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IS INDUSTRIAL DIVERSITY GOOD FOR REGIONAL GROWTH?

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Abstract

Financial advisors warn against putting all of your eggs in one basket, stressing the importance of diversification to protect against unexpected changes. Likewise, theory predicts regions specializing in a few industries will be tied closely to any fluctuations experienced by those industries. Fluctuations can lead to large swings in wage and employment growth for a region, resulting in higher levels of uncertainty in economic decisions. Volatility makes business planning more challenging, limiting sustainable employment growth opportunities. The diversification of a region's industries may promote sustainable economic growth through an increased mix of local production, creating new sustainable job opportunities and reducing volatility in the labor market. This paper estimates the effects of industrial diversification and volatility on employment growth in U.S. metropolitan statistical areas from 2009 to 2017 using a panel data set. Results suggest that industrial concentration is positively related to job growth, regardless of sector volatility. Regional employment effects closely follow fluctuations in the U.S. business cycle.

Keywords: employment growth, diversification, sector volatility

Introduction

In the financial world of investing, diversification is often recommended as a safe approach for investors to hedge against unforeseen market activity. Diversification suggests that as some industries are adversely affected by market fluctuations, others will benefit. Holding a diverse basket of investment securities will help minimize risk and smooth investment gains over time. Does this same logic carry over to a region's industry mix?

Theory predicts that regions specializing primarily in one or two industries will be tied closely to any fluctuations experienced by those industries, whether those fluctuations are positive or negative. Industry fluctuations can lead to large swings in wage and employment growth for a region. Large economic fluctuations lead to higher levels of uncertainty in economic decisions. Diversification of a region's industries may promote sustainable economic growth through an increased mix of local production, creating new sustainable job opportunities and reducing volatility in wages and employment.

Regional industrial diversification may occur for a variety of reasons, as discussed by Koech and Wynne (2017). First, the geographic location of a region or state is related to the production mix observed. This includes regional borders such as an international border or coastal location, weather patterns, and access to neighboring markets. The economic size and income levels of a region are also influencing factors regarding the degree of industrial diversification observed. Lastly, state policies regarding taxes, labor unions, and immigration also influence a region's level of diversity in production (Fort, Pierce & Schott, 2018; Pallares & Adkisson, 2017; Buch & Schlotter, 2013).

The motivation of this article is to observe the relationship between an area's level of industrial diversification and the factors influencing the labor market. The remainder of the paper is comprised of sections 2 through 6. Section 2 below provides an overview of the relevant literature regarding industrial diversification and economic performance, including employment growth. A discussion of the data set used and the econometric approaches employed are presented in sections 3 and 4, respectively. Section 5 shows the estimated results, while section 6 provides a discussion of these results along with suggestions for future research.

Literature Review

Many studies have estimated the impact of industrial diversification on regional economic performance and employment volatility. In several cases, there is a positive link shown between the diversification of industries and employment growth in a region. Other studies have shown the merits of the specialization of industries, including gains in employment and wages. Lastly, although some studies find a positive relationship between diversification and employment, volatility in regional labor markets may be relatively high. This section provides an overview of the relevant literature and research findings.

Several studies have found a positive impact between an area's industrial diversity and economic performance. Conroy (1975) observed a negative and significant correlation between increased diversification among industries in a given region and employment volatility. His study observed the economic performance of 52 U.S. metropolitan statistical areas (MSAs) between 1958 and 1967. Simon (1988) found a negative and significant correlation between a city's degree of industrial diversification and frictional unemployment. His study estimated the effects using a sample of 91 large MSAs between 1977 and 1981. In a similar study using 4 absolute measures of industrial diversity, Drucker (2011) found that regional industrial structure concentration is negatively and significantly correlated with employment growth using MSA data between 1987 and 1997. Fullerton and Villemez (2011) present similar findings that workers benefit from industrial agglomeration mainly due to greater organizational diversity among employers. They argue that higher wages are strongly correlated with increased organizational diversity, thus leading to more efficient matching between employees and employers. Izraeli and Murphy (2003) find a negative and significant relationship between industrial diversification and unemployment rates using state data from 1960-1997. In addition, their findings show no evidence of reductions in per capita personal income as a result of state policies aimed at diversifying a region's industrial base. Jouili and Khemissi (2019) find that increased economic diversification in Saudi Arabia is positively and significantly correlated with higher job placement rates for graduate students. Their study observed the unemployment rates among graduate and undergraduate students from 2005-2016 at a university located in northern Saudi Arabia.

