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The Long and Large Decline in State Employment Growth Volatility

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Abstract

This study documents a general decline in the volatility of employment growth during the period 1956 to 2002 and examines its possible sources. We use a panel design that exploits the considerable state-level variation in volatility during the period. The roles of monetary policy, oil prices, industrial employment shifts and a coincident index of business cycle variables are explored. Overall, these four variables taken together explain as much as 31 percent of the fluctuations in employment growth volatility. Individually, each of the four factors is found to have significantly contributed to fluctuations in employment growth volatility, although to differing degrees.

Understanding the determinants of economic volatility has long been a focus of macroeconomics. Until recently, most attention has focused on understanding the average changes in volatility before and after the mid-1980s, that is, the Great Moderation (e.g., Kim and Nelson 1999, Stock and Watson 2002, and McConnell and Perez-Quiros 2000). While the inter-period change in volatility that defined the Great Moderation was substantial, there were large movements in volatility within each of the two sub-periods as well. For example, we estimate that employment growth volatility decreased by around 80% between 1958 and 1964. In contrast, volatility grew by 450% from 1997 to 2002. We believe much is to be gained by studying the macroeconomic forces that have underpinned changes in employment growth volatility throughout the past fifty years.

While there is a large literature that examines the volatility pattern of aggregate economic variables and considers their determinants, there are few studies that use state-level data to better understand the factors driving fluctuations in volatility.[1] In this regard, we first document the variations in employment growth volatility across states since the mid-1950s. We then apply panel regression techniques to identify the underlying sources of the fluctuations in volatility. The regressions are structured to capture the effects of three aggregate factors that have been identified as being important for understanding movements in volatility (monetary policy, oil price, and industrial structure). In addition, we include a coincident index of other business cycle shocks.

Overall, the four variables considered in this study explain 26% to 31% of the fluctuations in employment growth volatility during the period 1956 to 2002. Each is

[1]Recent studies that used state-level data to examine volatility include Carlino et al (2003), Anderson and Vahid (2003), Owyang et al (2008), and Grennes et al (2010).

found to have contributed significantly to fluctuations in employment growth volatility, although to differing degrees. In particular, after controlling for banking de-regulation we find that monetary policy accounts for roughly 8 to 10% of the variation in employment growth volatility. By comparison, Stock and Watson (2002) attributed 20 to 30%t of reduced volatility since the mid-1980s to improved monetary policy. Thus, monetary policy's role in accounting for the Great Moderation does not appear representative of its impact over the most of the postwar period. The oil price index explains around 7 to 9% of the variation in employment growth volatility, the coincident index of business cycle shocks explains around 4 to 7%, and manufacturing's share of total employment explains between 3 and 7%.

Studies using aggregate data to examine volatility implicitly assume that the aggregate variables have identical effects across states, an assumption clearly rejected by the state-level data. We find that allowing each of the macro variables to have state-specific effects increases the estimated effects of these variables considerably. The overall contribution of the four macro variables when taken together is over 70% greater after allowing each of these variables to have separate state-level effects.

The use of state-level data provides a number of other benefits. A key benefit is the greater number of samples (48 for states compared with one in an aggregate study) and the corresponding additional dispersion that allows a more precise estimation of factors thought to influence fluctuations in volatility. Another important benefit from using state data is the mitigation of endogeneity issues that can plague aggregate studies. For example, studies that attempt to attribute volatility changes to shifts in monetary policy need to separate the impacts of policy from the reaction of policymakers. Since monetary policy does not likely react to individual state-level developments, the issue of endogeneity is much less of a concern in a state-level analysis of volatility.

Additionally, in regression studies of aggregate volatility, unobserved heterogeneity across states that affects volatility will be subsumed in the regression error term. This unobserved state heterogeneity would lead to omitted variable bias if the error term is correlated with an included regressor. State deregulation of banking markets is a relevant example of how such omitted variable bias might work. Deregulation began in the late 1970s, the same period in which monetary policy was thought to have improved. Stock and Watson (2002), for example, attributed 20 to 30% of reduced volatility since the mid-1980s to improved monetary policy. Yet financial deregulation itself could have led to greater aggregate stability, and so failure to control for the effect of deregulation on volatility can cause the contribution of monetary policy to be overstated. Not all states deregulated their banking markets at the same time, and the staggered timing allows us to identify the effects of banking deregulation on volatility.

