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Abstract

Much has been written by various scholars and practitioners over the years about the benefits of industrial clustering, whether the clustering revolves around mature industries or around new and innovative industries (innovation clustering). The benefits of such clustering or local agglomeration economies supposedly include greater regional exports, greater employment growth, greater payroll growth, and greater new business establishment creation, among other impacts. However, the work for this research note has not uncovered much if any literature on how agglomeration affects United States regional unemployment rates. In general, greater clustering is associated with lower US metro area unemployment rates on average, although this depends upon how one defines a cluster. Additionally, most growing industrial and innovation clusters over the last two decades or so require highly educated and skilled workers. Since most of the unemployed at any given time tend to be less educated and less skilled than most workers on average, local and state economic development policies that focus on clustering must be careful in targeting lower unemployment rates as a policy goal or outcome. On the other hand, greater clustering and greater industry concentration do not seem to be associated with greater levels of unemployment during stagnant economic times as some may expect. That is, it does not appear that diversity of industry has an advantage over industry clustering and concentration in bad economic times. Finally, the arguments that decentralized or local economic development planning is better for the macroeconomy than centralized planning at the national level is discussed in light of the results for industrial clustering found in this paper.

Key words: agglomeration economies, economic development, industrial clustering, and urban economics.

JEL Codes: R1, R3

Introduction

The concept of economies of agglomeration or clustering is a key concept in the field of urban and regional economics. It refers to the fact that in a city or region firms of similar or complementary industries tend to locate together in close proximity so as to benefit from a common labor pool with industry specific skills and to benefit from a pool of suppliers and/or distributors so as to obtain economies of vertical integration (O'Sullivan 2012). More specifically, this form of economies of agglomeration is called economies of localization. Even though sometimes competitors, firms in the same industry can enjoy productivity and efficiency gains that would not exist elsewhere if they were located away from their counterparts. The significant gains in output and productivity due to such clustering is a key determinant of regional economic growth and size as successful industries grow and hire more employees in a region. Such was the case for the Detroit, Michigan region during the growth stage of the auto industry in the US, and is currently the case for Silicon Valley in California as the computer and information technology industries continue to grow.

Ever since the publication of Michael Porter's seminal work *The Competitive Advantage of Nations* (1990) and his subsequent works on regional competitive advantage (1998,2003a, 2003b), local economic development writings, both scholarly and non-scholarly, have joined Porter's lines of analysis and reasoning on the benefits of industrial clustering policy. They have argued that greater industrial clustering or agglomeration for existing industries or newly emerging industries and/or for entrepreneurs can lead to greater employment growth and wages in a region, all else held constant (Kresl and Singh 1994, 1999 and 2003, National Governors Association 2002, De Blasio and Di Addario 2005, Kresl 2007, Muro and Fikri 2011, Chatterji, Glaeser and Kerr 2013, Gittel, Sohl and Tebaldi 2014, among many others). In these papers, there are often explicit or implicit arguments for policies that promote some type of industrial clustering, although specifics with regard to what type of planning for clustering should be done or which types of specific incentives should be offered are often not mentioned.[1] Instead policy makers at the regional level are informed that clustering is important and should be of paramount importance in regional economic development planning. Recently, the Obama administration began initiatives to help regional economic development where industry clustering benefits are an explicit goal of federal economic development policies (White House 2011).

Some papers have noted that clustering can be enhanced by coordinating industry development efforts among local governments and by getting out information to firms that could benefit from locating or participating in an industry cluster. (Rodreiquez-Clare 2005). Others emphasize the role of entrepreneurs in cluster success (Feldman, Francis and Bercovitz 2005). Eion O'Leary (2015) believes that much of Ireland's clustering success and later failure occurred because Ireland made itself a tax haven for larger corporations (Apple, for example), made itself attractive for foreign direct investment (FDI), pursued "beggar thy neighbor policies", and had a highly educated workforce which led to high tech job growth. In the 1990s, the nation decided to use government policy to promote clustering in order to mimic US success in the information and computer technology sector. Ireland's successful clustering or economic development was not so much due to indigenous business development but mostly due to the EU membership and the "beggar thy neighbor" policies according to O'Leary. He believes that too many industries focused on rent seeking activities in which they tried to extract favorable government policies.

[1] See for example "Kentucky's Target Industry Sectors" by EMSI and Maher and Maher(2011). This consultant's report does a good job of identifying the state's industry clusters and making future industry growth projections but does not really recommend to policy makers how to promote or grow the clusters.

For France, Martin, Mayer and Mayneris (2014) find that clustering does not help exporting firms that much when it comes to periods of economic downturns because the largest firm in the cluster suffers the most during recessions. They also find mixed results on cluster productivity impacts and the effects of government cluster policies in France (2011a, 2011b). Meanwhile, for the United Kingdom, Devereux, Griffith and Simpson (2007) find that government grants to promote and assist firm location to enhance clustering in urban areas has a mild impact, although the economic benefits of co-location tend to outweigh grant amounts.

William B. Beyers (2013a, pages 242-246) finds using correlation coefficients that at the state level, during and shortly after the Great Recession, greater clustering in construction, manufacturing, transportation, government and services are moderately associated with lower state unemployment rates whereas business services are associated with greater unemployment rates. The latter may be occurring according to him because of a dramatic fall in finance, insurance and real estate industries in the US after the recession started. However, most consider a job market a metro region, not a state (O'Sullivan 2012). Using cluster analysis, he also finds in another research piece (2013b) that states with more diverse economies have lower unemployment rates on average, although some of his results seem to contradict his other findings. He also explains that he did not choose to analyze metropolitan level industry and unemployment numbers because of data suppression at the industry level for many metro regions.

Yet in the course of performing research for this paper, no studies have been found that empirically document the impact of greater clustering on the *unemployment* rates of metro regions in the United States.[2] It is important to point out that gains in regional employment do not immediately and necessarily translate into proportional decreases in an area's unemployment rate. Many times, the new jobs created are filled by those currently working or those who move in from outside of the region (Bartik 1991, Persky, Felenstein and Carlson 2004). Some regions also suffer from greater degrees of structural unemployment than others. Structural unemployment exists where there is a large number of unemployed whose skills are obsolete because the industries in which they worked have dramatically shed jobs in the area or have left the region completely. These unemployed workers often do not derive much benefit from new jobs in newer industries that are created in a locale (Blair 1995). Therefore, higher than normal unemployment rates possibly can persist in a region which has seen the loss or decline of one or several key industries even as there are gains in local job growth. Although the literature on the benefits of clustering do not explicitly mention clustering as a way to address regional unemployment, the emphasis on clustering as a way to accelerate employment growth can be considered as implying that clustering can indirectly solve local unemployment problems, especially if regional job training and human capital investments can be done in such a way to help the unemployed get jobs in the clustered industries, which is a policy often recommended (e.g., National Governors Association 2002).

On the other hand, during periods of economic downturn or stagnant economic growth, a large degree of regional industrial concentration, especially in industries with mature or declining markets, can translate into higher unemployment levels for a metro area, all else held constant. Although the benefits of clustering imply lower unemployment rates, an area which

[2] Spencer, Vinodrai, Gertler, and Wolfe (2010) show a statistically significant and inverse relationship between industry clustering and unemployment rates for Canadian regions, although they use a different method for defining industry clusters than that conventionally used.

has too much concentration in one or a handful of industries (e.g., Detroit or Gary, Indiana with steel making) could end up with an abnormally high level of unemployment during a recessionary period. Therefore, the impact of a high degree of clustering can be uncertain with regard to the unemployment rates of different regions.

