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Abstract

In 1952, the average quarterly volatility of U.S. state employment growth was 1.5 percent. By 1995, it was just under 0.5 percent. While all states shared in the decline, some declined more dramatically than others. We analyze aspects of this decline using data covering postwar industry employment by state. Estimates from a pooled cross-section/time-series model indicate that fluctuations in macroeconomic and state-specific variables have both played an important role in explaining volatility trends. However, macroeconomic shocks account for more of the postwar fluctuations in state employment growth volatility than do state-specific forces.

I. Introduction

It is now widely recognized that the volatility of the U.S. economy has changed dramatically over the postwar period. At the national level, this change has been documented by Stock and Watson (22), McConnell and Perez-Quiros (17), Blanchard and Simon (3), and a host of others, who find that a significant drop in U.S. economic volatility occurred in the early 1980s. This decline in aggregate volatility has been identified in a wide range of series, including output and employment.

An aspect of the volatility change that remains unexplored is its manifestation at the sub-national level. In this paper we focus on a sample of 38 U.S. states for which there exists a long time series on employment. We first document features of the pattern of employment growth volatility across states, industries, and time. We find that all states and major industries have shared in the general decline in volatility, though to differing extents. For our sample, Table 1 shows the state with the largest postwar decline in employment growth volatility is Washington, which saw a drop of about 88 percent. The state with the smallest decline is New Hampshire, at about 21 percent. The table also suggests that the initially most volatile states experienced the largest declines in employment growth volatility, suggesting mean reversion.

What accounts for the large difference across states in the pattern of employment growth volatility? One possibility is that macroeconomic forces that affect volatility may have different impacts across states. For example, Carlino and DeFina (5) find that U.S. monetary policy has differential effects across states. Thus, postwar changes in the conduct of U.S. monetary policy may have contributed to cross-state differences in employment growth volatility. Similarly, one could imagine that changes in U.S. fiscal policy could have differential effects across states, which might help explain the observed volatility pattern.

In addition to the macroeconomic effects, state-specific idiosyncratic factors might, in and of themselves, lead to differences in employment growth volatility. For example, the composition of industries within a state is likely to help explain employment growth volatility. States that are more concentrated in a single industry are perhaps more likely to experience wide swings in employment growth as the state's fortunes rise and fall with those of its particular industry. States with a broader mix of industries may experience lower employment growth volatility as the fortunes of one industry are offset by the misfortunes of another.

To address the issue of the extent to which macroeconomic and state-specific factors explain employment growth volatility, a panel regression analysis is performed. We find that macroeconomic factors appear to explain more of the variance of employment growth volatility than do state-specific factors. In particular, macroeconomic factors explain from 56 percent to 78 percent of the error variance, while state-specific factors explain 8 percent to 30 percent of the variance.

The question of what drives employment growth volatility at the regional level is closely related to what drives volatility at the national level. Understanding the forces that govern employment growth volatility at the sub-national level is important to national and local policymakers. At the national level, researchers have one observation (the nation) to gain insight into these forces. The advantage of using regional data is that it gives a much larger testing ground for conducting the analysis. In addition, it is also important to note that by using state-level data, we mitigate potential endogeneity problems that plague other studies that exclusively use macroeconomic data. When using national data, one is never sure about the extent to which monetary policy actions, for example, lead to changes in employment growth volatility and to what extent changes in employment growth influence what actions the Fed takes. An advantage to using state-level data is that it's unlikely that employment growth volatility in any given state will have a significant influence on the formation of monetary policy.

II. Literature Review

Several recent studies have examined various aspects of the observed decline in volatility for many macroeconomic variables. McConnell and Perez-Quiros (17) used an assortment of empirical strategies to measure output volatility, including the estimation of AR(1) and Markov regime-switching models of output growth, and found that there was a one-time decrease in U.S. real output volatility in the first quarter of 1984. 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 (22) 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 the drop in volatility is best characterized as a trend break that occurred around 1984. Stock and Watson (22) argue that between 20 percent and 30 percent of the decrease resulted from improved monetary policy. The remaining decline is attributable to smaller output

[1]Stock and Watson (22) provide an extensive review of the literature on the volatility decline for macroeconomic variables.

shocks, which they term “good luck.” Kim and Nelson (14) also present evidence that aggregate output volatility experienced a one-time decline in 1984.

Blanchard and Simon (3) also examined the volatility of aggregate real output growth during the postwar period. They compute the standard errors of the residual from an AR(1) regression estimated using a rolling 20-quarter window. They argue that volatility declined steadily and persistently during the postwar period, “from about 1.5 percent a quarter in the early 1950s to less than 0.5 percent in the late 1990s.” Blanchard and Simon (3) further conclude that the decline in real output volatility is not simply due to the absences of large shocks during the past two decades.

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 decline in 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 growth volatility. For example, using employment data for metropolitan areas, Siegel (21), Conroy (6), Kort (15), and Malizia and Ke (16) find that industrial diversity explains a significant share of the differences in volatility across metropolitan areas. Wundt (23) and Sherwood-Call (20), 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 [13] using multi-county aggregates for Illinois, and Attaran [2] for all states).

A recent study by Hammond and Thompson (11) finds that the failure to control for various demographic characteristics of the local population leads to an overestimation of the impact of industrial specialization on employment volatility in the metropolitan regions in their study. Specifically, Hammond and Thompson (11) find that after taking demographic characteristics into account, the impact of industrial specialization on employment volatility is reduced by more than 22 percent for metropolitan regions.

Our study complements both the macroeconomic and regional literature in that we exploit the cross-sectional variation in employment growth volatility as well as the time-series dimension in analyzing postwar changes in employment growth volatility. As we will document, employment growth 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.

III. Measuring Employment Growth Volatility

Our data are quarterly nonagricultural payroll employment from the Bureau of Labor Statistics (BLS). We have observations on total employment for each of the 48 continental states as well as observations on each of the eight one-digit sectors within states. The data extend back to 1947. 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]

[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

Our analysis uses data on the 38 states for which full data are available and, by doing so, adds 29 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 10 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 percent of total employment. Therefore, we define aggregate employment as the 38-state sum of state-level employment.

Our measure of each state's employment volatility is based on the log first difference of the employment series. We first measure volatility by calculating a rolling 20-quarter standard deviation in the log differences of employment for each state. That is, the standard deviation in quarter t is computed using a state's log differences for quarter t and the 19 preceding quarters. For example, the standard deviation in 1952:1 is based on data for 1947:2 to 1952:1, that for 1952:2 is based on data for 1947:3 to 1952:2, and so on. We refer to this rolling standard deviation as the *unconditional* volatility of period t.[3] As displayed in Figure 1, the cross-state mean unconditional volatility declined dramatically between 1952 and the late 1960s. Volatility then rose until the early 1980s, at which point it began to fall once again. We will exploit both cross-sectional and time-series changes in employment growth volatility to understand these overall movements.

