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Abstract

This study documents a substantial decline in employment volatility at business-cycle frequencies over the postwar period using state-industry level data. The distribution of total employment volatilities at the state level has become less disperse over time, and mean volatility has fallen. Similar results are obtained using employment data on one-digit sectors across states: all sectors have seen a decline in employment volatility over the postwar period, and state-sectors are more alike in terms of volatility levels. A key source of the decline in volatility appears to be widespread (across states and industries) decreases in the size of shocks hitting employment levels. Shifts in the demographic factors, and industrial structures of state economies have had little or no impact. Neither have inter-state employment shifts, such as migrations from the Frostbelt to the Sunbelt. The sources of the smaller employment shocks are unclear, although the evidence points to macroeconomic phenomena.

Introduction

Many recent studies have identified a decline in the volatility of U.S. real output over the last half century. Indeed, the standard deviation of quarterly real GDP growth has fallen by a factor of three over the post-war period. Several researchers have argued that a structural break in output volatility occurred in the mid-1980s, although some describe the decline as more steady and protracted, one beginning in the mid-1960s [see, e.g., Kim and Nelson (1999), McConnell and Perez-Quiros (2000) and Blanchard and Simon (2001).] Reasons for the decline have proved elusive. The most obvious candidates, such as changes in the composition of aggregate demand away from durable goods and toward services, decreases in the volatility of investment spending, shifts in the behavior of inventories, and better monetary policy, have offered some, but relatively little, explanatory power.

A less discussed and studied trend, but one as equally profound and important as the drop in output volatility, is a substantial decline in employment volatility. While this might be viewed simply as the other side of the output volatility coin, it is not. For example, evidence provided later in the paper reveals that a large decline in employment volatility at business-cycle frequencies began in the mid-1940s and largely ended by the mid-to-late 1960s. The drop in employment volatility appears to have occurred much earlier than the drop in output volatility.

This study provides several new and significant pieces of evidence on the measurement and explanation of the decline in employment volatility. First, whereas most previous research measures volatility using quarterly or annual growth rates of employment, the present work employs band-pass filtered series that extract the business-cycle component of employment variations. Doing so places less emphasis on short-term noise and concentrates on the frequencies of most interest to business-cycle analysis [Baxter and King (1999) and Christiano and Fitzgerald (1999)].

Second, we allow the variance of employment to change over time unlike other studies, which calculate an average variance for entire sample periods. This allows us to examine how changes in the dynamics of the employment process, and the variance of shocks to process, affect total employment volatility.

Third, previous studies have attempted to explain movements in employment volatility using national data or a cross-section of sub-national regions, such as states. They consequently captured either time-series movements in the volatility or some cross-section variation, but not both. Moreover, they typically relied on data beginning after the majority of the decline in employment volatility had occurred. By contrast, the present study uses a unique data set on quarterly employment levels by state and one-digit SIC groupings that extends back to 1939. It thus exploits both the time-series and cross-section dimensions of the change in volatility, in addition to controlling for unmeasurable, but potentially significant, state-specific influences.

We document the decline in employment volatility and analyze some possible reasons for the decline. These reasons include: changes in the dynamic process generating employment cycles; changes in the size of the shocks hitting employment; shifts in demographic factors, and industry. The analysis suggests that declines in the average size of employment shocks account for the majority of the volatility decline. Structural factors also matter, but to a lesser extent. This is found despite the considerable industry and demographic shifts that are present in the sample period.

Changes in the propagation mechanism played almost no role; if anything, they contributed to greater volatility.

Literature Review

Several recent studies have examined various aspects of the observed decline in volatility for many macroeconomic variables. McConnell and Perez-Quiros (2000) used an assortment of empirical strategies to measure output volatility, including the estimation of AR1 and Markov regime-switching models of output growth, and found that there was a one-time decrease in U.S. real output volatility in 1984Q1. They investigated possible causes for the decline, ruling out shifts in the composition of aggregate demand and settling tentatively on a changed relationship between inventories and sales.

Stock and Watson (2002) used VARs to examine the time-series behavior of volatility for 168 macroeconomic variables during the period from the early 1960s to the present.[1] They find that the decline in volatility is broad-based and that, rather than a smooth trend decline, the drop in volatility is better characterized as a trend break that occurred around 1984. Stock and Watson (2002) argue that between 20 percent and 30 percent of the decrease has resulted from improved monetary policy. The remaining decline is attributable to smaller output shocks, which they term "good luck." Kim and Nelson (1999) also present evidence that aggregate output volatility experienced a one-time decline in 1984.

[1] Stock and Watson (2002) provide an extensive review of the literature on the volatility decline for macroeconomic variables.

Blanchard and Simon (2001) also examined the volatility of aggregate real output growth during the postwar period, using rolling standard deviations of actual growth, and standard errors from rolling AR1 regressions to gauge volatility. They present evidence that, regardless of the volatility measure, volatility declined steadily and persistently during the post-war period, "from about 1.5 percent a quarter in the early 1950s to less than 0.5 percent in the late 1990s." Their results indicated that the decline is accounted for by reductions in the residual variance of output growth and is not a function of changes in the persistence of output shocks (i.e., the estimated AR1 coefficients.). Blanchard and Simon (2001) further conclude that the decline in real output volatility is not simply due to the absences of large shocks during the past two decades. Tests of the different hypotheses studied by McConnell and Perez-Quiros (2000) failed to find a major reason for the decline.

A different strand of the literature has used cross-sectional data for states and metropolitan areas to analyze the role of industrial diversification on cross-sectional differences in output and employment stability and instability. These studies typically focus on the average unconditional volatility of a variable's quarterly or annual growth over some single time period (e.g., 1970 to 1990.) Thus, they lack time-series variation in volatility and so cannot offer evidence on the reasons for any trend decline. It is conceivable, though, that time variations in the cross-section variables are important determinants of changing aggregate trends.

The findings of the cross-section studies are somewhat mixed, but the bulk of the evidence indicates that more industrially diverse locations tend to be associated with lower employment volatility. For example, using employment data for metropolitan areas, Siegel (1966), Conroy (1975), Kort (1981) and Malizia and Ke (1993) find that industrial diversity explains a significant share of the differences in volatility across metropolitan areas. Wundt (1992) and Sherwood-Call (1990), using state level data, also find evidence that industrial diversification reduces economic volatility. Some studies, however, find no evidence favoring the diversity-stability view (Jackson (1984)) using multi-county aggregates for Illinois, and Attaran ((1986) for all states).

Our study compliments both the macroeconomic and regional literature in that we exploit the cross-sectional variation in employment volatility as well as the time-series dimension in analyzing postwar period changes in employment volatility. As we will document, employment volatility has fallen over time in all states for which we have data, although to differing degrees. Thus it is important to consider both the time-series dimension and the cross-sectional aspect of the changes in volatility.

We use new data on state-level employment in eight one-digit SIC categories to estimate pooled cross-section time-series models of employment volatility. The data have a quarterly frequency and extend back to 1939. Thus our sample period is longer than typically used in past regional and aggregate studies. For example Malizia and Ke's sample runs from 1972-88, and Sherwood-Calls' sample covers the period 1963-86.

Measuring Employment Volatility

The data we use for this study are not publicly available and were obtained by special order from the U.S. Labor Department. The data set consists of quarterly measures of nonagricultural employment in eight one-digit sectors for each of the 48 continental U.S. states extending back to 1939. In total, 38 of the 48 states have complete data for all sectors, while the remaining 10 states are missing early data for one or more sectors.[2] Our analysis uses data on the 38 states for which full data are available, and by doing so adds 40 additional years of data for the large majority of states (using all 48 states requires starting the analysis in 1981.) The cost of doing so – excluding the ten states with incomplete data – appears small. In 1982:1, one of the first quarters when data for all 48 states are available, the 38 states in this study comprised 81% of total employment. It is thus highly likely that our analysis captures a substantial fraction of employment variation. Consequently, for present purposes, aggregate employment is defined as the 38-state sum of state-level employment.

Our measure of volatility is derived from the business-cycle frequency component of each employment series. This measure was chosen rather than a first-difference-based measure so as not to put undue emphasis on high-frequency movements in employment, and to highlight the data movements of greatest interest to business-cycle research. The business cycle component of the log of employment is extracted using a band-pass filter that removes frequencies shorter than six months and longer than 32 months from the data. This frequency band is standard in the literature that describes business cycles [see, e.g., Baxter and King (1999) and Christiano and Fitzgerald (1999)].[3] The filter is two-sided and symmetric. The weights on the i^{th} leading and lagging values of log employment are of the form: $w_i = b_i + 1$ for $i \neq 0$, where $b_i = \{\sin(6i) - \sin(32i)\}/\mathrm{B}i$; the weight on the contemporaneous value is $w_0 = 2(1/6 - 1/32)$; and, the constant 1 is chosen

[2] The 10 states with missing observations are Connecticut, Delaware, Illinois, Massachusetts, Michigan, Maine, Minnesota, Maryland, Rhode Island, and Utah. The BLS employment series has state level data for manufacturing; services; trade; government; transportation, communication, and public utilities; mining, construction; and finance insurance and real estate.