Other studies have observed relative benefits to industrial specialization in regard to employment growth and reduced volatility. Grennes, Guerron-Quintana, and Leblebicioglu (2010) find that increases in a region's level of specialization are correlated with rising income and employment volatility. Their study observed fluctuations in the agriculture, mining, durable and nondurable manufacturing, and service sectors between 1960 and 2001. Large shares of durable goods manufacturing and service are negatively and significantly correlated with income volatility, supporting the results discussed in Owyang et al. (2008). Additionally, they estimate that states with relatively large shares of agriculture and mining should experience higher levels of income volatility, as found in Koren and Tenreyro (2007). Koren and Tenreyro (2007) observe that increased concentration in non-primary goods production leads to increases in employment and income. Industrial specialization is shown to be positively and significantly linked to increases in income and employment in Peach and Starbuck (2011). Their study showed overall benefits to U.S. counties in states that specialize in oil and gas production, including employment and income gains. Kemeny and Storper (2015) discuss the potential opportunity costs of diversification in their study observing U.S. counties between 1998 and 2010, finding that absolute specialization is positively and significantly related to wages. Additionally, the authors emphasize that it is the type of specialization, rather than the level, that is correlated with significant wage growth with their statement "It is good to do a lot of something, but even better to do a lot of something good (Kemeny & Storper, 2015, p.1015)."

Some studies have shown mixed results regarding industrial diversification and economic performance. Attaran (1986) observed a negative and significant correlation between industrial diversification and unemployment. On the other hand, his study found no significant relationship between diversity and regional growth rates. Felix (2012) finds a positive and significant correlation between a region's industrial diversification and reduced volatility from county observations between 1980 and 2007. However, this study suggests that diversification does not significantly impact long run growth in employment or wages.

Overall, the key findings suggest that the degree and type of industry concentration in an area can influence wages and employment fluctuations in the local labor market. The purpose of this paper is to estimate the effects of industrial diversification on regional employment growth. Furthermore, we will attempt to estimate the sustainability of employment fluctuations observed by industry over the sample period 2009-2017. As discussed in the literature review, there are few studies observing these employment growth fluctuations at the metropolitan statistical area, or MSA, level. As several papers have observed economic growth in larger areas, the purpose of this paper is to see if those results are reflected at the smaller MSA level of observation as well.

Data Collection

The empirical model used in this paper is based on specifications observed in Pallares and Adkisson (2017), Peach and Starbuck (2011), and Reed (2009). Economic growth is measured using the annual percentage change in wage and salary employment, referred to as ΔEMP. In this paper, ΔEMP serves as the dependent variable. Increases in ΔEMP demonstrate economic growth within an area, whereas decreases reflect labor market contractions and, thus, lower growth rates.

The geographic unit observed in Pallares and Adkisson (2017), and Reed (2009) is U.S. state data. Peach and Starbuck (2011) estimate economic growth using country-level data throughout central Asia in their analysis. This paper, however, estimates economic growth at the metropolitan statistical area, or MSA,level as seen in Drucker (2011), Simon (1988), and Conroy (1975). The data include 383 MSAs between 2009 and 2017, resulting in a sample size of 3447 observations. Table 1 below provides a brief description of each variable. Explanations of the calculations and their inclusion are given.