These general trends are also visible using estimates of the *conditional* volatility of employment. State-level conditional volatility is calculated using the same 20-quarter

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manufacturing; services; trade; government; transportation, communication, and public utilities; mining; construction; and finance, insurance, and real estate. Carlino and DeFina (4) analyze the cohesion properties of this data set and find that the 38-state sample is highly representative of the 48-state sample in the post-1982 period.

[3] Although the BLS web site has data back to 1939, it is widely believed that pre-World War II data are not as reliable as postwar data. Therefore, 1952 marks the first year in which we have enough reliable prior data to begin the computation of our volatility measures.

rolling samples that generated the unconditional volatilities. However, in contrast to the unconditional volatility measure, we use the errors from a rolling AR(1) regression model of the employment log differences. The use of anAR(1) model follows the approach employed in many previous studies (e.g., McConnell and Perez-Quiros [17], Blanchard and Simon [3], Ghosh and Wolf [7], and Hess and Iwata [12]). More specifically, we model the dynamic evolution of employment growth in each state, as the first difference in log employment, as:

$$y_{i,t} = \rho y_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is employment growth in state i at time t. Our estimates of state-level conditional employment growth volatility are then computed as the standard deviation of the 20-quarter rolling sample of the $\varepsilon_{i,t}$. Note that estimation of (1) will yield a different ρ for each state and rolling sub-sample.

Figure 1 shows the cross-state average *conditional* volatility of the 38-state sample for the period 1952:1 to 1995:4. The series displays a pattern very similar to that for the *unconditional* volatility, also shown in Figure 1. It falls from a bit under 1.4 percent in 1952 to just under 0.4 percent in 1995. The majority of the drop in volatility occurs between 1952 and the late 1960s, when the standard deviation falls to almost 0.5 percent. Beginning in the 1970s, employment growth 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 time the economy experienced rising inflation and slow growth. From the early 1980s on, however, volatility generally declined as economic performance improved relative to that of the 1970s.

Closer inspection of the data shows some differences between the patterns of the unconditional volatility and the patterns displayed by the conditional volatility. Most notably, after 1968, the difference between the two series widened and generally remained wider for the remainder of the sample. The greater difference between the series in more recent years reflects greater persistence in the AR(1) process (discussed below).

The general decline in conditional volatility was widespread across states and industry sectors. A set of histograms of conditional state-level employment growth volatility at the beginning, middle, and end of our sample -- 1952:1, 1971:3, and 1995:4 -- illustrates this finding. The histograms for total state-level employment growth volatility at each of these three periods are shown in Figure 2. Clearly, a significant change in the distribution of employment standard errors across states occurred between 1952 and 1971. In 1952, average employment growth volatility was much higher, and the dispersion of volatility across states was fairly wide. Most states had employment volatilities of between 0.5 percent and 1.5 percent. By 1971 virtually all states had employment volatilities of 0.5 percent or lower, and by 1995, the volatilities were lower still.[4] Similarly, median volatility for the 38 states fell from 1.2 percent in 1952:1 to 0.7 percent in 1995:4.

Figure 3 shows the change over time in the distribution of employment growth volatility across states for selected sectors -- manufacturing (Figure 3a) and services

[4]The dispersion of volatilities across states, as measured by the coefficient of variation, fell 30 percent between 1952 and 1995, indicating that employment growth volatility became more similar across states over time. The downward trend was briefly interrupted, however, by increased volatility in the coefficient of variation during the late 1970s and early 1980s.

(Figure 3b).[5] A general pattern is present across sectors that mimics the broad features of the change in distribution for aggregate employment growth volatility: the distributions tend to shift left and collapse over time. For manufacturing, average volatility across states in 1952 was about 2.3 percent. By 1995, it had declined to 0.7 percent. The distribution for the services sector also tends to shift to the left and to collapse over time (Figure 3b); average volatility declined from 1.3 percent in 1952:1 to 0.6 percent in 1995:4[6]

Changes in the Employment Process

As mentioned above, the data on unconditional and conditional employment volatilities indicate that the AR(1) coefficients on the employment growth process (equation [1]) rose in the late 1960s. This point is made explicit in Figure 4, which graphs the mean value (38-state average) of the estimated ρ coefficients from the state-level time-varying AR(1) regressions.[7] The figure indicates that the AR(1) coefficients increased slightly over time. The average value of ρ was about 0.4 for the period 1948 to roughly the late 1960s and has risen to about 0.43 since then. This relatively small, but statistically significant, upward movement in the ρ coefficient implies a *rise* in unconditional employment growth volatility relative to the conditional volatility because the variance of y_t from equation (1) is $\sigma_\varepsilon^2/(1-\rho^2)$.[8]

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[5] For brevity, we show trends for manufacturing and services. Figures for other sectors are available from the authors on request.
[6] The general decline in dispersion of volatilities remains even after adjusting for the declining mean volatilities. That is, the coefficient of variation of state volatilities generally fell during the sample period. An exception is the 1980s, during which the coefficient of variation was very erratic.
[7] Recall that estimation of equation (1) yields a series of ρ s, one for each state and rolling sub-sample.
[8] 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 highly statistically significant (t-statistic of 4.45).

A higher ρ means that a given shock has a more persistent effect on employment. 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. The situation reversed, especially during the 1970s and early to mid-1980s. 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 [8, 9]).

In any case, the implication of most direct relevance is that the rise in ρ cannot be a source of the trend decline in unconditional volatility; ρ must decline over time for this to be the case. Thus, the decline in volatility 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.

IV. Postwar Changes in Conditional State Employment Growth Volatility

In this section, we study possible sources of the observed fluctuations in conditional employment volatilities. We first identify economic and demographic variables that might have driven the observed variations in employment growth volatility, documenting the trends and suggesting theoretical reasons for their importance. We then quantify the effects of each variable on employment growth volatility using panel data.

Macroeconomic influences on state volatility

Many reduced-form macro models imply that volatility in real activity, such as employment, arises from changes in policy regimes and movements in productivity. Indeed, three variables that have received attention in the relevant literature are monetary policy, fiscal policy, and multifactor productivity.

Figure 5a and Figure 5b show the volatilities of growth in real government purchases and in multifactor productivity. Volatilities are computed using the regression standard errors from rolling 20-quarter AR(1) models, the identical procedure used to measure employment growth volatility.[9] The figures show that each series generally declined during the sample period and that each appears to mirror other aspects of employment growth volatility. The volatility in multifactor productivity, for instance, trends down until the late 1960s, after which it rises for a while before falling again throughout the 1980s. Apart from its downward trend, the volatility in real government purchases is less obviously linked to employment growth volatility movements. It appears, though, that the underlying pattern in the volatility of these variables mirrors the decline in employment growth volatility.