[3] Some authors use a Hodrick-Prescott filter to extract business cycle frequencies from data. See, for example, Ghosh and Wolf (1997).

so that all weights sum to zero, which ensures that the filtered series is stationary [Baxter and King (1999).] Following the suggestions of Baxter and King (1999), a window of 25 quarters is used, with 12 leading and 12 lagging periods.

Measuring Employment Volatility

As displayed in Figure 1, the mean volatility of state level employment, as measured by rolling 20-quarter standard deviations of filtered employment, declined dramatically between 1947 and the mid 1960s.[4] Volatility then rose until the early 1980s, at which point it began to trend downward once again. As we have discussed, we will exploit both cross-sectional and time-series changes in employment volatility to understand these overall movements.

Following many previous studies [e.g., McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Ghosh and Wolf (1997) and Hess and Iwata (1997)] we model the systematic component of filtered employment as a time-varying AR(1) process, estimated using rolling samples of 20 quarters. Hess and Iwata (1997) make an especially forceful empirical case for this approach. Our model for the dynamic evolution of filtered employment then is:

$$y_t = \rho y_{t-1} + \varepsilon_t \tag{1}$$

where y_t is the business-cycle component of employment. Our estimates of random employment shocks (the ε_t 's) and of the error variance come directly from the estimates of equation (1). We use this model to estimate the evolution of total employment and of all state and sectoral employment series. Figure 2 shows the residual standard deviation of the 38-state filtered aggregate employment for the period 1947:1 to 1995:4. Observe that the standard deviation of employment displays a pattern very similar to that for the unconditional volatility of filtered employment. Thus, it falls from a bit over 2.3 percent in 1947 to just under 0.5 percent in 1995. The lion's share of the drop in volatility occurs between 1947 and the early-1960s, when the standard deviation falls by a factor of three. Beginning in the 1970s, employment volatility reversed its previously declining trend and nearly doubled. This rise in volatility coincides with the generally poor economic outcomes of the 1970s during which the economy experienced rising inflation and slow growth. From the late 1970s on, however, volatility generally declined as economic performance improved relative to that of the 1970s. The patterns show some differences in that the unconditional volatility, $\left(\sigma_y^2\right)$, did not resume declining in the late 1970s as soon as the conditional volatility, $\left(\sigma_\varepsilon^2\right)$, did. Moreover, the conditional volatility ultimately fell to its previous low level, while the unconditional volatility did not. The difference between the two series in the more recent years must coincidence with a change in the AR1 coefficient. Specifically, the AR1 coefficient must have risen (discussed below.)

A general decline in the conditional volatility was widespread across states and industry sectors. A set of histograms of conditional state-level employment volatility at the beginning, middle and end of our sample -- 1947:1, 1971:3, and 1995:4 -- illustrate this finding. The histograms for total state-level employment volatility at each of these three periods are shown Figure 3. Clearly, a significant change in the distribution of

[4] The plot begins in 1947:1, rather than 1939:1 because our filter uses 12 lags of the data and the standard

employment standard errors across states occurred between 1947 and 1971. In 1947, average employment volatility was much higher and the dispersion of volatility across states was fairly wide. Most states had employment volatilities in the range of between 2 and 3 percent. By 1971 virtually all states had employment volatilities below 1 percent, and they are less disperse. Finally, also note that there is little difference in the distributions for 1971 and 1995.

We also examine histograms of employment volatility by sector across states (again for the periods 1947:1, 1971:3, and 1995:4). Figure 4 shows the change over time in the distribution of employment volatility across states for selected sectors -- manufacturing (Figure 4a), transportation, communication, and public utilities (TPU, Figure 4b), and services (Figure 4c).[5] A general pattern is present across sectors that mimic the broad features of the change in distribution for aggregate employment volatility: the distributions tend to shift left and collapse over time. Thus, average volatility for each sector has dropped, and there is less dispersion in volatility across states.

Another way to see the magnitude of the drop in volatility is by considering the trend decline in average volatility. For manufacturing, average volatility across states in 1947 was about 5.9 percent. By 1995, it had declined to 0.9 percent. For the services sector, average volatility declined from 2.2 percent in 1947:1 to 0.6 percent in 1995:1. The decline in volatility for TPU is similar to services: from 1.8 percent in 1947:1 to 0.8 percent in 1995:1. Note that while services and TPU employment volatility is much lower than manufacturing volatility in 1947, the volatilities of all three sectors were much more similar by 1971. We conclude that average employment volatility has declined in

errors are constructed using a 20-quarter rolling window.

each sector and that the dispersion of volatility is much tighter by the end of the sample period.

Changes in the Employment Process. As mentioned above, the data on unconditional and conditional employment volatilities indicate that the AR1 coefficient rose sometime around the 1970s. This point is made explicit in Figure 5, which graphs the mean value (38-state average) of the estimated ρ coefficients from the state level time-varying AR1 regressions. The figure indicates that the AR1 coefficients have generally increased over time. The average value of ρ was about 0.87 for the period 1947 to roughly the mid-1960s and has risen to about 0.91 since then. This relatively small upward movement in the ρ coefficient, other things equal, implies a *rise* in unconditional employment volatility relative to the conditional volatility because the variance of y_t from equation (1) is $\sigma_\varepsilon^2/(1-\rho^2)$. This is precisely what occurred.[6]

A higher ρ means that a given shock has a more persistent affect on employment. Given its timing, a plausible explanation for the increase in persistence can be found in the changing nature of the shocks hitting employment. One view is that prior to the 1970s demand shocks were more prevalent and more important sources of economic volatility than aggregate supply shocks. Especially during the 1970s and early to mid-

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[5] For brevity, we show trends for manufacturing; transportation, communication, and public utilities; and services. Figures for other sectors are available from the authors on request.

[6] We regressed the 38-state average AR(1) coefficient series on a dummy variable for which 1966:1 and after equals unity; the coefficient was positive (10.96) and highly significant (t-statistic of 20). We also conducted a counterfactual experiment in which each state's average AR(1) coefficient was held constant for the entire sample period at the state's average value for the period 1947:1 to 1965:4. These state AR(1) coefficients were used to calculate a synthetic set of errors for each state, and the associated state mean absolute error. A comparison of this synthetic mean absolute errors series with the series for the actual mean absolute errors reveals that the two series are quite close. Thus, despite a clear and statistically significant upward shift in the AR(1) coefficient, the shift is not a quantitatively important source for the variation in the conditional variance of aggregate employment.

1980s, the situation reversed. Even in the 1990s, the emphasis on productivity increases supports a view that aggregate supply shocks remained important, at least more important than in the pre-1970 period. To the extent that aggregate supply shocks have long-lasting, or even permanent, effects, their increased presence would cause the average level of persistence to rise [see, e.g., Hamilton (1983,1996).]

In any case, the implication of most direct relevance here is that the rise in ρ cannot be a source of the trend decline in unconditional volatility. The decline must stem either from decreases in the average size of shocks hitting employment or from changes in the shape of the distribution of those shocks.

The Postwar Decline in Conditional State Employment Volatility

Changes in the size of employment shocks. We first examine the time pattern in the size of the employment shocks. To investigate this, we calculated the mean absolute error of shocks to total state employment across the 38 states. The resulting series is plotted in Figure 6a. Clearly, the mean absolute error exhibits a profile that is roughly similar to that for the mean conditional volatility across states. The error falls from about 0.014 in the late 1940s to about 0.004 in the late 1960s. It then rises to a plateau just under 0.01 before falling in the 1980s and 1990s. By 1995 it had reachieved its previous low value of about 0.004.

Variations in the average size of the εs translates directly into a decline in the conditional volatility, other things equal. Indeed, when we scale the conditional employment volatility series (shown in Figure 2) by the mean absolute error, we see little overall trend in volatility for the sample period as a whole, although some downward trend between 1947 and the late 1960s remains (Figure 6b).

It appears that variations in the size of employment shocks are a key factor for the decline in employment volatility. Although the average error fell during the sample period as a whole, Figure 6a shows two sub-periods – the mid to late 1970s and the mid-1980s – in which the average shock spiked upward. Reasonable candidates for the sharp increases are the large oil price increases in the 1970s and the large decreases in the mid-1980s. Based on Hamilton's (1983,1996) work, such large relative price changes require substantial labor reallocations and could result in exceptionally large deviations from the employment cycle process described by equation (1).