1. MEASURING STATE-LEVEL EMPLOYMENT GROWTH VOLATILITY

We focus on employment growth because it is a widely used indicator of real activity at the state level, is available quarterly, and extends sufficiently far back in time to track longer-run movements in the series. The data are seasonally adjusted quarterly nonagricultural payroll employment from the Bureau of Labor Statistics (BLS). Real state GDP was considered; however, consistent and reliable data are available beginning only in 1977, and only on an annual basis. State personal income data exist for the entire period of our study but only in nominal terms.

We measure state-level volatility using an approach similar to that in Morgan et al (2004). Specifically, the quarterly growth rate of state employment (measured as log differences) is regressed on state dummies (a_i , where i indexes states) for the period 1956:3 to 2004:2:

$$\text{Employment growth}_{\text{i,t}} = a_0 + a_i + \varepsilon_{i,t} \qquad (1)$$

Volatility is then measured as the absolute value of the regression error,

$$\text{Volatility}_{\text{i,t}} = \left|\varepsilon_{i,t}\right| \qquad (2)$$

which is measured as the deviation of employment growth in a given state-quarter from the average growth for a given state.[2] The estimated equation has an adjusted R^2 of 0.0671. F-tests indicate both that the state fixed effects are jointly significant (p = 0.00) and significantly different from each other (p = 0.00).

Figure 1 shows the average volatility of U.S. quarterly employment growth.[3] As can be seen, average employment growth volatility exhibits a general downward trend over time. A simple regression of smoothed volatility on time produces a negative and highly significant coefficient. Despite the general declining trend in average state employment growth volatility, there is considerable time variation in volatility around the trend, with volatility increasing dramatically in periods of recession (e.g., the early years of 2000).

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[2]Alternatively, other researchers have computed volatilities using rolling standard errors or regression standard errors from rolling AR(1) models (e.g., Blanchard and Simon 2001). However, the use of rolling standard errors complicates the panel estimation because it induces serial correlation in the data series.

[3] The volatility series shown in Figure 1 is constructed as the employment-weighted average of state volatilities, allowing the weights to change each quarter. The volatility series is smoothed using a one-sided four-quarter moving average.

Figure 2 contains a scatter plot of the levels and trends of the average volatility for individual states for the 1956:2 to 2002:4 period. To calculate averages for each state we weight each state's volatility in a year by the corresponding level of employment in that year. State volatility trends were estimated using a weighted OLS regression of volatility on state-specific time trends. Weights are state employment levels. The vertical and horizontal lines on the graph indicate the cross-state means of each variable.

Regarding the levels of volatility, the cross-state mean is 0.571 with a minimum of 0.425 in New York and a maximum of 0.859 in Michigan. Five states (Michigan, Wyoming, West Virginia, Nevada, and Arizona) have average volatilities 25 to 50% greater than the average volatility. Consistent with the cross-state average data, the volatility in each individual state has a downward trend during our sample period, with all but Wyoming's being highly significant. The data indicate that those states with the highest average levels of volatility tended to be those with the smallest percentage declines during the period of study.

It has become popular to analyze volatility by focusing on the post-1984 years associated with the Great Moderation. Studies have, for example, searched for trend breaks and have sought to identify the sources of the shift in volatility between the pre- and post-break periods. Nevertheless, as seen in Figure 1, employment growth volatility fluctuates widely throughout the sample period, including within the time spans researchers identify as being pre- and post-break. While volatility fell 75% between 1983 and 1997, it also fell 80% between 1958 and 1964. Similarly, Figure 1 shows that there are other periods in which volatility increased substantially. This intra-period variation in employment growth volatility is potentially helpful to analyses of the sources of fluctuations in volatility (e.g., Owyang et al 2008, and Grennes et al 2010).