Characterizing changes in monetary policy over our sample period is not straightforward. The Federal Reserve has followed several official operating procedures through the sample period, including targeting free reserves, non-borrowed reserves,

[9] We display actual real government purchases rather than, say, full employment purchases or the full employment deficit, because these alternatives introduce unknown but perhaps significant degrees of measurement error. For example, construction of the high employment deficit requires an estimate of potential output, which is tricky at best. Furthermore, real purchases are largely exogenous with respect to contemporaneous employment growth and the degree of economic activity in general, and so the regression standard error represents a good proxy for present purposes. Similar logic holds for multifactor productivity growth; its regression standard error is not likely to be caused by contemporaneous employment growth volatility. For the purpose of the pooled regression estimations, we use a one-period lag of each variable to mitigate any endogeneity.

monetary aggregates, and the federal funds rate. These changes in operating procedures could have been endogenous responses to changing economic conditions in the nation. As we have noted, this endogeneity is less problematic when using sub-national data. Nonetheless, we chose to represent shifts in monetary policy using a variable that represents the different policy regimes followed by the Fed during our sample period. We identify policy regimes using the narrative analysis of Romer and Romer (18, 19) that is based on FOMC policy directives. Their reading of the directives allowed them to identify four different policy regimes, characterized by reactions to inflation and output fluctuations for the nation. The regimes cover 1952:1 to 1963:4; 1964:1 to 1979:3; 1979:4 to 1987:3; and 1987:4 to the present. In the first and third regimes, the Romers find that the FOMC engaged in virtually no output stabilization and, instead, focused on inflation. In the second regime, they found more active concern for output stabilization, but much less than in the fourth regime (the current period), in which the FOMC appears to be running a stronger countercyclical policy.[10]

Although employment growth volatility fell during the sample period as a whole, Figure 1 shows two sub-periods – the mid to late 1970s and the mid-1980s – in which volatility 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 (8, 9) work, such large relative price changes require substantial labor reallocations and could result in exceptionally large deviations from the employment growth process described by equation (1). Following Hamilton (10) we recognize that oil price shocks have an asymmetric effect on the economy: increases in oil prices lead to

[10] The monetary policy variable takes on four different values corresponding to the four different regimes identified in Romer and Romer (18, 19). The values correspond to the coefficients on the output gap in

slower growth, while decreases in the price of oil have little or no effect on growth. We capture the asymmetry by measuring oil price shocks as follows: the relative price of oil is measured as the spot price of West Texas Intermediate Crude divided by the CPI. We take the log difference of this series. If the log difference is positive, we keep the observation. If it is negative, we set it to zero.

Structural changes in the economy

Variations in employment growth volatility across states and time might also stem from changes in the economy's structure. An often-cited example is the shift of employment from the goods-producing sector to the service-producing sector. As shown in Table 2, the average state share of employment in manufacturing fell from almost 26 percent in 1950 to less than 17 percent in 1990, while the share in services essentially doubled. Historically, the volatility of manufacturing employment has been higher than that of services, although the volatility of manufacturing relative to services has declined. By 1995 the ratio of manufacturing volatility to services volatility had fallen to 1.25 versus 1.7 in 1952. The shifting shares, other things equal, could contribute to more stable employment.

Other structural changes have occurred as well, although they have not usually been incorporated into analyses of volatility trends. Concerning the demographic structure of employment, the data in Table 2 reveal large increases in the fractions of the workforce that are female; with a college degree; and nonwhite. To the extent that the different groups have varying degrees of labor force attachment, the changing shares could affect volatility. Finally, the U.S. economy has become increasingly open. Since 1950, total trade (real exports plus real imports) has risen as a fraction of real GDP from 6.4 percent

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their estimated Taylor rules, as reported in Table 1 on page 21 of their article.

to 17.7 percent. This increased international presence affects volatility in different ways. On the one hand, greater imports may increase the economy's automatic stability, while, on the other hand, greater exports may increase the economy's exposure to potentially destabilizing foreign demand shocks. Any or all of these factors conceivably could have had an important influence on employment growth volatility.

Industrial concentration

A final issue that we address is how changes in industrial concentration affect volatility. We use a Herfindahl Index to measure industrial concentration. The index is calculated as the sum of the squared shares of each industry's employment. The upper bound of the index is unity (all employment is in one industry). The lower bound is equal to the reciprocal of the number of industries (0.125 in our case).

It is difficult to sign the coefficient on the Herfindahl Index a prior. On the one hand, the more diverse a state's industrial structure, the less susceptible it is to shocks to specific industries. The averaging out of shocks would then lead to lower total volatility. The boom and subsequent bust experienced by Silicon Valley provides a recent example of how lack of diversity results in high employment growth volatility. On the other hand, industrial concentration might reduce a state's volatility if its employment tends to be concentrated in industries that historically display low volatility.

The model

We model the postwar pattern of state-level conditional employment growth volatility using a pooled cross-section/time-series regression.   The framework takes each state's employment growth volatility at a point in time as a separate observation and relates it to the variety of macroeconomic (e.g., monetary policy, productivity, etc.) and cross-sectional (e.g., industrial and demographic) variables identified in the preceding section.

In theory, we have 6,688 observations for estimation: 176 quarters of data for 38 states. But because our measures of conditional state employment volatilities are 20-quarter rolling regression standard errors, using each quarter's volatility results in overlapping data and artificially builds in autoregressive patterns in the data. To mitigate this problem for the purposes of the panel estimation, we construct a non-overlapping sample of volatilities for nine separate periods.

For each state, our first observation is the state's volatility for 1955:4, which is constructed using data from 1951:1 to 1955:4.[11] To avoid overlap in the state-volatility observations, the next data point used in the panel estimation is that for 1960:4. The volatilities for 1960:4 are estimated using data from 1956:1 to 1960:4. Thus, none of the data used to estimate the 1955:4 volatility measure are used to estimate the 1960:4 volatility measure. It is in this sense that the observations are non-overlapping. Continuing this procedure produces 9 non-overlapping observations for each state's employment growth volatility: 1955:4, 1960:4, 1965:4, 1970:4, 1975:4, 1980:4, 1985:4, 1990:4 and 1995:4. In total, the non-overlapping sample contains 342 observations (9 non-overlapping observations for 38 states). Data for the other variables are averaged over the relevant non-overlapping sample periods. For example, we construct a regression observation for oil shocks in 1960:4 by taking an average of the quarterly oil-shock series over the 20-quarter interval from 1956:1 to 1960:4.

[11] Our first observation is 1955:4 instead of 1951:4 because we used lagged values of some of the macroeconomic variables; thus, we had to drop an observation from the panel data analysis.

All macro variables are interacted with 37-state dummy variables to permit macro shocks to have differential state effects.[12] The model takes the form:

$$\sigma_{i,t} = \alpha_0 + \sum_{i=1}^{37} \beta_i state_i + \sum_{s=1}^{8} \xi_s T_s + \sum_{j=1}^{J} \delta_j X_{i,j,t} + \sum_{i=1}^{37} \phi_i state_i * Z_t + \varepsilon_{i,t} \qquad (2)$$

where:

t indexes the nine non-overlapping samples, i indexes the 38 states, and j indexes the subset of cross-sectional explanatory variables to be estimated.