Changes in the shape of the distribution of **εs.** While adjusting for variations in the mean size of the errors seems to account for a noticeable part of the fluctuations in the conditional employment volatility, as Figure 6b shows, a fair amount of the variation remains. The residual variation presumably comes from changes in the shape of the error distribution.

Changes in the shape of the distribution of the εs can arise from structural shifts specific to particular industry and demographic groups in the economy. For example, the conditional employment volatility in the manufacturing sector has fallen over time (see below.) Other things equal, this contributes to a decrease in the volatility of total employment. Alternatively, even if volatility in manufacturing had not fallen, the share of total employment in manufacturing did decrease markedly. The changing share of manufacturing, since it had above-average volatility earlier in the sample, would lead to less volatility in total employment. Similar logic holds for changing shares and volatility in state employment patterns and in a variety of demographic groupings.

The Roles of Changing Industry and State Employment Shares. Consider now evidence on the possible importance of shifts in the shares of employment across industries and states. These factors have received considerable attention in the literature. As mentioned earlier, changing industry and state employment shares can affect both the mean size of employment shocks and the distribution of the shocks.

The issue arises because of the large changes observed during the sample period in industry and state employment shares. Our data show, for instance, that three of our eight sectors showed significant changes in employment shares over time: services, manufacturing, and TPU (Figure 7). The mean share of state employment in manufacturing declined from a peak of a bit above 25 percent in the late 1940s to slightly above 15 percent in 1995. Similarly, TPU's mean share of total state employment declines from about 10 percent in the late 1940s to about 5 percent in 1995. On the other hand, the average state share of employment in services rose from about 10 percent in the late 1940s to about 27 percent in the mid-1990s. Thus, there was a significant shift in employment from manufacturing and TPU to services. The remaining sectors showed little change in share over time.

In the early years of the sample manufacturing was a significant contributor to high average state-level employment volatility both because manufacturing was a very volatile sector relative to other sectors and because it had a large share of state-level employment. While it is true that the manufacturing sector lost employment and the services sector gained employment, by 1995 the ratio of manufacturing volatility to services volatility had also fallen to 1.33 versus 2.7 in 1947:1. Thus, volatility may have declined both because of an employment shift away from manufacturing and because manufacturing became less volatile relative to other sectors in the economy. The shift in employment from manufacturing to services may have made the largest contribution to the measured decline in aggregate volatility in the early-to-mid part of the sample period.

The usual method for examining the contribution of changing industry shares to movements in volatility is to create a synthetic, or counterfactual data series, for which the employment shares of different industries are held constant at a base period's values. The synthetic series is then compared to the actual series for differences. We perform a counterfactual experiment, where the shares of each state's total employment in the eight industries are held constant at their 1947 values:

$$s_{i,j,1947} = e_{i,j,1947} / e_{US,1947}$$

where $s_{i,j,1947}$ is state i sector j's share of (38 state) aggregate employment in 1947; $e_{i,j,1947}$ is employment in state i, sector j in 1947, and $e_{US,1947}$ is the sum of 38 state aggregate employment in 1947. If the shift in employment among industries (e.g., from manufacturing to services) largely accounts for the drop in volatility, the volatility of the synthetic series would be higher than the volatility of the actual series. This would be so because the implied fraction of manufacturing employment is much higher at the end of the sample for the synthetic data than it is for the actual data.

The results are shown in Figures 8a and 8b. The exercise was done using both the conditional (Figure 8a) and unconditional (Figure 8b) volatilities. Clearly, there is very little difference in the time pattern of volatility between the synthetic and actual series, regardless of which volatility series is used. The figures suggest that shifting industry mix contributed almost nothing to fluctuations in volatility during the sample period. It appears that although employment shifted from manufacturing to services, declines in the volatility of manufacturing employment relative to services employment offset much of the effect. These results generally confirm those found in other studies [McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Stock and Watson (2002)].

An identical analysis using state shares of total employment, rather than industry shares, was conducted. This experiment holds constant the share of state employment in aggregate employment at its 1947 level. The results are displayed in Figures 9a and 9b, which show that shifting employment shares appear to explain little of the decline in aggregate employment volatility: the synthetic counterfactual series and actual employment series are virtually identical under either volatility measure.

We tentatively conclude that shifting employment patterns across sectors and shifting employment patterns across states explains little of the decline in employment volatility during the post-war period.

Regression Analysis

The Model and Data. We empirically model the conditional volatility of state-level employment using a fixed-effects pooled regression, which captures both cross-section and time-series variation in the data. The framework takes each state's employment volatility at a point in time as a separate observation. These are regressed on a set of state/time variables: the mean absolute employment shocks, measures of industrial and demographic structure, and state employment shares. In addition, 37 state dummy variables are included to account for unobservable time-invariant influences specific to each state. Dummies identifying periods of large oil price shocks are also included.

The regressions are estimated both with and without the volatility of aggregate employment as an explanatory variable. Including aggregate employment volatility as a regressor controls for systematic movements in volatility, shared by all states. Regressions that include aggregate volatility thus indicate how explanatory variables matter for the idiosyncratic portion of volatility, which could be diversified away. Finally, all regressions included a lagged dependent variable to account for serial correlation in the volatility measure. The model takes the form:

$$\sigma_{i,t} = \alpha + \beta_1 I_{i,t} + \beta_2 size_{i,t} + \beta_3 x_{i,t} + \beta_4 \sigma_{i,t-1} + \beta_5 \sigma_{us,t} + \beta_6 oil_t + \sum_{i=1}^{37} state_i + e_{i,t} \qquad (2)$$

where

$\sigma_{i,t}$ standard deviation of the business cycle component of employment in state i.

$I_{i,t} = (\sum_{j=1}^{8} (ss_{i,j,t} - ns_{j,t})^2)^{1/2}$

$ss_{i,j,t}$ share of employment in industry j for state i at time t.

$ns_{j,t}$ share of employment in industry j for the nation at time t.

$size_{i,t}$ employment share of state i in aggregate employment.

$x_{i,t}$ a vector of state-level demographic variables.

$\sigma_{us,t}$ standard deviation of the business cycle component of aggregate employment.

oil_t dummy variable for exogenous oil shocks.

$state_i$ dummy variable set to 1 for state i, 0 otherwise.

The sectoral diversity index, $I_{i,t}$, measures diversity in state i relative to the nation. So, an index value of zero indicates a state whose industry mix is as diversified as the nation. A higher level of the index indicates a more concentrated mix for the state. If industrial diversification leads to a decline in employment volatility, we expect β_1 to be positive and significant in equation (2). Past researchers have suggested including a measure of state size. We used state share of aggregate employment as our size proxy. Following the regional literature, a number of state-level demographic factors are used in the regression: percent female in labor force, percent aged 24 and over who have a college education, percent of population aged 65 and over, and percent of population that is nonwhite. These variables were gathered from decennial census data, and so new observations for each state are available only at 10-year intervals. The regressions hold fixed the values of the demographic variables between census years.

The regressions use quarterly employment data for each of the 38 states over the period 1947:2 to 1995:4. The sample thus contains 7410 state/time observations. There are, however, fewer independent observations since each of these observations belong to one of 38 well-defined clusters (the 38 states). Unless there is no correlation within the clusters, the usual standard errors calculated by OLS estimation are incorrect. We use an estimation procedure that corrects standard errors for cluster sampling. In addition, the error term in equation (2) may have non-constant variance, something often encountered in cross-sectional data. We use the White robust standard error correction to account for heteroskedastic errors.

Empirical Results. Three versions of the model were estimated: the coefficients and t-statistics are reported in Table 1. Equation R2 is similar to R1, except that it includes the conditional volatility of aggregate employment, $\sigma_{us,t}$, to account for common aggregate shocks. Earlier we noted that the average size of shocks is declining over time, and that the decline possibly helps to explain the downward trend in conditional employment volatility. To explore this issue, the mean absolute error of state employment rolling regressions (shown in Figure 5a) was added as an explanatory variable to equation R3 to control for smaller average shocks.

The industry mix variable is significant in all regressions, and its coefficient is similar across regressions at a value of about 0.003. The coefficient on $I_{i,t}$ suggests an elasticity of volatility with respect to industry diversity of 0.012 evaluated at the sample means. Recall that the index measures diversity relative to the nation, and that higher values of the index represent less diversified states. A positive coefficient is what we expect: less diverse employment across industries is associated with higher employment volatility. Note though that the coefficient value and elasticity are small. While diversity is significant in the regression, changes in diversity do not seem to matter much for state employment volatility.

