Employment Risk in Nonmetropolitan Counties in the Southern United States

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Abstract

Most U.S. residents depend on labor income to maintain their standard of living. This makes changes in employment an important indicator of the health of a local economy. In addition, the stability of employment changes is frequently cited by state and local government officials as a policy goal. While employment (and unemployment) stability has been the topic of a large literature in regional science and economics, most of this research has focused on states and metropolitan areas. However, many U.S. residents live in rural and nonmetropolitan areas. In this research, we examine the employment uncertainty across metropolitan and nonmetropolitan counties in the South Census region. We find that employment uncertainty varies across counties, states, and county placement in a Rural/Urban Continuum. Specifically, our results suggest that employment uncertainty is nearly twice as large in nonmetropolitan counties as it is in metropolitan counties. We relate employment uncertainty to several county labor supply-and-demand variables, and find that industrial (and employer) diversity are significant demand-side factors. We also find that the female labor force participation rate has a significant influence on county employment uncertainty.

Keywords: economic uncertainty; employment volatility; metropolitan and nonmetropolitan counties; industrial diversification; employer diversification; regional labor supply-and-demand

I. Introduction

Most U.S. residents depend on labor income to maintain their standard of living. This makes changes in employment an important indicator of the health of a local economy. In addition, the stability of employment changes is frequently cited by state and local government officials as a policy goal. While employment (and unemployment) stability has been the topic of a large literature in regional science and economics, most of this research has focused on states and metropolitan areas. However, many U.S. residents live in rural and nonmetropolitan areas. We will examine the issue of employment (and unemployment) stability from the perspective of both metropolitan and nonmetropolitan counties in the southern United States.

This research examines differences in employment risk across counties in the southern United States. Employment risk (or uncertainty) is measured by the predictability of net employment growth during the 1969-1998 period. Employment predictability matters because the standard of living of most U.S. residents depends primarily on labor income. Thus, employment shocks represent significant changes in standards of living to most U.S. residents.

The literature on regional stability and regional diversification has, to this point, focused primarily on states and metropolitan areas. Examples include Conroy (1975), Hunt and Sheesley (1994) and Malizia and Ke (1993), among many others. However, large numbers of U.S. residents live in rural and nonmetropolitan counties. Indeed, in the South Census region, over 70 percent of counties are classified as nonmetropolitan in the Rural/Urban Continuum (Beale Codes).[1] While several authors have addressed portfolio diversification issues for nonmetropolitan counties (including Schoening and Sweeney (1989) and Thompson and Shaffer (1996)), there has not been much emphasis on nonmetropolitan performance in terms of employment volatility or employment uncertainty.

[1] The South Census Region includes: Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, Tennessee, South Carolina, Texas, Virginia, and West Virginia.

We focus on possible differences in employment uncertainty across nonmetropolitan and metropolitan counties and examine the influence of several factors on these differences, including local economic diversity, female percentage of the labor force, and percentage of the population with a college education. Finally, we examine the impact of employment uncertainty on county unemployment rates. The literature suggests that regions with a higher degree of employment uncertainty will suffer higher unemployment rates.

Our estimates of employment uncertainty show a large degree of variation in uncertainty across counties, states, and across Beale Codes. We find the highest levels of employment uncertainty in Texas, followed by Louisiana, Mississippi, Tennessee, and Georgia. Each of these states registered employment uncertainty in excess of the South Census region average. The District of Columbia registered the lowest level of employment uncertainty, while Delaware, North Carolina, and Maryland also posted levels less than half of the South Census region average.

Employment uncertainty also varied strongly across the Rural/Urban Continuum, with metropolitan counties posting levels of employment uncertainty about half as large as nonmetropolitan counties. Further, for nonmetropolitan counties, we find that employment uncertainty rises as the number of residents living in urban areas falls.

Both factors that effect the demand for and the supply of labor were related to the magnitude of county employment uncertainty. An industrial diversification measure was an important determinant of county employment uncertainty. Relative specialization of employment in a handful of employers also was a significant demand-side factor. Greater participation of women in the labor force was a supply-side factor that influenced county employment uncertainty. Greater employment uncertainty, however, was not found to lead to a higher unemployment rate in counties.

This paper proceeds as follows: Section II discusses the literature which underpins the current research, Section III explains the methods employed to estimate employment uncertainty, while Section IV contains the results of our efforts to account for differences in employment uncertainty across counties in the South Census region. The paper concludes with Section V.

II. Background and Literature

Risk and uncertainty are important facts of economic life. Regional economics has long recognized that regions exhibit large differences across a wide range of dimensions, including the predictability of growth. This predictability or volatility has also concerned policymakers at the regional level. It has long been recognized that regional specialization in a volatile industry will tend to make aggregate regional employment and income volatile as well. Borrowing from the financial literature, regional economists have connected this uncertainty with diversification of the regional industrial portfolio. Starting with Conroy (1975), researchers have sought to pin down the optimal relationship between risk and return in specific regional economies. While several problems with a literal application of portfolio theory to regional growth have been identified, the general approach has dominated the literature.