This paper proceeds as follows. In the next section (Methods), bivariate relationships between the IUPU clustering data and the employment growth and unemployment rates for metro and micro regions in the US are examined. Next, additional variables are added to the IUPU data to see if after controlling for these variables clustering effects are statistically significant. Then, CBP data is used to construct a cluster index for the years 2007 to 2013 for 50 major US metro regions to which additional variables are added for form panel data to test for agglomeration effects on the unemployment rates for these regions over 2007-2013. After the Methods sections, the data analysis results are discussed, which is then followed by a concluding section which makes policy recommendations and recommendations for further research.

Methods

This paper primarily used two databases for indicators of industry clustering. One was from the Indiana Business Research Center at Indiana University and the Purdue (University) Center for Regional Development and funded by the US Economic Development Administration titled "Innovation in American Regions: Tools for Economic Development" (http://www.statsamerica.org/innovation/). The database 1) classifies employment, payroll and establishments in US metropolitan and micropolitan regions according to whether they are in one of seventeen industry clusters such as mining, energy, manufacturing (a "super-cluster"), etc.; and 2) has "innovation index" scores for different US metro regions according to the metro area's level of human capital, research and development, economic dynamics[3], productivity and employment, and economic well-being[4] (http://www.statsamerica.org/innovation/innovation_index/weights.html). The database also has data on employment gains in each region from 2012 to 2013. The clustering data from 2011 are matched against the metro or micro area's average unemployment rate from 2010 to 2012 (US Bureau of Labor Statistics, Local Area Unemployment Statistics) and employment growth from 2012 to 2013. The Innovation Index scores from 2010 are matched with metro area unemployment rates from 2010 (Local Area Unemployment Statistics). These years are post the Great Recession period of December 2007 to June 2009. The greater the degree of industry clustering and the greater the degree of innovation in a metro or micro area, one would expect, given the literature on industry clustering and all else held constant, that employment growth should be higher, and unemployment should be lower on average. A drawback of the Indiana and Purdue University (IUPU) database, however, is that the same metro regions are not used each year which hinders the formation of a panel dataset. The year 2011 was chosen because it had the most comprehensive list of metro areas among all the years in the dataset.

The other database is the US Census Bureau's County Business Patterns (CBP) (http://www.census.gov/econ/cbp/) from which a cluster index based on location quotients for major industry classes was calculated for the largest 50 metro areas in the US for the years 2007-2013. The location quotients (LQs) for each major industry were summed to form an overall industry concentration index. These could also be interpreted as an export index as well. The largest 50 were chosen because these had full data disclosure for each industry. That is, there

[3] A measure of local business climate such as, for example, the availability of research and development funding (Slaper and Justis, 2010).

[4] Factors such as per capita income, earnings, etc. (Slaper and Justis, 2010)

were no missing values for the major industries whereas it was possible for smaller MSAs. Additionally, the indices for these 50 regions were calculated for the years 2007 to 2013 to form a panel dataset so as to look for any clustering impacts on unemployment rates over time, especially before, during and after the Great Recession.

Bivariate Analysis

(Insert Figures 1, 2, and 3 around here)

First, the relationship between the different degrees of clustering and employment growth are examined using the Indiana University and Purdue University (IUPU) data. Figure 1 shows the relationship between the number of employees in clusters as a share total employment in a metro area in 2011 and the percentage change in employment in the metro/micro area from 2013 to 2014.[5] The independent variable is not statistically significant at $\alpha < 0.05$. In looking at the graph, there appears to be a very weak relationship between employment growth and industry clustering as of 2011 over the period August 2013 to 2014 for the 366 regions for which there is data. The r-squared value for the linear trend equation underscores this as its value is less than 1%.

Next, the portion of payroll classified as being part of an industry cluster is used to predict regional employment growth. Figure 2 shows no relationship between these two variables, and the independent variable is not statistically significant at $\alpha < 0.05$.

Finally, the percentage of establishments classified as being part of an industry cluster is used as a predictor of employment growth. The scatterplot shown in Figure 3 suggests the

[5] The portions for industries classified as "super-clusters" are counted twice so as to give them greater weight because the US Economic Development Administration considers these to be important in job growth and regional economic development.

strongest relationship among the pairs of variables considered so far, albeit it is still an overall weak relationship since the r-squared is only around 5%. Yet in this case the independent variable is statistically significant $\alpha < 0.05$. This variable, therefore, will be examined in multivariate analysis.

(Insert Figures 4, 5, and 6 around here)

Next, the same measures of the degree of industrial clustering according to employment, payroll, and number of establishments are used to predict the average of the unemployment rates for the years 2010 to 2012 for the 366 regions. Figure 4 shows that there is only a very slight, negative relationship between the portion of employment in a region classified as being part of a cluster and the unemployment average for these years. Only about 1% of the variation in the unemployment rate average can be explained by the concentration of cluster employment, although it is statistically significant at $\alpha < 0.05$.

Meanwhile, Figure 5 shows similar results when cluster payroll totals as a portion of total payroll in the regions are used as predictors of the average unemployment levels. The relationship between the concentration of payroll in clusters is inversely related to average unemployment rates, yet the clustering effect can only explain about 1% of the variation in the average level of unemployment, although it is statistically significant at $\alpha < 0.05$.

Figure 6, however, shows better results for industry clustering effects. When the share of establishments that are part of clusters are plotted against the average unemployment rates, the linear trend line fits much better with a r-squared value of around 23%, and it is statistically significant at $\alpha < 0.05$. Given that cluster employment and payroll measures are not that strong with regard to explaining the variation in average unemployment levels, further research is needed to determine why the cluster establishment portion is. One possibility is that the metro areas with a high degree of establishments in clusters and low average unemployment rates have a large number of small firms in their clusters. With a disproportionate number of small firms, perhaps the payroll and employment effects at a regional level are smaller if the firms are very new and their sizes are very small.[6] Further research is needed to somehow estimate typical firm size within each cluster in the data to see if this is correct. Currently, these numbers are not available. Firm sizes for metro areas are available from the US Census Bureau's County Business Patterns (http://www.census.gov/econ/cbp/), but these are broken down according to the North American Industrial Classification System (NAICS) and not according to the classification system used by the IUPU database. Much of the literature examined for this note mentioned the benefits of small, entrepreneurial firms in job creation in many areas. Perhaps the benefits also apply to keeping unemployment rates low as well. Interestingly, some regions that had lower, average unemployment rates and a high concentration of cluster establishments tended to be in parts of the US with high concentrations of mining and energy production clusters such as eastern Texas and North Dakota. These two states also had among the lowest unemployment rates in the nation during the Great Recession (Local Area Unemployment Statistics).[7]

(Insert Figures 7, 8, and 9 around here)

Additionally this stage of the analysis looks at the database's Index of Innovation and how well scores based on this index predict the unemployment rates and change in earnings for

[6] These findings could also reflect something idiosyncratic to the IUPU database, about which few details are given on the website except a mention of how clustering is done according to location quotients.
[7] Data using 2007 unemployment rates show the same results in general.