$\sigma_{i,t}$ = Conditional standard deviation of employment growth for state i at time t
(t = 1955:4, 1960:4, 1965:4, 1970:4, 1975:4, 1980:4, 1985:4, 1990:4 and 1995:4)

$state_i$ = 1 for state i and 0 otherwise;

T_s = 1 for time period s and 0 otherwise.

$X_{i,j,t}$ the set of J explanatory variables for state i at time t (cross-sectional variables):

- Share of employment in services for each state and time period.
- A Herfindahl Index of industry employment intended to gauge the degree of industrial concentration.
- Percent of state employment that is female.
- Two state population variables are used: percent of state population over 25 years old with college degree and percent of state population that is nonwhite.

Z_t is the set of national (macroeconomic) explanatory variables:

- A variable capturing the policy regimes identified by Romer and Romer (18). The four regime periods are 1952:1 to 1963:4; 1964:1 to 1979:3; 1979:4 to 1987:3 and, 1987:4 to 1995:4. This variable is interacted with $state_i$.
- The volatility in multifactor productivity growth, measured as the regression standard errors from 20-quarter rolling AR(1) processes. The variable is interacted with $state_i$. A one-period (20-quarter) lag is used to reduce potential simultaneity problems.

[12] Wyoming is the omitted state.

- Oil shock variable is based on the log difference of the relative price of oil. If the log difference is positive, we keep the observation. If it is negative, we set it to zero. This series is interacted with $state_i$.

- One-period (20-quarter) lag of the volatility in the growth of real government purchases, measured as the regression standard errors from 20-quarter rolling AR(1) processes. The variable is interacted with $state_i$. A lag is used to reduce potential simultaneity problems.

- Real total trade as a percent of real GDP interacted with $state_i$.

Note that we have a two-way fixed effects estimator: our regression includes state fixed effects and a time dummy. The state fixed effects capture unobserved, time-invariant state-level heterogeneity. The time dummy variables control for macroeconomic influences that are common across states. By including a time dummy, the state-level interaction with macroeconomic variables will capture the differential (rather than total) effect of macroeconomic variables on state employment growth volatility. The regression consists of 342 observations and 236 variables, leaving 106 degrees of freedom.[13]

Given that the time dummies control for common effects of the macroeconomic variables, and since any one state is small relative to the nation, it is reasonable to treat the macroeconomic variables as exogenous. For example, as already noted, monetary policy is unlikely to respond to unique circumstances in any one state.

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[13] Because the data contain a time-series dimension, the issue of whether the data contain unit roots needs to be addressed. Many of our variables, however, are bounded between 0 and 1 (the population, trade,and industry share variables) or between unity and 0.125 in the case of the Herfindahl Index. These variables can contain a unit root only under relatively complicated circumstances (in the presence of reflecting bands), making them virtually impossible to detect with a limited number of time-series observations, as is the case here. We tested the remaining variables (employment volatility, volatility in productivity and government spending, and oil prices) using a Phillips-Perron unit root test devised for panel data. The null

Estimation

Equation (2) is estimated using a robust least squares dummy variable model (LSDV). Specifically, we use a two-way fixed effects approach (state and time fixed effects). A two-way random effects, or error components, specification is an alternative, but was rejected in favor of the fixed effects model by the Hausman specification test.

Given that the data contain a cross-sectional dimension, we tested for the possible presence of spatial dependence in state employment volatility. Following Anselin and Hudak (1), we consider three tests for spatially autocorrelated errors: Moran's I test, the Lagrange multiplier (LM) test, and a robust Lagrange multiplier test (robust LM). We also conduct two tests for the spatial lag model (an LM test and a robust LM test). The Moran's I test is normally distributed, while the LM tests are distributed χ^2 with *k* and one degree of freedom, respectively.

The results for these various tests for spatial dependence are summarized in Table 3. The results from all three tests for spatial error dependence indicate that we cannot reject the null hypothesis that $\lambda = 0$. Similarly, both tests for the presence of a spatial lag indicate that we cannot reject the null hypothesis of no spatial dependence. Thus, robust LSDV estimation without correction for spatial dependence is appropriate.

Column 2 of Table 4 contains the estimated coefficients and associated t-statistics based on the nine non-overlapping samples spanning the period 1951:1 to 1995:4. The first five rows of Table 4 contain the estimated coefficients for the cross-sectional variables (the $X_{i,j,t}$). The coefficient on the share of services is negative as expected, but is not significant at the 10 percent level. While the finding that the shift in employment

of a unit root is rejected for each variable. Consequently, the levels of each variable are used in the to the service industry over time has not significantly contributed to the decline in volatility, it is consistent with the evidence for the national economy presented in Blanchard and Simon (3) and McConnell and Perez-Quiros (17).[14] Industry concentration, as measured with the Herfindahl Index, has no significant influence on volatility. This result is consistent with those of Jackson (13) and Attaran (2), who argue that a more diversified industrial structure does not reduce employment growth volatility. Still, it runs counter to the vast majority of literature that has considered the issue (Siegel [21], Conroy [6], Kort [15], Malizia and Ke [16], Wundt [23], Sherwood-Call [20], and Hammond and Thompson [11]).

For the entire sample, the mean value of the Herfindahl Index is 0.1937 and the standard deviation is 0.0232. The minimum value is 0.1559 (in 1965 for Indiana) and the maximum is 0.2757 (in 1955 for Louisiana). For a perfectly diversified state, the value of the index is 0.125, and the value is unity when employment in a state is concentrated in one industry. For our states even the maximum value of the index (0.2757 for Louisiana in 1955) is far enough below unity, so that we should not be surprised to find little action from the Herfindahl Index.

Among the demographic variables, the percent of college graduates over 25 years old has a positive and significant impact on volatility, while the percent female has a positive but insignificant effect. The sign of the effect of percent college graduates on volatility is something of a surprise, since our prior was that jobs for high-skill workers

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regression estimations.

[14] For comparability with other studies, we also conducted a counterfactual experiment in which we constructed a synthetic employment series, holding constant industry shares at the observed initial levels. The volatility of the synthetic series closely mimicked that of the volatility of the actual series. This finding has led other researchers (Blanchard and Simon [3] and McConnell and Perez-Quiros [17]) to conclude that changes in industry shares have played no role in volatility trends. In addition, we find the decline in volatility is not explained by time variation in state shares of total employment.

are more stable than those for low-skill workers. We find that the percent of a state's population that is nonwhite enters with a negative and significant coefficient. This suggests that a greater share of nonwhite population is associated with lower employment growth volatility.

