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Abstract

This paper studies the transmission of monetary shocks to state unemployment rates, within a novel structural factor-augmented VAR framework with a time-varying propagation mechanism. We find evidence of large heterogeneity over time in the responses of state unemployment rates to monetary policy shocks, which do not necessarily comply with the response of the national unemployment rate. We also find evidence of heterogeneity over the spatial dimension, although geographical proximity seems to play an important role in the transmission of monetary shocks.

Keywords: regional unemployment, structural VAR, factor model, monetary policy
JEL Classification: R15, C11, E52

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1 INTRODUCTION

During the last 40 years, the US has experienced many important economic adjustments. Monetary policy is currently more reactive to fluctuations in real aggregate variables, mainly inflation and output, than in the past (Clarida, Gali, and Gertler, 2000). Aside from changes in monetary policy, the recent literature identifies a large reduction over time in the volatility of many macroeconomic variables, a phenomenon called the Great Moderation (see Stock and Watson, 2003 for a concise review). Nonetheless, little is known about how these changes in the US economy have been accumulated over time at the regional level.

Our current empirical understanding of the regional economies suggests that there are obvious differentials among regions and states. In particular, states within a region may have quite varied responses to monetary policy actions (Carlino and DeFina, 1999), and these cross-state differences can be quite "large" (Owyang and Wall, 2003). Additionally, Chappell Jr. et al. (2008) using data from the minutes of the Federal Open Market Committee (FOMC) meetings, document that regional economic conditions may affect policy-makers' decisions. Subsequently there is empirical evidence showing a strong interrelation between monetary policy and not only the aggregate economy, but also regional conditions.

The purpose of this paper is to examine empirically the transmission of monetary policy shocks over time with regards to state unemployment rates in the US. Using a novel structural Factor-Augmented vector autoregression (FAVAR) with time-varying mean coefficients and stochastic volatility, We show that state responses to monetary policy are heterogeneous across different time periods, as well as across states. The specific modeling approach incorporated in this paper allows to weigh differently state responses during different periods, like recessions and expansions.

Why is it important to examine the evolution of regional and state unemployment? There are many attempts in the literature to identify the causes of regional unemployment differentials; see for example Patridge and Rickman (1995) and references therein. However, Blanchard and Katz (1992) give a nice demonstration of the "mystery" underlying the variability (volatility) of state unemployment rates over time:

> "*In 1987, the unemployment rate in Massachusetts averaged 3.2 percent, three percentage points below the national rate. Only four years later, in 1991, it stood at 9.0 percent, more than two points above the national rate. For firms taking investment decisions and for unemployed workers thinking about relocating, the obvious question is whether and when things will return to normal in Massachusetts*." Blanchard and Katz (1992)

Part of the question of "whether and when things will return to normal in Massachusetts" has to do with the efficiency of national monetary policy. Evaluating how different states respond to a monetary shock is very important during times where monetary policy is expected to be most effective in reducing unemployment and increasing output, i.e. economic downturns. In particular, post-World War II national unemployment rate bears no clear patterns of convergence towards a long-run trend, so there is a strong incentive to examine how monetary policy actions have affected state unemployment differentials.

In that respect, this article follows a typical structural VAR exercise, i.e. impulse response analysis and forecast error variance decomposition. However, the proposed modelling approach has large differences compared to standard VAR analysis. First, because regional data have usually large cross-sectional (number of regions/states) and small time-series (number of observations) dimensions, extracting factors can really help meditate curse of dimensionality problems. Essentially factor methods allow to extract just a few unobserved variables - called factors - which can account for most in the variability in the original regional variables, which can even be in the order of some hundreds of regions. Then the factors can be used to draw statistical inferences with considerable gains in estimation, by saving degrees of freedom. Lastly, allowing for time-varying coefficients there are large empirical gains from being able to evaluate the transmission mechanism of non-systematic monetary policy to the regional economies.

The next section discusses briefly the conventional VAR modeling used extensively by regional economists, and the new approach to regional monetary policy analysis introduced in this paper. Then the subsequent sections describe the data and methodology in an empirical assessment of the state-level effects of US monetary policy. The last section concludes with thoughts for further research.

2 STRUCTURAL REGIONAL MODELS

VAR model

The standard tool to examine the effects of monetary policy on the economy is to estimate a structural VAR (SVAR) on some key macroeconomic variables. In a regional setting in particular, this SVAR may include both regional and national variables, as well as the monetary policy tool. Models of this type admit the following reduced-form VAR(1) representation[1]

$$X_t = BX_{t-1} + v_t \tag{1}$$

where $X_t = [X_t^{state}, X_t^{nat}, r_t]'$, X_t^{state} is a vector of variables of interest at the regional level (state unemployment in the US, in this paper), X_t^{nat} is a vector of aggregate (national) macroeconomic variables that may proxy real activity, prices or monetary aggregates, and r_t is a scalar containing the monetary policy instrument, i.e. the control variable of the Central Bank. The errors v_t are Gaussian iid with mean zero and covariance matrix Ω. This model has been used extensively to study the impulse responses of each region, when an unanticipated shock in the monetary policy occurs; see, among others, Arnold and Vrugt (2002), DiGiacinto (2003), Carlino and DeFina (1999), Owyang and Wall (2009) and Georgopoulos (2009).