51 metro areas.[8] A Super Index that is based upon a composite scoring of human capital, economic dynamics, productivity and employment, and economic well-being factors in the region is the main composite of the Index of Innovation for the year 2009. Figure 7 shows that these factors have a mild impact upon the unemployment rate (2010) of a region, although there does exist an inverse relationship, and the Super Index is statistically significant at $\alpha < 0.05$. On the other hand, a region's degree of innovation does appear to play a role in the change in earnings that it experiences. Figure 8 shows that the higher the Super Index, the higher the change in earnings for a metro area from 2010 to 2011, and the index is statistically significant at $\alpha < 0.05$. The r-squared value indicates that the innovation index can explain around 20% of the variation in a region's change in earnings, which means that it has modest predictive power. Finally, because the database uses an ordinal scale to show employment or job growth per population, a linear trend line is not appropriate to use as a gauge to see if there is a relationship between it and the Super Index. However, Figure 9 is presented without a trend line to indicate the general relationship between the index and the job growth scale. As one can see, there is not much of a relationship between the two variables. However, the innovation or Super Index is used with other variables in the next section to see if the relationships hold.

Multivariate Analysis using IUPU data

As a follow up to the bivariate regression analysis of the 366 metro areas, in Table 1 Model 1 shows that the percentage of cluster establishments is still a statistically significant predictor of employment growth with a 1% increase in the percentage of firms being in a cluster predicting a 0.03 increase in employment growth on average. This is after controlling for

[8] When requesting recent data from StatsAmerica.org, data for only around 51 metro areas for 2009 for the Innovation Index were sent to us.

whether the central county(ies) of the MSA is in a right to work law state (1=Yes, 0=No) and the percentage of the population 25 years of age and older (American Community Survey, US Census, 2011). These variables are included because right to work laws are argued to promote employment growth because labor markets are more fluid than with a union presence, and a more educated workforce should result in a more vibrant local economy, all else held constant, given that the college educated are supposed to be more productive (Florida 2002). Neither of these two variables are good predictors of employment growth, however.

To extend the bivariate analysis of the unemployment rate, Models 2, 3, and 4 in Table 1 show that only the percentage cluster establishment is a statistically significant predictor of the average unemployment rate for 2010-2012 for the 366 metro areas. A 1 percent increase in cluster establishment concentration predicts a 0.1221 percent decrease in the unemployment rate for a metro region on average and all else held constant. Percentage cluster employment and percentage cluster payroll are not good predictors. In all three models, the right to work dummy variable and the percentage college educated variable are statistically significant and have their expected signs. MSAs which have a central county or counties in a state which has a right to work law have lower unemployment rates on average, and the greater the college educated in a metro areas, the lower the unemployment rate on average and all else held constant.

For the follow up to the Super Index for year 2009 bivariate regression, Models 1and 2 in Table 1 show the results of using the index along with the presence of a right to work law in the metro area (defined according to the whether the central/core county(ies) in the MSA is in a right to work law state) to predict a region's change in earnings from 2010-2011 and a region's 2010 unemployment rate. Since the Super Index already includes a human capital index in it, a separate variable for the portion of college educated is not included in this model. Both variables are statistically significant in each case, although the explanation of variation in the earnings change is stronger than that for the unemployment rate with the r-squared for Model 1 at 23.5% and for Model 2 at 12.6%. In Model 1, a 1 unit change in the index is associated with 0.55% increase in earnings on average whereas in Model 2, a 1 unit change in the index is associated with a 0.004 decrease in the unemployment rate on average.

Multivariate Analysis using CBP Panel data

Table 3 shows the results of using the CBP data for employment, payroll and establishments to predict the unemployment rates of 50 metro regions from 2007-2013 along with the following independent variables[9]:

1. Capacity Utilization Index, 2007-13. This is the metro area's real GDP as a portion of the 2007 real GDP (US Bureau of Economic Analysis 2007-2013). For 2007, this is 1.0 for each region. This variable is used to assess the degree of economic activity in each area for each year.
2. Percentage College Educated for Population 25 years of age or more (US Bureau of the Census, American Community Survey, 2009 and 2011). Similar to the reasoning in the previous models, this is used because higher levels of education in a region should predict lower levels of unemployment on average.
3. Recession Dummy variable (1=2009, 0=other years). This is used because the unemployment effects of the Great Recession really did not have their greatest impacts until 2009. The recession also officially ended in June 2009 according the National Bureau of Economic Research (2010).

[9] Changes in employment and changes in earnings are not examined as dependent variables in this part of the paper because Porter (2003) demonstrated a relationship between CBP data and these variables to show cluster effects for US metro regions.

4. Right to Work Law. Like with the previous models, this is used because right to work laws are argued to create a more dynamic and fluid labor market which minimizes unemployment.

Location quotients for each of the 2-digit North American Industry Classification System (NACIS) categories were calculated and summed so as to estimate a cluster index or some measure of agglomeration for each of the 50 major regions for each year according to employment, payroll and number of establishments. For example, for the Buffalo-Cheektowaga-Niagara Falls, NY MSA, the LQ totals for 2-digit NAICS employment were 17.03; for annual payroll, the LQ sum was 17.88; and for establishments, it was 18.16. Hausman tests for random versus fixed effects found that fixed effects models were preferred.

Model 1 in Table 3 shows that the higher the degree of clustering or agglomeration employment overall in a metro region, the lower the unemployment rate during the 2007 to 2013 time period on average. A 1 point increase in the employment cluster index predicts an unemployment rate decrease of 0.562 on average. Except for the right to work variable, all of the other variables in the model are statistically significant. All of the independent variables have their expected signs except for the percentage college educated variable, which has a positive sign. This can possibly be explained by the fact that data was only available for this variable for the years 2009 and 2011, and therefore educational attainment rates for 2009 were applied for the years 2007, 2008, 2009, and 2010, and rates for 2011 were applied for the years 2011, 2012, and 2013. Because of little variation in the data, the results may be an anomaly and so must be discounted somewhat. There were also no signs of multicollinearity among the independent variables as the variance inflation factors for each of them was below 2.0.

Models 2 and 3 show that the other two clustering measures based on payroll and number of establishments are not statistically significant predictors of the unemployment rate for each region, although the other variables are with the exception of the right to work variable.

Discussion and Conclusion

Using two different databases, the models presented show some support for greater clustering as a possible way to boost earnings, employment and, most of all for the purposes of this paper, to minimize unemployment. However, much depends upon how clusters are defined and operationalized. In some models, the number of establishments was a good predictor of the unemployment rate, in others, it was not. The same is true of cluster employment effects.

One limitation to this paper is that data are examined in the aggregate, and for the CBP data, clusters are only defined at the 2-digit NAICS level. Case studies could point to different results. Also, if the IUPU database had been around longer (it was started in 2009), perhaps longer run effects of clustering could have been explored. This is another limitation of the study.

Nevertheless, the findings presented here point to the need for discernment when it comes to using clustering and innovation as key economic development policies. If decentralized (state and local level) economic development policies are to be preferred to national ones because clustering and innovation are mostly regional phenomena (Porter 2003), the evidence presented herein does not appear to overwhelmingly favor this. There is some but mostly moderate evidence that clustering has an impact. Additionally, if the research in other nations is correct, especially in the UK and in France, then clustering effects could be almost entirely the result of market forces and to a lesser degree to governmental economic development policies. That is, market signals and information exist in sufficient amounts to let firms know where and when to locate in or closer to an existing industrial cluster from which the firm can benefit. If the cynical view that most firms which take economic development incentives are being rewarded for behavior or actions they would have undertaken anyway is correct, then incentives for industry clustering may not be necessary or productive (Story, Fehr, and Watkins 2012). [10]On the other hands, if there are spillover effects or positive externalities due to high levels of clustering, such as lower unemployment rates, then perhaps some incentives can be justified. An overall lower unemployment rate than what would normally be the case due to high levels of agglomeration could justify an amount for incentives in that clustering generates a positive externality that causes less money to be spent for unemployment compensation and welfare relief than what would usually be spent.