Recall that Hammond and Thompson (11) report that the failure to control for various demographic characteristics of the local population may lead to an overestimation of the impact of industrial concentration on employment volatility. Unlike Hammond and Thompson (11), we find that the coefficient on the Herfindahl Index decreases once we drop other variables that control for characteristics of the population (excluded variables are percent of the population over 25 years old with a college degree, percent of the nonwhite population, and percent female in labor force) from the regression. Specifically, the estimated coefficient drops to -0.07 when variables for the characteristics of the population are excluded from the regression, from -0.17 when these variables are included in the regression. Still, in neither case are the coefficients statistically significant.

The next five rows of Table 4 present results for the interactions between the macro variables and the state dummies. Individual coefficients are not reported to conserve space. However, we do report the results from an F-test of the joint significance of the coefficients for the macro/state interaction variable coefficients.   These exclusion tests indicate that all macro/state interactions are jointly significant except for the oil price variable.

Recall that our specification includes a set of time dummies and state macroeconomic variable interactions. Thus, we allow each state to respond differently to a common national shock. However, the time dummies capture the common response to macroeconomic, time-varying shocks across states. These time-varying shocks include both those that are explicit in our model, such as monetary and fiscal policy, and omitted macroeconomic shocks. Consequently, we interpret the coefficients on the state macroeconomic variable interactions as capturing differential effects of macroeconomic shocks on state volatility. Thus, the focus is on how states respond differently (relative to each other) to national shocks. For example, a finding that the coefficients on monetary policy are jointly significant suggests that employment growth volatility responds differently across states to a change in monetary policy.

Table 5 presents summary results for the five interacted macro variables. The second and third columns report the differential response for the most responsive state and least responsive state to shocks to each of the five macroeconomic variables. In general, we find that state employment growth volatility has a quite varied response across the five macroeconomic shocks. The final column of Table 5 reports the finding of F-tests of whether the coefficients are equal across states for each macro variable. With the exception of oil, we reject the null hypothesis that the coefficients are equal across states. Thus states appear to have differential responses to macroeconomic shocks.

Accounting for volatility

An advantage of a two-way random effects estimation is that it provides a decomposition of the error variance into a cross-sectional component and a macroeconomic component. Since a two-way fixed effects model is the preferred specification given our data, we approximate the contribution of the cross-sectional variables and the macroeconomic variables using an alternative approach. Our method is as follows. We first estimate a regression with only the cross-sectional variables and the state fixed effects. The R^2 from this regression represents the upper bound for the cross-sectional variables, since all of the explanatory power of the co-variances is attributed to these variables. Call this R_U^2. To get a lower bound (called R_L^2) we first get the R^2 (referred to as R_M^2) from a regression that includes only the interacted macroeconomic variables and the time dummies. This regression assigns all the explanatory power to the macroeconomic variables. Next, we get the R^2 (called R_{ALL}^2) from a regression that includes all the variables in the model. To get the lower bound for the contribution of the cross-sectional variables we define $R_L^2 = R_{ALL}^2 - R_M^2$. We conduct an analogous exercise to get the upper-bound and lower-bound for the contribution of the macroeconomic variables.

The results of this exercise are shown in Table 6. The results indicate that the macroeconomic variables explain between 56 percent and 78 percent of the total variation in employment growth volatility, while cross-section factors explain 8 percent to 30 percent of the variance. These findings suggest that state-specific forces account for an economically significant portion of the total variation in employment growth volatility during the postwar period. Still, the bulk of variation of state-level employment growth is tied to national forces.

V. Conclusion

This study documents a general decline in the volatility of employment growth and examines some of its possible sources. A unique aspect of our analysis is the use of panel data covering industry employment by state since 1952. These data provide a richer analysis than those based only on time series or on cross-sectional data. Indeed, the decline in conditional employment growth volatility was found to be widespread across states and industries, albeit to differing degrees. This variation across industries and states contains valuable information that allows researchers to sort out the causes of movements in volatility.

Our analysis indicates that both cross-sectional and macroeconomic variables play a significant role in explaining fluctuations in employment growth volatility. However, the differential state responses to the macroeconomic variables are found to matter substantially more in accounting for employment growth volatility than do state differential responses to state idiosyncratic factors (such as the skill and gender composition of the population and state industrial structure).

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Table 1: Percent Change in Employment Volatility by State, 1947-1995

Top 5		
State	**Percent Change in Volatility 1952-1995**	**1952 Volatility Rank**
Washington	-88	11
Wyoming	-83	6
Alabama	-82	8
W. Virginia	-81	1
Idaho	-80	9

Bottom 5		
State	**Percent Change in Volatility 1952-1995**	**1947 Volatility Rank**
New Mexico	-41	34
New York	-41	37
Georgia	-37	27
Vermont	-27	31
New Hampshire	-21	17

Table 2: Economic and Demographic Structure Variables

	Manufacturing Share	Services Share	Percent Female	Percent Over 25 with College	Percent Nonwhite	Total Trade/GDP	Herfindahl Index of Industry Diversity
1950	25.9	12.1	27.0	5.7	11.8	6.4	0.1991
1970	24.0	15.8	40.3	10.1	13.7	10.5	0.1948
1990	16.8	24.0	56.5	18.9	15.3	17.7	0.1934

Table 3: Tests for Spatial Dependence

Test Statistic	(1) Spatial Error State Employment growth volatility	(2) Spatial Lag State Employment growth volatility
Moran's I $\lambda = 0$	0.80 (p = 0.42)	
LM - $\lambda = 0$ Robust LM- $\lambda = 0$	0.015 (p = 0.70) 1.06 (p = 0.30)	
LM - $\eta = 0$		1.75 (p = 0.19)
Robust LM - $\eta = 0$		2.66 (p = 0.10)

Table 4: Regression Results[a]

Cross-Section Variables	**Estimated Coefficient (t-statistic)**
Services Share	-0.1083 (-1.57)
Herfindahl Index	-0.1662 (-1.46)
Percent Female Labor	0.0007 (1.02)
Percent Population > 25 with College Degree	0.0035 (3.25)***
Percent Population Nonwhite	-0.0002 (-1.68)*
Constant	0.0045 (0.22)
State Interactions of Macro Variables	**Test of Joint Significance,** $F_{(37,106)}$
Monetary Policy Dummies	2.9***
Productivity Dummies	9.8***
Oil Shock Variable	0.89
Total Trade/GDP	2.0***
Government Spending	5.3***
R^2	0.8622
$\bar{R}^2$	0.5568

[a] All regressions include 37 state dummy variables (Wyoming is the excluded state) and 8 time period dummies.
 * and *** denotes statistical significance at the 10% and 1% levels, respectively.
Robust errors, t-statistics in parentheses.

Table 5: Summary of State Interaction Coefficients

Macro Variable	High State[a]	Low State[b]	**Test of Equality of Coefficients** $F_{(36,106)}$
Productivity	0.5314 (Arizona)	-0.0886 (Louisiana)	10.1***
Oil Shock	0.1956 (Florida)	-0.3537 (Arizona)	0.9
Monetary Policy	0.0294 (Colorado)	-0.0258 (W. Virginia)	2.8***
Total Trade/GDP	0.2471 (W. Virginia)	-0.3599 (N. Hampshire)	2.1***
Government Spending	0.0506 (Indiana)	-0.2666 (Nevada)	5.4***

[a]Highest of the 37 states.
[b]Lowest of the 37 states.
Wyoming is the excluded state.