There are two practical restrictions associated with this model making it inappropriate for the study of the transmission mechanism of monetary policy in regional

[1]For simplicity the variables are centered (i.e. substract from each variable its sample mean), so that the intercept is ommited.

economies. The first one, is that the shocks and the way these are propagated into the regional variables are all constant. As shown in the next, this problem can be addressed by using time-varying parameters. A second and more important caveat of VARs, is that the size of the vector of variables X_t^{state} can be unreasonable large and a curse of dimensionality problem may occur. Bloor and Matheson (2009) show how to solve this issue using shrinkage. However, the shrinkage priors they use cannot provide sufficient shrinkage when time-varying parameters are present, or when the number of regions is larger than the number of time-series observations (which is the case with many regional datasets).

Factor-Augmented, time-varying coefficients VAR

Following the dynamic factor model literature (c.f. Stock and Watson (2005)), the information in contained in the variables in X_t^{state} is summarized in a few latent factors using a standard factor model of the form

$$X_t^{state} = \Lambda F_t + u_t. \tag{2}$$

The so-called *common component*, ΛF_t, summarizes most of the variability in the regional data using just a few factors F_t. Dependent on the regional disaggregation level we want to choose, X_t^{reg} can be in the order of hundreds of regional variables, while the number of factors empirically will not be more than 10. Subsequently, the factor model is a parsimonious representation of regional data which are characterized by long cross sections (number of regions) but short time-series observations. The innovation errors u_t contain the region-specific variations and, of course, any other econometric estimation or measurement error. The identifying assumption is that u_t comes from a Normal distribution with zero mean and diagonal covariance matrix Ψ. The factors F_t, the national variables X_t^{nat} and the monetary policy tool r_t, follow a VAR with time-varying coefficients of the form

$$Y_t = B_{1t} Y_{t-1} + \ldots + B_{pt} Y_{t-p} + v_t \tag{3}$$

where in this case $Y_t = [F_t, X_t^{nat}, r_t]'$, with F_t the vector of latent factors, Λ^F is a matrix of factor loadings and B_{jt} are time varying coefficient matrices of each lag $j = 1, \ldots, p$. Regarding the innovations, it holds that $u_t \sim N(0, H)$ with H a diagonal covariance matrix, and $v_t \sim N(0, \Omega_t)$ with Ω_t a time-varying full covariance matrix, for each $t = 1, \ldots, T$. Following Cogley and Sargent (2005), the error covariance matrix Ω_t is decomposed into a diagonal matrix Σ_t, and a lower triangular matrix A_t with ones' on the diagonal, which has the form $\Omega_t = A_t^{-1} \Sigma_t \Sigma_t' A_t^{-1\prime}$.

The time-varying parameters are summarized in B_t, α_t and $\log \sigma_t$, which are vectors that stack the autoregressive coefficients $B_{1t}, ..., B_{pt}$, the non-zero and non-one elements of A_t and the logarithms of the diagonal elements of Σ_t, respectively. The standard assumption is that these vectors of parameters evolve according to a random walk specification

$$\begin{aligned} B_t &= B_{t-1} + \delta_t \\ \alpha_t &= \alpha_{t-1} + \zeta_t \\ \log \sigma_t &= \log \sigma_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

where the errors δ_t, ζ_t and ε_t are Normal with zero mean and covariances Q, S and W respectively, and they are uncorrelated with each other, as well as v_t and u_t, at all leads and lags. This formulation is very popular whenever time variation in the parameters is desirable, because estimation is feasible using *state-space* methods like the popular Kalman filter, see for example Durbin and Koopman (2001).

The whole model consisting of equations (2) and (3) is a time-varying VAR augmented with factors (time-varying parameters factor-augmented VAR, or TVP-FAVAR, using the terminology of Bernanke, Bovin and Eliasz, 2005). In equation (3), impulse responses are obtained at each point in time for the whole vector Y_t as it is shown for example in Canova and Gambetti (2009). The important implication of the TVP-FAVAR, is that the impulse responses for the observable variables X_t^{state} can be recovered as well, even though they do not explicitly enter equation (3). It is easy to prove that if we substitute equation (3) into equation (2), we end up with a reduced-form VAR model where the vector $X_t = [X_t^{state}, X_t^{nat}, r_t]'$ is the dependent variable, and lags of the vector $Y_t = [F_t, X_t^{nat}, r_t]'$ are on the R.H.S.; see Stock and Watson (2005) for more details on structural FAVARs.

A different common approach to modeling regional data using dynamic factor models (see for example Stock and Watson, 2007), is to assume that all regions load to a national factor, what is denoted by F_t in equation (2), and at the same time, each state i loads on a state-specific factor, say $F_{i,t}^{state}$. If the ultimate goal is to extract impulse responses, then the approach proposed in this paper is more parsimonious, since there is no need to estimate additional state factors $F_{i,t}^{state}$. Additionally, while estimating only one 'national' factor has the advantage of structural interpretability, empirically it explains only a low proportion of the variability (i.e. information) in the regional data. If we only care about measuring the effects of monetary on the regional economy, then it is more appropriate to extract more factors (probably 2 or 3), which results in more accurate estimation of the impulse responses.

Estimation and Priors

When using a dynamic factor model, the aim is to find estimates of the factors and the model parameters, which are both not observed. Bernanke, Boivin and Eliasz (2005) propose a Bayesian sampling procedure to estimate the factors and the parameters in one step. However it is difficult to follow the same estimation procedure when time-variation of the parameters is present in the model. That is because several identification issues arise in this case, which are not desirable in a structural model; see for example the discussion in Korobilis (2009). DelNegro and Otrock (2007) use a dynamic factor model to extract a national house price index from regional variables and then at a second step they run a simple VAR on the estimated national house price index and some national variables. This is one example of a two-step approximation procedure, and DelNegro and Otrock (2007) use this approach for computational efficiency. In this paper, a different two-step estimation procedure is adopted, where the factors are first approximated using standard principal components (PC), and at a second stage the parameters are estimated using Markov Chain Monte Carlo Methods (MCMC), conditional on the PC estimates of the factors.