One of the latest examples of this line of research is a study of the Colorado economy by Hunt and Sheesley (1994). These authors apply modern time series techniques to identifying regional variability, which is important in order to properly estimate regional risk. In particular, the authors are careful to ensure that the underlying deviations from trend growth are white noise. This is a crucial improvement, since portfolio theory emphasizes that only non-systematic risk can be influenced by diversification of the portfolio (this point is made forcefully in Sherwood-Call (1990)). Hunt and Sheesley also discriminate between export (or footloose industries) and local industries, arguing that only export industries should be considered part of the choice set in optimal portfolio selection.

A related literature has sought to investigate the influence of diversification on regional volatility. An example here is Kort (1981), who studied the relationship between employment instability and several different measures of industrial diversification for 106 MSAs. The results depended on the measure of industrial diversification employed, but the author concludes that diversification is one factor which influences regional employment variability. However, the measure of regional instability employed in this study does not isolate non-systematic instability and does not include any other control variables beyond a measure of diversification.

Malizia and Ke (1993) also focus on MSAs, but their work extends the analysis in a number of ways by including important control variables (population size, labor force characteristics, in addition to a measure of diversification) and by extending the analysis to include a possible relationship between diversity and the unemployment rate. Their results suggest that diversified regions have lower unemployment rates and lower levels of employment instability, but that the control variables matter as well. However, this research also fails to isolate non-systematic employment instability.

Most of the research on regional instability has focused on states and MSAs. However, much of the nation's population lives and works in rural areas that are not part of an MSA. Schoening and Sweeney (1989, 1992) analyze possible pitfalls in applying regional portfolio analysis to small rural areas, using data for Alabama counties. They show that a common practice of using national data to reflect regional risk levels may cause serious problems. Thompson and Shaffer (1996) apply regional portfolio analysis to Wisconsin data (including rural areas) and extend the analysis to occupation data.

Attempts to relate economic instability and growth in rural areas include Smith (1990) and Keinath (1985). Smith (1990) analyzed a group of counties in Kentucky while Keinath (1985) explored Bureau of Economic Analysis areas nationwide (including metropolitan and rural areas). In both studies, no attempt is made to focus on the non-systematic risk which diversification is likely to reduce.

This study adds to the literature in a number of ways. While it focuses on the South Census region, we consider performance of both metropolitan and nonmetropolitan counties. In addition, we follow recent approaches that consider the time series properties of employment in order to better estimate differences in non-systematic risk/uncertainty. Further, we also include variables to address differences in labor force characteristics across counties, which may also impact volatility.

III. Estimating Employment Uncertainty

Employment Data

In the analysis to follow, we analyze employment uncertainty for counties in the South Census region. Our measure of employment is total full- and part-time employment from the U.S. Bureau of Economic Analysis (BEA). This data is consistently available for the nation, states, and counties, and we take our estimates from the Regional Economic Information System (REIS) CD-Rom released in May 2000. The data from this release cover the 1969-1998 period for most counties in the nation.

Econometric Issues in Estimating Uncertainty

We begin by estimating employment risk across counties in the South Census region. Following Hunt and Sheesley (1994), we need to pay attention to the time series properties of our employment measures. In particular, we perform unit root tests on all series in order to assess stationarity properties and we also check for cointegration between county employment and national employment. Unit root tests are necessary in order to ensure that our measure of employment risk comes from a white noise process, which is, in turn, necessary to ensure a consistent estimate of employment uncertainty. Cointegration tests provide further information on the final form of the regression to estimate employment uncertainty.

Specifically, we first perform augmented Dickey-Fuller tests by estimating regressions of the following form:

$$\Delta y_{c,t} = \beta_0 + \beta_1 y_{c,t-1} + \sum_{i-2}^{p} \beta_i \Delta y_{c,t-i+1} + \varepsilon_{c,t}, \qquad (1)$$

where yt is the log of employment in county c at time t, Δ is the first difference operator, and p is the number of lags of the dependent variable included in order to remove serial correlation from the residuals (limited to a maximum of 5). The Null hypothesis of the unit root test is $\beta_1 = 0$. Failure to reject the Null hypothesis is evidence in support of a unit root in the series. We include a drift term (β_0) in order to capture trends present in many county employment series.

Figure 1 summarizes the results of unit roots carried out for all 1,393 counties in the South Census region. The figure shows the distribution of t-statistics and includes the critical t-value at the 5 percent significance level for 50 observations (critical t-value from Fuller (1976)). As the figure suggests, most county employment series fail to reject the Null hypothesis of a unit root and indeed only 5.2 percent of counties in the South Census region reject the null of a unit root at the 5 percent significance level.

These results suggest that the bulk of the county employment series need to be differenced in order to achieve stationarity. We perform identical unit root tests on the first difference of all county employment series to determine if first differencing is adequate. Figure 2 shows the distribution of t-statistics from unit root tests on the first difference of the log of county employment. The vast majority of county employment series reject the Null of a unit root at the 5 percent level (78 percent of all counties reject the Null at the 5 percent level). We conclude from these results that first differencing the county employment series is sufficient to achieve stationarity. We also subject national employment to the same tests and find that national employment requires first differencing to achieve stationarity.

