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States and the Business Cycle[*]

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Abstract

We model the U.S. business cycle using a dynamic factor model that identifies common factors underlying fluctuations in state-level income and employment growth. We find three such common factors, each of which is associated with a set of factor loadings that indicate the extent to which each state's economy is related to the national business cycle. According to the factor loadings, there is a great deal of heterogeneity in the nature of the links between state and national economies. In addition to exhibiting geographic patterns, the closeness of state economies to the national business cycle is related not only to differences in industry mix but also to non-industry variables such as agglomeration and neighbor effects. Finally, we find that the common factors tend to explain large proportions of the total variability in state-level business cycles, although, again, there is a great deal of cross-state heterogeneity.

JEL classifications: E32, R12
Keywords: State business cycles, Common factors

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1. Introduction

The U.S. economy is not a monolithic entity composed of geographic subparts with perfectly uniform business cycles. Instead, the national economy can be thought of as a composite of its geographic subparts, each moving in relation to each other but not necessarily in tandem. Just as one cannot understand a regional or local economy by looking solely at national data, an understanding of the national economy is incomplete without an understanding of regional and local economies. Furthermore, given this need for a simultaneous understanding of national and regional economies, it is desirable to have a modeling framework that accounts explicitly for the interrelations between national and regional economies.

With this in mind, we use dynamic factors to model the U.S. business cycle as the co-movement in state-level variables. The dynamic factor model allows fluctuations in state economic variables to have both common and idiosyncratic components. The common component in each state-level variable is composed of a relatively small set of latent common factors representing various fluctuations in the aggregate U.S. economy and a set of factor loadings indicating the direction and strength of the relationship between the state-level variable and each common factor.[1] Because the model recognizes both the interrelatedness and the heterogeneity in movements in state-level economic variables, it provides an especially informative empirical framework for studying the links between state and national economies.

We estimate a dynamic factor model for U.S. state-level real-income and employment growth rates for 1990:1–2006:3. We first use the Bai and Ng (2002) procedure to determine the

[1] The idea of modeling the national business cycle using a small set of latent factors is in the spirit of Burns and Mitchell (1946); see, for example, Geweke (1977); Sargent and Sims (1977); Stock and Watson (1989, 1991); Forni, Hallin, Lippi, and Reichlin (2000); and Marcellino (2006).

number of common factors underlying fluctuations in state-level income and employment growth. Using principal components, we then estimate the common factors and the factor loadings for each variable. Our estimation provides us with two sets of indicators of the closeness of the links between states and the national economy: The factor loadings provide estimates of the links between each of the state-level variables and each common factor, while the R^2 statistics measure the overall closeness of the links between each state-level variable and the set of common factors.

Previewing our results, we identify three common factors underlying the fluctuations in state-level income and employment growth, with the first factor corresponding very closely to the aggregate fluctuations in real activity associated with the national business cycle. The common factors—especially the first factor—tend to explain large proportions of the total variability in state-level variables, although there is a great deal of cross-state heterogeneity. We also find, perhaps unsurprisingly, that the closeness of the links between a state's economy and the national business cycle are related to the state's industry mix. More interestingly, non-industry characteristics—including agglomeration—also play a significant role, as do the characteristics of neighboring states.

Our analysis fits into the line of research examining the similarities and co-movements between the national and state or regional economies.[2] Much of this research demonstrates how national economies can be seen as the aggregate of related local economies. Further, models of the business cycle based on national data alone mask important spatial heterogeneities, which

[2] Also see the literature examining the interrelationships between subnational- and national-level analytic relationships, such as Beveridge curves (Börsch-Supan, 1991; Wall and Zoega, 2002) and Phillips curves (Wall and Zoega, 2004).

could potentially be exploited to improve our understanding of how the aggregate economy works.[3] This literature can be categorized by the ways in which regional economies are compared to the aggregate economy and to each other. Carlino and Sill (2001), for example, perform trend/cycle decompositions on regional real income and conclude that there is "considerable divergence of regional business cycles from national cycles." In assessing the suitability of the United States as a common currency area, Partridge and Rickman (2005) calculate the average correlations of states' cyclical components. Crone (2005) and Carlino and DeFina (2004) use the cohesion index of Croux, Forni, and Reichlin (2001) to measure the co-movement of state economies. Finally, Owyang, Piger, and Wall (2005) apply the Markov-switching model of Hamilton (1989) to U.S. states and find significant intranational differences in the occurrence of recessions and expansions.[4]

These studies highlight the tradeoffs associated with avoiding parameter proliferation in disaggregate analysis in that each sacrifices either the level of disaggregation, the number of variables for each region, the complexity of the interrelationships between regions, or some combination of all three. Dynamic factor models, on the other hand, are not subject to restrictions on the number of economic series, thereby making them well suited for analyzing the interrelatedness of national and subnational economies. Forni and Reichlin (2001) and Del

[3] For example, Owyang, Piger, and Wall (2008) show that the reduction in the volatility of U.S. variables around 1983–84 (called the "Great Moderation") can be broken down into distinct state-level moderations occurring between 1977 and 1990. They used this cross section of volatility reductions to test the plausibility of various explanations of the Great Moderation.

[4] The co-movement literature described above fits into a larger literature looking at the interrelationships between the aggregate economy and the economies of states and/or regions. These have examined, for example, state and regional differences in monetary policy (Carlino and DeFina, 1998, 1999; Fratantoni and Schuh, 2003; Owyang and Wall, forthcoming) and state differences in aggregate volatility reduction (Carlino, DeFina, and Sill, 2007; Owyang, Piger, and Wall, 2008).

Negro (2002), for example, exploit these advantages to disentangle state business cycles into national, regional, and state components.[5]

The rest of the paper is organized as follows. Section 2 outlines the basic structure and estimation of the dynamic factor model. Section 3 describes the data and reports estimation results for the dynamic factor model. Section 4 reports estimation results for a series of spatial cross-section regression models that investigate possible explanations for the differences in the estimated income and employment factor loadings across U.S. states. Section 5 concludes.