Recently, Stock and Watson (2008) use a regional dynamic factor model for housing construction data, with stochastic variances but constant mean-equation coefficients. They approximate the model solution using a two-step procedure which is different from the one followed in this paper. They first estimate the dynamic factor model assuming that all parameters are constant. Then they save the mean equation coefficients from the first step and at a second step they use Bayesian MCMC methods to estimate the unknown factors and the stochastic variances. As it turns out, the estimate of the factor they obtain from their dynamic factor model with drifting volatilities using their specific two-step estimation method, is very close to the principal component estimate (see Stock and Watson, 2008, Figure10). This result supports the use of principal components method in this paper for the approximation of a time-varying coefficients dynamic factor model.

Treating the factors as observed (using the principal components estimates), reduces equation (2) to a simple multivariate regression and equation (3) to a TVP-VAR model. In particular, following for example Cogley and Sargent (2005), the priors on the initial conditions on the states are of the form

$$\begin{aligned} B_0 &\sim N\left(0, 4\underline{V}_B\right) \\ \alpha_0, \log\sigma_0 &\sim N\left(0, 4I\right) \end{aligned}$$

while priors on the covariance matrices of the time varying parameters are of the form

$$\begin{aligned} Q &\sim iW(k_Q(1+n_Q)\underline{V}_B, 1+n_Q) \\ S &\sim iW(k_S(1+n_S)I, 1+n_S) \\ W &\sim iW(k_W(1+n_W)I, 1+n_W) \end{aligned}$$

where n_Q, n_S and n_W are the number of rows (or columns) of the matrices Q, S and W respectively. The matrix $\underline{V}_B$ is constructed based on the Minnesota prior (Litterman, 1986). This prior involves running first a p-lag univariate autoregression for variable Y_{it} and saving each residual standard error s_i. Then the the prior variance of the r-th lag ($r = 1, ..., p$) of variable j in the FAVAR equation i takes the form

$$\underline{V}_B^{ij} = \left\{ \xi \frac{s_i^2}{r^2 s_j^2} \right.$$

The parameter ξ controls the tightness of the Minnesota prior and is set to 0.001 (see also Bloor and Matheson, 2009).

The hyperparameters k_Q, k_S and k_W are set to 0.0001, 0.01 and 0.0001 respectively. These choices are discussed in detailed in Cogley and Sargent (2005) and the reader is referred to this paper. Equation (2) has only parameters which are constant, and a noninformative ('Jeffreys') prior is used. Full estimation of the time-varying factor model involves a posterior simulator which draws the vector of parameters $\theta = (\Lambda, H, B_t, A_t, \Sigma_t, Q, S, W)$. This is easily implemented as it is shown in Korobilis (2009); see also Koop and Korobilis (2009) for a review of Bayesian inference in VAR and FAVAR models with time-varying coefficients, using MCMC methods. The posterior densities convey all we need to know about the parameters, and allow to incorporate parameter uncertainty when extracting impulse responses. That is, we do not need to use the Bootstrap to obtain 'error bands' - the whole distribution of the impulse responses and quantities of interest, like quantiles, are readily available from the output of the MCMC algorithm.

3 EMPIRICAL RESULTS

The Data

We use quarterly observations that span the period 1976:Q1 - 2008:Q3, available from the FRED database of the St. Louis Fed. In particular, the vector X_t^{state}, from which factors are extracted, contains unemployment rates for 48 contiguous U.S. states. The aggregate variables that consist the vector X_t^{nat} are inflation and real GDP. Following the suggestions of Bernanke and Blinder (1992), the monetary policy instrument r_t is the Federal Funds rate. All variables are seasonally adjusted and transformed to be approximately stationary. Where monthly observations are available, quarterly series are constructed using the average over the three months of each quarter.

Model Selection

The first step in the analysis is to assess the usability of extracting factors from regional data. Model selection methods may suggest an optimal number of factors from a statistical point of view, but this not need to be the number of factors actually needed for policy analysis. Subsequently, experimentation is needed assuming different number of factors, see for example Bernanke, Boivin and Eliasz (2005). It turns out that two factors provide reasonable impulse responses and explain more than 70% of the variation in the data, so results are based on the parsimonious choice of two factors. A visual assessment of how simple factors estimated with principal components can capture the comovements in regional data, is provided in Figure 1. The reader should note that the data in Figure 1 are demeaned and standardized (mean zero, variance one), which is a prerequisite in order to extract principal components, but this does not affect the quality of inference.

Insert Figure 1 around here

The main movements of the state-level unemployment rates and periods of high variability (like the period 1982-1984) are well explained by the principal component estimates of the factors. This can be seen by comparing in Figure 1 the top panel which plots the observed unemployment rates, with the middle panels which plots the component $\Lambda^F F_t$. What remains unexplained from the factor regression in (2), i.e. the innovations u_t, are plotted on the bottom panel of the same figure. Experimenting with different number of lags of Y_t in the FAVAR equation (3) shows that the impulse responses are qualitatively the same for two to four lags. However, the estimation error gets larger as the number of lags increases so that all results presented here are based on the parsimonious choice of two lags.