Table 1

Variable Descriptions and Expected Signs

Variable	*Description*	*Expected Sign on Coefficient*
ΔEMP	Dependent variable showing annual percentage change in employment by MSA	
HHI	Annual Herfindahl-Hirschman Index by MSA. Calculations include employment shares in 20 NAICS sectors.	+
SVOL	MSA share of employment in volatile industries as measured by the top 5 NAICS sectors with the highest coefficients of variation from 2009 to 2017.	-
SNVOL	MSA share of employment in nonvolatile industries as measured by the 5 NAICS sectors with the lowest coefficients of variation from 2009 to 2017.	+
LQVOL	MSA location quotient showing employment in volatile industries relative to national employment shares in volatile industries as measured by the top 5 NAICS sectors with the highest coefficients of variation from 2009 to 2017.	-

LQNVOL	MSA location quotient showing employment in nonvolatile industries relative to national employment shares in nonvolatile industries as measured by the 5 NAICS sectors with the lowest coefficients of variation from 2009 to 2017.	+
RPCGDP	Real per capita GDP (2009 U.S. dollars) by MSA 2009-2017.	+
ΔPOP	Annual percentage change in populations by MSA for 2009-2017.	+
LFPRCHSQ	Author estimation of labor force participation rate calculated by summing MSA total employment and unemployment and dividing this by MSA population for each year. Annual percentage changes are then calculated and squared for 2009-2017.	+
$UNEMP_{t-1}$	MSA unemployment lagged by one year (2008-2016)	+
YEAR2009-2017	Dummy variables used to identify the year of observation	+/-

Note: All data listed above was originally retrieved from the U.S. Bureau of Economic Analysis Regional Accounts (http://www.bea.gov). Authors' calculations are provided for annual changes among variables, as well as employment share variables HHI, SVOL, SNVOL, LQVOL, and LQNVOL.

There are several independent variables included in this analysis to help identify factors of economic growth. The Herfindahl-Hirschman Index, known as HHI, provides an estimate of industrial concentration in an area. HHI is calculated by summing the squared percentage market shares of all firms operating in an industry. MSA industry shares were calculated using total wage and salary employment data from the U.S. Bureau of Economic Analysis for 20 North American Classification System (NAICS) sectors. The higher the HHI value, the more industrial concentration occurs within a few sectors. Lower values, however, signal increased diversity among industrial sectors. Table 2 provides descriptive statistics for each of the variables used here.

Volatility within and among industrial sectors is calculated following the process used in Pallares and Adkisson (2017). Using U.S. full-time and part-time employment in the 20 NAICS sectors reported by the U.S. Bureau of Economic Analysis for 2009-2017, means and standard deviations of 2009 – 2017 sectoral employment growth were calculated. Next, coefficients of variation were calculated by dividing each sector's standard deviation by the mean. These coefficients of variation were used to estimate volatility within each sector, with a higher value showing more variation in that sector over time. Table 2 lists the five most volatile and five least volatile sectors according to their coefficients of variation.

Table 2

NAICS Sector Volatility

NAICS	Most Volatile	CV	NAICS	Least Volatile	CV
21	Mining	0.1657	44-45	Retail	0.0273
62	Health Care	0.1155	22	Utilities	0.0271
61	Education	0.1114	42	Wholesale Trade	0.0267
31-33	Manufacturing	0.1088	52	Finance and Insurance	0.0256
23	Construction	0.1031	90	Government	0.0166

Note: Means and standard deviations were calculated for U.S. full-time and part-time employment in the 20 NAICS sectors for 2009-2017 as reported by the U.S. Bureau of Economic Analysis. Coefficients of variation were then calculated by dividing each sector's standard deviation by the mean. The five most volatile sectors are shown, along with the five least volatile sectors.

The most volatile sectors largely mirror the list provided in Pallares and Adkisson (2017), including mining, education, manufacturing, and construction. In our analysis, health care exhibits high volatility relative to the information sector included previously. Likewise, four of the five least volatile sectors shown in Table 3 are also listed in Pallares and Adkisson (2017). In this case, retail, wholesale trade, finance and insurance, and government services are included. The utility sector is also included here rather than other services, as seen in previous studies. The small differences in the list of sector volatility are most likely due to differing time and geographical units involved.

The variable SVOL represents the share of MSA employment in volatile industries, whereas the share of MSA employment in nonvolatile industries is shown by SNVOL. These sector measures differ from the HHI mainly due to their emphasis on volatility. The HHI shows the concentration of employment across a large number of industrial sectors with no differentiation based on volatility.