2. EMPIRICAL MODEL AND ESTIMATION

Having documented the substantial and disparate declines in state employment growth volatility, we now turn to an examination of the possible sources. The fact that most states experienced volatility declines during the 1956-2005 sample period suggests that part of the variance might be due to common aggregate shocks. A pooled cross-section/time-series, or panel, model is useful in studying the determinants of changes in volatility. The analysis of possible sources of fluctuations in volatility concentrates on a selection of factors that previous studies have found to be important. These include monetary policy, oil prices, an index of coincident business cycle indicators, and changes in industrial structure. Each of the four factors is measured at the aggregate level, but is permitted to have state-specific effects on volatility.[4] The models also incorporate state-level controls to more precisely estimate the effects of the aggregate variables. Controls include state fixed effects, state-specific time trends and dummy variables indicating quarters in which each state's banking system was de-regulated.[5] State fixed effects account for time-invariant idiosyncratic state-level factors that can influence state

[4] Although monetary policy, oil prices and other business cycle shocks are inherently macroeconomic, industrial structure can vary from state to state. Anderson and Vahid (2003), and Grennes et al (2010) have found that state-specific changes in industrial structure alter the time-series profile of a state's employment growth volatility. We rely on an aggregate measure of industrial structure for consistency with the other factors examined.

[5] Morgan et al (2004) found that de-regulation significantly affected employment growth volatility, although they restricted de-regulation to have a single effect on all states. Our analysis allows a state's de-regulation to have a unique effect on that state's volatility. In 1978, Maine was the first state to pass a law that allowed entry by bank holding companies from any state that reciprocated by allowing Maine banks to enter their banking markets. Following Maine's lead, states deregulated in waves, with the bulk of them approving legislation to allow deregulation between 1985 and 1988. With the exception of Hawaii, all states allowed interstate banking by 1993.

volatility, and state-specific time trends to capture slow-moving influences in each state (e.g., demographic change). Banking de-regulation has been found to have its own significant effect on volatility (Morgan et al (2004)). Additionally, periods of de-regulation overlapped part of what several researchers have argued was a time of regime change in monetary policy. Developing accurate estimates of monetary policy's impact on volatility thus requires netting out whatever role de-regulation played.

2.1 Empirical Specification

The analysis uses a fixed effects panel data model to analyze quarterly data on state employment growth volatility.[6] The sample consists of quarterly data covering the period 1956 to 2002.[7] The sample contains 8,976 observations: 187 quarters of data for 48 states. Contemporaneous and lagged values of each explanatory variable are used to allow for delayed or persistent impacts.

The panel design offers several empirical benefits. First, it relies on 48 different data samples, as opposed to one when strictly aggregate data are used. The panel also mitigates potential simultaneity problems, especially between monetary policy and volatility, because policymakers' decisions are made using macro data and from the perspective of aggregate economic health. An additional benefit is the ability to allow variables measured at the aggregate level to have state-specific effects. Some studies have shown, for example, that monetary policy has differential state impacts (Carlino and DeFina (1998, 1999)). Allowing cross-state variation in impacts potentially increases the variation in volatility explained by the aggregate variables since, in essence, an

[6] A Hausman test indicated that a two-way fixed effects specification, both for time and states, was preferred to a two-way random effects specification.

[7] The Bureau of Labor Statistics reported employment using the SIC classification until 2002 and on a NAICS basis thereafter. Since there is no comprehensive concordance between SIC and NAICS, we use data only through 2002 for consistency.

identifying constraint is lifted from the data (i.e., the estimated coefficient on an aggregate variable is identical for all states.) Finally, as just mentioned, a state-level panel allows us to effectively control for bank de-regulation and various other state developments that can be correlated with aggregate variables (e.g., monetary policy).

The model takes the form:

$$\left|\varepsilon_{i,t}\right| = \alpha_0 + \alpha_i + \beta_i t + \delta_i dreg_{i,t} + \sum_{m=1}^{4}\sum_{n=1}^{nlag}\varphi_{i,m,n} X_{m,t-n} + \upsilon_{i,t} \tag{3}$$

where: $\left|\varepsilon_{it}\right|$ is volatility in quarterly employment growth fluctuations, measured as in equation (2); *t* indexes time (quarters); *i* indexes the 48 states; *m* indexes the four aggregate-macroeconomic variables whose effects on volatility are to be estimated; *n* indexes lags; ; *t* is a time trend for each state; $dreg_{i,t}$ is a dummy for state *i*, indicating quarters in which state banking was de-regulated; and, X_m indicates the m^{th} explanatory variable measured at the aggregate level. The effects of the macro variables on state volatility are captured by interacting these variables with the state dummy variables.[8]

The four macro explanatory variables are chosen to reflect their emphasis in the literature. There has been longstanding interest in the impacts of monetary policy and oil price shocks in general, and special attention has been accorded to these variables in the recent literature seeking to explain swings in volatility (Clarida et al 2000, Orphanides 2004, Leduc et al 2007, Stock and Watson 2002, Leduc and Sill 2007, and Hamilton, 1983, 1996, and 2003). Similarly, the effects of employment shifts away from manufacturing jobs has likewise been scrutinized [e.g., Blanchard and Simon (2001) and

[8] The constant term measures the fixed effect for the omitted state, Georgia. We include all 48 states when interacting the macro factors and the state fixed-effects since concerns about colinearity does not arise for the interacted variables.