Our results regarding stationarity in county employment series suggest that we use the first difference of county (and national) employment when estimating employment uncertainty. However, if county and national employment series are cointegrated, then we lose some information if we simply regress the first difference of county employment on the first difference of national employment. The information lost is the degree to which a common stochastic trend influences the evolution of both county and national employment. In order to assess the degree to which counties in the South Census region share a common trend with the national economy, we perform Engle-Granger tests for cointegration between the county and national employment series (see Engle and Granger (1987)).

Engle-Granger tests for cointegration are performed in two steps: 1) regress the level of county employment on national employment and save the residuals, 2) test the saved residuals for a unit root. We use an augmented Dickey-Fuller test to check for a unit root in the saved residuals (using critical values from Engle and Yoo (1987)). The basic idea of the test is that when one integrated series (a series containing a unit root) is regressed on another, the residuals will contain a unit root unless the two series are cointegrated. Thus, when we reject the Null hypothesis of a unit root in the saved residuals, that is evidence for cointegration.

Summary results from our Engle-Granger tests for cointegration are presented in Figure 3. The vertical line shows the critical value at the 5 percent level from Engle and Yoo (1987). As the figure shows, we find little evidence for cointegration of county and national employment levels. Indeed, the Null hypothesis of a unit root in the residuals is rejected for 7.8 percent of counties. These results are similar to those of Schmidt (1995) who found little evidence of cointegration among states and the nation in the macroeconomic aggregates (personal income, gross state product).

Overall, our analysis of the univariate and multivariate time series properties of county and national employment series leads us to estimate employment uncertainty by first estimating the following regression:

$$\Delta y_{c,t} = \beta_0 + \gamma_1 \Delta y_{US,t} + \sum_{i-2}^{p} \beta_i \Delta y_{c,t-i+1} + \sum_{j=i}^{p} \gamma_j \Delta y_{US,t-j+1} + \varepsilon_{c,t}, \tag{2}$$

where $y_{US,t}$ is national employment at time t. We add lags until serial correlation in the residuals is eliminated and the save the residuals $\varepsilon_{c,t}$. In order to estimate employment uncertainty for each county we compute:

$$Var\_d_c = \frac{\sum_t \varepsilon^2_{c,t}}{T}, \tag{3}$$

where T is the number of years of data available.

Employment Uncertainty in the South Census Region

Our estimates of employment uncertainty are summarized in Table 1, which contains results by state and by Beale Code (Butler and Beale (1994) and see Table 2 for Beale Code definitions). Averaged across all counties in the South Census region, Var_d (multiplied by 1,000) is 1.23, which is associated with an average standard deviation of 3.0 percent. Thus, the average residual from our growth rate regression (both over time and across counties) is ±3.0 percent.

Employment uncertainty varies strongly across states, with the District of Columbia registering the lowest value for Var_d. Delaware, North Carolina, and Maryland also posted levels of Var_d less than half of the South Census region average. Texas had the highest level of Var_d, followed by Louisiana, Mississippi, Tennessee, and Georgia.

Figure 4 shows how the state results are distributed across counties in the region. Counties which are shaded white have employment uncertainty below the national average, counties shaded gray have employment uncertainty above (but less than double) the national average, and counties shaded black have employment uncertainty more than double the national average. As the figure shows, most states display significant differences in employment uncertainty across counties. Indeed, Delaware is the only state that does have a county with employment uncertainty above the national average. For most states, county employment uncertainty ranges from well below the national average to well above.

Since most states contain counties with a wide range of urban/rural characteristics, we present Var_d averaged across counties with the same Beale Codes.

Beale Codes (defined in Table 2) classify counties into 6 groups of nonmetropolitan counties and 4 groups of metropolitan counties. Beale Codes differentiate classes of nonmetropolitan counties according to size and proximity to a metropolitan area. Beale Codes also differentiate metropolitan counties by size within the metropolitan area.

As Table 1 shows, employment uncertainty in metropolitan counties (Beale Codes 0-3) is about half as large as employment uncertainty in nonmetropolitan counties (Beale Codes 4-9). Indeed, we find the lowest overall level of employment uncertainty in the largest metropolitan counties.

While we generally find higher levels of employment uncertainty in nonmetropolitan counties, unemployment uncertainty varies across Beale Codes 4-9. Beale Code groups 4, 6, and 8 are for nonmetropolitan counties that are adjacent to a metropolitan area. Beale Code 4 refers to nonmetropolitan counties that are adjacent to metropolitan areas and have an urban population of 20,000 or more. Beale Code 6 refers to counties adjacent to metropolitan counties with an urban population of 2,500 to 19,999, and Beale Code 8 refers to counties with an urban population less than 2,500 and which are adjacent to metropolitan areas.