Evidence on the evolution of monetary policy responses

A close examination of the evolution of the model parameters can give a picture of how the US economy has evolved over the course of the data sample. The time varying covariance matrix Ω_t conveys all we need to know about the exogenous shocks to the economy. The time-varying mean equation parameters B_t, along with the loadings Λ^F, allow us to assess how the exogenous shocks are propagated in the economy. Given that the model parameters are stochastic, and hence they admit a different value at each quarter, there are too many to present here. However of interest is to graphically assess the evolution of the exogenous shocks (time-varying volatilities) as implied by the Dynamic Factor model.

Insert Figure 2 around here

Figure 2 presents a plot of the median and 16-th and 84-th percentiles of the time-varying standard deviations of the 2 factors, inflation, GDP, and the federal funds rate. These are the diagonal elements of the time-varying covariance matrix Ω_t. This Figure shows how the Dynamic Factor model with time-varying parameters adopts to events empirically observed during the course of the last 30 years or so. There is evident variation between 1976 - 1984. This period corresponds to a period of large oil shocks (1970's), and the targeting of monetary aggregates by the Fed during the first half of the Volcker chairmanship (early 1980's). Beyond 1984, the level and variation of the volatility of the five variables of interest are substantially lower. This corresponds to a well-known phenomenon called the Great Moderation (Stock and Watson, 2003). However there is an evident increase in the volatility of inflation during the last 7 quarters of the sample which can be attributed to the current global financial crisis[2].

The advantage of the TVP-FAVAR is that we can extract time-varying impulse responses for all 51 observed variables of interest for all time periods. However, presenting all these responses for $t = 129$ periods and $N = 51$ variables is impossible. Figure 3 plots the impulse response functions for 10 states[3], and for two time periods, 1985:Q1 (left-hand side plots) and 2002:Q1 (right-hand side plots). The inclusion of these specific US states and time periods in this figure was made arbitrarily. Nevertheless they are a representative sample of the similarities and differences in the way that regional

[2]The other two real variables - interest rate and GDP - experienced large drops (increased volatility) after 2008:Q2. This period is in the very end of the sample, and hence their large volatility is not captured by the model.

[3]There are five states (New York, Oklahoma, Connecticut, North Carolina and Montana) in the top panel, and five states (South Carolina, Massachusetts, Wyoming, Florida and Colorado) in the bottom panel of Figure 2.

economies respond to monetary policy. As expected from economic theory, almost all responses are positive and hump-shaped. It is only Montana in the top panels (both in 1985 and 2002) which responds to a rise in short-term interest rates with a sudden increase in unemployment, which eventually dies out at a geometric rate.

Despite some similarities in the shape of impulse responses, the differences in magnitude of the within- and between- regions responses over time are striking. To summarize these differences quantitatively, Table 1 reports the cumulative impulse responses at the 8-quarter horizon, for the first quarter of selected years. These long-run state responses are very high in magnitude for all states in the 70s, but they are significantly reduced after 1985 (great moderation). By 2007 and exactly before the financial crisis, many cumulative responses would actually become negative, implying that at that time even a contractionary monetary shock would not be enough to increase unemployment (as the events turned out, it was the Global crisis shock which would) Among all states, we can see that in 1979 West Virginia, Montana, Idaho and Kentucky responded much more than the rest of the states. By 2007 only West Virginia and Montana would have the highest long-run responses.

Insert Table 1 around here

A question of interest is which is the mechanism underlying the different responses of states to monetary policy actions at different time periods. Answering this question would imply a full examination of how monetary policy affects regional financial conditions (Dow and Montangoli, 2007), and how the response of each state is determined by its structure (Carlino and DeFina, 1999). However, following the methods described in Crone (2005), we can characterize the state responses to monetary policy shocks using cluster analysis. The idea is to get a definition of regions based on similarities of state unemployment responses, so that homogeneous states belong to the same region. This is done using K-means clustering of the long-run state responses of unemployment presented in Table 1 (Crone, 2005; Stock and Watson, 2008). One could use a grouping of the states based on BEA regions. This grouping is done in terms geographical contagion, which is a valid spatial interpretation of economic linkages between regions[4]. However, geographical proximity might not be the only explanation of economic performance and sensitivity to monetary policy actions (Crone, 2005).

Table 2 provides the clusters memberships of the 48 states. In order to chose the number of clusters, we followed the iterative algorithm described in Stock and Watson (2008). There are no formal criteria to determine the number of clusters, and dendrograms and silhouette plots provide an approximate visual assessment. Hence we provide results for five clusters, which is the number that maximizes the silhouette value (Kaufman and Rousseeuw, 1990). We can see that many of the states geographically belonging to the Mideast and New England regions are grouped together in cluster 3. However, this geographical separation is not always the case for all clusters. In cluster 5, the western states like California, Arizona and Oregon are clustered with eastern states like Florida, Maryland and Virginia.

Insert Table 2 around here

[4]For example, notice that among the four states with the highest long-run responses in 1979, Kentucky and West Virginia, and Idaho and Montana, are neighboring states.

Other than impulse responses, and their clustering of those we implemented, another exercise typical performed in VAR models is forecast error variance decompositions. Table 3 examines the fraction of the forecasting error of each state unemployment rate at the 30-quarter ahead horizon, that is attributable to a monetary policy shock. Notice first that the Federal funds rate accounts for around 10% of the forecast error variance of national unemployment rate at the 60-month horizon (see Bernanke, Boivin and Elsiasz, 2005, Table I). Given this result, Table 3 shows significant variation in the way the Federal funds rate affects the forecast error variance of state unemployment rates. For states like West Virginia, Montana, and Kansas monetary policy shocks account for up to 20% of variation in their unemployment rates, with Colorado being the only state well exceeding this percentage at all periods. We would expect, as is the case with national unemployment rates, that the effects of monetary policy have increased during the Monetarist Experiment period (the first 5 years of the Volcker Chairmanship, 1980-1985) and just before the Global crisis of 2007-2008 (see for instant Texas). However the variation in forecast error decompositions is quite random, revealing the heterogeneity in state unemployment rates.