McConnell and Perez-Quiros (2000).] In addition to these variables, we examine how other cyclical shocks might matter using a summary coincident business cycle index developed in Aruoba et al (2008), hereafter ADS.

2.2 Variable Measurement

Monetary policy shocks are measured using the general strategy of Christiano et al (1999). That is, we estimate a small VAR (described below) in which the federal funds rate is included as a policy instrument. The structural errors from the federal funds rate equation are interpreted as shocks to monetary policy. We then measure changes in monetary policy that are potential sources of more general economic volatility using the squared structural residuals. The idea is that shifts in monetary policy manifest themselves as changes in the volatility of policy shocks. To measure structural monetary policy shocks we employ a two-variable VAR that includes four lags of both the federal funds rate and the composite index of business cycle activity developed by ADS. A recursive identification scheme is used with the ADS index ordered first. Consequently, aggregate activity (the slow-moving variable) is assumed not to respond to monetary policy shocks within a quarter, while monetary policy (the fast-moving variable) responds to the aggregate activity within the quarter.

The ADS index is designed to track real macroeconomic activity at high frequency and has zero mean so that progressively more negative (positive) values indicate progressively weaker (stronger) business conditions. Its underlying economic indicators include weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP, and the index mixes high- and low-frequency information and stock and flow dynamics. For this analysis, we aggregate the weekly ADS index into quarterly values.

The oil price shock at time *t* is measured as the net oil price increase over the previous 12 months (Hamilton 2003). Denote the spot price of West Texas Intermediate oil as p_t^o. The net oil price increase ($\tilde{p}_t^o$) is defined as

$$\tilde{p}_t^o = \max\left(0, \frac{p_t^o - \max[p_{t-1}^o, p_{t-2}^o, \ldots, p_{t-12}^o]}{\max[p_{t-1}^o, p_{t-2}^o, \ldots, p_{t-12}^o]}\right)$$

This measure of oil-price shocks demonstrates a more stable link to real activity than does the actual price of crude oil over the postwar sample. Industrial structure is measured as the ratio of manufacturing employment to total non-farm employment. Employment data are seasonally adjusted.

In addition to state fixed effects and state-specific time trends, we use a set of state-specific dummies to indicate when a state allowed interstate banking. The dummies equal zero before a state experienced financial deregulation and unity otherwise. The dates of state-level deregulation are from Morgan et al (2004).

2.3 Estimation and Results

Prior to estimation, the variables in equation (3) were checked for non-stationarity. The null of non-stationarity could be rejected for employment growth volatility using the Im et al (2003) panel unit root test, which allows the unit root process for the state-specific variable to differ across states. The monetary policy, oil price and coincident index variables are each stationary by construction, and so are used in their original level form in the estimations. (A formal ADF test for each of these variables using a trend and six lags easily rejects non-stationarity ($p < 0.000$).) The share of total employment in manufacturing was found to be non-stationary, and so the (stationary) first difference is used.

We begin by investigating the effect of the macro aggregate variables when each is restricted to have a common effect across states. This is accomplished by including each macro factor without allowing them to have state-specific effects:

$$\left|\varepsilon_{i,t}\right| = \alpha_0 + \alpha_i + \beta_i t + \delta_i dreg_{i,t} + \sum_{m=1}^{4}\sum_{n=1}^{nlag}\phi_{m,n} X_{m,t-n} + \mu_{i,t} \tag{4}$$

A series of regressions were run to determine the appropriate lag length for each macro variable.[9] Based on the results from these regressions, four lags of the oil-price variable, six lags of the monetary policy variable, three lags of the economic activity index and four lags of the change in the manufacturing share are used, along with their contemporaneous values. Equation (4) is estimated by OLS; the standard errors are corrected both for heteroskedasticity and serial correlation.