[10] This is especially problematic if, as some claim, most of the incentives almost always go to large, established corporate firms rather than small, innovative business startups (LeRoy, Fryberger, Tarczynska, Cafcas, Bird and Mattera 2015).

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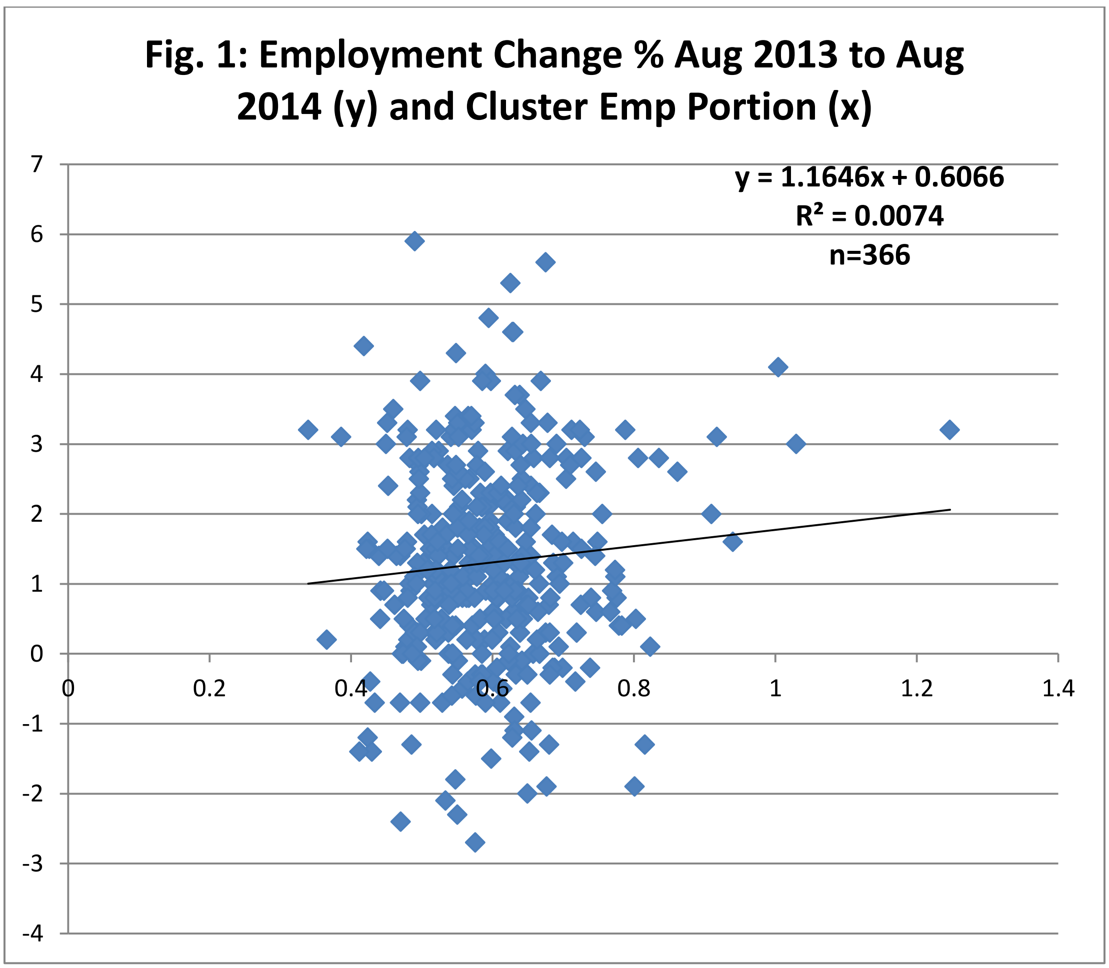


Fig. 1: Employment Change % Aug 2013 to Aug 2014 (y) and Cluster Emp Portion (x)
y = 1.1646x + 0.6066
R² = 0.0074
n=366
7
6
5
4
3
2
1
0
-1
-2
-3
-4
0
0.2
0.4
0.6
0.8
1
1.2
1.4

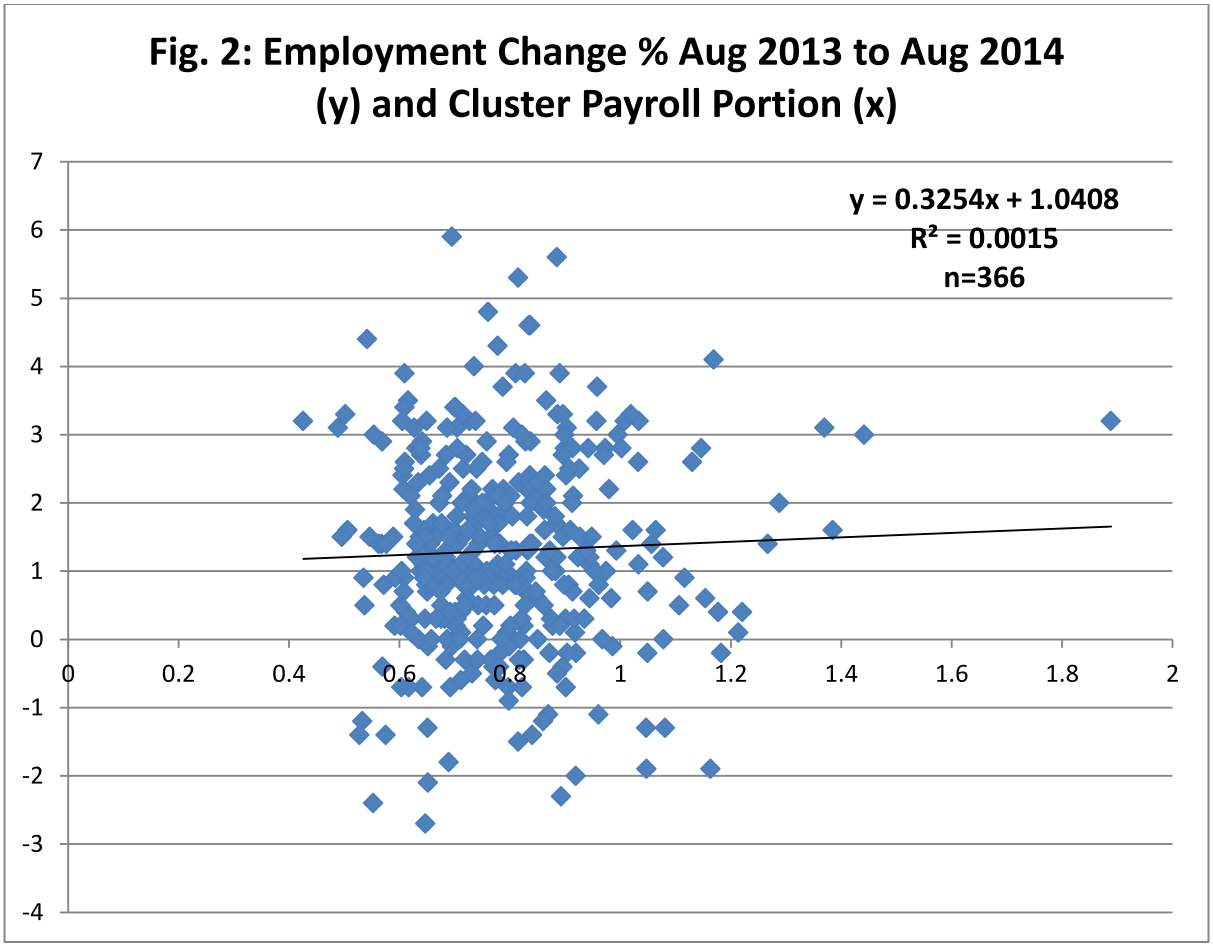


Fig. 2: Employment Change % Aug 2013 to Aug 2014
(y) and Cluster Payroll Portion (x)
y = 0.3254x + 1.0408
R² = 0.0015
n=366
7
6
5
4
3
2
1
0
-1
-2
-3
-4
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2