Table 6: Accounting for the Decline in Employment Volatility

Variables	Range of Contribution
Cross-sectional Variables[a]	8 percent to 30 percent
Common National Variables[b]	56 percent to 78 percent

[a]The **cross-sectional variables** This regression includes only the cross-sectional variables and the state fixed effects: state share of employment in services, a Herfindahl Index of industrial concentration, an index of industrial diversity, the percent of state employment that is female, the percent of state population that is: (i) over 25 years old with college degree; (ii) nonwhite; and the state fixed effects. The time and state dummies are not included in this regression.

[b]The **common national variables.** This regression includes only the interacted macro variables and the time dummies: monetary policy variable, two-period lag of the volatility in the growth of real government purchases interacted with a state dummy, two-period lag of volatility in multifactor productivity growth interacted with a state dummy, an oil shock dummy interacted with a state dummy, percent of real national total trade as a percent of real GDP interacted with a state dummy, and the 8 time dummy variables.

Figure 1: Aggregate Employment Volatility

(rolling standard deviations and regression standard errors for the 38 state total)

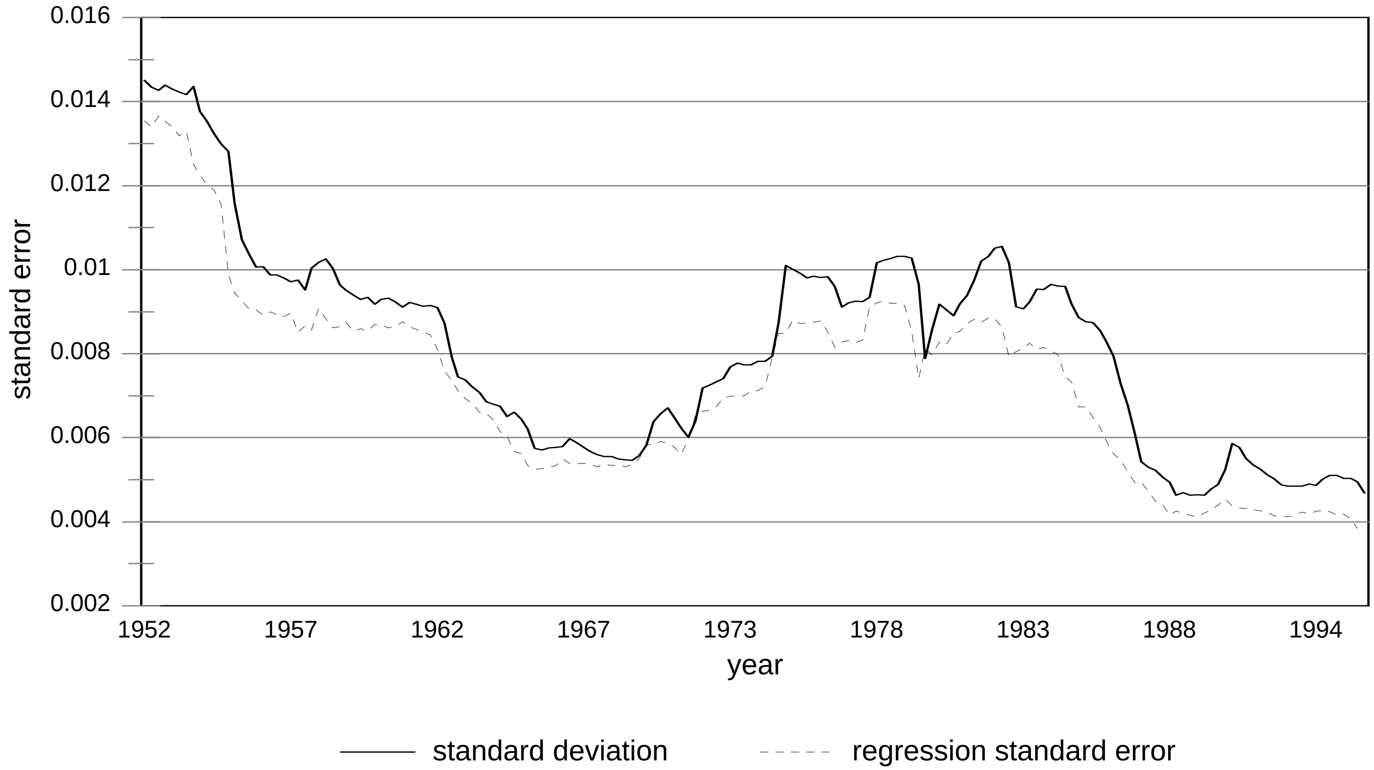
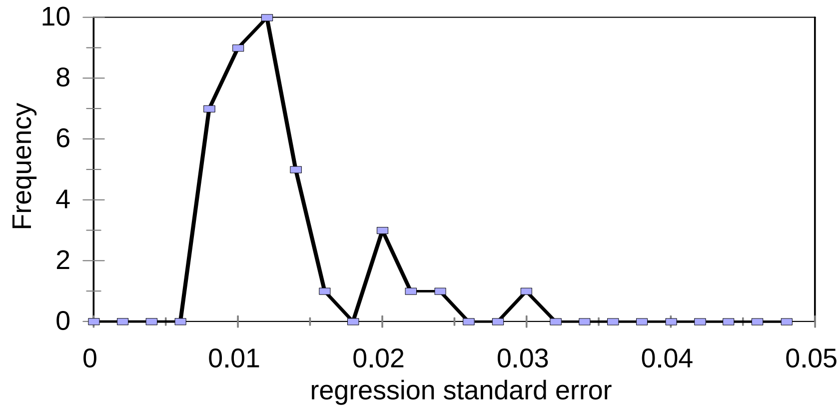


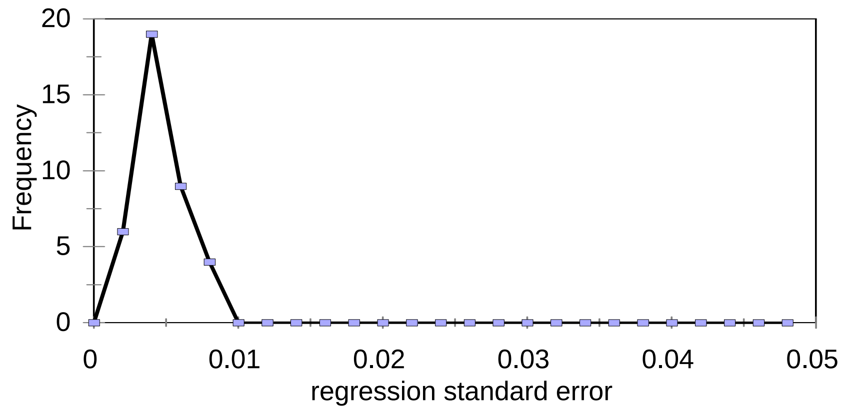
Figure 2: Distributions of Aggregate Employment Rolling Regression Standard Errors