2. Dynamic Factor Model

The dynamic latent factor model (DFM) that serves as the basis for our empirical analysis can be expressed as

$$X_{it} = \lambda_i' F_t + e_{it} \, , \tag{1}$$

where X_{it} is period t's observation of variable i and each i corresponds to a state-level real economic or financial variable that fluctuates over the business cycle.[6] There are N of these variables, and each is observed for T periods. The term $\lambda_i' F_t$ is the common component of X_{it}, while e_{it} is the idiosyncratic component. $F_t = (F_{1t}, ..., F_{rt})'$ is a vector of the r latent common factors, where the number of common factors is small relative to the number of individual state-level and financial variables. The extent to which X_{it} is related to the common factors is represented by a vector of factor loadings, $\lambda_i = (\lambda_{i1}, ..., \lambda_{ir})'$. The vector of common factors, F_t, is

[5] Their analysis is similar in spirit to Clark (1998), who uses a structural vector autoregression (VAR) to model regional employment fluctuations. While the VAR relaxes the restrictions on the co-movement of variables, the number of parameters to be estimated makes it impractical for modeling large disaggregate systems.

[6] Given that a constant terms in not included in (1), X_{it} is specified in terms of deviations from its mean. This does not affect the generality of the model, as one could instead include a constant terms in (1) and not specify X_{it} in terms of deviations from its mean.

naturally interpreted as representing the national economy because it is common across all of the state-level economic variables and is thus pervasive or national in scope. When X_{it} is a state-level economic variable, the vector of factor loadings indicates the extent to which the state-level variable is related to the national economy. Overall, the factor model given by (1) provides a unified framework for relating fluctuations in state-level economic variables to the national economy.

The key challenge to estimating the latent factor model is that both the factors and factor loadings on the right-hand-side of (1) are unobservable, so we cannot use conventional regression techniques. We estimate (1) using principal components, a popular technique for estimating latent factor models. Principal component estimation of latent factor models has received renewed attention recently in the econometrics literature; see, for example, Bai and Ng (2002, 2006, 2007), Stock and Watson (2002), and Bai (2003). To briefly describe principal component estimation of the factors and factor loadings, it is convenient to express (1) using matrix notation as

$$X = F\Lambda' + e, \tag{2}$$

where $X = (X_1,...,X_N)$, $X_i = (X_{i1},...,X_{iT})'$, $F = (F_1,...,F_r)$, $F_i = (F_{i1},...,F_{iT})'$, $\Lambda = (\lambda_1,\ldots,\lambda_N)'$, $e = (e_1,...,e_N)$, and $e_i = (e_{i1},...,e_{iT})'$. Principal component analysis is based on the following objective function:

$$V(r) = \min_{F,\Lambda}(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - \lambda_i' F_t)^2 . \tag{3}$$

The solution to (3) can be obtained by first concentrating out Λ and using the normalization that $F'F/T = I_r$, which reduces the problem to maximizing $\text{tr}(F'(XX')F)$. The estimated factor matrix, $\tilde{F}$, is thus given by $\sqrt{T}$ times the eigenvectors corresponding to the *r* largest eigenvalues of XX', and the estimated factor loading are given by $\tilde{\Lambda}' = \tilde{F}'X/T$.

While (1) takes the form of a so-called static factor model, the model can be viewed as a dynamic factor model. Stock and Watson (2002) and Bai (2003) show that principal components consistently estimate the factors and factor loadings when we allow F_t to follow a vector autoregressive (VAR) process and e_{it} to obey an autoregressive (AR) process.[7] Furthermore, in contrast with the so-called strict factor model, we can allow for a limited degree of correlation between e_{it} and e_{jt}, as in the approximate factor model of Chamberlain and Rothschild (1983). The overall framework for our DFM is thus quite general, and the factors and factor loadings at the center of our analysis can be conveniently estimated in this framework using principal components.

While principal components provide consistent estimates of the factors and factor loadings in (1), as shown by Bai (2003), it is important to account for the dynamic and approximate aspects of our DFM when constructing standard errors for $\tilde{F}$ and $\tilde{\lambda}$. We do this using the limiting distribution theory in Bai (2003, Sections 3.1 and 3.2). In Monte Carlo simulations, Bai (2003) finds that the limiting distribution theory provides accurate inferences for a variety of finite sample sizes, including sample sizes close to ours.[8]

[7] More-general dynamics could also be introduced directly into (1); see, for example, Forni, Hallin, Lippi, and Reichlin (2000) and Stock and Watson (2005).

[8] The VAR (AR) coefficients of the factor (idiosyncratic) process can be consistently estimated using OLS and the principal component estimates of the factors (fitted residuals). We briefly describe features of these estimates as well as the extent of the contemporaneous correlations of the idiosyncratic components in Section 3 below. Note

The real variables that we include in X_t are the growth rates of real personal income and payroll employment for each of the 48 contiguous states plus the District of Columbia. Alaska and Hawaii are excluded because their business cycles are quite distinct from those of other states (Owyang, Piger, and Wall, 2005). We also include eight financial variables in X_t that are assumed to be common across states: the growth rates of the M1 and M2 money stocks, S&P 500 stock price index, and personal consumption expenditures (PCE) deflator; and first differences of the federal funds rate, 3-month Treasury bill yield, 10-year Treasury bond yield, and Moody's Seasoned Baa Corporate Bond yield. Thus, we have a total of $N = 2 \times 49 + 8 = 106$ variables in X_t for our DFM.[9] We begin with quarterly data for 1990:1–2006:3 and, after losing one observation for differencing, we have $T = 67$ observations for each series.[10]

Using these data, our estimation yields a factor loading for each variable/factor combination, although our concern is with the factor loadings on state-level personal-income and employment growth. Put simply, the r factor loadings for, say, Missouri's employment growth rate measure the co-movement between Missouri's employment growth and each of the r common factors representing the national business cycle. As discussed above, taken together, the set of states' factor loading vectors provides us with convenient measures of state-level differences in the co-movement between the business cycles of the states and the country as a

that estimates of the factor loadings as well as the VAR (AR) coefficients for the factor (idiosyncratic) process could be used to construct a restricted VAR model for $X_t = (X_{it}, \ldots, X_{Nt})'$ that could be used to forecast the individual elements of X_t. While forecasting is beyond the scope of the present paper, it is a potentially fruitful area for future research.

[9] With respect to the estimated factors and state-level real-income and employment factor loadings, we stress that our results are not sensitive to the particular set of financial variables included in X_{it}. Indeed, we obtain similar factor and factor loadings estimates when X_{it} only contains the state-level real-income and employment growth rates.

[10] Our data begin in 1990 to avoid state-level structural breaks associated with the Great Moderation. As mentioned above, Owyang, Piger, and Wall (2008) show that, for some states, breaks associated with the Great Moderation occurred several years after the aggregate break, which they place at September 1984.

whole. Intuitively, a particular state-level variable *i* with "large" ("small") factor loadings is strongly (weakly) linked to the national business cycle, as fluctuations in the common factors representing the national business cycle are associated with large (small) fluctuations in the state-level variable *i*.