Alternative measures of employment concentration in volatile and nonvolatile sectors are provided by location quotients as used in Pallares and Adkisson (2017). Location quotients provide a ratio of MSA shares of industrial concentration to national shares using employment data. Location quotients greater than 1 show that an MSA has a higher concentration of employment in that specific sector, while values less than 1 demonstrate less concentration at the MSA level. Location quotients for industries operating in volatile industries (LQVOL) and nonvolatile industries (LQNVOL) are calculated using the following:

$$LQVOL_{xi} = \frac{\frac{EMP_{xi}}{EMPT_i}}{\frac{EMP_{xn}}{EMPT_n}} \qquad LQNVOL_{xi} = \frac{\frac{EMP_{yi}}{EMPT_i}}{\frac{EMP_{yn}}{EMPT_n}}$$

In the equations above, EMP represents employment while the top 5 most volatile and nonvolatile sectors are identified by x and y, respectively, for each i = MSA as well as U.S. sector employment = n. Total employment is represented by T.

Several control variables are also included in the model and discussed below. Real per capita gross domestic product, or RPCGDP, is included to control for differing levels of economic development throughout the country. Increasing real per capita GDP in an MSA is expected to show a positive correlation with job growth in the area. Population growth, or ΔPOP, shows the annual change in the MSA population and is expected to relate positively to local employment growth. Percent changes in the MSA labor force participation rate are squared following Pallares and Adkisson (2017) and referred to as LFPRCHSQ in the analysis. Lastly, unemployment is included here. To control for any previous changes in unemployment that may affect current labor markets, unemployment is lagged by 1 year in the analysis and is represented by UNEMPt-1. Rising unemployment observations in previous years are expected to relate positively to MSA employment growth. Table 3 provides descriptive statistics for each of the variables used here.

Table 3

Descriptive Statistics of Variables

Variable	Mean	Max	Min	Standard Deviation	Variance
ΔEMP	0.0048	0.1171	-0.1711	0.0243	0.0006
ΔPOP	0.0069	0.0799	-0.0435	0.0091	8.23E-05
RPCGDP	0.0415	0.1787	0.0172	0.0131	0.0002
$UNEMP_{t-1}$	7.2827	28.900	2.300	2.8323	8.0217
LFPRCHSQ	0.0002	0.0097	9.36E-12	0.0004	1.92E-07
HHI	0.1435	3.1613	0.0503	0.0748	0.0056
SVOL	0.2825	0.5857	0.0106	0.0914	0.0084
SNVOL	0.4265	0.7731	0.2224	0.0716	0.0051
LQVOL	1.1394	6.4914	0.0364	0.3129	0.0979
LQNVOL	1.1283	2.0758	0.6133	0.1879	0.0353

Note: Descriptive statistics are included in Table 3 for each variable employed in this analysis. The descriptive statistics shown include the mean, maximum, minimum, standard deviation, and variance.

The descriptive statistics provided in Table 3 show a range of values for the different variables. Many of the variables used are ratios, thus leading to relatively small values such as those seen for RPCGDP, HHI, and LFPRCHSQ. The ratios for SVOL, SNVOL, LQVOL, and LQNVOL show a larger range in their values, demonstrating industrial concentration in relatively volatile sectors for some MSAs while others show more industrial diversification in their region. These variables are discussed in more detail in the following section. Lagged unemployment, UNEMPt-1, is shown as a percentage and thus appears relatively large in the data set. For example, the mean value for this variable is 7.2827%, while the maximum value observed is 28.9%. There are only two negative values presented in the table, with ∆EMP and ∆POP having minimum values of -0.1711 and -0.0435, respectively. The following section provides the model employed as well as the methodology used.

Model and Methodology

The panel data set used in this analysis was created to explain MSA level variation in employment growth over time. It is based on the model used in Pallares and Adkisson (2017), employing industry employment shares and location quotients to observe variation in employment changes from 2009 to 2017. Time period fixed effects are represented by the yearly dummy variables for 2009 – 2017 in the models shown below. These dummy variables help to control for national economic influences on MSA employment growth over the period observed. The resulting coefficients on the yearly dummy variables are expected to reflect the national business cycle. The inclusion of the 383 MSA dummy variables provides cross-sectional fixed effects to the analysis as well. Industrial concentration may lead to regional reliance on one or a few sectors for employment stability and growth. This paper aims to observe the relationship between industrial concentration, volatility, and employment growth.