Beale Code groups 5, 7, and 9 cover more remote nonmetropolitan counties that are not adjacent to a metropolitan area. Beale Code 5 refers to nonadjacent counties with an urban population over 20,000. Beale Code 7 refers to nonadjacent counties with an urban population of 2,500 to 19,999. Beale Code 9 refers to nonadjacent counties with an urban population less than 2,500.

We find the highest levels of employment uncertainty are present in the counties with the smallest urban populations (Beale Codes 8-9). Indeed, employment uncertainty generally rises as the size of the county population living in urban areas decreases. Proximity to metropolitan areas for these rural counties does not appear to offer much improvement in employment uncertainty.

IV. Explaining Employment Uncertainty

The level of employment uncertainty in a local economy may be related to a number of supply and demand factors in the local labor market. Random variation in the demand for labor is related to the fluctuations in the labor needs of local businesses. These fluctuations in turn may be related to the diversity of businesses in the local economy. A diversified local economy has a major presence in all the aggregate industries found in the national economy such as services, retail, and manufacturing. A specialized economy is heavily focused in only one or two particular industries. Such specialization may lead to greater variation in labor demand if these similar businesses all tend to expand or contract at the same time. This may be particularly likely if a local economy is specialized in an industry that fluctuates strongly over the business cycle, as is the case for some manufacturing and mining industries.

Along with industrial diversity, employer diversity can be a driving factor related to the fluctuation of labor demand. Employer diversity refers to the number and size of major employers in a local economy. An economy with a significant number of medium and large employers has relatively large employer diversity. But, a local economy where a significant share of employment is with just a few major employers has relatively little employer diversity. Such a specialized economy can experience wide variation in local labor demand just due to idiosyncratic shocks to one or two very large employers.

Labor supply factors also can influence employment uncertainty in the local economy. In particular, the characteristics of workers in the local labor market may influence the variation in local labor supply. Do local workers have a tendency to exit or enter the labor market from year to year, or stay in the local labor market consistently? Do local workers have a tendency to experience longer bouts of unemployment due to more frequent bouts of job switching, or more difficulty in finding new employment when separated from a job? From the perspective of individual workers, greater education and experience are factors that are associated with workers that remain consistently in the labor force, and employed. From the perspective of the overall labor market, higher rates of labor force participation may indicate that a greater percentage of workers in the local economy maintain a steady presence in the labor force.

More educated workers tend to reap higher returns from work in the formal sector, that is, wages. This creates a greater incentive for attachment to the labor force, rather than moving between periods of formal and informal work. More educated workers also tend to have lower unemployment rates. Both factors suggest that local labor markets with a more educated workforce would tend to offer a steadier supply of labor. There is no single measure of the level of education in a local workforce, although the percentage of the local population that graduated from high school is an aggregate indicator, as is the percentage of college graduates. Since it is unclear which of these measures would be a superior indicator of a steady local labor supply, both should be considered.

Along with higher education levels, higher labor force participation rates may indicate more consistent labor force attachment by the local population. Given that there are some elderly or other workers that will not participate in the labor force, a high labor force participation rate can only be achieved if most other workers in the local economy remain in the labor force on a consistent basis year after year. However, this need not be the case for areas with low rates of labor force participation. Such low participation rates could simply mean that few people ever participate in the labor force, but also could mean that many people participate on an inconsistent basis, leading to low measured participation in any given year. Greater participation rates by women may be particularly important since on average they may have more reason to be loosely or periodically attached to the labor force due to family responsibilities. This suggests that the overall level of labor force participation as well as the particular participation rate of women may be important indicators of the steadiness of labor supply.

The preceeding suggests that both the characteristics of the local population as well as the structure of local industry may contribute to employment uncertainty in a local economy. The importance of the various factors is examined below in a regression equation. The following section explains the regression equation and the data that are utilized in the equation.

The labor supply and demand factors discussed above were included to develop a reduced form regression equation for employment uncertainty, which is Equation (4) below. The dependent variable in the equation is the employment uncertainty variable that has been summarized previously in this report (Var_d_c).

The independent variables include two factors expected to lead to fluctuation in the local demand for labor. The first of these is industrial specialization (IS_c), which is a measure of how specialized the economy is in each county relative to the national average. The second variable is employer specialization (ES_c), which indicates the degree to which employment in each county is concentrated within a handful of employers. We also include the log of total county employment ($LTOTEMP_c$) to account for the influence of county size on employment uncertainty.

$$\begin{aligned} Var\_d_c = {} & b_0 + b_1 * IS_c + b_2 * ES_c + \\ & b_3 * LTOTEMP_c + b_4 * PHSG_c + \\ & b_5 * PCG_c + b_6 * LFPR_c + \\ & b_7 * PFLF_c + b_8 * UNR_c + u_c . \qquad (4) \end{aligned}$$

Factors that contribute to the fluctuation in the supply of labor also were included among the independent variables. The first supply variable was the percentage of the persons age 25 or older in each county who are high school graduates ($PHSG_c$). The second supply variable was the percentage of persons age 25 or older who are college graduates (PCG_c). The third supply variable is the county labor force participation rate ($LFPR_c$), and the fourth supply variable is the percentage of the labor force which is female ($PFLF_c$). The county unemployment rate also was included as a supply variable (UNR_c). All of the labor supply variables were taken from the 1970, 1980, and 1990 Census of the Population. The variables were either reported directly in the Census data, or calculated from other data. The county labor force participation was the participation for all civilians over age 16. The variables are simple average values from the 1970, 1980, and 1990 Census.