4 CONCLUSIONS

This article examined a factor-augmented vector autoregression with time-varying parameters and stochastic volatility. We modify the studied of Korobilis (2009) to the case of studying the effects of monetary policy on regional economies. We examined the dynamic effects of monetary policy on US state unemployment rates and find that at the disaggreted level there is large heterogeneity which can only be attributed to the regional economic conditions.

Subsequently our future work is focused to use the parsimonious dynamic factor model to analyze state economies using many indicators. This would involve using state unemployments (as we did in this paper), employment, production and other indicators of economic activity, and extract a single factor from each regional indicator. Given available data, this would allow a wholistic approach to the isse of examining how monetary policy has affected the economy both in space (states/regions) and time.

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APPENDIX - TABLES AND FIGURES

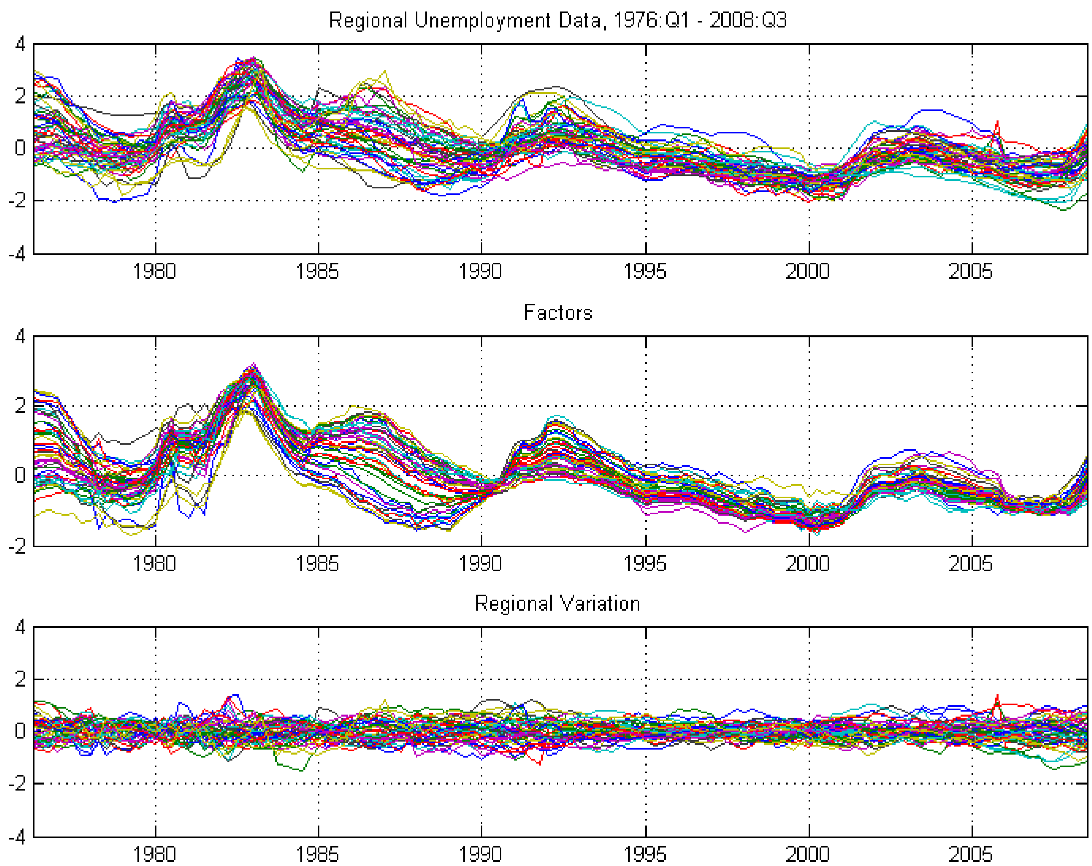

Figure 1: State-level Unemployment Data, Variation Explained by the Factors, and Variation Attributed to State Characteristics. *Notes:* The middle graph shows the comovement in regional unemployment rates, as captured by the two factors, i.e. the component $\Lambda^F F_t$. The third graph, plots what remains unexplained by the factors, and it is either attributed to state variation (and measurement error), i.e. the innovations u_t.