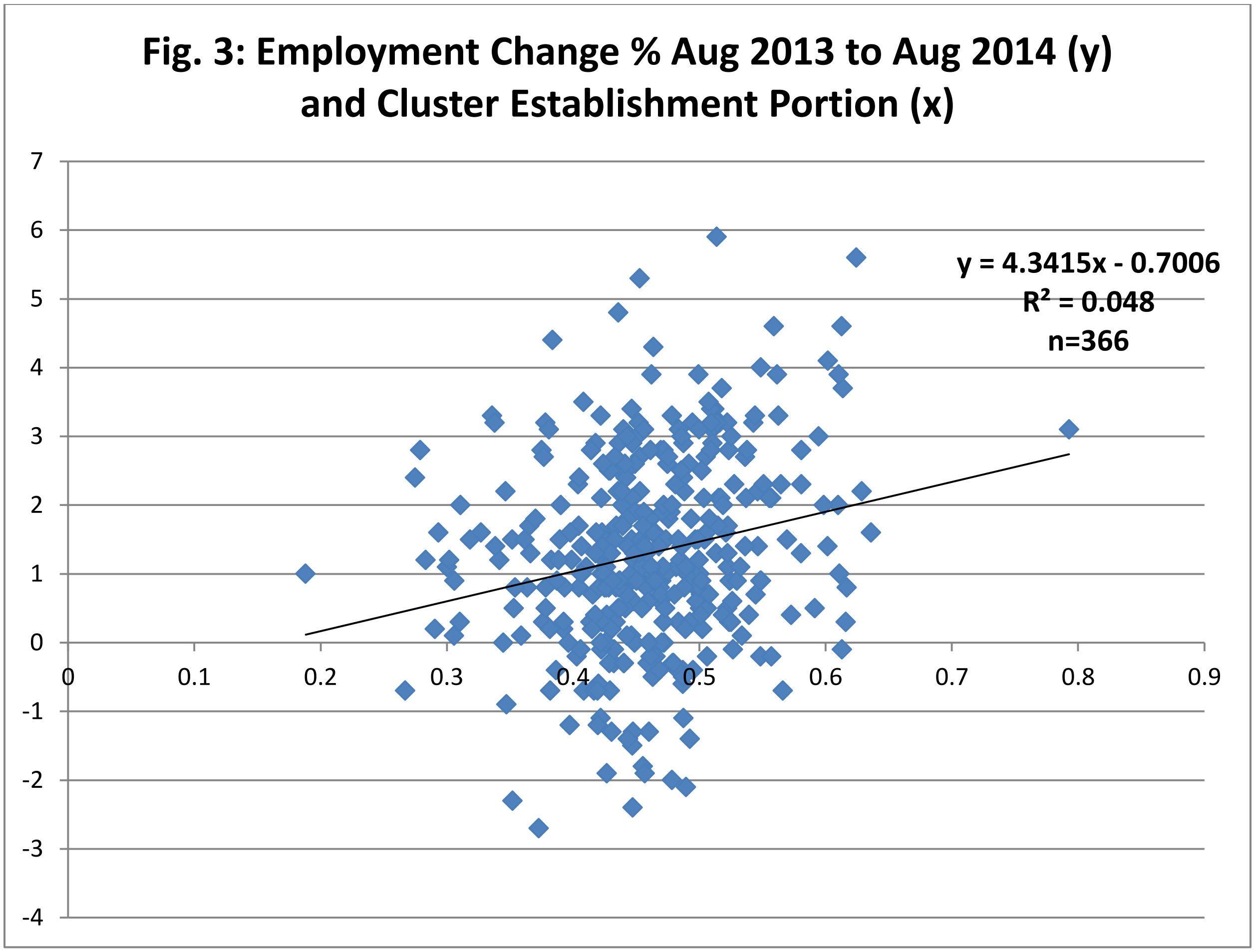


Fig. 3: Employment Change % Aug 2013 to Aug 2014 (y) and Cluster Establishment Portion (x)
y = 4.3415x - 0.7006
R² = 0.048
n=366
7
6
5
4
3
2
1
0
-1
-2
-3
-4
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9