Data for the two labor demand variables were taken from the Regional Economic Information System compact disk and the 1990 County Business Patterns compact disk, each of which is published by the United States Department of Commerce. Recall that employer specialization (ESc) is a measure of the extent to which employment in a county is concentrated in a handful of business, and therefore, subject to significant variation simply due to idiosyncratic shocks in one or two individual businesses. We measure employer specialization as the share of county employment that is concentrated in the three largest employers in each county. The size of the three largest employers and total employment is gathered from the 1990 County Business Patterns CD from the Bureau of Census. That data source provides the number of businesses in 11 size categories such as businesses with 1 to 4 employees, 5 to 9 employees, all the way up to 1,000 to 2,499 employees, 2,500 to 4,999 employees, and 5,000 and above employees. We simply observe which of these size categories the three largest businesses fall into in each county. Range midpoints are used to estimate employment in each of the three.[2]

Industrial specialization (ISc) measures the extent to which a county economy is as diversified as the national economy. Therefore, we generate an aggregate measure comparing each county's and the nation's concentration of employment in 1-digit SIC groupings.[3] The difference in the percentage of employment in each industry is squared and then summed across all industries, and then the sum of this square root is taken. The formula for industrial specialization is

$$IS_c = [\sum_{i=n}^{N} (PE_{c,I} - PE_{US,I})^2]^{(1/2)}, \qquad (5)$$

where PE_i is the percentage employment in industry i either in county c or the United States. A larger value for IS_c indicates that a county is relatively specialized in certain industries, that is, has relatively large differences from the national industry mix. County employment at the 1-digit SIC level is taken from the Regional Economic Information System compact disk that has employment data from 1969 to 1998.[4] The variable used is the industrial specialization in 1980.

The results of the regression indicate the importance of the variables that influence the demand for labor, and at least one of the variables that influenced the supply of labor, in county employment uncertainty. The size of the local economy also was a significant variable. As is seen in Table 3, a negative coefficient on the variable for log of total employment suggests that employment uncertainty will decline as county employment rises.

Table 3 also lists estimates for the coefficients on the other 7 variables in the model. Focusing on the results for all counties, coefficients on both the industrial specialization and employer specialization variables are both positive and statistically significant. These results suggest that employment uncertainty rises as the county economy becomes more specialized in particular industries than the nation as a whole, or as employment is specialized in a handful of employers. Both reduced industrial and employer diversity had been predicted to raise uncertainty in the demand for labor, and therefore, raise county employment uncertainty.

Among supply factors, the only consistently significant variable is the percentage of the labor force that is female. The negative coefficient on the variable suggests that those counties with a high female labor force participation rate, or at least a rate for women that is similar to that for men, have less employment fluctuation. This outcome was expected since there may be less variation in the supply of labor when a greater percentage of women are consistently attached to the labor force. The coefficient on the variable for the overall labor force participation rate was not statistically significant. Neither was the coefficient on the two education attainment variables, or the unemployment rate variable.

The results for metropolitan and nonmetropolitan counties are essentially the same as for the overall results for all counties. The same

[2] Businesses in the 5,000 employees and above category are assumed to have 5,000 employees.

[3] These are farming, agricultural services, mining, construction, manufacturing, transportation, communications, and public utilities (TCPU), wholesale trade, retail trade, finance, insurance, and real estate (FIRE), services, and government.

[4] Employment at the 1-digit level is sometimes suppressed for privacy reasons in individual counties. We estimated any suppressed employment values by calculating the total amount of employment in industries where the value is suppressed, and then sharing that employment out based on the relative employment in those industries in the nearest year where employment was reported.

coefficients are statistically significant in the nonmetropolitan equation as in the overall equation, which may not be surprising since nonmetropolitan counties accounted for roughly two-thirds of counties in the overall sample. The metropolitan equation also had two additional significant variables. The first was a positive and significant coefficient on the unemployment rate, indicating the employment fluctuation is greater in metropolitan counties with higher unemployment rates. There also was a positive and significant sign on the coefficient for the percentage of adults who are high school graduates, indicating that metropolitan counties with more high school graduates had higher employment uncertainty. This result is the opposite of the expected result that more education would lead to more consistent attachment to the labor market, and therefore, less employment fluctuation.

However, outside these two variables in the metropolitan county equation, there was a great consistency in the regression results. Both factors that effect the demand for and the supply of labor were related to the level of fluctuation in county employment over time. An industrial specialization measure was an important determinant of county employment fluctuation, as had been found in previous research. However, relative specialization of employment in a handful of employers also was a significant demand side factor. Greater participation of women in the labor force was a supply-side factor that reduced fluctuation in county employment.