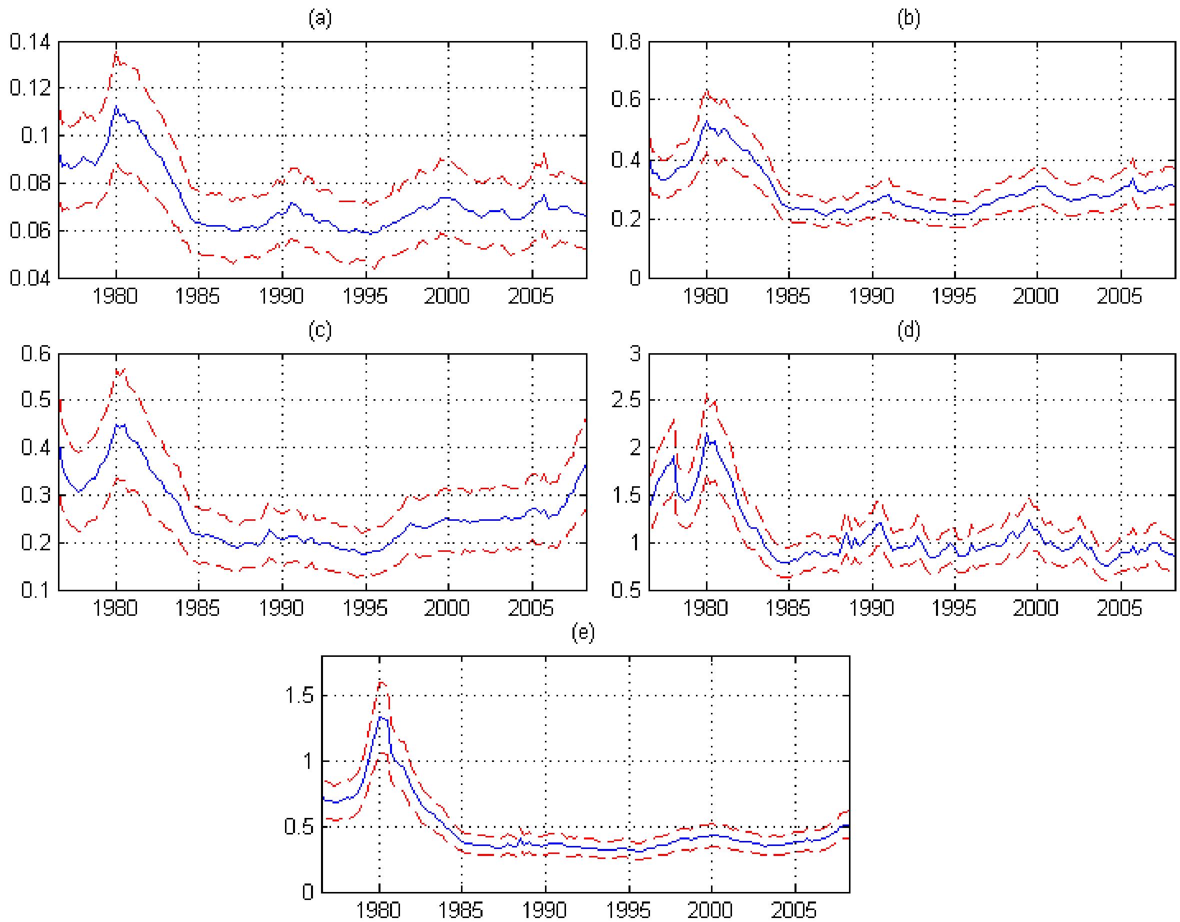

Figure 2: Time-Varying Volatility of (a) 1st Factor, (b) 2nd Factor, (c) Inflation, (d) GDP and, (e) Fed-Funds Rate. The solid line is the median of the posterior of each volatility parameter, and the dashed lines are the 16-th and 84-th percentiles.

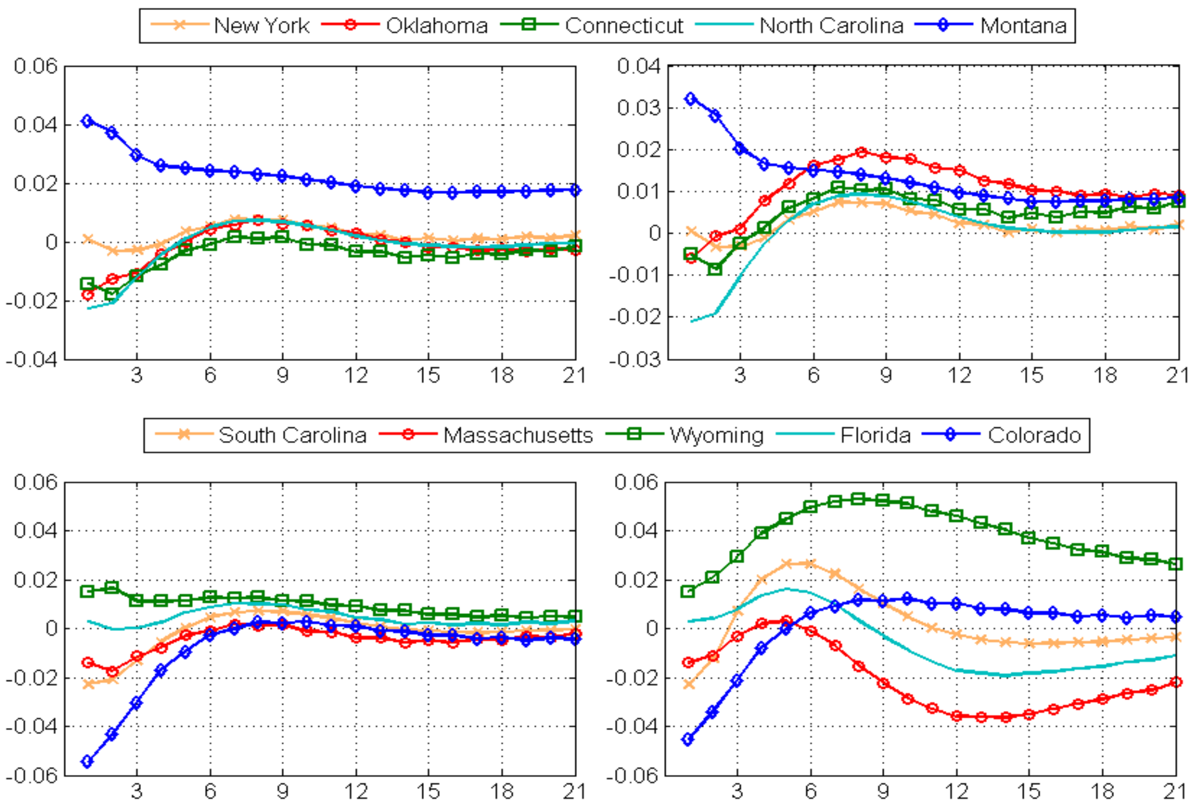

Figure 3: Impulse Responses for selected regions, for two periods: 1985 (left panel) and 2002 (right panel). These lines are medians of the estimated posterior densities of impulse responses.