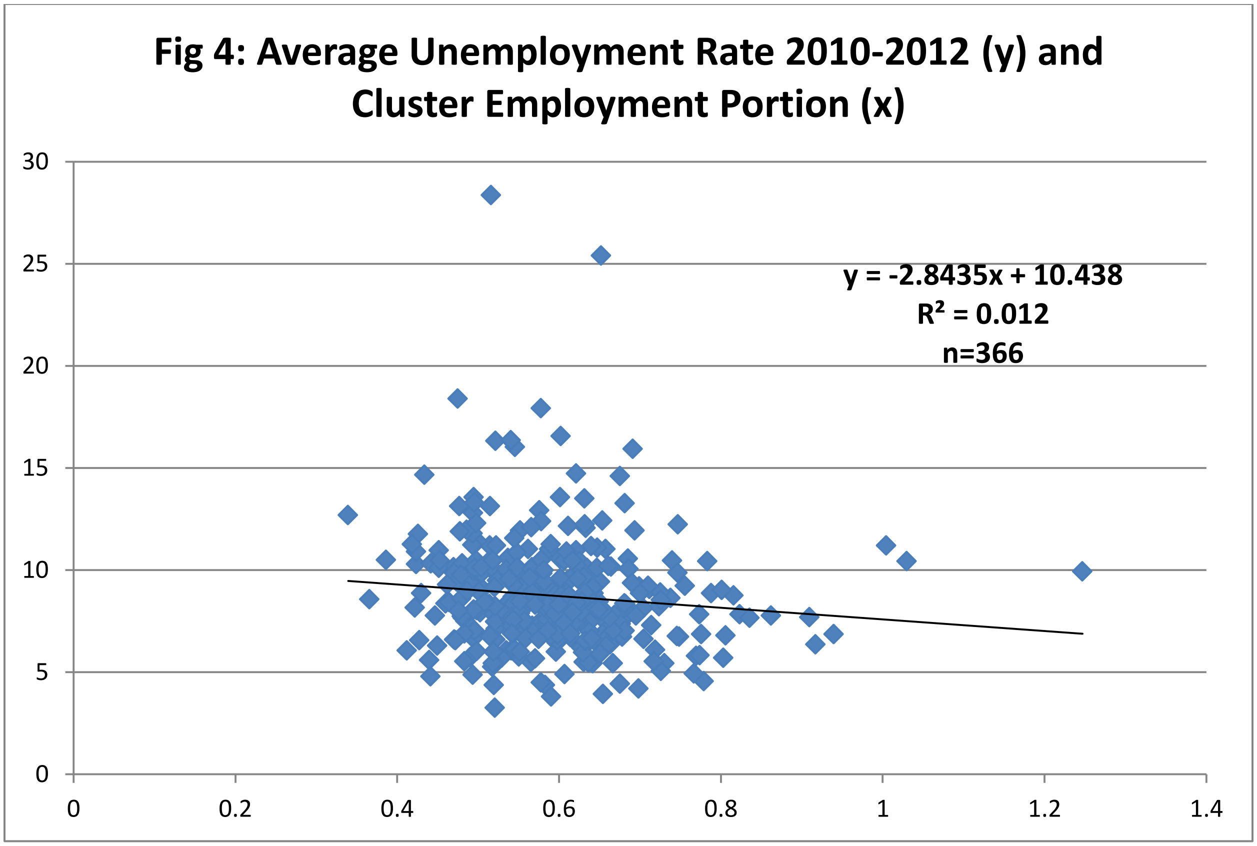


Fig 4: Average Unemployment Rate 2010-2012 (y) and Cluster Employment Portion (x)
y = -2.8435x + 10.438
R² = 0.012
n=366
30
25
20
15
10
5
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4

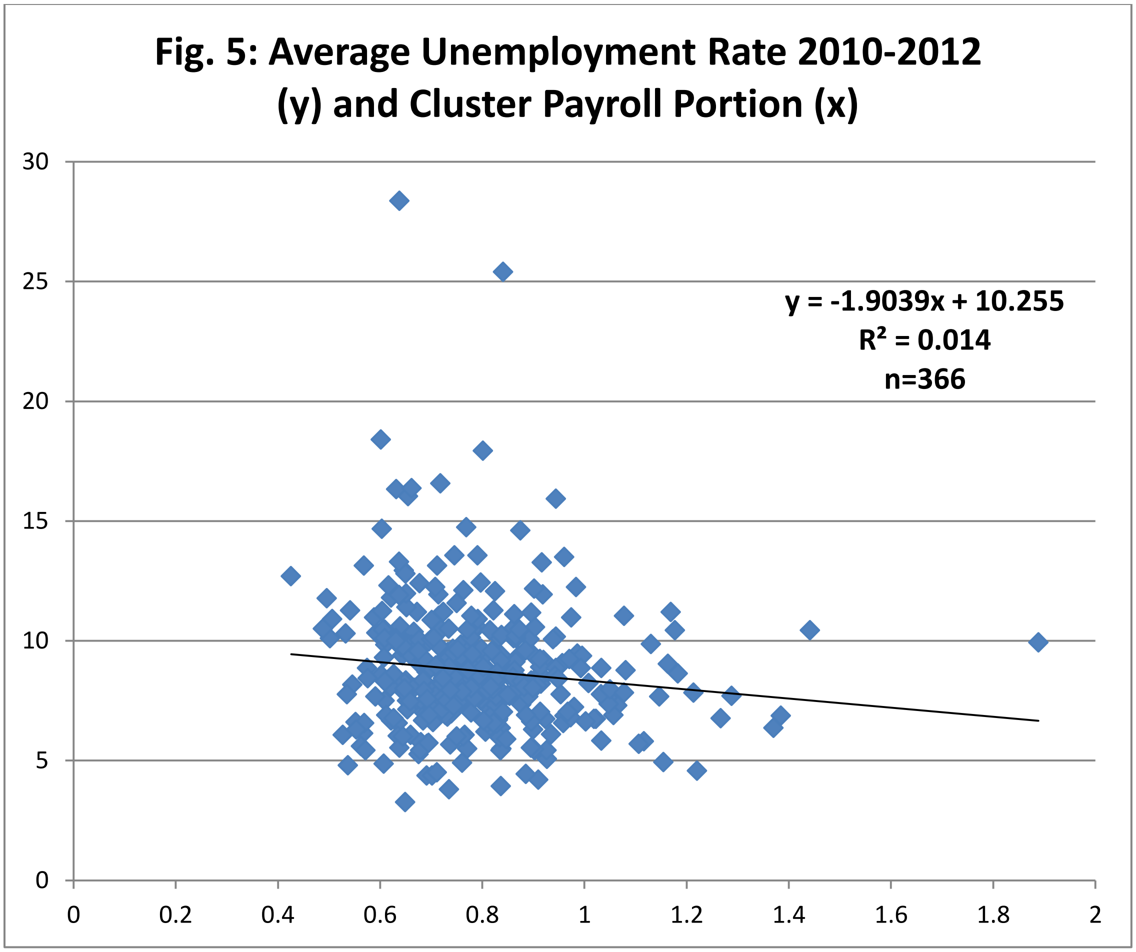


Fig. 5: Average Unemployment Rate 2010-2012
(y) and Cluster Payroll Portion (x)
y = -1.9039x + 10.255
R² = 0.014
n=366
30
25
20
15
10
5
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2