The second column of Table 1 reports the sum of the lag coefficients for *each* aggregate variable and in parentheses the *Z*-statistic for the test of the null hypothesis that the sum of coefficients for that variable is equal to zero (i.e., for the *m*th aggregate $H_0^m : \sum_{n=1}^{nlag} \phi_{m,n} = 0$). We find that monetary policy variance has an insignificant long-run effect on employment growth volatility, while the other macro variables are significant at least at the 10% level. Oil-price increases lead to increased employment growth

[9] The usual AIC or BIC could not be used due to the panel structure of the data. Instead we estimated equation (3) without the state interactions on the macro variables, using five lags of each macro variable and of the state manufacturing share. State interactions are ignored so that average effect can be measured. The contemporaneous plus all lags up to the maximum significant lag for a variable were used. For instance, if the fourth lag of the oil price was significant, the contemporaneous through the fourth lag were included in the estimation.

volatility, as does an increase in manufacturing share. An increase in the business cycle index leads to lower volatility, suggesting that when the aggregate economy is growing at an above average pace, employment growth volatility is low and vice versa. We also test whether each of the aggregate variables can be excluded from equation (4) and report the results in column three of Table 1. Specifically, we test the null hypothesis: $H_0^m : \phi_{m,1} = \phi_{m,2} = \ldots = \phi_{m,nlag} = 0$. The test suggests that, with the exception of monetary policy, the macro variables have a significant effect on state employment growth volatility.

We use equation (3) to estimate the state-specific effects of each macro variable. The equation is estimated by OLS; standard errors are corrected both for heteroskedasticity and serial correlation. Estimation of equation (3) produced an R^2 = .3821. Due to the large number of state interactions, lags, etc., results are summarized in the form of two sets of *F*-statistics. The fourth column of Table 1 reports the *F*-statistic for the test that a given macro variable has the same influence on volatility across states. That is, we test the null hypothesis for the *m*th macro aggregate:

$$H_0^m : \sum_{n=1}^{nlag} \varphi_{1,m,n} = \sum_{n=1}^{nlag} \varphi_{2,m,n} = \ldots = \sum_{n=1}^{nlag} \varphi_{48,m,n}$$

against the alternative hypothesis that state-specific responses to the particular macro variable differ.

The fifth column of Table 1 reports the *F*-statistics for the test that state-specific responses to *each* macro variable, *m*, are jointly (i.e., across states) equal to zero:

$$H_0^m : \sum_{n=1}^{nlag} \varphi_{i,m,n} = 0 \quad i = 1, \ldots, 48$$

against the alternative hypothesis that at least one state differs from zero. Based on the test results reported in columns 4 and 5 of Table 1, we find that the individual state responses to each of the four macro variables (monetary policy variance, oil-price index, business cycle index and change in manufacturing share) vary significantly across states (column 4 in Table 1) and have a jointly significant impact on employment growth volatility (column 5 in Table 1). Note that in contrast to the results from the aggregate specification of equation (4), the variance of monetary policy is now highly significant once we allow policy to have differential effects across states. We also find that the other macro aggregate variables have differential effects across states that are statistically significant.

The joint significance of the deregulation dummies provides new support for the findings of Morgan et al (2004) in that the present model has considerably more controls than theirs. In addition, Morgan et al restricted deregulation to have the same effect on each state. The results show that these restrictions are perhaps too strict, in that the null hypothesis of the equality of 48 estimated coefficients on the deregulation variable is soundly rejected.

2.4 Accounting for Volatility

We now turn to an exercise that accounts for the relative contribution of the macro factors and the state-specific factors on state employment growth volatility. The contribution to volatility of the macro factor is determined by dropping the state fixed-effects and state-specific time trends from equation (3) yielding the following auxiliary regression:

$$\left|\varepsilon_{i,t}\right| = \alpha_0 + \delta_i dreg_{i,t} + \sum_{m=1}^{4}\sum_{n=1}^{nlag}\varphi_{i,m,n}X_{m,t-n} + U_{i,t} \quad \text{for } i = 1,\ldots,48 \tag{5}$$

The R^2 from this regression gives the upper bound for the contribution of the macro variables since all co-variance between them and the excluded state controls (fixed effects and state-specific time trends) is allocated to the aggregate factors. We refer to the R^2 from equation (5) as R_M^2. A second auxiliary regression that includes *only* the state-specific controls maximizes the measured contribution of these variables since all co-variance with the now excluded macro factors is ascribed to them:

$$\left|\varepsilon_{i,t}\right| = \alpha_0 + \alpha_i + \beta_i t + \delta_i dreg_{i,t} + \nu_{i,t} \qquad (6)$$

The R^2 from equation (6) is called R_S^2.