Table 1: Eight-quarter cumulative impulse responses of regional unemployment to a one basis point increase in the Fed-funds rate.

Region	1979:q1	1985:q1	1991:q1	1995:q1	1999:q1	2002:q1	2007:q1
Alabama	0.5715	0.2645	0.1672	0.1951	0.153	0.0717	0.0187
Arizona	0.2621	0.1146	0.1169	0.1158	0.0963	0.0453	0.0230
Arkansas	0.6158	0.2786	0.1643	0.2092	0.1815	0.1239	0.0460
California	0.2027	0.0995	0.1371	0.0848	0.0779	0.0316	0.0831
Colorado	0.1453	0.0766	-0.0174	0.0678	-0.0553	-0.1781	-0.3351
Connecticut	-0.1118	-0.0705	0.0238	-0.0030	-0.022	-0.0548	-0.0472
Delaware	0.0524	-0.0029	0.0619	0.0691	0.0791	0.0824	0.0439
District of Columbia	0.3318	0.1615	0.1839	0.1225	0.1495	0.1316	0.2056
Florida	0.1607	0.0682	0.1056	0.0831	0.0733	0.0355	0.0414
Georgia	0.1981	0.081	0.0811	0.103	0.063	-0.0012	-0.0600
Idaho	0.7105	0.3252	0.2187	0.2346	0.2294	0.1814	0.1440
Illinois	0.5813	0.2700	0.1715	0.1965	0.153	0.0675	0.0171
Indiana	0.4577	0.1910	0.1349	0.1848	0.1567	0.0974	0.0124
Iowa	0.6442	0.2955	0.1673	0.2121	0.1805	0.1154	0.0415
Kansas	0.3493	0.1910	0.0749	0.0938	-0.0039	-0.1324	-0.1809
Kentucky	0.7164	0.3333	0.1953	0.2281	0.1999	0.1293	0.0708
Louisiana	0.5927	0.2966	0.1352	0.1769	0.1371	0.0728	0.0144
Maine	0.0870	0.0215	0.0901	0.0695	0.0756	0.058	0.0626
Maryland	0.2364	0.0919	0.1382	0.1189	0.1364	0.1209	0.1237
Massachusetts	-0.0871	-0.0581	0.0318	0.0025	-0.0173	-0.0544	-0.0430
Michigan	0.4534	0.1895	0.1398	0.1812	0.1517	0.0890	0.0163
Minnesota	0.4077	0.1845	0.1267	0.1572	0.1026	0.0135	-0.0503
Mississippi	0.6532	0.3180	0.1638	0.1980	0.1569	0.0807	0.0273
Missouri	0.4636	0.2072	0.1429	0.1724	0.1278	0.0450	-0.0125
Montana	0.7829	0.3643	0.2601	0.2471	0.2790	0.2637	0.2668
Nebraska	0.3884	0.1968	0.0583	0.1256	0.0436	-0.0620	-0.1687
Nevada	0.4415	0.2095	0.1841	0.1628	0.1532	0.0958	0.1011
New Hampshire	0.0662	0.0227	0.0947	0.0475	0.0469	0.0098	0.0601
New Jersey	-0.0114	-0.0237	0.0607	0.0320	0.0299	0.0125	0.0248
New Mexico	0.5515	0.2595	0.1777	0.1814	0.1698	0.1234	0.1005
New York	0.0336	0.0029	0.0713	0.0438	0.0386	0.0179	0.0295
North Carolina	0.2137	0.0953	0.0829	0.0972	0.0424	-0.0509	-0.1003
North Dakota	0.5462	0.2534	0.1322	0.1838	0.1416	0.0728	-0.0085
Ohio	0.5486	0.2465	0.1721	0.1965	0.1643	0.0910	0.0394
Oklahoma	0.4823	0.2627	0.1111	0.128	0.0508	-0.0520	-0.0885
Oregon	0.3412	0.1501	0.1138	0.1391	0.0969	0.0233	-0.0339
Pennsylvania	0.4145	0.1861	0.1674	0.1628	0.1561	0.1092	0.0895
South Carolina	0.1883	0.0846	0.0752	0.0902	0.0349	-0.0530	-0.1051
South Dakota	0.6060	0.2781	0.1483	0.2032	0.1710	0.1075	0.0206
Tennessee	0.6316	0.2854	0.2045	0.2207	0.2076	0.1518	0.1088
Texas	0.4307	0.2396	0.0931	0.1086	0.0293	-0.0749	-0.1078
Utah	0.4571	0.2108	0.1105	0.1643	0.1030	0.0139	-0.0753
Vermont	0.0509	0.0061	0.0724	0.0578	0.0466	0.0162	0.0074
Virginia	0.2839	0.1214	0.1341	0.1278	0.1135	0.0606	0.0423
Washington	0.4022	0.1783	0.1346	0.1568	0.1207	0.0500	-0.0022
West Virginia	0.8068	0.3843	0.2670	0.2489	0.2671	0.2304	0.2408
Wisconsin	0.4922	0.2200	0.1359	0.1815	0.1365	0.0568	-0.0168
Wyoming	0.6956	0.3661	0.1812	0.1727	0.1533	0.0914	0.1040