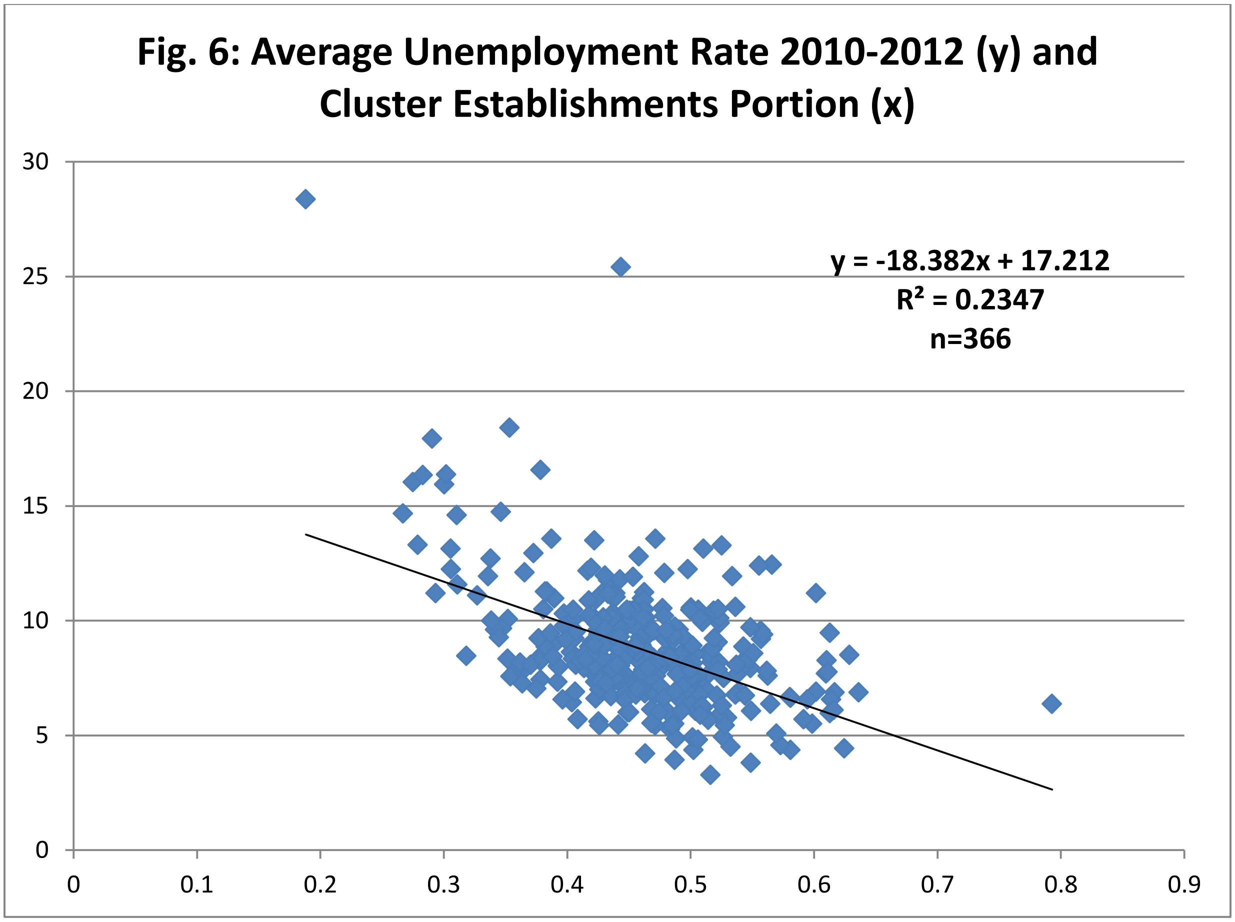


Fig. 6: Average Unemployment Rate 2010-2012 (y) and Cluster Establishments Portion (x)
y = -18.382x + 17.212
R² = 0.2347
n=366
30
25
20
15
10
5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9

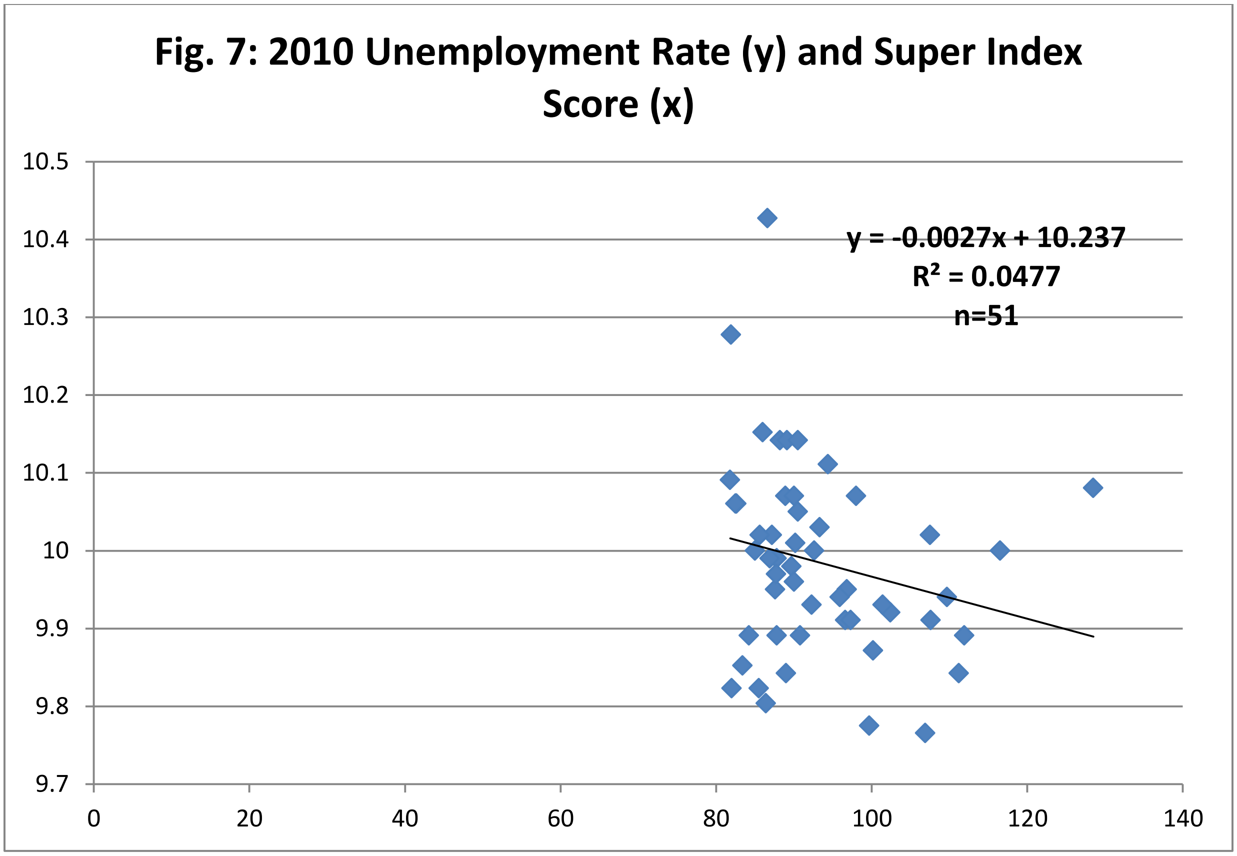


Fig. 7: 2010 Unemployment Rate (y) and Super Index Score (x)
y = -0.0027x + 10.237
R² = 0.0477
n=51
10.5
10.4
10.3
10.2
10.1
10
9.9
9.8
9.7
0
20
40
60
80
100
120
140

