. These results were observed given our use of dis-aggregated measures to capture industry structure (i.e., sectoral employment across super-sectors) as opposed to an aggregate measure that captures industry diversity and/or specialization (for example, Herfindahl index). In addition to sector-specific impacts, we were able to observe variation in results across conditional distributions with our use of QR, implying outcomes vary across locations. As such, when policymakers ascertain to implement policies to alleviate unemployment during economic downturns, they must (have to) be mindful of tailoring policies that are targeted for both the location and sectors to maximize the impact rather than a blanket policy with minimal impact.

Second, the fact that the moderating effect of education remains even in areas that are heavily reliant on manufacturing, particularly in Q75 counties where the proportion of college graduates is lower than the Midwest average and the Q25 counties, highlights the value of human capital and skilled labor in mediating the adverse impact of an economic downturn. Policies at the national level to build human capital through higher education across all areas can be complemented by state and local policy initiatives aimed at regional universities, notably for the manufacturing-heavy Eastern region of the Midwest. This can lead to relatively recession-resilient economies. For future studies, it would be interesting to investigate if the moderating effect of education during an economic downturn is stronger in regions of the country that are not as reliant on manufacturing and have a relatively larger proportion of the educated population, for example, the Northeast. Further, it would be worthwhile to consider a modeling approach that incorporates both spatial auto-correlation and modeling the tails of the distribution (of the dependent variable) in a single methodology, i.e., spatial quantile regression.

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