As indicated, we included a state's share of aggregate employment as an explanatory variable to proxy for size. States with higher levels of employment may have thicker labor markets and be able to support a wider range of industries that could help smooth industry-specific shocks. While the sign on the coefficient is what we expect (larger states have lower volatility), the variable is not significant. The demographic variables have the expected signs across all regressions. The coefficients on percent of population 25 years and over and percent of population with a college education are negative and significant -- lower employment volatility is associated with a higher skill workforce. A higher fraction of females in the labor force is associated with higher employment volatility, possibly because females tend to have a weaker attachment to the workforce. Percent nonwhite and percent 65 years and older do not enter the regressions significantly, but we would expect that a higher fraction of retirees would be associated with lower employment volatility, since retirees living on fixed incomes may help smooth demand. The coefficient on percent nonwhite is insignificant, but has a positive sign. To the extent that the percent nonwhite is correlated with employment in more volatile industries, or with lower levels of skill training and/or weaker attachment to the labor force, we would expect a higher fraction to be associated with higher employment volatility. The high coefficient on the lagged dependent variable suggests a great deal of persistence in employment volatility.

Regressions R2 and R3 include aggregate employment volatility (plotted in Figure 2) as an explanatory variable. As mentioned, the variable is meant to capture common volatility across states. National volatility enters equation R2 significantly and with a positive sign; it was positive but insignificant in equation R3. In neither case did its inclusion have an important effect on the coefficients of other explanatory variables. Industrial and demographic structure variables continue to explain relatively little of the volatility of state employment. Thus, our variables seem to do no better in accounting for idiosyncratic employment volatility than they do in accounting for total state employment volatility.

Finally, equation R3 includes the mean absolute error term, which is positive and significant, indicating that smaller shocks contributed to the fall in employment volatility in the postwar period. The coefficients on the other explanatory variables are essentially unchanged after adding the mean absolute error variable to the regression. Taken together, the evidence suggests that industrial structure and demographics are largely capturing the cross-sectional dispersion of volatility rather than the trend decline over time.

Does Volatility Cause Employment Migration? We also conjectured that employment volatility might be falling over time because workers are shifting from relatively more volatile to relatively less volatile states. If workers are not being adequately compensated for employment risk they might migrate to areas with lower volatility. It is well known that the south and west have gained employment share relative to the midwest and northeast. If the south and west tend to have lower relative volatility, we might then see lower aggregate volatility as a consequence of shifting. To explore this issue we regressed state share of aggregate employment on the standard deviation of state employment volatility, lagged employment share, and state dummy variables:

$$eshare_{i,t} = \gamma + \delta_1 \sigma_{i,t} + \delta_2 eshare_{i,t-1} + \sum_{i=1}^{38} state_i + u_{i,t} \tag{3}$$

with:

$eshare_{i,t}$ the share of state i employment in national employment

Note that our regression does not examine the employment-shifting hypothesis directly, but rather picks up the correlation between employment share and volatility at the state level. We would nonetheless expect to find a significant, positive coefficient if employment shifted in response to state volatility. The regression results are reported in Table 2 and reveal that there is no significant effect of employment volatility on state employment share. We repeated the regression using lagged employment volatility to allow for a more dynamic response and found the same result. It seems that the general decline in employment volatility for the U.S. is independent of workers shifting to less volatile states.

Conclusion

This study has documented a general decline in the volatility of employment measured at business-cycle frequencies and examined some of its possible sources. Using quarterly data on employment by states and industries, we find that the decline stems largely from a drop in the volatility of employment shocks, and that the decline is widespread across industries and states. Our analysis indicates that fluctuations in the average size of employment shocks have been a major influence, although the reasons for the smaller shocks are not well understood. We found that industry and demographic structure affected volatility, though the effect was small. Consistent with other research we are able to empirically rule out an important role for changing shares of industry employment. We also determine that changing state employment shares matter little.

Given the substantial impact of the decline in the size of employment shocks, research into its possible causes is warranted. Is it driven by fundamental changes in economic, financial and policy structures? Or is it, in the words of Stock and Watson (2002), mainly "good luck"?

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Table 1

Regression Results*

	R1	R2	R3
Industrial Structure, $I_{i,t}$	0.0039833 (2.60)	0.003955 (2.86)	0.003964 (3.33)
State Share of Aggregate Employment	-0.00212 (-0.77)	-0.002423 (-0.65)	-0.002293 (-0.74)
Percent of Pop with a College Degree	-0.0000238 (-2.35)	-0.0000402 (-3.0)	-0.0000244 (-2.13)
Percent Female Labor	0.0000144 (2.73)	0.0000265 (3.45)	0.0000169 (2.73)
Percent Nonwhite Pop	2.81e-06 (0.82)	1.76e-06 (0.43)	8.79e-07 (0.27)
Percent Pop Over 65	-0.0000301 (-1.51)	-0.000027 (-1.04)	-0.0000181 (-0.85)
Lagged Dependent Variable, $\sigma_{i,t-1}$	0.95915 (239.81)	0.9371 (113.71)	0.9349 (114.38)
Aggregate Employment Volatility, $\sigma_{US,t}$	-----	0.02593 (4.12)	0.004859 (0.84)
Oil Shocks	0.0000739 (3.28)	0.0000581 (2.42)	0.00016 (6.01)
Mean Absolute Error			0.0622 (12.26)
Constant	0.000237 (1.75)	-0.000051 (-0.36)	-0.0001214 (-0.96)
Adjusted R^2	0.9815	0.9817	0.9829

*Numbers in parentheses are t-statistics. All regressions include 37 state dummy variables.

Table 2

Regression Results*

$$eshare_{i,t} = \gamma + \delta_1 \sigma_{i,t} + \delta_2 eshare_{i,t-1} + \sum_{i=1}^{38} state_i + u_{i,t}$$

γ	$\sigma_{i,t}$	$eshare_{i,t-1}$
0.0004	-0.0055	0.8322
(1.06)	(-0.19)	(20.02)

$R^2 = 0.991$

*Numbers in parentheses are t-statistics.

Figure 1: Aggregate Employment Rolling Standard Deviations

(38 state total)

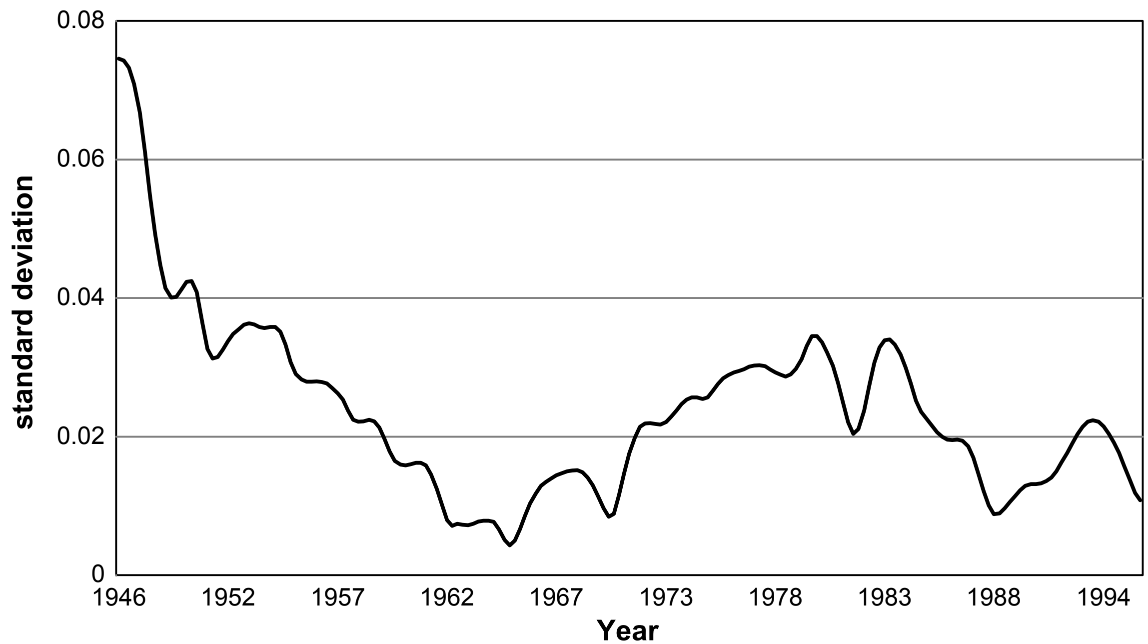


Figure 2: Aggregate Employment Rolling Regression Standard Errors

(38 state total)