Table 2: Cluster memberships of individual regions based on cumulative impulse responses of unemployment

Region	Cluster	Region	Cluster	Region	Cluster
Alabama	1	Arkansas	2	Colorado	4
Illinois	1	Idaho	2	Georgia	4
Indiana	1	Iowa	2	Kansas	4
Louisiana	1	Kentucky	2	Nebraska	4
Michigan	1	Mississippi	2	North Carolina	4
Minnesota	1	Montana	2	South Dakota	4
Missouri	1	New Mexico	2	Texas	4
Nevada	1	South Carolina	2	Arizona	5
North Dakota	1	Tennessee	2	California	5
Ohio	1	West Virginia	2	District of Columbia	5
Oklahoma	1	Wyoming	2	Florida	5
Pennsylvania	1	Connecticut	3	Maryland	5
Utah	1	Delaware	3	Oregon	5
Washington	1	Maine	3	Virginia	5
Wisconsin	1	Massachusetts	3		
		New Hampshire	3		
		New Jersey	3		
		New York	3		
		Vermont	3		

Table 3: Proportions of forecast error variance 30 periods ahead accounted for by innovations in the Federal funds rate

Region	1979:q1	1985:q1	1991:q1	1995:q1	1999:q1	2002:q1	2007:q1
Alabama	7.4	8.0	7.3	7.5	8.2	7.3	10.4
Arizona	6.5	4.7	8.5	8.6	9.6	7.9	7.4
Arkansas	5.6	7.8	3.3	4.1	4.7	7.7	9.3
California	8.5	9.8	18.8	14.6	15.2	8.9	11.0
Colorado	22.0	22.7	23.4	28.5	24.4	23.5	27.3
Connecticut	7.8	12.6	11.2	11.8	12.1	6.3	6.8
Delaware	10.8	6.0	3.5	4.2	5.7	10.7	4.1
District of Columbia	12.2	12.5	19.4	15.1	15.0	17.4	12.6
Florida	7.0	7.0	11.4	10.5	11.8	9.1	8.2
Georgia	8.1	5.3	8.7	10.3	11.3	8.7	9.5
Idaho	9.2	10.5	7.4	7.3	7.3	12.3	8.9
Illinois	7.9	8.4	8.0	8.1	8.8	7.2	10.7
Indiana	6.6	4.0	3.4	5.0	5.7	8.1	7.5
Iowa	5.8	9.1	3.4	4.2	4.5	6.6	9.1
Kansas	17.6	16.7	19.1	18.9	15.6	10.3	14.9
Kentucky	7.5	11.4	5.0	5.2	5.3	7.0	8.9
Louisiana	5.6	11.8	2.7	2.5	2.7	3.3	9.1
Maine	8.5	8.7	8.5	8.6	10.0	10.4	6.7
Maryland	10.7	8.6	10.4	10.1	11.2	15.1	8.2
Massachusetts	7.4	12.1	12.0	12.4	12.6	6.1	7.2
Michigan	6.9	4.3	4.6	6.1	6.9	8.5	8.0
Minnesota	8.1	6.8	9.2	10.6	11.0	7.4	11.0
Mississippi	7.0	11.8	4.5	4.2	4.4	4.5	9.6
Missouri	7.2	6.2	7.6	8.7	9.2	7.1	9.6
Montana	16.3	16.8	14.2	13.9	12.3	22.8	11.7
Nebraska	9.6	14.4	8.7	10.7	9.5	7.9	15.7
Nevada	9.8	8.0	14.0	12.1	12.9	11.8	10.4
New Hampshire	6.1	10.4	14.0	11.9	12.1	6.1	8.7
New Jersey	7.5	10.7	9.5	9.3	10.6	8.2	6.6
New Mexico	6.8	7.1	6.6	5.8	6.3	8.9	7.9
New York	7.0	9.1	10.0	9.5	10.9	8.7	7.0
North Carolina	9.5	7.8	13.3	15.1	14.5	7.7	10.6
North Dakota	5.0	7.9	3.1	4.0	4.6	5.6	10.1
Ohio	7.5	6.7	7.3	7.8	8.6	8.8	9.6
Oklahoma	14.0	15.0	12.6	10.1	9.1	5.0	12.6
Oregon	6.9	5.0	7.5	8.7	9.5	7.2	9.1
Pennsylvania	8.8	6.5	10.2	9.8	11.1	13.0	9.7
South Dakota	9.4	7.7	13.1	14.9	14.5	8.2	10.8
South Carolina	4.9	8.7	2.2	3.4	3.7	5.9	9.2
Tennessee	8.7	8.2	7.7	7.8	8.3	12.0	9.4
Texas	14.0	14.5	12.2	10.1	8.7	5.2	11.3
Utah	6.9	8.1	6.2	7.8	8.1	6.5	12.1
Vermont	8.1	8.3	9.2	9.8	11.1	8.5	6.8
Virginia	8.2	6.1	10.5	10.6	11.8	10.1	8.7
Washington	7.2	5.4	7.7	8.6	9.7	8.4	9.8
West Virginia	16.7	16.8	14.8	13.2	12.2	19.7	11.8
Wisconsin	6.1	6.1	5.0	6.4	7.0	6.5	9.4
Wyoming	13.9	16.5	6.1	3.3	2.9	3.0	5.9