We present the goodness of fit statistics from estimating equations (3), (5), and (6) in Panel A of Table 2. The R^2 from the estimation of equation (3), referred to as R_{ALL}^2, indicates that all explanatory variables, both the macro variables and the state variables, explain 38% of the total variation in state-level employment growth volatility. The value for R_S^2 indicates that the state-level variables explain *at most* 12.6% of the variation in employment growth volatility. The value for R_M^2 indicates that the macro variables explain at most 31.3% of the variation.

To generate the lower bound estimate for the contribution of the macro variables we subtract R_S^2 from R_{ALL}^2. The result of this calculation provides a lower bound estimate of 25.6%. Consequently, the range of contributions for the macro variables is from 25.6

to 31.3% of the total variation in employment growth volatility, which is reported in the second column of Panel B in Table 2.

Next, we calculate the individual contribution of each of the four macro variables using versions of equation (3) and equation (5) with only one macro variable at a time in each regression. Panel B of Table 2 reports the upper and lower bound contributions for each of the individual macro variables. We find that monetary policy accounts for between 7.8 and 9.6% of the variation in volatility. This range falls well below the estimated explanatory power of monetary policy found by others who have examined the post-1984 decline in GDP volatility, e.g., Leduc and Sill (2007). Those estimates fall in the 15 to 20% range. The oil-price index explains around 6.7 to 8.6%, the aggregate activity index explains around 4.1 to 7.2%, and the manufacturing share change explains between 3.3 and 7.4%.

As already noted, the ability to control for banking deregulation is potentially important, especially for measuring the effects of monetary policy. The third column of Panel B, Table 3 provides some evidence on the issue. Essentially, the same procedures used to generate the estimates in column 2 of Panel B were used, except that the banking deregulation controls were removed from all estimated equations. The results show that the estimates of monetary policy's impact are indeed overstated when the deregulation controls are removed. Without the deregulation controls, the lower bound of the range for policy's impact is about 30% higher and the upper end is about 11% higher. The impacts of removing the controls for banking deregulation are much less dramatic for the other macro variables.

It was also noted that the panel design allows each of the macro variables to have state-specific effects. It is possible to estimate the importance of this aspect of the estimation following the foregoing methodology. That is, the models can be re-estimated without allowing for state-specific interactions, the range of contributions of each variable can be calculated and these ranges can be compared to those allowing state-specific effects. The results of this exercise (not shown) indicate that allowing state-specific effects substantially increases the estimated contributions of each variable. For example, the combined effects of all the macro variables is close to 72% greater using the state interactions compared to when the variables are constrained to have the same cross-state effect. The estimated impact of monetary policy alone is about 32% greater. Consequently, the use of state-level data appears to have important implications for research in this area and future research would benefit from greater reliance on it.

3. CONCLUSION

This study documents a general decline in the volatility of employment growth since the mid-1950s and examines its possible sources. We studied several potential sources of volatility that have received attention in the literature on volatility, i.e., monetary policy, oil prices, changes in industrial structure and other business cycle shocks. A unique aspect of our analysis is the use of state-level panel data on employment growth to examine how each of these variables affected employment growth volatility. Panel data allow a richer analysis than one based only on time series data (e.g., Stock and Watson 2002) or alternatively on cross-sectional data (e.g., Hammond and Thompson 2004). This includes the benefits of greater data variation, decreased simultaneity and the ability to allow variables measured at the aggregate level to have state-specific affects. State-level data also permitted us to control for the effects of state banking deregulation, which has been found to have significant effects on employment growth volatility and could be correlated with monetary policy, thus confounding efforts at identifying policy's effects.

Our analysis indicates that each of these factors has played a significant role in explaining fluctuations in employment growth volatility, and that each had significantly different effects across the states. Monetary policy had the largest measured effects, accounting for between 8 and 10% of the variation in volatility. These estimates are noticeably lower than others based only on the change in volatility pre- and post- the Great Moderation. Our estimates indicate that changes in industrial structure had a significant impact and could explain up to about 7% of the variation in volatility in the sample period.