Employment Uncertainty and the Unemployment Rate

Random variation in the employment level may be associated with higher unemployment rates within counties. A highly variable environment for labor may lead to uncertainties that reduce the utilization of labor resources. Further, to the extent that employment shocks have an asymmetric effect on unemployment, the larger downswings in higher variance counties may lead to greater unemployment levels in those counties.

This said, higher unemployment rates would likely tend to be associated either with short-term shocks to the demand or supply of labor, or with long-term factors that cause certain areas to have higher permanent unemployment rates. These long-term factors include education attainment, reservation wages, and state unemployment insurance policies.

A regression approach was utilized to test the relationship between employment uncertainty and the unemployment rate in counties. As illustrated in Equation (6) below, the 1990 county unemployment rate ($UNR90_c$) is the dependent variable. The independent variables included the employment uncertainty in the county from 1969 to 1998 (Var_d_c). The 1970 county unemployment rate ($UNR90_c$) was included to reflect long-term factors that may lead to a higher permanent unemployment rate in the county. A matrix of state dummy variables (STATE) also was included to capture any changes in state unemployment insurance laws during the period.

$$UNR\,90_c = b_0 + b_1 * Var\_d_c + b_2 * UNR\,70_c + b_3 * STATE + u_c\,. \tag{6}$$

Table 4 shows the results of the regression in Equation (6). State dummy variables were not significant, and for brevity, were omitted from the table. The coefficient on the variable for the 1970 unemployment rate was positive and significant at the 1 percent level, indicating the importance of the permanent unemployment rate in the unemployment rate later in the period. The county employment uncertainty variable was not statistically significant. Therefore, we reject the hypothesis that higher employment uncertainty leads to any permanent increase in the unemployment rate within counties.[5]

V. Conclusion

Uncertainty in employment opportunities is an issue of policy concern because earnings from work are a large share of household income. This paper assesses patterns in and sources of employment uncertainty in both metropolitan and nonmetropolitan counties through the South Census region of the United States. This study also adds to the existing literature on employment risk in a number of ways. While it focuses on the South Census region, we consider performance of both metropolitan and nonmetropolitan counties. In addition, we follow recent approaches that consider the time series properties of employment in order to better estimate differences in nonsystematic risk/uncertainty. Further, we also

[5] This same results also held in other regressions if counties are rated according to their position in rural/urban continuum.

include variables to address differences in labor force characteristics across counties, which may also impact volatility.

Our estimates of employment uncertainty show a large degree of variation in uncertainty across counties and states. Employment uncertainty also varied strongly across the Rural/ Urban Continuum, with metropolitan counties posting levels of employment uncertainty about half as large as nonmetropolitan counties. Further, for nonmetropolitan counties, we find that employment uncertainty rises as the number of residents living in urban areas falls.

Both factors that effect the demand for and the supply of labor were related to the magnitude of employment uncertainty in counties over time. An industrial specialization measure was an important determinant of county employment uncertainty. Relative specialization of employment in a handful of employers also was a significant demand side factor. Greater participation of women in the labor force was a supply-side factor that influenced county employment uncertainty. Greater unemployment uncertainty, however, was not found to lead to a higher unemployment rate in counties.

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Figure 1
Distribution of Unit Root Tests
t-Statistics from ADF Test