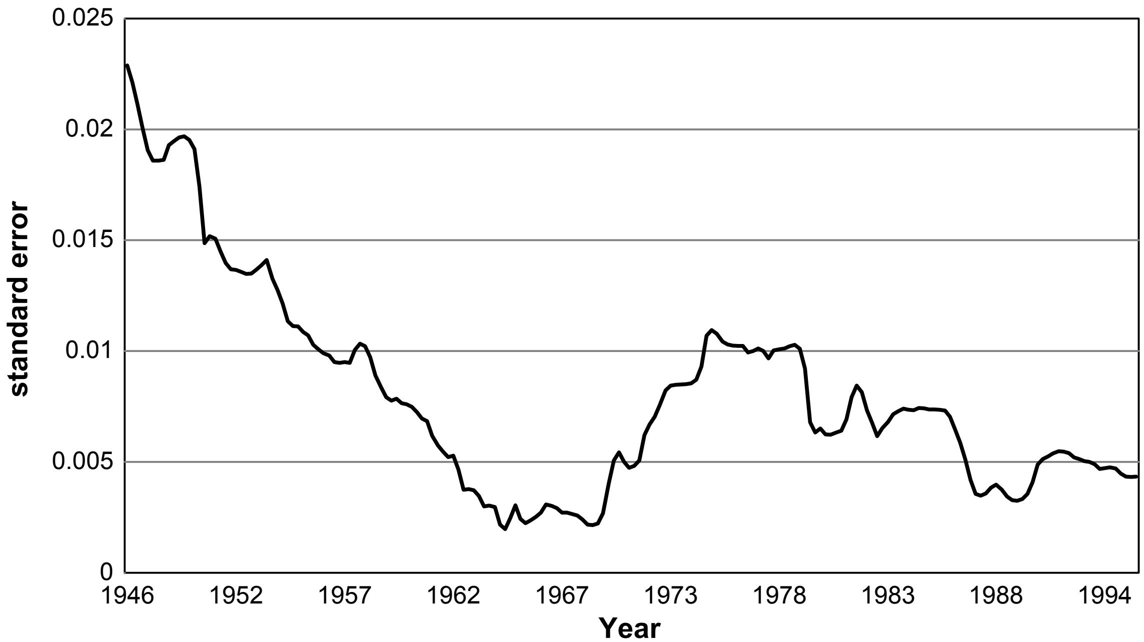


Figure 3: Distributions of Aggregate Employment Rolling Regression Standard Errors
(38 state total)

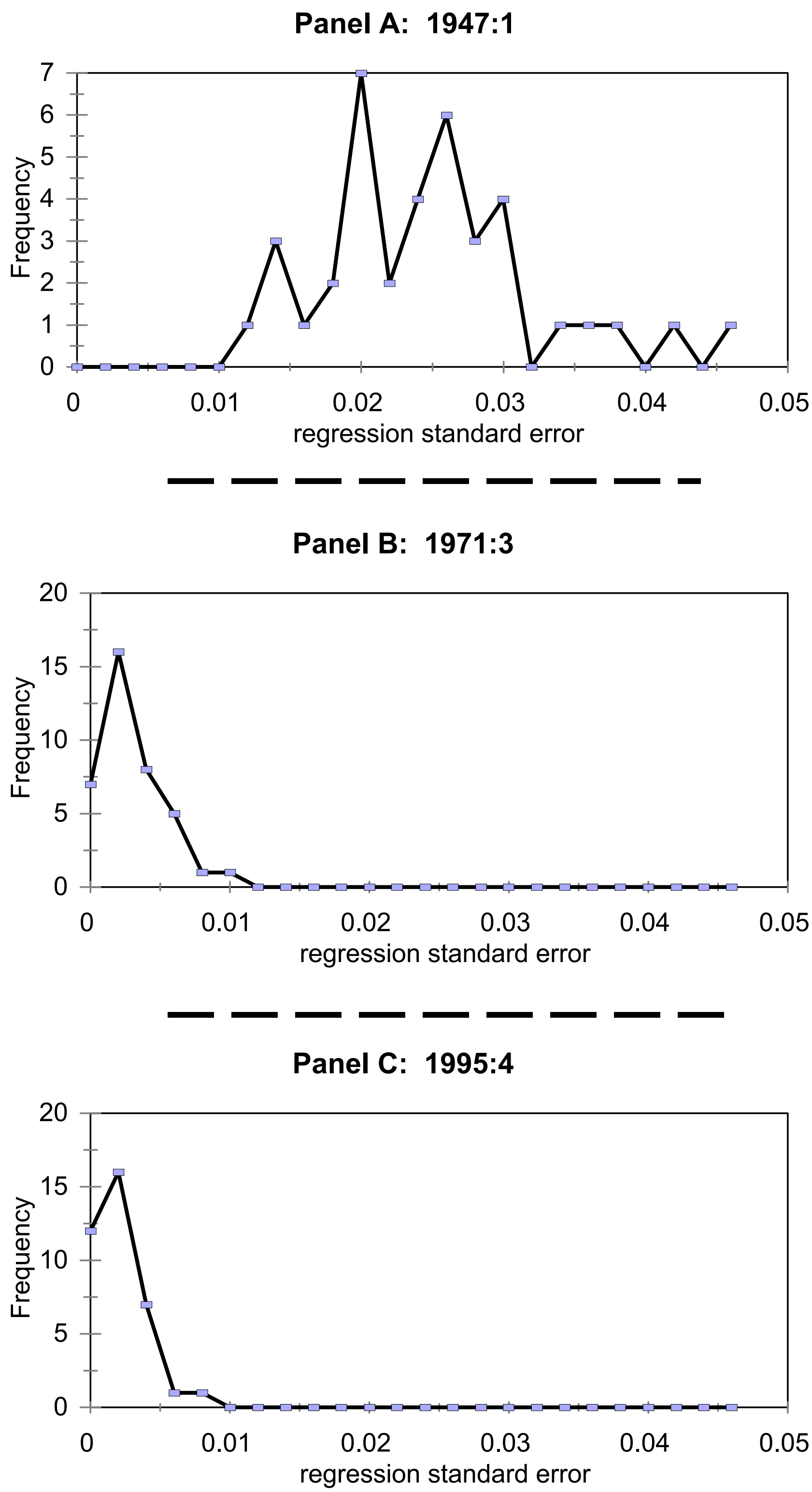


Figure 4a: Distributions of Manufacturing Employment Rolling Regression Standard Errors

(38 state total)