(38 state total)

Panel A: 1952:1



Panel B: 1971:3



Panel C: 1995:4

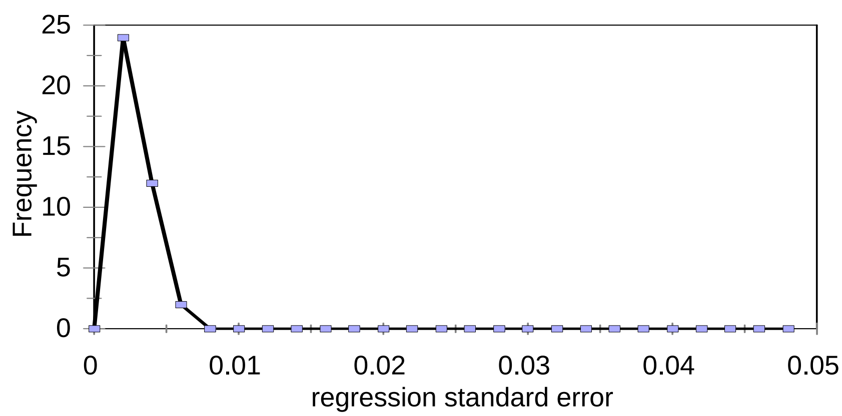
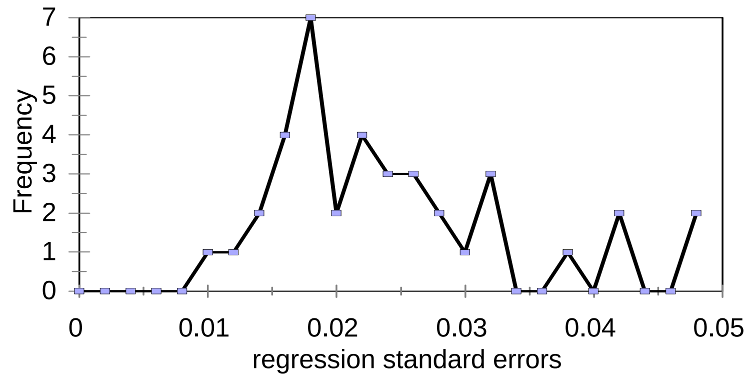


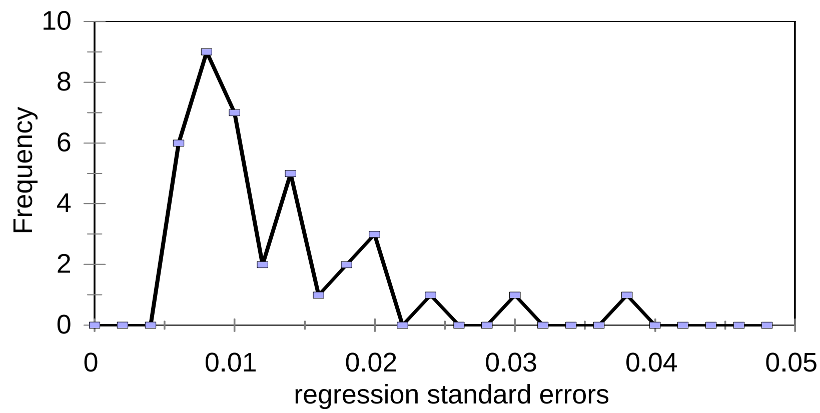
Figure 3a: Distributions of Manufacturing Employment Rolling Regression Standard Errors

(38 state total)

Panel A: 1952:1



Panel B: 1971:3



Panel C: 1995:4

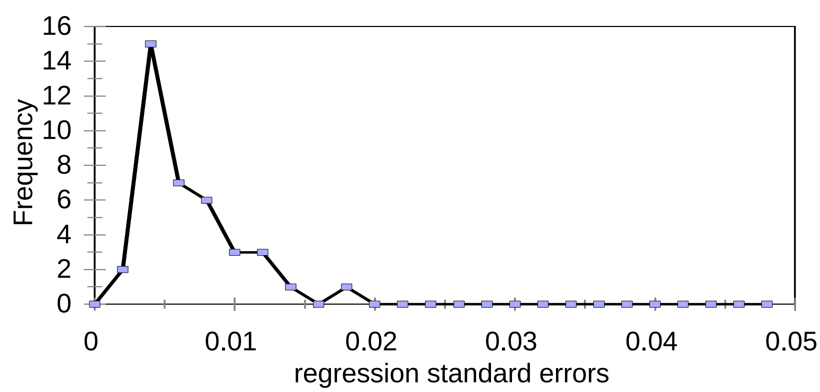


Figure 3b: Distributions of Services Employment Rolling Regression Standard Errors

(38 state total)