The evidence also demonstrates the importance of controlling for banking de-regulation, consistent with the results of Morgan et al (2004). Allowing aggregate-level variables to have state-specific effects is also found to be crucial. We presented evidence that doing so increases the estimated contributions considerably; indeed, the overall contribution of the four macro variables was close to 72% higher. We think the evidence described in this paper suggests that future research would benefit from increased reliance on regional data, rather than using only aggregate-level data. Future research might also consider the possible roles played by other factors, such as shocks to productivity growth, foreign trade and fiscal policy. All such variables can be analyzed within the framework developed here and could offer additional clues to the factors driving volatility.

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Table 1: *F*-tests for the Estimated Coefficients

	F-tests for aggregates[†]		*F*-tests for individual state-specific sums	
	Sum of lag coefficients[a]	Exclusion test[b]	Equal across states[c]	Exclusion test[d]
Variable				
Monetary Policy Variance	$2.57e^{-5}$ (0.08)	0.93	2.48***	2.46***
Oil Price Index	0.086 (4.3)***	12.94***	3.97***	4.04***
Business Cycle Index	-0.006 (-2.92)***	2.54**	2.24***	2.20***
Change in Manufacturing Share	0.907 (1.75)*	1.93*	2.99***	3.02***
Banking De-regulation Dummies	N/A	N/A	2.09***	2.06***

[†]*F* statistics are calculated by dividing the reported χ^2 statistic by the degrees of freedom.
*,**,*** indicates *p*- values <.1, <.05, and <.01, respectively.

[a]Z-statistics for $H_0 : \sum_{n=1}^{nlag} \phi_{m,n} = 0$ in equation (4)

[b]*F*-statistic for $H_0 : \phi_{m,1} = \phi_{m,2} = \ldots = \phi_{m,nlag} = 0$ in equation (4)

[c]*F*-statistic for $H_0 : \sum_{n=1}^{nlag} \varphi_{1,m,n} = \sum_{n=1}^{nlag} \varphi_{2,m,n} = \ldots = \sum_{n=1}^{nlag} \varphi_{48,m,n}$ in equation (3)

[d]In equation (3), the *F*-statistic for $H_0^m : \sum_{n=1}^{nlag} \varphi_{i,m,n} = 0 \quad i = 1,\ldots,48$

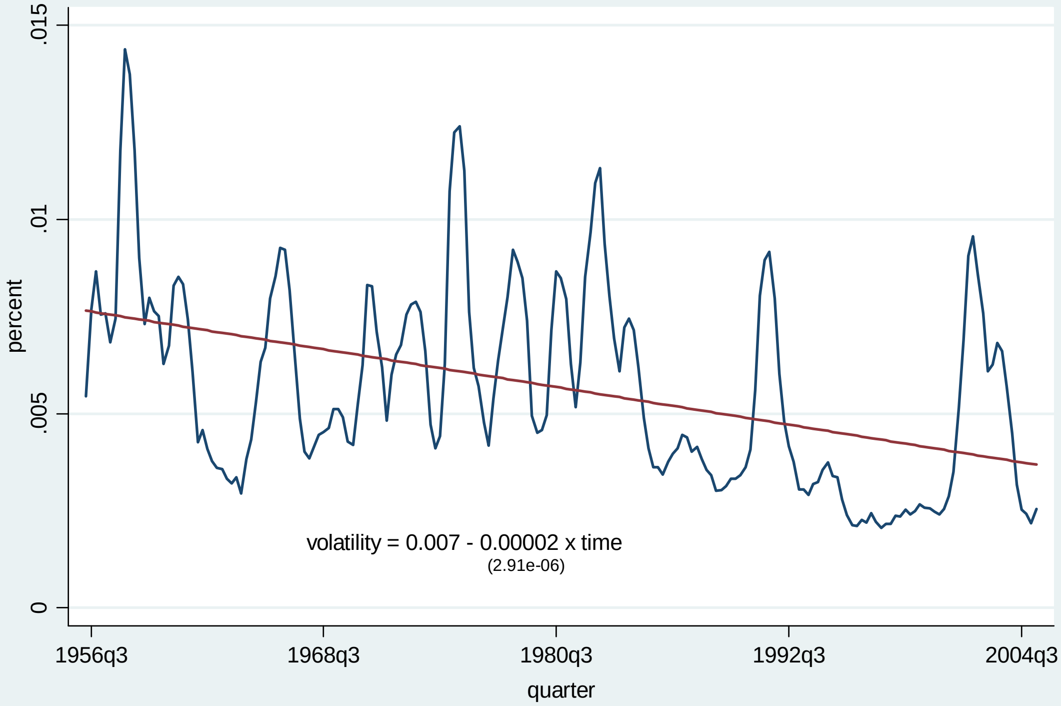
Table 2: The Contribution of Variables to Employment Volatility[a]