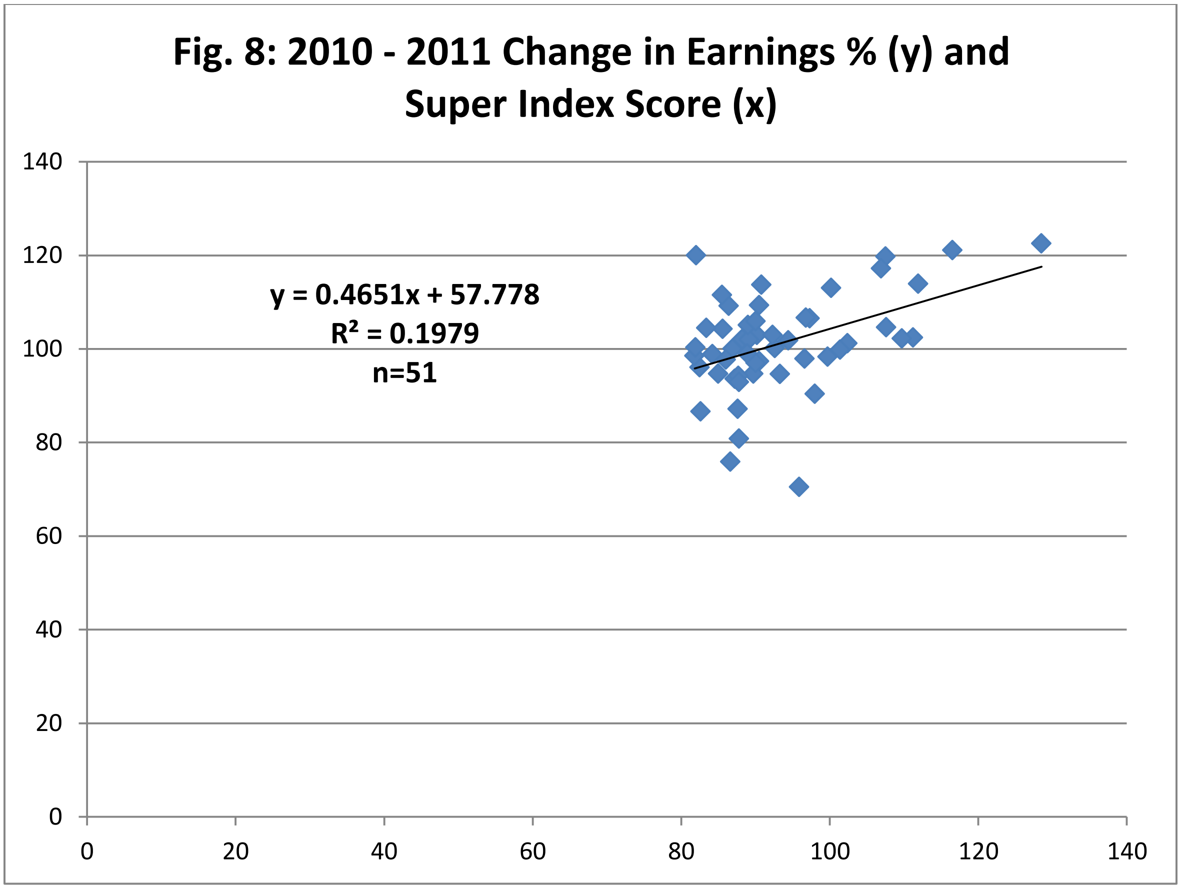
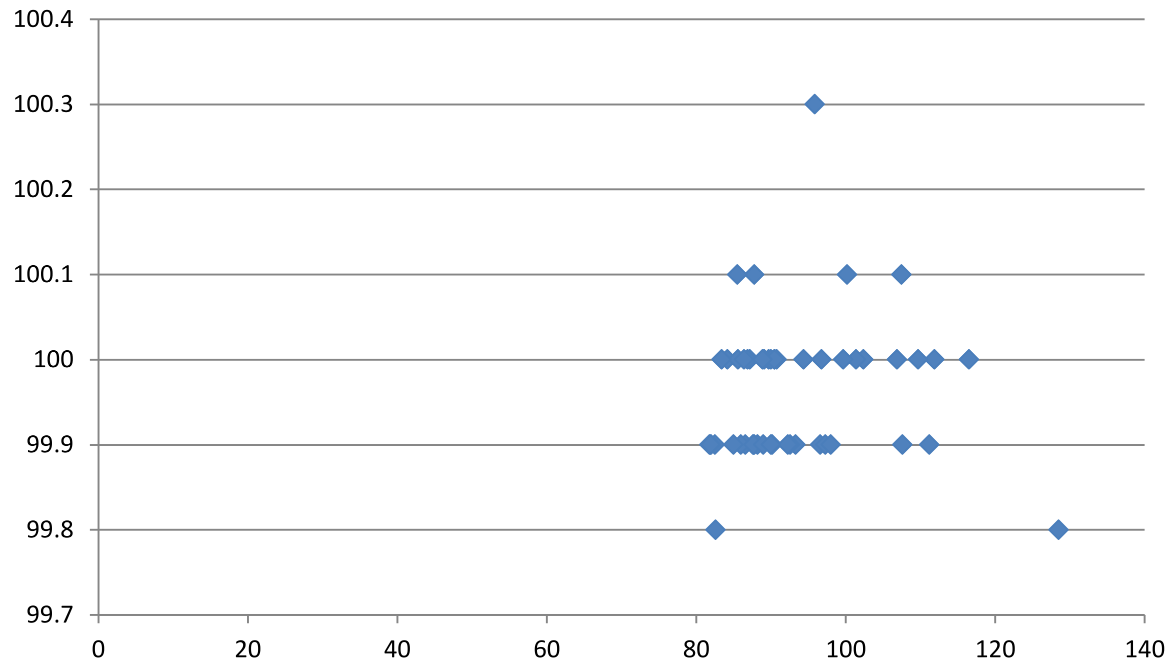


Fig. 8: 2010 - 2011 Change in Earnings % (y) and Super Index Score (x)
y = 0.4651x + 57.778
R² = 0.1979
n=51
140
120
100
80
60
40
20
0
0
20
40
60
80
100
120
140

Fig. 9: Job Growth/Population Growth Scale (y) and Super Index Score (x)



<u>Table 1: Multivariate Least Squares with IUPU Data—366 Metro and Micro Areas</u>

Model 1: Dependent Variable is Employment Growth Pct., 2013-14

	b (Std. Error)
Constant	-0.6928
Right to Work (1=Yes, 0=No)	0.1262 (1.513)
Pct. College Educated	1.595 (1.060)
Pct. Cluster Establishments 2011	0.03318** (1.203)
Adjusted r-sq.	0.047

*p < 0.05
**p < 0.01
n=366

Models 2, 3 and 4: Dependent Variable is Average Unemployment Rate, 2010-2012

Model:	**(2)** b (Std. Error)	**(3)** b (Std. Error)	**(4)** b (Std. Error)
Constant	13.9096	13.7851	17.2312
Right to Work (1=Yes, 0=No)	-1.1654** (0.2550)	-1.1536** (0.2525)	-0.6379* (0.2493)
Pct. College Educated	-15.053** (1.625)	-15.048** (1.623)	-9.982** (1.745)
Pct. Cluster Employment 2011	-0.0126 (1.268)		
Pct. Cluster Payroll 2011		-0.00798 (0.778)	
Pct. Cluster Establishments 2011			-0.1221*** (1.982)
Adjusted r-sq.	0.223	0.223	0.295

*p < 0.05
**p < 0.01
n=366

<u>Table 2: Multivariate Least Squares with IUPU Data—Super Index and 51 Metro Areas</u>

Model 1: Dependent Variable is the Change in Earnings, 2010-2011

	b (Std. Error)
Constant	47.10
Right to Work (1=Yes, 0=No)	5.756* (2.744)
Super Index	0.5528** (0.1360)
Adjusted r-sq.	0.235

*p < 0.05
**p < 0.01
n=51

Model 2: Dependent Variable is the Unemployment Rate, 2010

	b (Std. Error)
Constant	10.402
Right to Work	-0.0884* (0.03473)
Super Index	-0.004* (0.00172)
Adjusted r-sq.	0.126

*p < 0.05
**p < 0.01
n=51

Table 3: Multivariate Fixed Effects Regression with CBP Panel Data[11]

Models 1, 2 and 3: Dependent Variable is Unemployment Rates for 2007-2013

Model:	**(1)**	**(2)**	**(3)**
	b (Std. Error)	b (Std. Error)	b (Std. Error)
Constant	21.598	10.202	9.016
Capacity Utilization	-7.703** (2.53)	-6.751* (2.135)	-6.727* (2.65)
Pct. College Educated	0.1852** (0.0554)	0.227** (0.057)	0.227** (0.057)
Recession (1=2009, 0=Others)	1.489** (0.2902)	1.586** (0.301)	1.586** (0.301)
Right to Work (1=Yes, 0=No)	-0.499 (1.04)	-0.221 (1.08)	-0.221 (1.08)
Cluster Employment Index	-0.562** (0.113)		
Cluster Payroll Index		-0.035 (0.0984)	
Cluster Establishments Index			-0.026 (0.338)
r-sq. within	0.2617	0.2004	0.166
r-sq. between	0.0350	0.0371	0.275
r-sq. overall	0.1480	0.0440	0.199

*p < 0.05
**p < 0.01
n=350

[11] Hausman tests showed Fixed Effects Regression as more appropriate than Random Effects, GLS.