Latent factor models are subject to a rotational indeterminacy, as an observationally equivalent model is given by (1) with $\lambda_i H^{-1}$ (HF_t) replacing λ_i (F_t), where H is an $r \times r$ nonsingular matrix. Principal components employ a normalization that chooses a unique *H*. While we could pursue other strategies to identify the factors and factor loadings, we rely on principal component analysis for three primary reasons. First, our results are based in part on the R^2 statistics for each state-level economic variable, which do not depend on *H*. Second, the first common factor corresponds very closely to the concept of a national business cycle and is clearly the most important factor in terms of the R^2 statistics. Finally, for $r > 1$, other estimated factors have reasonable economic interpretations, so principal component estimates of the loadings on the other factors across state-level variables still appear economically meaningful.[11]

3. DFM Estimation Results

As described in Section 2 above, we compute estimates of the factors and factor loadings using principal components. Following common practice and without loss of generality, all of the X_{it}s are standardized to have zero mean and unit variance. Considering a maximum value of

[11] One could try to impose economically motivated restrictions on *H* in order to pursue "structural" identification of the factors and factor loadings; see, for example, Stock and Watson (2005). However, determining the "best" particular set of economically motivated restrictions to impose on *H* can be controversial, and, fortunately, principal component estimation appears to provide economically meaningful estimates of the factors and factor loadings in our application. Analyzing the robustness of different economically motivated restrictions to identify the factors and factors loadings when $r > 1$ is an interesting area for future research.

20 for r, both the Bai and Ng (2002) IC_{p1} and IC_{p2} information criteria indicate three common factors (r = 3) for the DFM.[12]

3.1. Common Factors

Estimates of the three factors are displayed in Figure 1, from which it is clear that the factors each characterize a distinct facet of the national economy.[13] To get an idea of the differences and similarities among the three factors, and to provide an idea of what sort of information each factor represents, we calculate the correlations of each factor with a variety of observable national variables. These correlations are provided in Table 1 and are illustrated by Figures 2–4, which plot the factors along with three select observable variables that the factor is correlated with.

From Figure 2 and the second and third columns of Table 1, we see that the first factor is highly positively correlated with growth in real GDP, real aggregate personal income, and aggregate employment. Because this factor is representative of the real national business cycle, we will refer to this factor henceforth as the "business-cycle" factor. This is also evident in Figure 1, which shows that the first factor exhibits two distinct local minima during the two most recent NBER-dated recessions. The factor also takes on relatively high values during the mid-to-late 1990s, when the U.S. economy experienced especially strong growth. In contrast, although the second factor also is closely correlated with growth in personal income and employment, the

[12] We also used the procedures in Bai and Ng (2007) to identify the number of "primitive" factors in the DFM. The number of primitive factors corresponds to the rank of the spectrum of F_t and is interpreted by Bai and Ng to be the number of shocks driving economic fluctuations. Interestingly, their procedures generally indicate that the number of primitive factors is also three in our DFM, so the spectrum of F_t has full rank.

[13] We computed 95 percent confidence intervals for the factor estimates. However, given that the confidence intervals are very narrow (especially for the first two factors), we omit them from Figure 1, as they would be barely visible.

correlations have opposite signs (see the fourth and fifth columns of Table 1 and Figure 3). Thus, this factor appears to capture what could be termed the "dissonance" between personal-income growth and employment growth.[14] This dissonance factor helps to explain historical episodes such as the "jobless" recovery from the 2001 recession, when income growth was relatively strong but employment growth was relatively weak; see, for example, Aaronson, Rissman, and Sullivan (2004). Indeed, the second factor remained relatively low in the wake of the 2001 recession, helping to account for the sluggish growth of employment during the recovery.

Of the financial variables represented in our DFM, the third factor is most closely related to core inflation (see columns six and seven of Table 1 and Figure 4), although, with reasonably stable real returns, this can be interpreted as capturing movements in the nominal returns on our financial variables. Interestingly, the third factor is also highly correlated with the unemployment rate, which is not included in our DFM. This is likely a remnant of the widely documented simple correlation between inflation and unemployment, sometimes referred to as the wage curve (Blanchflower and Oswald, 1994). Note that this factor behaves quite differently during the two most recent NBER-dated recessions: It is near its maximum value during the 1990–91 recession and takes on a relatively low value during the 2001 recession, signaling differences in the behavior of inflation during the two recessions.[15]

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[14] This factor could also be capturing fluctuations in productivity. However, we found no significant correlation between productivity and this factor.

[15] With respect to the dynamic structure of the DFM, the SIC selects a lag length of one for the common factor VAR process and lag lengths ranging from zero to four for the idiosyncratic component AR processes for state-level personal-income and employment growth. In addition, the average of the absolute values of the contemporaneous correlations across all of the idiosyncratic components for state-level personal-income and employment growth is only 0.13, so the three common factors account for almost all of the contemporaneous correlation across the state-

3.2. State Factor Loadings

As we set out in the introduction, our main interest is in examining the links between the national and state economies, which in the DFM are provided by the states' factor loadings. The six factor loadings for each state provide the statistical relationships between each of the state's two observed series (personal-income and employment growth) and each of the three national common factors. To highlight their geographic patterns, the factor loadings and the R^2s for (1) are portrayed in map form by Figures 5–8. Estimates of the loadings and the R^2s are reported in Appendix A along with indicators of statistical significance.

Note first that the loadings on the business-cycle factor are statistically significant for nearly all states for personal-income growth and employment growth (46 and 47 states, respectively).[16] Second, unsurprisingly, the two sets of factor loadings are highly correlated (0.76 simple correlation), although D.C. and Wyoming are outliers in that for each, personal-income growth is much more closely linked to the business cycle than is employment growth. Third, except for that on employment growth for the District of Columbia, the loadings are all positive, indicating the strong tendency for states' economies to move in the same direction as the national economy. Nevertheless, as depicted by Figure 5, there is a great deal of heterogeneity across states. The states that follow the national business cycle most closely (i.e., those with the highest factor loadings) are spread fairly widely across the United States and include Texas, Arizona, Colorado, Oregon, Illinois, Wisconsin, Minnesota, and Massachusetts,

level variables. The complete set of VAR and AR coefficient estimates and contemporaneous correlations are available upon request from the authors.

[16] Throughout, we will use "statistical significance" to mean at the 5 percent level or better, although for reference we also denote 10 percent significance in all of our tables.

along with much of the Atlantic seaboard, especially the Southeast. There are stronger regional groupings among the states with the smallest loadings, such as the six adjacent states in the upper Midwest and Mountain regions (North Dakota, South Dakota, Nebraska, Idaho, Wyoming, and Montana) and Mississippi and Louisiana.