(1956:2 to 2002:4)

Panel A		
Equation Specification	R^2	
Full Equation	$R^2_{All} = 0.3821$	Equation (3)
Aggregate Variables Only	$R^2_M = 0.3128$	Equation (5)
State Controls Only	$R^2_S = 0.1264$	Equation (6)
Panel B		
Variable	% Contribution to Volatility (with deregulation controls)	% Contribution to Volatility (no deregulation controls)
All Macro Variables	25.6 to 31.3	26.7 to 31.3
Monetary Policy Variance	7.8 to 9.6	10.2 to 10.7
Oil Price Index	6.7 to 8.6	6.8 to 9.0
Business Cycle Index	4.1 to 7.2	3.9 to 4.2
Manufacturing Share Change	3.3 to 7.4	3.3 to 7.9

[a] Aggregate variables include monetary policy, oil prices, the ADS business cycle index and change in manufacturing employment share, all interacted with state dummy variables. The state controls include state fixed effects, state-specific time trends and state banking deregulation dummy variables.

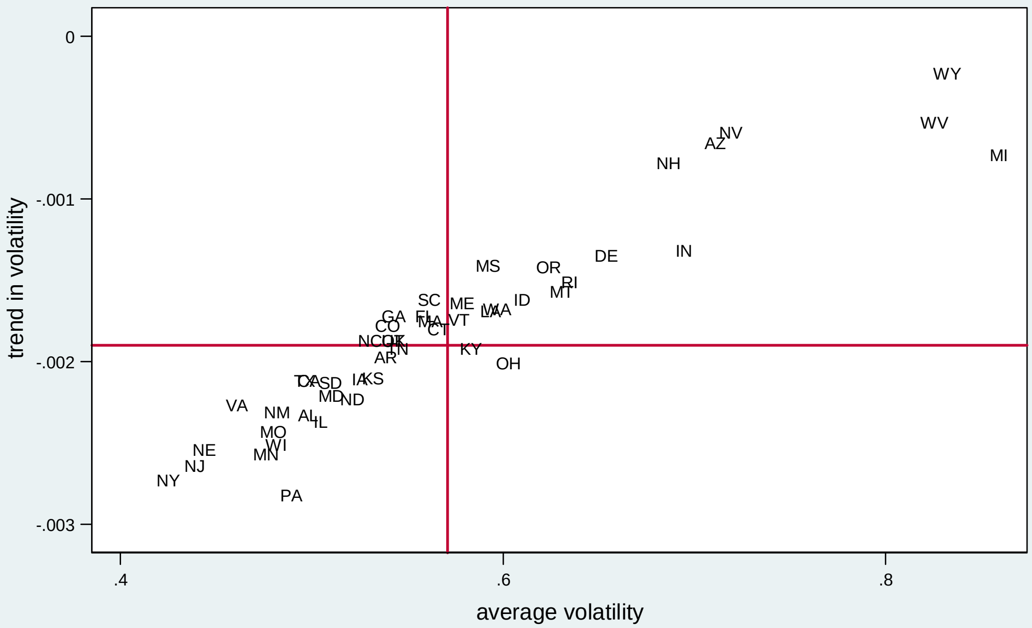
Figure 1: Average State Employment Growth Volatility



Four-quarter moving avergage of employment growth volatility.

Figure 2: State Employment Growth Volatility Average and Trend

(1956:1 to 2002:4)



Note: Average state volatility is calculated by weighting a state's volatility in each year by state employment levels. State volatility trends are estimated using an employment-weighted OLS regression of volatility on state-specific time trends. The vertical and horizontal lines on the graph indicate the cross-state means of average volatility and the trend in volatility, respectively.