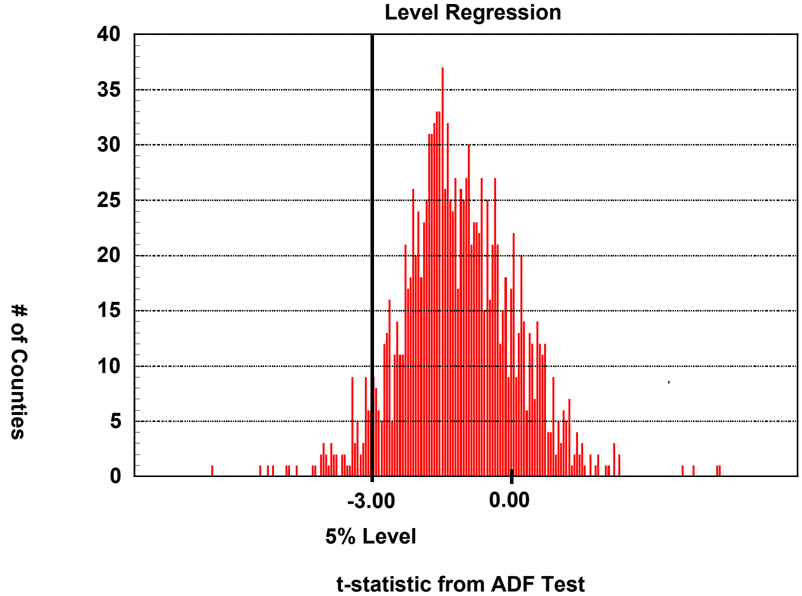

Figure 2
Distribution of Unit Root Tests
t-Statistics from ADF Test

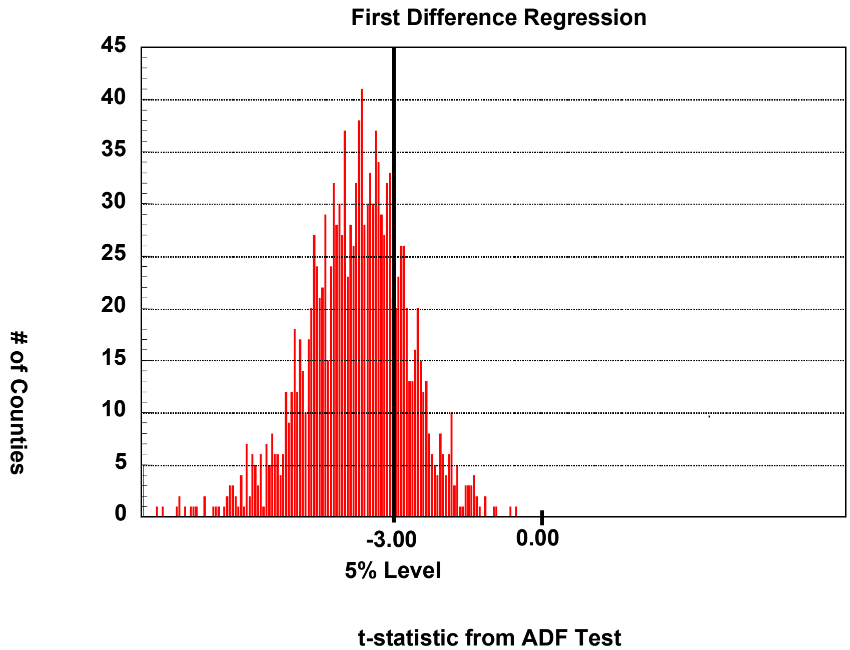

Figure 3
Distribution of Cointegration Tests
t-Statistics from Engle-Granger Test

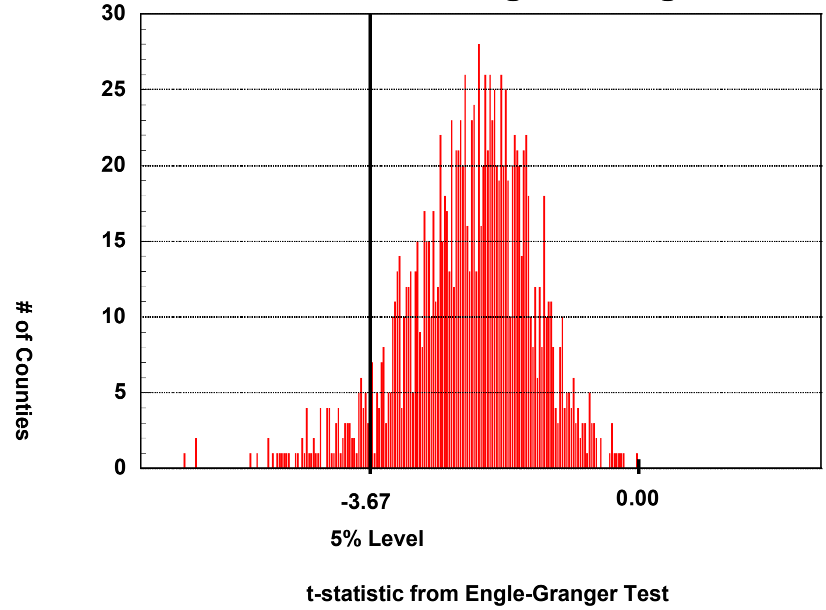

Table 1
Average Employment Uncertainty
By State and Rural/ Urban Continuum

State	Average Employment Uncertainty (Var_d X 1,000)	Beale Code	Average Employment Uncertainty (Var_d X 1,000)
Alabama	0.71	Metropolitan Counties	0.73
Arkansas	0.79	Beale 0	0.49
Delaware	0.24	Beale 1	0.99
District of Columbia	0.16	Beale 2	0.77
Florida	0.75	Beale 3	0.63
Georgia	1.24	Nonmetropolitan Counties	1.42
Kentucky	1.12	Beale 4	0.99
Louisiana	1.63	Beale 5	0.54
Maryland	0.61	Beale 6	1.10
Mississippi	1.31	Beale 7	0.92
North Carolina	0.58	Beale 8	2.32
Oklahoma	0.98	Beale 9	2.37
South Carolina	0.68		
Tennessee	1.28		
Texas	2.11		
Virginia	1.11		
West Virginia	1.13		
South Census Region	1.23		

Figure 4
South Census Region
County Employment Uncertainty

Employment Variance
(Var_d X 1000)