Most loadings on the dissonance factor are statistically significant (41 for personal income and 40 for employment), and the two sets of loadings are positively correlated (0.44 simple correlation), with D.C. again as an outlier. Regional groupings are perceptible for the loadings on personal-income growth. Specifically, personal-income growth in Pennsylvania, New Jersey, Delaware, Maryland, Virginia, West Virginia, Kentucky, Missouri, and Arkansas have the strongest (negative) relationship with dissonance, while the link is weakest for seven adjacent states in the western half of the country (New Mexico, Arizona, Utah, Colorado, Nevada, Idaho, and Oregon). The regional patterns are less obvious for the loadings on employment growth, but, unsurprisingly, the states with the weakest links between dissonance and personal-income growth tend to have the strongest links between dissonance and employment growth, and vice versa.

The links between states' economies and the third factor (nominal returns) are quite a bit more disparate than for the first two factors, although the two sets are highly correlated (0.75 simple correlation), with Wyoming as an outlier. There are fewer states whose loading on nominal returns is statistically significant (26 for personal income and 33 for employment) and, of these states, the signs of the loadings can be positive or negative. Specifically, there are 20 of these states whose personal-income growth tends to move in the same direction as this factor, and six with a positive co-movement. For employment growth, 17 states tend to move alongside the factor, while there are 16 that tend to move counter to it. As shown by Figure 7, the largest negative loadings are for California and most of the states from Maryland through Maine, while the largest positive loadings are all for states between Mississippi and Idaho.

Taken together, the three factors generally do a good job of explaining movements in states' personal-income growth, and an even better job of explaining movements in employment growth: The mean R^2 on personal-income growth is 0.54 while that on employment growth is 0.64. There is significant cross-state variation, however, as the standard deviations of the R^2s are 0.21 and 0.18, respectively. The geographic patterns are illustrated by Figure 8. The states for which the factors explain personal-income growth best (i.e., $R^2 > 0.75$) are Georgia, Massachusetts, Maryland, Texas, and Wisconsin. The largest concentration of low-R^2 states is the six-state cluster from Washington state to the Dakotas. The highest and lowest R^2s on employment growth are more concentrated geographically, with the highest tending to be along the East Coast and the lowest located between Louisiana to Montana.

Note that the first (business-cycle) factor is the most important in terms of explanatory power for state-level personal-income and employment growth. Given that the factors are orthogonal by construction, we can cleanly decompose the R^2 into the portions accounted for by each factor. Of the total average R^2 across states of 0.54 for personal-income growth, 0.35 is attributable to the first factor. Similarly, the first factor accounts for 0.42 of the total average R^2 of 0.64 for employment growth.

4. Examining the Links between State and National Cycles

As we have emphasized, the first factor clearly captures aggregate fluctuations in real variables corresponding to the national business cycle. Consequently, the factor's two sets of loadings, which measure the closeness of state-level income and employment outcomes to the aggregate business cycle, are the most interesting. The next natural step is to search for the determinants of these measures of closeness.

4.1. Spatial Durbin Model

To begin this search, we estimate a series of spatial Durbin models, each of which takes the form:

$$\tilde{\lambda}_1^j = \rho W \tilde{\lambda}_1^j + D\beta_0 + Z\beta_1 + +WZ\beta_2 + \nu \,, \tag{4}$$

where $\tilde{\lambda}_1^j$ is the 49×1 vector of estimated factor loadings for the business-cycle factor for state-level income growth ($j = y$) or state-level employment growth ($j = e$). We estimate (4) using maximum-likelihood under the assumption that $\nu \sim N(0, \sigma^2 I_{49})$.[17] The possibility of spatial autocorrelation is captured by ρW, where ρ is a scalar parameter and W is a 49×49 contiguity matrix. Census-region-specific effects are captured by the 49×4 matrix D. The state-level variables of interest are collected into the 49×10 vector Z. Finally, we include WZ to capture the effects that the characteristics of state's neighbors' might have on its responsiveness to the national business cycle.

The variables in Z fall into two categories: industry mix and non-industry characteristics. This distinction is useful because industries themselves will differ in their relationships with the

[17] We use maximum-likelihood estimation because, as is well known, least squares estimation of (4) produces biased and inconsistent estimates; see, for example, LeSage (1999).

aggregate business cycle, regardless of the states in which the industry's employees are located. It would be more interesting, perhaps, if states' cycles differed from the national cycle because of factors other than their industry composition. Clark (1998), for example, found that roughly 40 percent of the variations in Census-division employment growth was division-specific, even after controlling for industry effects.

To account for differences in industry mix, we include employment shares in manufacturing; natural resources, mining and construction; professional and business services; and government, each calculated as the difference between the average state share over the sample period and the cross-state mean over the sample period. At the aggregate level, employment growth in mining, natural resources, and construction; manufacturing; and professional and business services have been highly correlated with real GDP growth, while employment growth in the government sector has been much less correlated with GDP growth.[18] We would, therefore, expect positive coefficients on employment shares in the first of these three sectors and a negative coefficient on employment share in government.

To capture non-industry effects, we include in *Z* measures of human capital, exposure to the international economy, firm size, and agglomeration. Each variable is again calculated as the sample period average relative to the cross-state mean. Our two human capital variables are the shares of the population aged over 25 with a high school diploma (but no college degree) and the share with at least a bachelor's degree, both averaged over 1990 and 2000. As documented by

[18] According to our own calculations for 1990–2006, the simple correlations between quarterly GDP growth and employment growth in mining, natural resources, and construction; manufacturing; professional and business services; and government were 0.53, 0.41, 0.57, and 0.10, respectively. The average correlation across all 10 major sectors is 0.27, and across the 6 excluded sectors is 0.18. Note that, to be consistent with state-level data, we have combined the mining and natural resources and construction sectors.

Hoynes (2000), employment and wage outcomes for those with the most education fluctuate the least over the business cycle. We would expect, therefore, that outcomes in states with relatively large shares of educated adults would be less responsive to fluctuations in the aggregate business cycle.