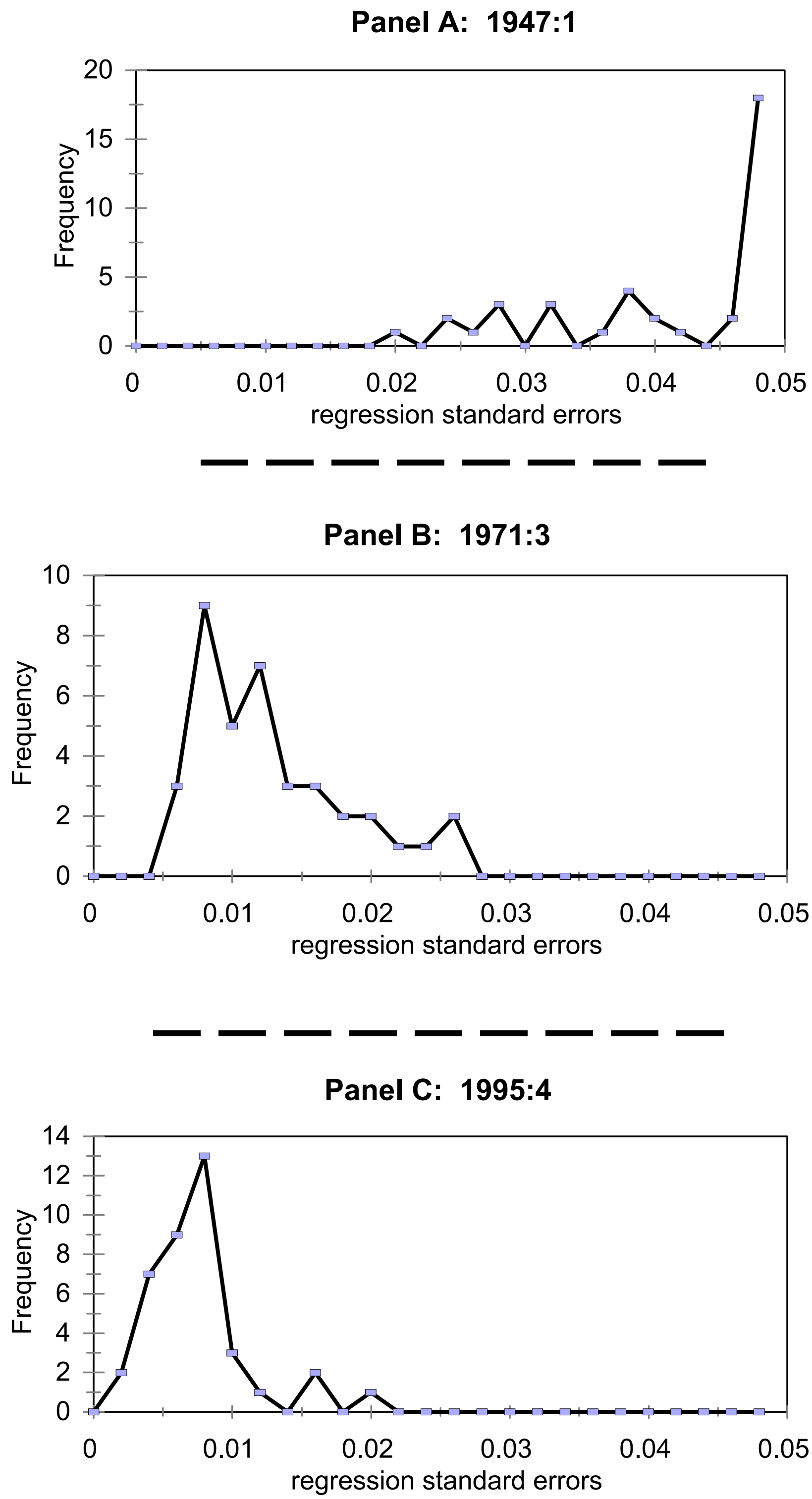
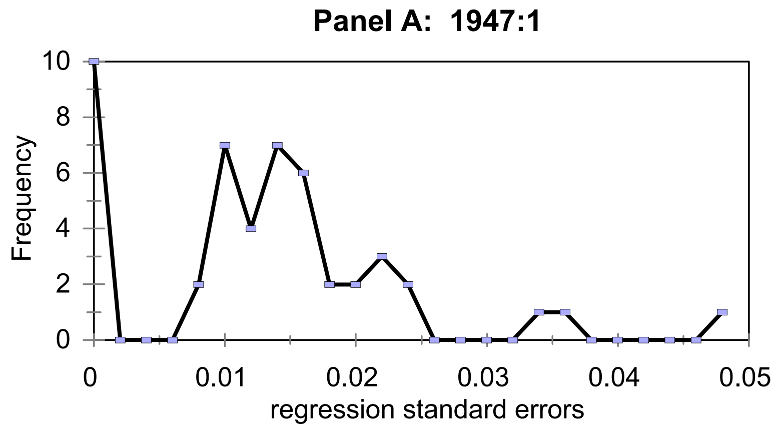
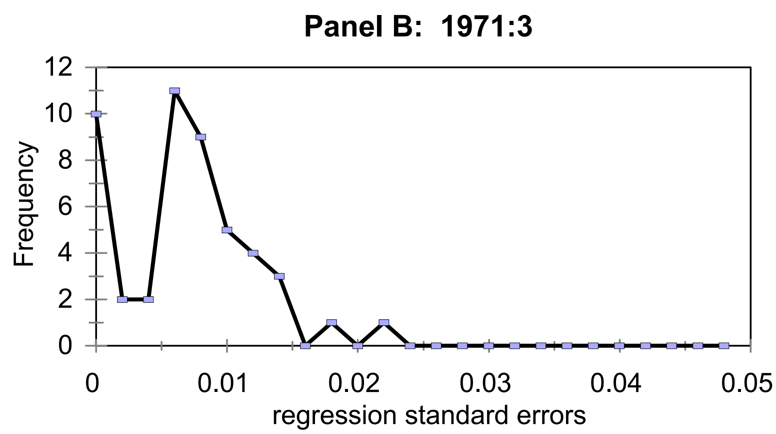


Figure 4b: Distributions of Transportation and Public Utilities Employment Rolling Regression Standard Errors

(38 state total)





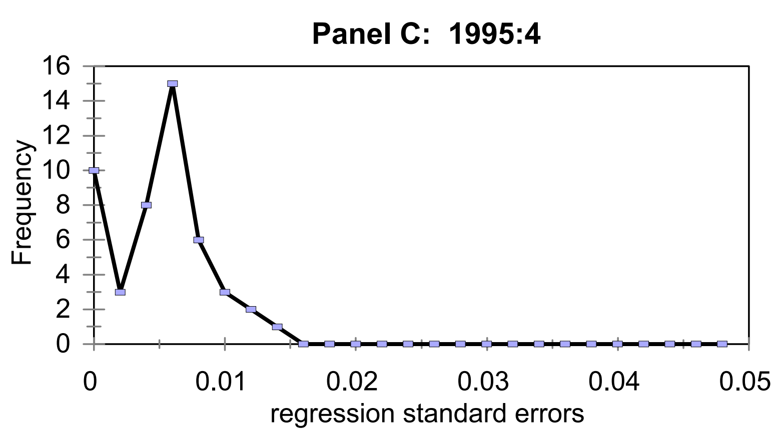


Figure 4c: Distributions of Services Employment Rolling Regression Standard Errors
(38 state total)

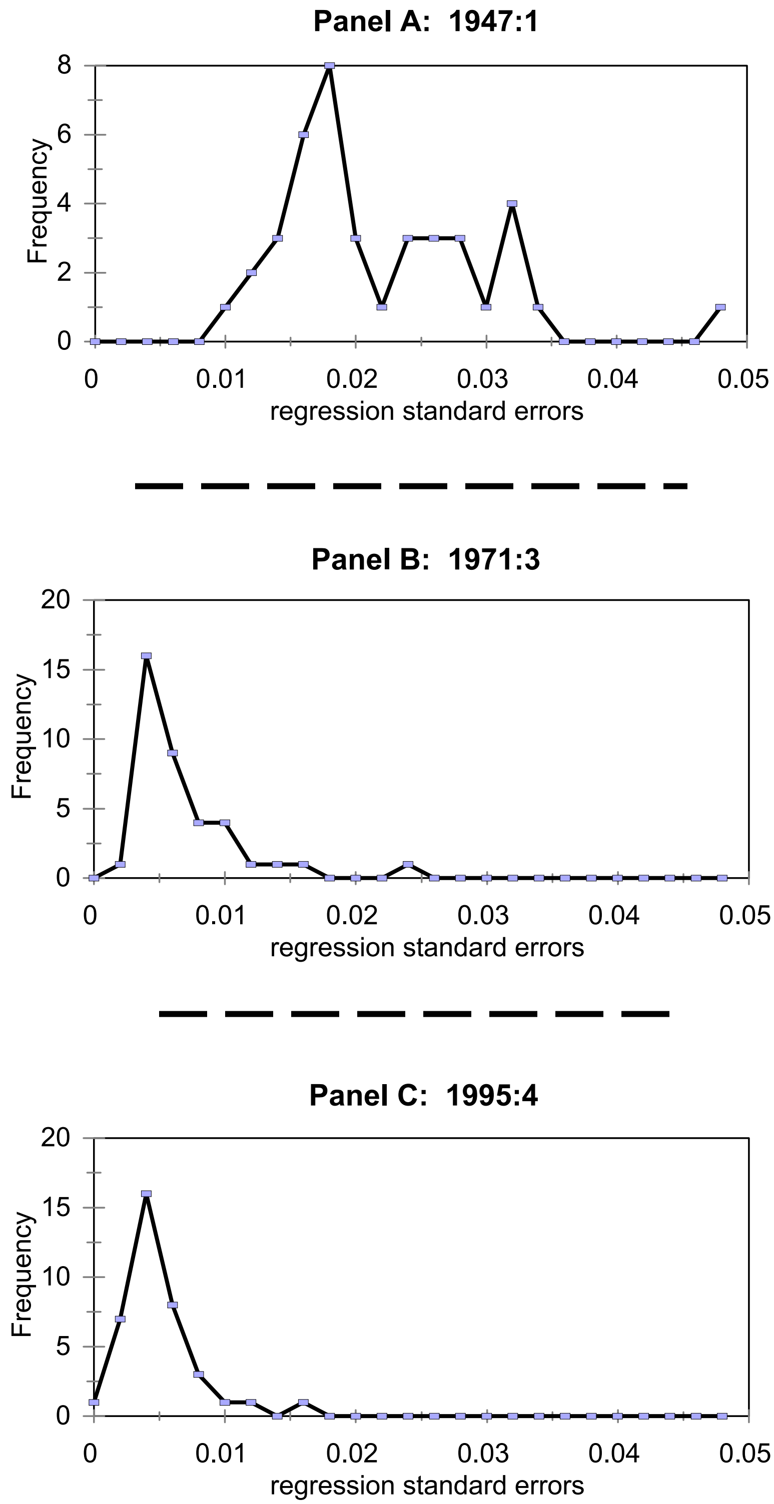


Figure 5: Average State AR1 Coefficients

(38 states, 12 quarter moving average)