The first model employed is shown in the equation below. Model 1 uses the shares of volatile and nonvolatile industries (SVOL and SNVOL) to explain the observed variation in employment growth. For this reason, we will refer to it as the "Share Model" in later sections. Each MSA is represented by i, while t represents each year.

Model 1:

$$\Delta EMPit = \alpha 1HHIit + \alpha 2SVOLit + \alpha 3SNVOLit + \alpha 4RPCGDPit + \alpha 5\Delta POPit + \alpha 6LFPRCHSQit + \alpha 7UNEMPit\text{-}1 + \alpha 8YEAR2009 + \ldots + \alpha 23YEAR2017 + \varepsilon it.$$

The specification shown in Model 2 replaces the industrial share variables with location quotients (LQVOL and LQNVOL). The inclusion of location quotients provides a ratio of MSA shares of industrial concentration to national shares using employment data, as discussed previously.

Model 2:

$\Delta EMPit = \beta 1HHIit + \beta 2LQVOLit + \beta 3LQNVOLit + \beta 4RPCGDPit + \beta 5\Delta POPit + \beta 6LFPRCHSQit + \beta 7UNEMPit\text{-}1 + \beta 8YEAR2009 + \ldots + \beta 23YEAR2017 + \mu it.$

Results

The estimated coefficients from the analysis are provided in Table 3 below, with t-statistics shown in parentheses. This analysis employs the least squares method using SPSS statistical software. Variance Inflation Factors, or VIFs, are included in the results to detect multicollinearity. Results shown in Table 4 include analysis using specifications shown in Model 1 and Model 2.

Table 4

Estimation Results

Variable	*Model 1*	*Model 2*
HHI	0.010 (2.42)**, *1.61*	0.010 (2.55)** , *1.61*
SVOL	-0.002 (0.64) , *1.77*	-
SNVOL	-0.003 (0.63), *2.18*	-
LQVOL	-	-0.001 (0.86) , *1.77*
LQNVOL	-	-0.002 (0.73) , *2.16*
RPCGDP	0.059 (3.38)*** , *1.20*	0.058 (3.33)***, *1.20*
ΔPOP	0.943 (50.82)*** , *1.11*	0.943 (50.82)***, *1.1*
LFPRCHSQ	-0.464 (0.21), *1.04*	-0.463 (1.27), *1.04*
$UNEMP_{t-1}$	0.022 (1.91)* , *1.90*	0.021 (1.89)*, *1.90*
R^2	0.569	0.567

Table 4 provides the regression results for Models 1 and 2, respectively. T-ratios are included in parentheses while Variance Inflation Factors (VIFs) are included after the T-ratios to detect multicollinearity. Statistical significance at the 10%, 5%, and 1% critical values are denoted by *, **, and ***, respectively.

HHI is positive and significant in each case, as predicted. The direct relationship with ΔEMP suggests that as industrial concentration increases within an MSA, regardless of sector volatility, MSA employment growth rises. A five percentage point increase in industry concentration relates to a 0.05 percentage point increase in annual employment growth. This result supports the findings of Pallares and Adkisson (2017).

The coefficients for SVOL and SNVOL were not significant in Model 1 analysis. Likewise, LQVOL and LQNVOL were also not significant in the estimation for Model 2. This finding suggests that volatility in industrial sectors does not play a significant role in determining regional employment growth at the MSA level. These findings fail to support the results of Pallares and Adkisson (2017), showing that different geographical units may demonstrate differing levels of variability.

The estimated coefficient on the real per capita gross domestic product (RPCGDP) is positive and significant in each case. As predicted, higher income relates to higher job growth in an area. A one percentage point increase in real per capita GDP is positively correlated with a 0.059% rise in yearly employment growth. Changes in regional demographics and the labor force can certainly affect employment. The resulting coefficients for ΔPOP are positive and significant at the 1% level, suggesting that the rising population in an MSA is positively correlated with higher levels of job growth. The model predicts that a one percentage point increase in population will result in a 0.943 percentage point increase in employment. On the other hand, the relationship between employment growth and changes in the labor force participation rate is not significant. This finding supports the results of Pallares and Adkisson (2017) and Grennes, Guerron-Quintana, and Leblebicioglu (2010).