Between 1996 and 2006, the average state's exports comprised just over 6 percent of gross state product (GSP), with values ranging from a low of 1 percent for Delaware to a high of 19 percent for Vermont. Because demand from overseas markets might help to separate a state's economy from the fluctuations in the domestic business cycle, we include states' average export shares in *Z*. We also include in *Z* the average size of establishments in the states over 1990–2005. According to Gertler and Gilchrist (1994), among others, large firms are relatively insulated from business cycle fluctuations because they have better access to financial markets. According to this hypothesis, we would expect a negative relationship between states' factor loadings and their average establishment sizes.[19]

We include two variables—establishment density and urban population share—to capture the effects of agglomeration on the links between state economies and the national business cycle.[20] At least two of the standard sources of agglomeration economies on local productivity might play a role.[21] First, through labor-market pooling, greater agglomeration means that the process of matching of workers to firms is more flexible and more efficient, thereby allowing local economies to respond more readily to fluctuations in the national business climate, thereby

[19] Helfand, Sadeghi, and Talan (2007), however, report that employment losses experienced during and after the 1990–91 recession were larger for small firms, while the opposite was true for the 2001 recession.

[20] Density is the number of establishments per square mile of land area, averaged over 1990–2005. Urban share is the share of population in urban areas averaged over 1990 and 2000 using the 2000 definitions of urban areas.

[21] See Rosenthal and Strange (2004) for a discussion of the nature and sources of agglomeration economies.

reducing the impact of the national business cycle on the local economy. Second, similar to the argument for exposure to international economies, a large and concentrated home market for a state's firms means a relatively smaller role for the rest of the economy in determining state-level outcomes, again potentially insulating the local economy from the national business cycle.

4.2. Spatial Durbin Results

In addition to the general specification of (4), we also estimated four restricted versions: no regional effects, no industry effects, no non-industry state characteristics, and no neighbor effects. For each of the restricted versions we report the results of likelihood ratio tests of the null hypothesis that the restrictions do not have an effect on the general results.[22]

Our results are reported in Table 2. First, region effects matter, at least for the personal income loadings. The positive and statistically significant coefficient on the South dummy indicates that economies of states in that region tend to follow the national business cycle more closely than states in the Northeast. Neither of the other two regions is statistically different from the Northeast in this respect. A likelihood-ratio test rejects the null that region effects do not matter statistically for the personal income loadings, although it fails to reject it for the employment loadings.

Consistent with the notion that industry cycles move heterogeneously with the national cycle, a state's industry mix is important in determining the closeness of its economy to the national business cycle. According to the likelihood-ratio tests, our industry-mix variables are statistically significant as a group. Individually, the coefficients on the industry employment

[22] In addition, we report in appendices cross-section estimation results for the loadings on the other two factors using the same independent variables and likelihood-ratio tests.

shares all have the expected signs when they are statistically significant. The negative sign on the government share indicates that the economies of states with a relatively high share of employment in the government sector are less-closely linked with the national business cycle. Put another way, a large government sector acts as a buffer (during upswings as well as downswings) between the national business cycle and state economies. In contrast, and consistent with expectations, the economies of states with a relatively high share in the professional and business services sector are more closely linked to the national business cycle.

As a group, according to a likelihood-ratio test, our non-industry state characteristics are statistically significant, dispelling the notion that state cycles are mere reflections of industry cycles. Not all of the non-industry variables are statistically significant, however. For example, we find no evidence to support the hypothesis that the average education level of a state's population has a role in determining the strength of the links between the state's economy and the national business cycle: Neither of the coefficients on our education variables is statistically different from zero for either set of loadings. Likewise, our results provide no support for the possibility that the links between state and national economies are related to states' exposure to international markets.[23]

Average establishment size tends to matter statistically for the link between the national business cycle and state employment growth, but not for the link with state personal-income growth. This is consistent with larger firms being better able to smooth their employment across fluctuations of the business cycle than they are the wages and salaries that they pay.

[23] This is one aspect with which Hawaii and Alaska probably differ from the contiguous states. Owyang, Piger, and Wall (2005), for example, report how the recession and expansion phases for Hawaii are more similar to those of Japan than to the United States.

We also identify a new manner by which agglomeration affects state economies, namely, as a determinant of the strength of the relationship between the state economies and the national business cycle. Both of our measures of agglomeration are related to links between state and national economies, and the directions of these links are consistent with expectations. The negative signs on establishment density for both sets of factor loadings mean that the economies of more-dense states are less closely linked to the national business cycle. Through labor-market pooling and/or home-market effects, the economies of a densely populated state can be partly insulated from the national business cycle. On the other hand, only the coefficient on urbanization for employment loadings is statistically significant. So, while the ability to find labor-market matches independent of the national cycle appears to be enhanced by urbanization, the growth of personal income (which includes non-labor income and income from outside a state) is not.

Finally, taken as a group, neighbor effects are statistically significant for personal-income growth loadings but not for employment loadings, according to likelihood-ratio tests. Taken individually, there are similarities in which variables matter for the state directly and which matter via its neighbors. For example, the sizes of a state's neighbors' government and professional services sectors are related in the same way as the state's own government and professional services sectors, as is average establishment size. There is a difference, however, between the importance of own-state and neighboring-states agglomeration. We find that the effects that labor-market pooling and dense home markets have on the separation between state and national economies do not extend beyond the state's borders. This echoes previous findings that agglomeration externalities are a relatively localized effect and can attenuate fairly rapidly with distance (Rosenthal and Strange, 2003). Finally, there are interesting and, for now, inexplicable differences between own-state and neighboring-state variables: The economies of states with relatively manufacturing-intensive neighbors or neighbors with relatively large numbers of adults with bachelors degrees tend to be less-closely linked to the national business cycle. Recall, however, that neither a state's own manufacturing intensity nor its own average human capital levels were found to be related to the factor loadings.

5. Summary and Conclusions

This paper uses a dynamic factor model to identify common factors underlying fluctuations in state-level income and employment growth. We find that the national economy can be summarized with three such common factors representing the national business cycle, the dissonance between personal-income growth and employment growth, and core inflation and/or nominal returns. Associated with each factor is a set of loadings that indicate the extent to which each state's economy is related to the corresponding factor. According to the factor loadings, there is a great deal of heterogeneity in the strength, and sometimes the direction, of the links between state and national economies.

We also estimate a series of spatial Durbin models to find covariates of the loadings for the business cycle factor. We find that the links between state economies and the national business cycle are related to differences in states' industry mix, average establishment size, and agglomeration. Lastly, we find that the characteristics of a state's neighbors are also related to its economy's closeness to the national business cycle.

We conclude by highlighting two implications of our results. First, empirical models of the business cycle based on aggregate data alone mask important heterogeneities in the behavior of state economies. These heterogeneities could potentially be exploited to improve our understanding of how the aggregate economy works. Although such exploitation along the lines of Owyang, Piger, and Wall (2008) is beyond the scope of this paper, our approach does present a way to extract the national business cycle from fluctuations in state-level variables, rather than as fluctuations in the aggregate of state-level variables. Our real business cycle factor is, therefore, less subject to aggregation bias and might provide a more accurate picture of the national economy.