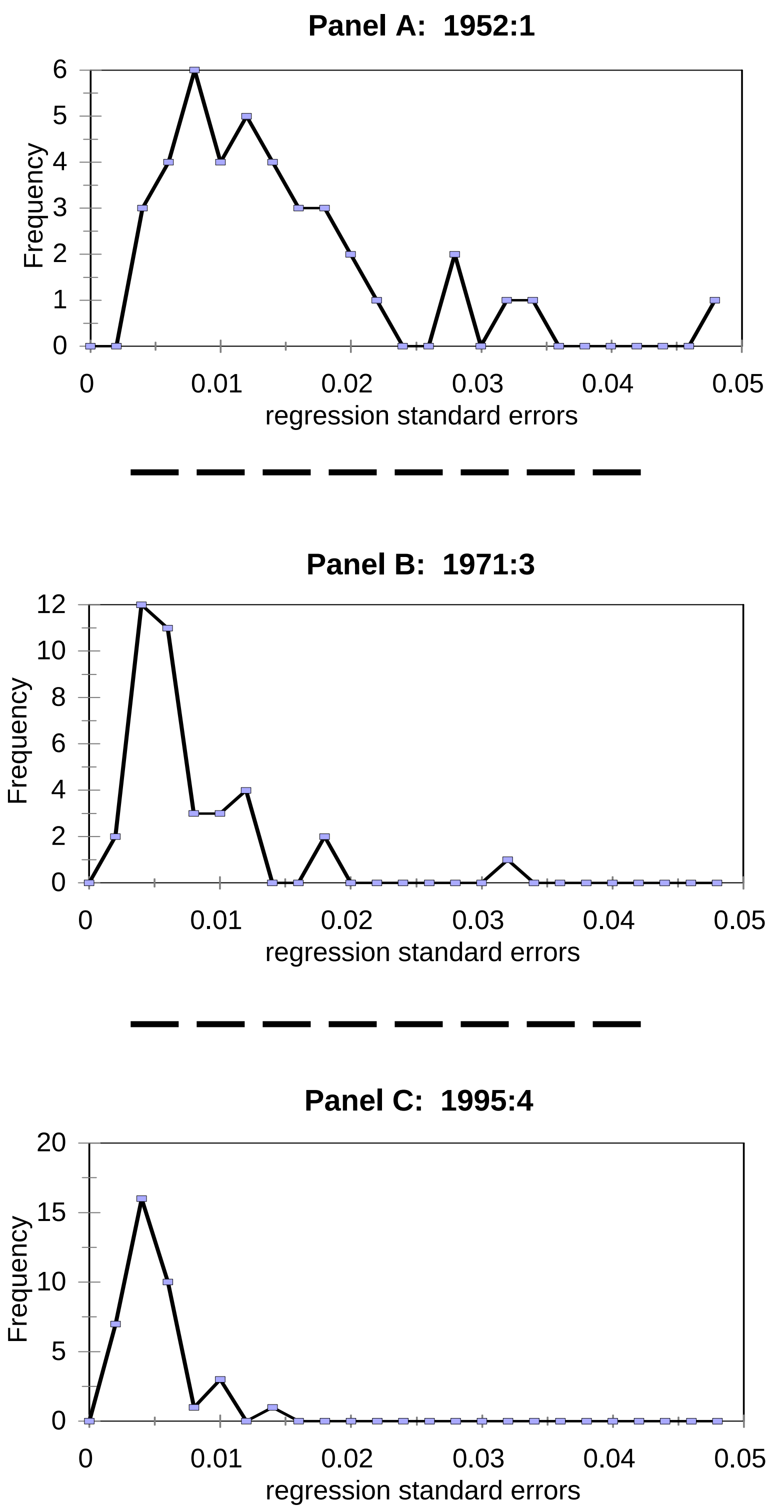


Figure 4: Average State AR1 Coefficients

(38 states, 12 quarter moving average)

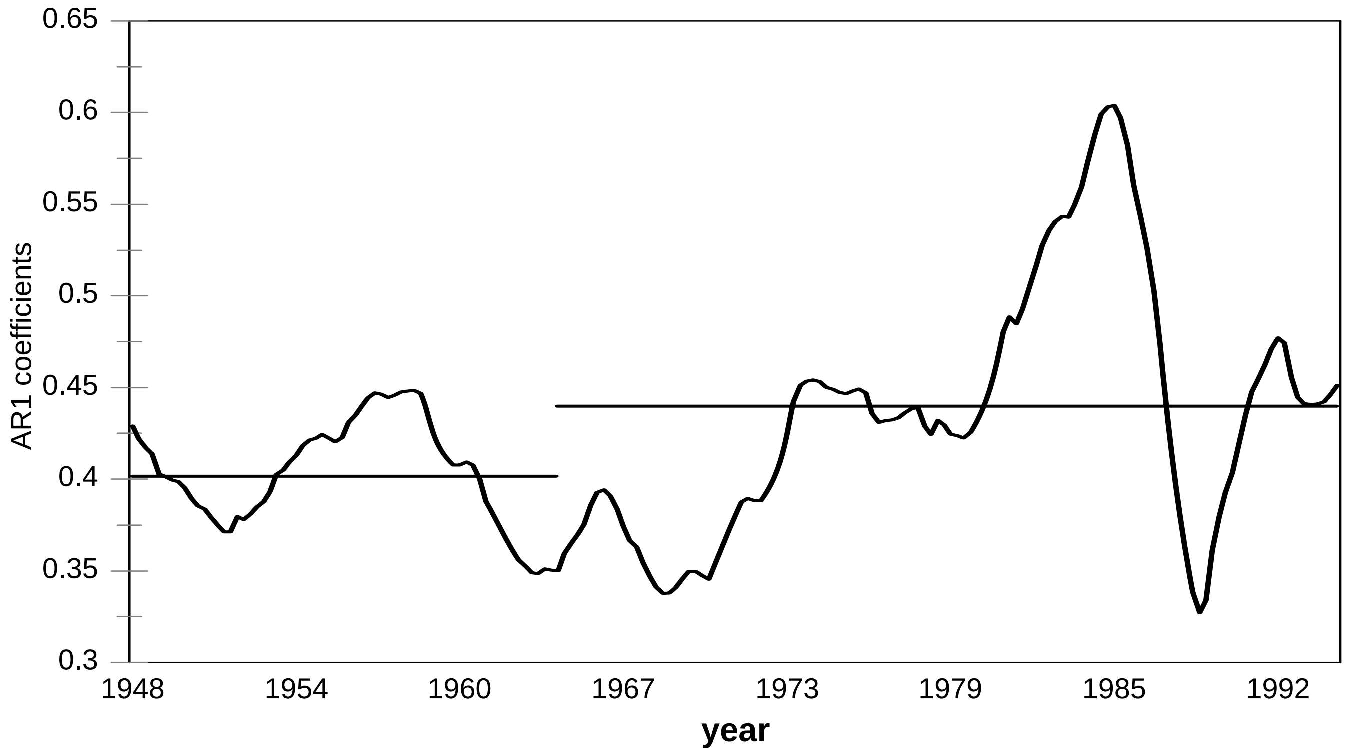


Figure 5a: Volatility in Real Government Purchases

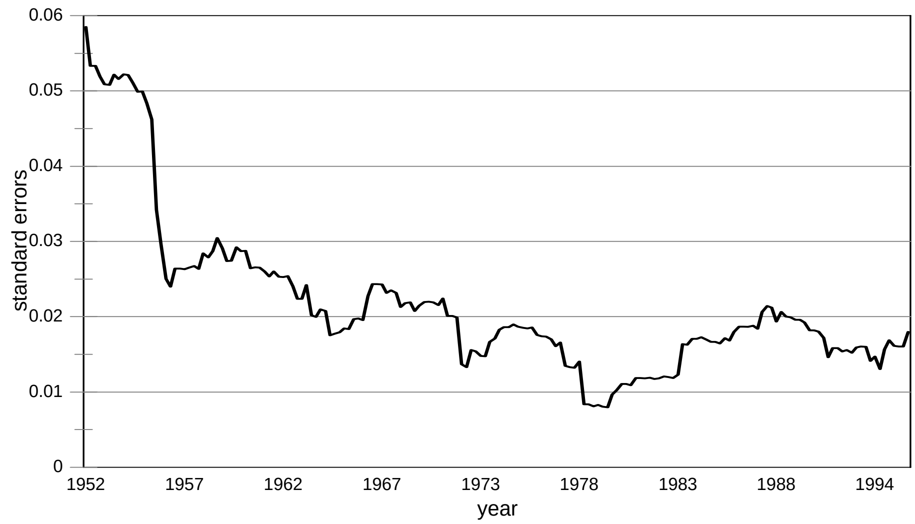


Figure 5b: Volatility in Multifactor Productivity