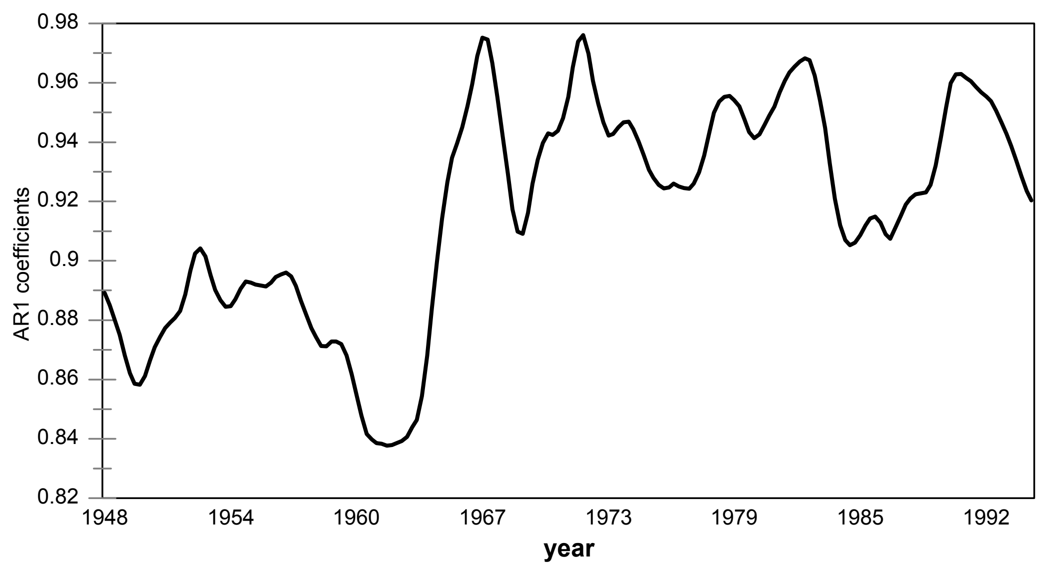


Figure 6a: State Mean Absolute Errors

(38 states, 12 quarter moving average)

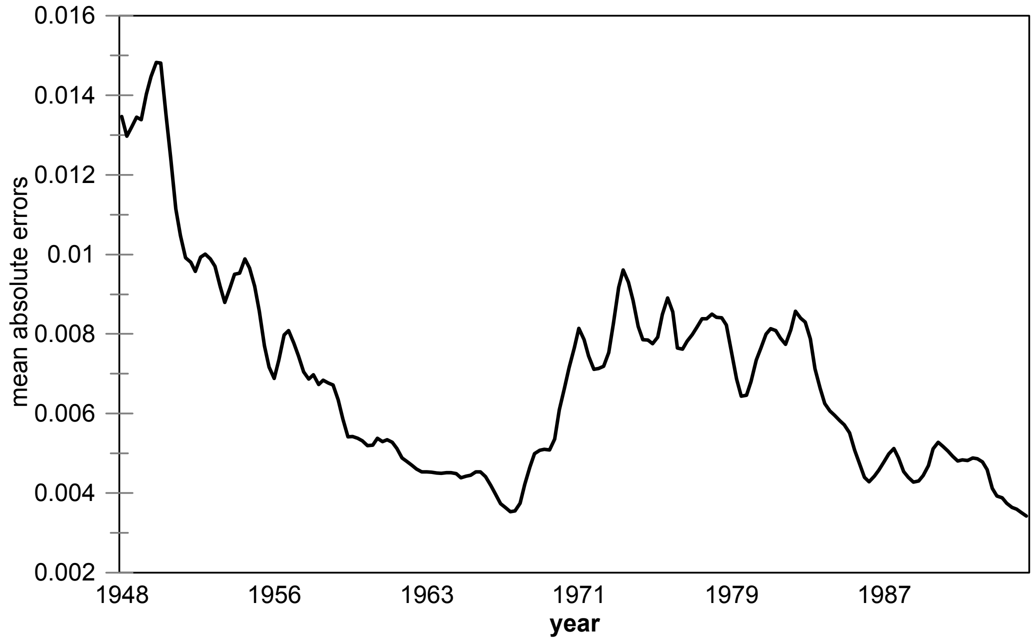


Figure 6b: Aggregate Employment Regression Standard Errors Divided by the State Mean Absolute Errors

(38 states, 12 quarter moving average)

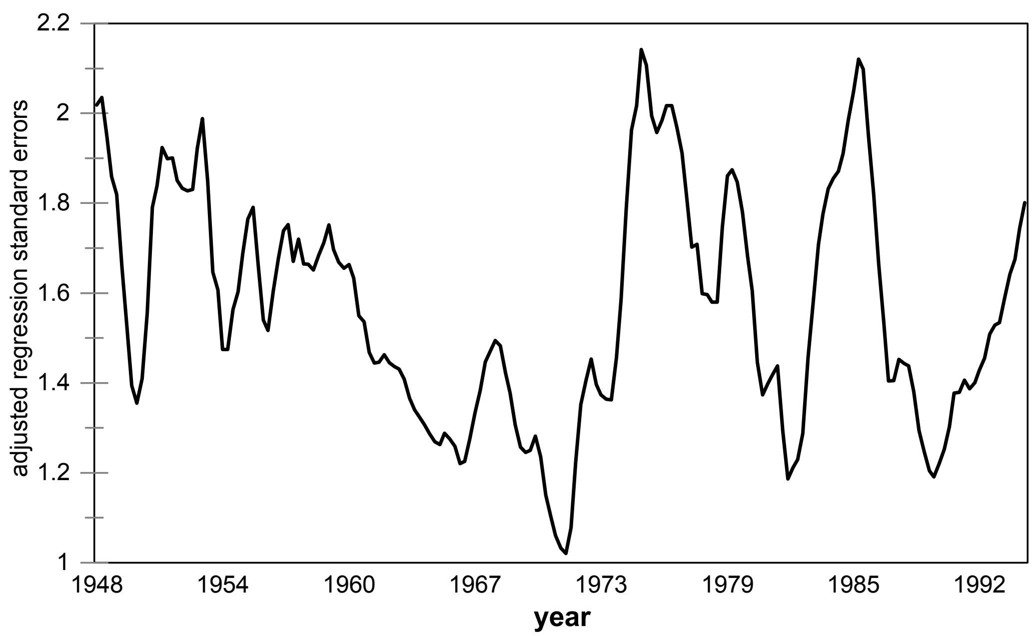


Figure 7: Industry Employment Shares

(38 states)