Second, the links between state and national economies are affected by a variety of factors and are not merely reflections of industry effects. Specifically, estimating a version of the cross-section model that excludes the non-industry state characteristics yields an R^2 of 0.44 for the personal-income loadings and 0.40 for the employment loadings. As reported in Table 2, when these variables are included the R^2 for both sets of loadings is 0.82.

Appendix A. Estimated Factor Loadings

	Business Cycle		Dissonance		Nominal Returns		Fit	
	Personal Income	Employ-ment	Personal Income	Employ-ment	Personal Income	Employ-ment	Personal Income	Employ-ment
State	$\hat{\lambda}_{i1}$	$\hat{\lambda}_{i1}$	$\hat{\lambda}_{i2}$	$\hat{\lambda}_{i2}$	$\hat{\lambda}_{i3}$	$\hat{\lambda}_{i3}$	R^2	R^2
Alabama	0.549*	0.634*	-0.449*	0.515*	0.241*	0.203*	0.569	0.719
Arizona	0.739*	0.679*	-0.201*	0.415*	-0.015	-0.098	0.595	0.653
Arkansas	0.497*	0.617*	-0.496*	0.515*	0.347*	0.387*	0.623	0.807
California	0.697*	0.586*	-0.473*	0.123	-0.142*	-0.486*	0.741	0.604
Colorado	0.723*	0.711*	-0.152	0.501*	0.009	0.100	0.555	0.778
Connecticut	0.699*	0.651*	-0.467*	0.114	-0.020	-0.516*	0.718	0.714
Delaware	0.433*	0.586*	-0.504*	0.163*	-0.063	-0.281*	0.452	0.455
Dist. Of	0.166†	-0.084	-0.320*	-0.111	-0.055	-0.442*	0.135	0.218
Florida	0.682*	0.723*	-0.449*	0.317*	-0.096	-0.295*	0.686	0.722
Georgia	0.796*	0.797*	-0.393*	0.365*	0.131*	-0.005	0.817	0.780
Idaho	0.511*	0.559*	-0.110	0.506*	0.124	0.306*	0.294	0.673
Illinois	0.709*	0.790*	-0.431*	0.374*	0.133*	0.004	0.717	0.776
Indiana	0.719*	0.606*	-0.408*	0.464*	0.215*	0.171*	0.741	0.621
Iowa	0.442*	0.693*	-0.332*	0.435*	0.260*	0.248*	0.379	0.742
Kansas	0.629*	0.642*	-0.471*	0.256*	0.195*	0.156†	0.665	0.510
Kentucky	0.660*	0.712*	-0.499*	0.451*	0.168*	0.057	0.723	0.725
Louisiana	0.014	0.225*	-0.103	0.141*	0.091	0.133*	0.019	0.090
Maine	0.495*	0.662*	-0.461*	-0.008	-0.151*	-0.421*	0.488	0.625
Maryland	0.604*	0.663*	-0.587*	0.117	-0.230*	-0.592*	0.774	0.816
Massachusetts	0.741*	0.771*	-0.443*	0.224*	-0.129*	-0.422*	0.774	0.836
Michigan	0.577*	0.676*	-0.266*	0.435*	0.148	0.023	0.432	0.656
Minnesota	0.663*	0.736*	-0.422*	0.279*	0.116	0.140*	0.641	0.649
Mississippi	0.247*	0.541*	-0.139	0.464*	0.231*	0.341*	0.136	0.634
Missouri	0.629*	0.700*	-0.515*	0.449*	0.182*	-0.041	0.705	0.704
Montana	0.241*	0.438*	-0.326	0.256*	0.080	0.457*	0.174	0.473
Nebraska	0.435*	0.563*	-0.453*	0.292*	0.220*	0.317*	0.449	0.510
Nevada	0.638*	0.573*	-0.222*	0.437*	0.286*	-0.066	0.546	0.532
New Hampshire	0.573*	0.685*	-0.405*	0.245*	-0.044	-0.353*	0.502	0.665
New Jersey	0.681*	0.651*	-0.498*	0.030	-0.029	-0.587*	0.723	0.781
New Mexico	0.281*	0.494*	-0.240	0.362*	0.270*	0.259*	0.213	0.449
New York	0.545*	0.685*	-0.412*	0.246*	-0.089	-0.603*	0.482	0.907
North Carolina	0.763*	0.790*	-0.312*	0.386*	0.077	-0.064	0.696	0.789
North Dakota	0.222†	0.426*	-0.302*	0.257*	0.237*	0.436*	0.200	0.444
Ohio	0.697*	0.731*	-0.388*	0.486*	0.153*	0.035	0.670	0.784
Oklahoma	0.610*	0.606*	-0.406*	0.324*	-0.073	0.044	0.550	0.482
Oregon	0.740*	0.678*	-0.007	0.544*	0.119	0.054	0.570	0.769
Pennsylvania	0.637*	0.763*	-0.548*	0.212*	0.003	-0.400*	0.717	0.799
Rhode Island	0.515*	0.533*	-0.493*	0.057	-0.273*	-0.486*	0.592	0.532
South Carolina	0.764*	0.649*	-0.309*	0.377*	0.029	-0.155*	0.691	0.597
South Dakota	0.262*	0.452*	-0.314*	0.383*	0.242*	0.536*	0.229	0.648
Tennessee	0.640*	0.729*	-0.367*	0.414*	0.241*	0.182*	0.611	0.747
Texas	0.802*	0.717*	-0.408*	0.457*	-0.002	-0.042	0.822	0.736
Utah	0.700*	0.581*	-0.196	0.574*	0.181*	0.291*	0.569	0.763
Vermont	0.623*	0.660*	-0.407*	0.207*	-0.075	-0.322*	0.569	0.591
Virginia	0.579*	0.797*	-0.489*	0.281*	-0.159	-0.387*	0.609	0.878
Washington	0.378*	0.672*	-0.360*	0.219	0.140	0.126	0.296	0.523
West Virginia	0.465*	0.713*	-0.497*	0.159*	0.270*	0.190*	0.545	0.579
Wisconsin	0.749*	0.721*	-0.472*	0.451*	0.203*	0.179*	0.838	0.766
Wyoming	0.305*	0.188	-0.370*	0.034	-0.338*	0.109	0.349	0.049
Mean	0.561	0.629	-0.373	0.515	0.069	0.203	0.543	0.639
Std. Deviation	0.186	0.163	0.129	0.163	0.162	0.312	0.206	0.180

Statistical significance of 5 and 10 percent is indicated by "*" and "†", respectively.