Additionally, the one-year lagged unemployment rate exhibits a positive and significant relationship. High levels of unemployment in the previous period may help to spur employment growth in the present. Specifically, a one percentage point increase in the previous period's unemployment rate relates to a 0.02 percentage point rise in current job growth. Our observation of a positive correlation between lagged unemployment and employment growth supports the findings of Pallares and Adkisson (2017).

The results of the second model, including location quotients, support those shown for Model 1. Overall, results are very robust across the two models in regard to coefficient size, sign, and significance. In both cases, HHI is positive and significant, showing that as an area's industrial concentration increases into one or more sectors, MSA employment growth increases. This finding suggests that MSAs may benefit more from industrial concentration than by maintaining a diverse set of industrial sectors, emphasizing a potential role for specialization in certain areas. On the other hand, the non-significant findings for shares of volatile and non-volatile industries (SVOL and SNVOL), as well as the location quotients (LQVOL and LQNVOL), suggest that sector volatility does not significantly influence employment growth at the MSA level.

Lastly, the results on yearly dummy variables are not shown in Table 4. The coefficients are all statistically significant for each of the 9 years included in this analysis. The results demonstrate that the yearly dummy variable coefficients largely reflect the business cycle for the U.S. economy, contracting in times of recession and expanding during periods of growth.

To check the robustness of our results, dummy variables were included for each of the 383 MSAs in the data set. Using the same specifications as shown for Models 1 and 2, the regressions were run using MSA dummy variables. In Model 1, only 2 of the resulting coefficients on the MSA dummy variables were significant at the 1% critical value level. For Model 2, there were 6 coefficients that were significant at the 1% level. The inclusion of the MSA dummy variables does not appear to be an overall significant factor in the model. The following section provides a summarized discussion of the analysis as well as ideas for future research.

Discussion and Future Research

The original purpose of this paper was to observe the relationship between an area's level of industrial diversification and the factors influencing the labor market. Specifically, our goal was to estimate the effects of industrial concentration on regional employment growth. Based on the results presented in Table 3, there is a significant correlation between industry concentration and regional employment growth. The positive and significant coefficient on HHI suggests that as industrial concentration increases within an area, that area will experience an increase in employment growth, regardless of sector volatility. At the same time, the results for the volatility measures (SVOL, SNVOL, LQVOL, and LQNVOL) were not significant, demonstrating that at the MSA level, sector volatility does not directly impact employment growth.

Increases in population growth (ΔPOP) and the lagged unemployment rate (UNEMPt-1) relate positively to job growth. These findings demonstrate that for job growth to occur, an increasing supply of available workers will be needed to take advantage of market opportunities. In addition, the positive correlation between job growth and real per capita GDP (RPCGDP) shows that higher income levels are positively correlated with regional employment growth.

The results discussed in this analysis largely support the findings of Pallares and Adkisson (2017) and Reed (2009), both of which employed state-level data in their estimations. However, the size of the coefficients is comparably smaller for several variables observed in this analysis using MSA-level data. One explanation for this difference in results may be explained by the geographical scale of data employed. Chen (2019) discusses the magnitude and significance of the effect of industrial diversity varies greatly when different geographical units are used. Chen argues that smaller geographical units, such as MSAs, create a small population problem whereby measurement issues can commonly occur with place-of-residence and place-of-job observations.

There are several opportunities for future research observing industrial diversification and fluctuations in the labor market. As discussed in Chen (2019), geographical units employed can greatly influence a study's results. In that case, perhaps comparative analyses observing similar relationships between industry concentration, volatility, and job growth could be conducted using county and/or regional area data. Individuals engaged in policymaking and city planning efforts should take these findings into consideration when developing efforts to attract new businesses to a region. It is important that these policymakers and city planners have the right tools, as well as the right economic data, to make decisions that will promote economic growth in their respective areas.

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