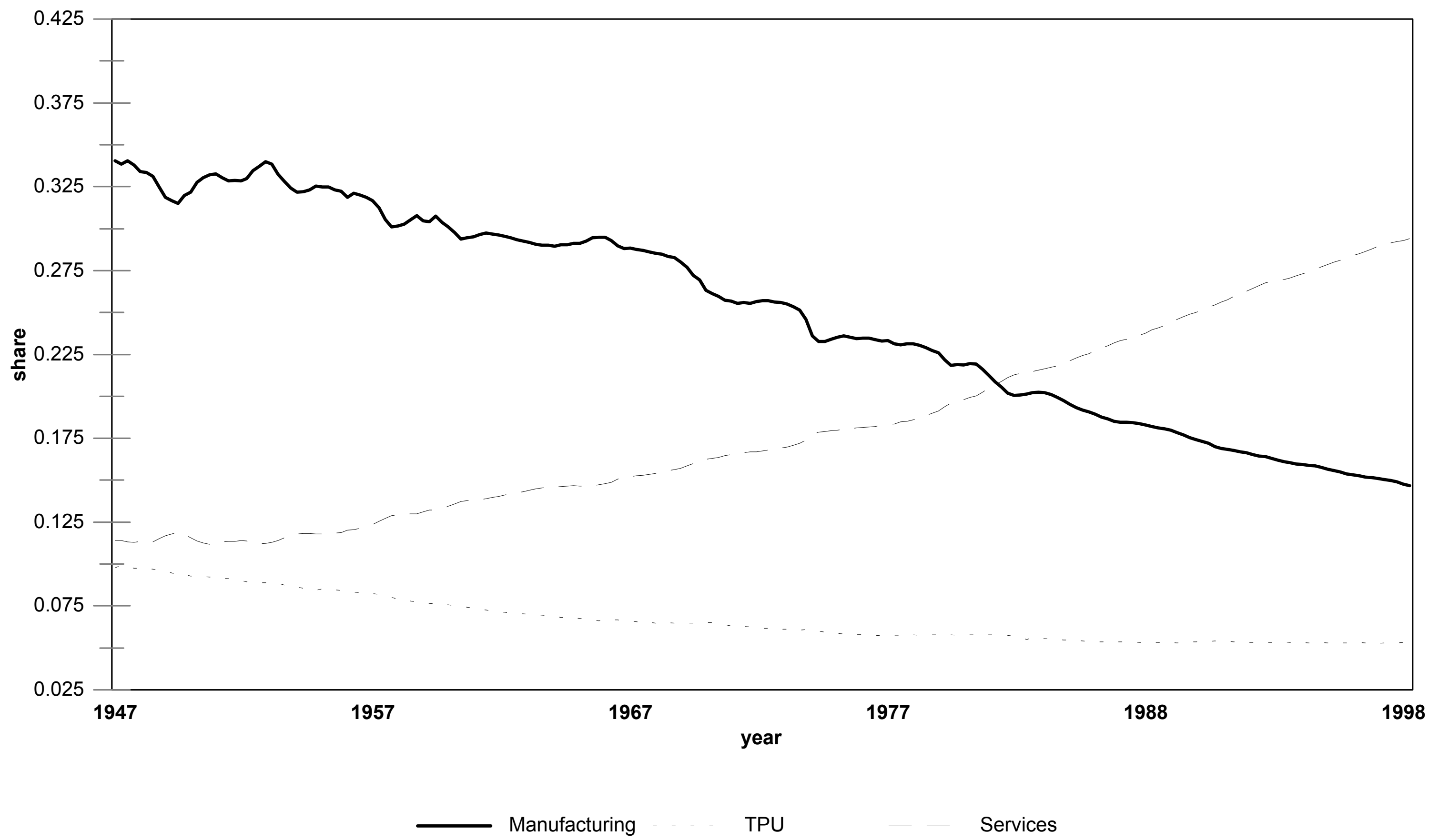


Figure 8a: Aggregate Employment Rolling Regression Standard Errors Using Actual and Fixed Industry Shares
(38 state total)

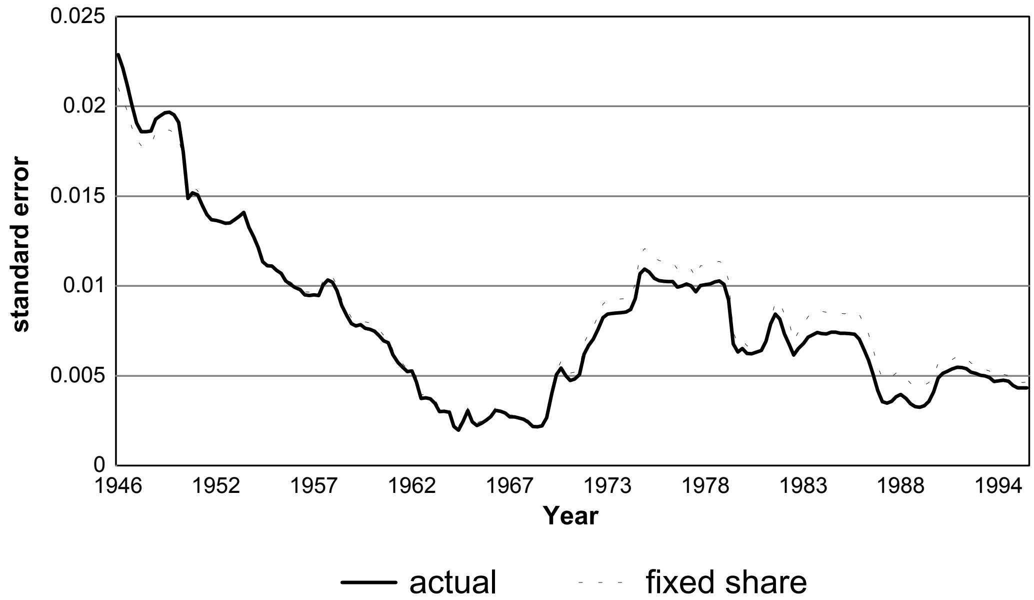


Figure 8b: Aggregate Employment Rolling Standard Deviations Using Actual and Fixed Industry Shares
(38 state total)

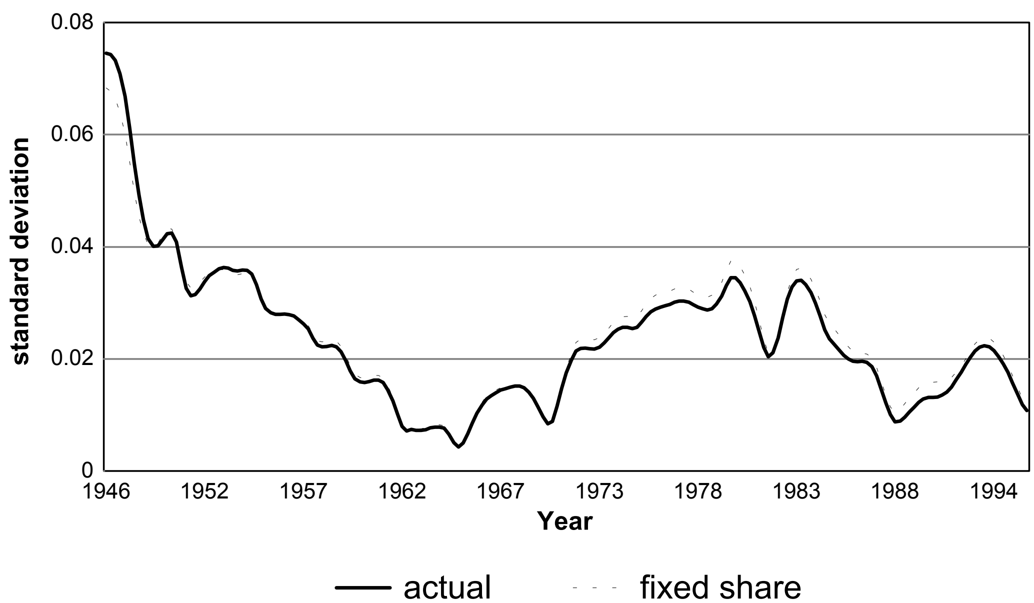


Figure 9a: Aggregate Employment Rolling Regression Standard Errors Using Actual and Fixed State Employment Shares

(38 state total)

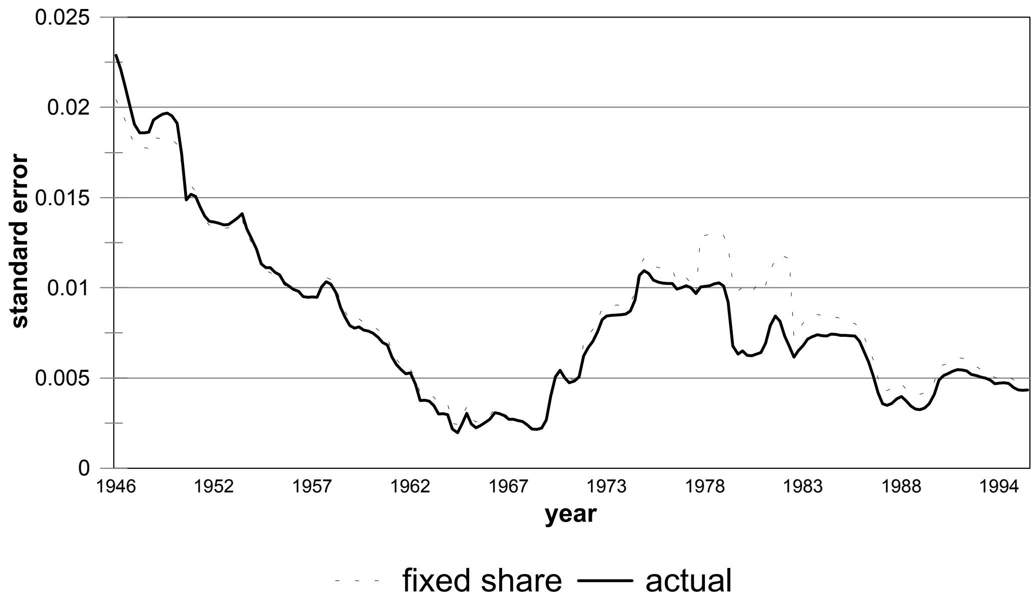


Figure 9b: Aggregate Employment Rolling Standard Deviations Using Actual and Fixed State Employment Shares

(38 state total)