Appendix B. Covariates of the Loadings on the Dissonance Factor

	Personal Income		Employment	
General Durbin model	coeff.	*t*-stat.	coeff.	*t*-stat.
Constant	-3.902*	-2.68	-1.410	-0.82
Midwest	-0.136	-1.24	0.013	0.10
South	-0.198†	-1.86	-0.027	-0.21
West	-0.079	-0.59	-0.065	-0.41
Manufacturing share	-0.012	-0.19	0.095	1.38
Natural resource, mining, & constr. share	0.575*	3.31	0.249	1.22
Professional & business services share	-0.272*	-2.45	-0.036	-0.27
Government share	0.132	1.32	-0.235 *	-1.99
HS degree share	0.058	0.18	0.443	1.19
BA degree share	0.500*	3.11	0.180	0.94
Export share	0.004	0.20	-0.032	-1.30
Establishment size	0.210	1.24	-0.027	-0.14
Establishment density	0.008†	1.96	-0.002	-0.44
Urban share	-0.147	-1.21	-0.124	-0.87
W-Manufacturing share	0.506*	3.14	0.080	0.41
W-Natural resource, mining, & constr. share	0.807*	3.65	0.059	0.24
W-Professional & business services share	-0.757*	-2.95	0.130	0.43
W-Government share	0.308	0.97	0.480	1.26
W-HS degree share	-0.699	-0.86	0.225	0.24
W-BA degree share	0.547*	2.13	-0.587 †	-1.93
W-Export share	0.101†	1.85	0.110 †	1.72
W-Establishment size	1.388*	2.75	0.469	0.79
W-Establishment density	-0.013	-0.93	-0.043 *	-2.66
W-Urban share	0.251	1.11	0.414	1.55
Rho	-0.374†	-1.92	-0.319	-1.58
R-squared	0.698		0.743	
Likelihood-ratio tests	L ratio	*p*-value	L ratio	*p*-value
Region effects	5.570	0.135	0.721	0.868
Industry mix	29.817*	0.000	16.151 *	0.040
Non-industry state characteristics	25.193*	0.001	13.843 †	0.086
Neighbor effects	30.444*	0.001	13.906	0.177

The table reports maximum likelihood estimates for the spatial Durbin model (4). Northeast is the reference Census region and a "W" indicates that the variables are interacted with the spatial weighting matrix. The likelihood ratio corresponds to a test of the null hypothesis that restricting the coefficients on the variables to zero has no effect on the results. Statistical significance of 5 and 10 percent is indicated by "*" and "†", respectively.

Appendix C. Covariates of the Loadings on the Nominal Returns Factor

	Personal Income		Employment	
General Durbin model	coeff.	*t*-stat.	coeff.	*t*-stat.
Constant	1.529	0.85	0.576	0.27
Midwest	0.357*	2.62	0.484*	2.98
South	0.108	0.83	0.287†	1.85
West	0.085	0.52	0.338†	1.75
Manufacturing share	-0.093	-1.28	0.094	1.08
Natural resource, mining, & constr. share	0.484*	2.24	0.805*	3.20
Professional & business services share	-0.238†	-1.74	-0.618*	-3.78
Government share	-0.206†	-1.67	0.149	1.02
HS degree share	-0.461	-1.18	-0.108	-0.24
BA degree share	0.085	0.42	0.056	0.24
Export share	-0.035	-1.37	-0.038	-1.27
Establishment size	0.277	1.33	0.032	0.13
Establishment density	-0.001	-0.16	0.008	1.23
Urban share	-0.481*	-3.16	-0.170	-0.92
W-Manufacturing share	0.259	1.30	0.525*	2.23
W-Natural resource, mining, & constr. share	0.108	0.43	-0.228	-0.74
W-Professional & business services share	0.038	0.12	-0.441	-1.14
W-Government share	-0.269	-0.68	0.293	0.61
W-HS degree share	-0.816	-0.81	-1.330	-1.12
W-BA degree share	-0.493	-1.56	-0.026	-0.07
W-Export share	0.102	1.53	0.005	0.06
W-Establishment size	-0.555	-0.87	-0.944	-1.30
W-Establishment density	0.011	0.62	0.012	0.60
W-Urban share	0.708*	2.50	1.032*	3.14
Rho	-0.380*	-1.95	0.078	0.44
R-squared	0.707		0.905	
Likelihood-ratio tests	L ratio	*p*-value	L ratio	*p*-value
Region effects	13.701*	0.003	9.641*	0.022
Industry mix	6.565	0.584	24.540*	0.002
Non-industry state characteristics	23.832*	0.002	17.470*	0.026
Neighbor effects	11.516	0.319	16.225†	0.093

The table reports maximum likelihood estimates for the spatial Durbin model (4). Northeast is the reference Census region and a "W" indicates that the variables are interacted with the spatial weighting matrix. The likelihood ratio corresponds to a test of the null hypothesis that restricting the coefficients on the variables to zero has no effect on the results. Statistical significance of 5 and 10 percent is indicated by "*" and "†", respectively.

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Table 1. Correlations Between Estimated Factors and Observable Aggregate Variables

Standardized Observable Variable	First factor coeff.	First factor *t*-stat.	Second Factor coeff.	Second Factor *t*-stat.	Third Factor coeff.	Third Factor *t*-stat.
Real GDP growth	0.60*	5.60	0.00	0.02	-0.18	-0.95
Unemployment rate	-0.14	-0.86	0.22†	1.89	0.66*	5.95
Real personal-income growth	0.77*	7.65	-0.56*	-3.36	0.06	0.33
Employment growth	0.83*	10.91	0.42*	2.95	-0.21	-0.87
CPI inflation	-0.10	-0.42	0.30	1.59	0.27†	1.94
Core CPI inflation	-0.20	-0.76	0.19†	1.73	0.68*	3.80
PCE deflator inflation	-0.15	-0.64	0.24	1.37	0.41*	3.17
Core PCE deflator inflation	-0.19	-0.83	0.12	1.40	0.76*	6.01
CPI food and beverage inflation	-0.04	-0.28	-0.13†	-1.88	0.11	0.76
CPI piped gas and electricity inflation	0.02	0.18	-0.07	-0.77	-0.04	-0.69
Commodity-price inflation	0.04	0.25	0.20*	2.06	-0.02	-0.13
Oil-price inflation	0.07	0.60	0.24	1.24	-0.22*	-3.06

The table reports correlation coefficients for the estimated factors and standardized observable variables. The *t*-statistics are based on Newey and West (1987) HAC standard errors computed using a lag truncation parameter of eight. Statistical significance of 5 and 10 percent is indicated by "*" and "†", respectively.