0.0 - 1.23

1.24 - 2.46

2.47 - 11.4

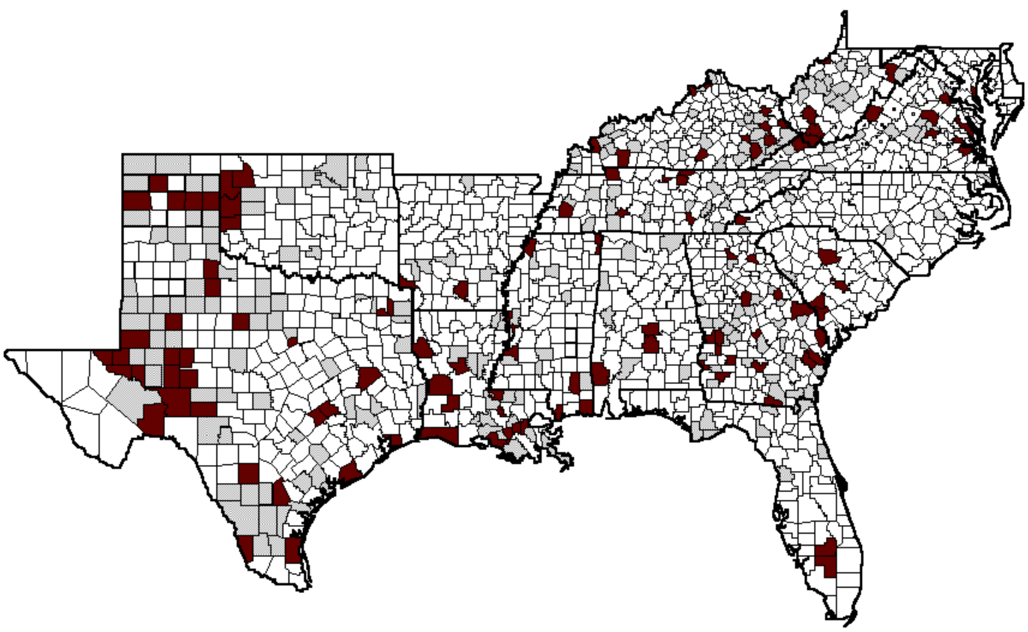

Table 2
Beale Code Definitions

Metropolitan Counties	
Beale 0	Central counties of metropolitan areas of 1 million population or more
Beale 1	Fringe counties of metropolitan areas of 1 million population or more
Beale 2	Counties in metropolitan areas of 250,000 to 1 million population
Beale 3	Counties in metropolitan areas of fewer than 250,000 population
Nonmetropolitan Counties	
Beale 4	Urban population of 20,000 or more, adjacent to a metropolitan area
Beale 5	Urban population of 20,000 or more, not adjacent to a metropolitan area
Beale 6	Urban population of 2,500 to 19,999 adjacent to a metropolitan area
Beale 7	Urban population of 2,500 to 19,999, not adjacent to a metropolitan area
Beale 8	Completely rural or fewer than 2,500 urban population, adjacent to a metropolitan area
Beale 9	Completely rural or fewer than 2,500 urban population, not adjacent to a metropolitan area

Source: Rural-Urban Continuum Codes for Metro and Nonmetro Counties, 1993. By Margaret A. Butler and Calvin L. Beale. Agriculture and Rural Economy Division, Economic Research Service, U.S. Department of Agriculture, Staff Report No. 9425, September 1994.

Table 3
Regression Results for the Employment Uncertainty Equation (Equation (4))
All Counties, Metropolitan Counties, and Nonmetropolitan Counties

	Coefficients		
Variable	**All Counties**	**Metropolitan Counties**	**Non-metropolitan Counties**
Intercept	0.0013*** (0.0004)	0.000045 (0.00045)	0.0034 (0.0008)
IS_C	0.0034*** (0.0004)	0.0021*** (0.0004)	0.0033*** (0.0006)
ES_C	0.0010*** (0.0003)	0.0027*** (0.0005)	0.0011*** (0.0004)
$LTOTEMP_C$	-0.00084** (0.000036)	-0.00014*** (0.00004)	-0.00011* (0.00007)
$PHSG_C$	-0.000016 (0.000079)	0.0019*** (0.0005)	-0.000039 (0.000082)
PCG_C	0.000016 (0.00015)	-0.000074 (0.000096)	0.0021 (0.0016)
$LFPR_C$	-0.0000083 (0.000013)	-0.000021 (0.000018)	-0.0000021 (0.000015)
$PFLF_C$	-0.0016*** (0.0005)	-0.00065** (0.0003)	-0.0066*** (0.0014)
UNR_C	0.0022 (0.0015)	0.0042* (0.0023)	0.0018 (0.0019)
Adjusted R^2	0.195	0.407	0.165
N	1064	325	739

* Significant at 10%
** Significant at 5%
*** Significant at 1%

Table 4
Regression Results for the Unemployment Equation (Equation (6))†

Variable	Coefficient
Intercept	0.0443* (0.0262)
Var_d_c	0.0609 (0.1926)
$UNR70_c$	0.7341*** (0.0390)
Adjusted R^2	0.367
N	1286

* Significant at 10%
** Significant at 5%
*** Significant at 1%
† Coefficients on state dummy variables were not statistically significant and were omitted for brevity.