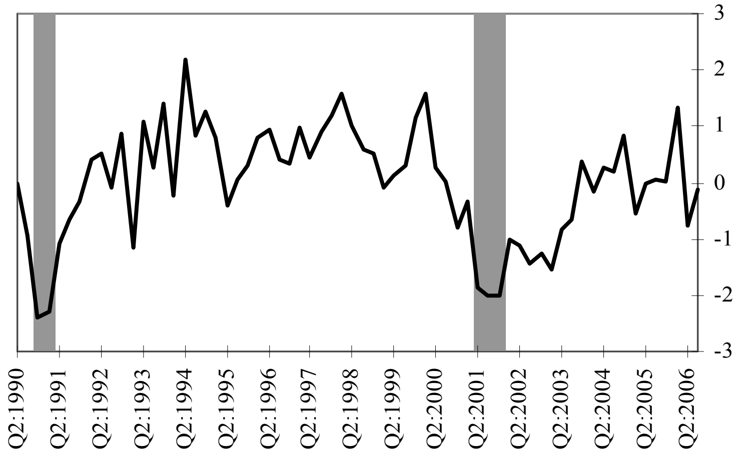
Table 2. Covariates of the Loadings on the Business-Cycle Factor

	Personal Income		Employment	
General Durbin model	coeff.	*t*-stat.	coeff.	*t*-stat.
Constant	2.092	1.21	4.341*	2.86
Midwest	0.082	0.63	0.172	1.51
South	0.269*	2.14	0.189†	1.73
West	0.102	0.64	0.172	1.25
Manufacturing share	0.112†	1.61	0.070	1.15
Natural resource, mining, & constr. share	-0.191	-0.93	-0.259	-1.46
Professional & business services share	0.333*	2.46	0.434*	3.76
Government share	-0.679*	-5.65	-0.808*	-7.86
HS degree share	0.512	1.36	-0.140	-0.43
BA degree share	0.218	1.14	-0.147	-0.89
Export share	-0.002	-0.07	0.000	0.01
Establishment size	-0.196	-0.98	-0.353*	-2.03
Establishment density	-0.023*	-4.58	-0.009*	-2.06
Urban share	0.018	0.13	-0.325*	-2.63
W-Manufacturing share	-0.404*	-2.08	-0.282†	-1.69
W-Natural resource, mining, & constr. share	-0.271	-1.13	-0.245	-1.17
W-Professional & business services share	0.809*	2.57	0.588*	2.15
W-Government share	-0.903*	-2.30	-0.420	-1.19
W-HS degree share	0.798	0.83	-0.094	-0.11
W-BA degree share	-0.638*	-2.10	-0.555*	-2.11
W-Export share	-0.099	-1.55	0.003	0.05
W-Establishment size	-0.860	-1.44	-1.151*	-2.22
W-Establishment density	-0.015	-0.95	0.007	0.47
W-Urban share	-0.168	-0.62	-0.116	-0.47
Rho	-0.057	-0.30	-0.095	-0.48
R-squared	0.816		0.817	
Likelihood-ratio tests	L ratio	*p*-value	L ratio	*p*-value
Region effects	8.375*	0.039	3.029	0.387
Industry mix	42.680*	0.000	58.948*	0.000
Non-industry state characteristics	37.304*	0.000	26.648*	0.001
Neighbor effects	24.457*	0.006	11.123	0.348

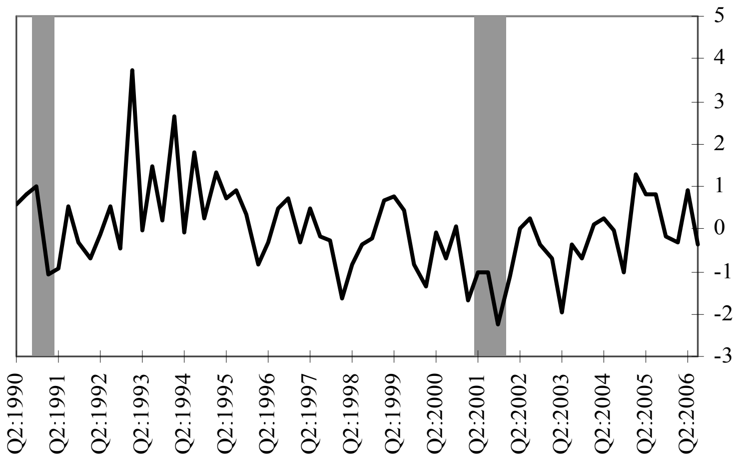
The table reports maximum likelihood estimates for the spatial Durbin model (4). Northeast is the reference Census region and a "W" indicates that the variables are interacted with the spatial weighting matrix. The likelihood ratio corresponds to a test of the null hypothesis that restricting the coefficients on the variables to zero has no effect on the results. Statistical significance of 5 and 10 percent is indicated by "*" and "†", respectively.

Figure 1. Estimated Factors
(Gray areas indicate NBER recessions)

First Factor



Second Factor



Third Factor

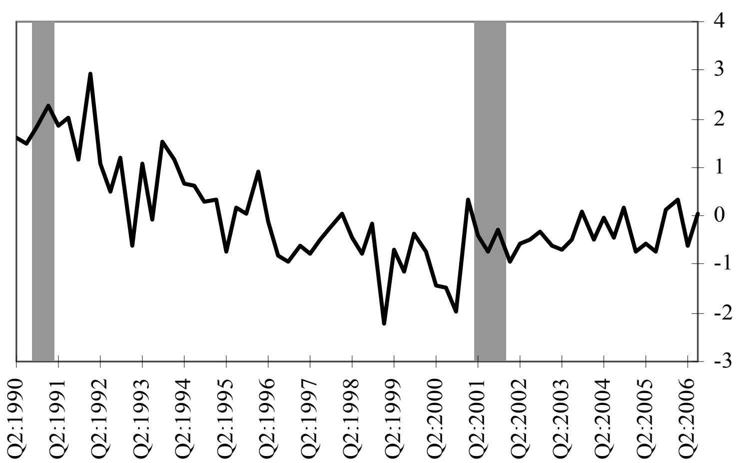


Figure 2. Aggregate Covariates of the First Factor
(Factor in black and covariate in gray)

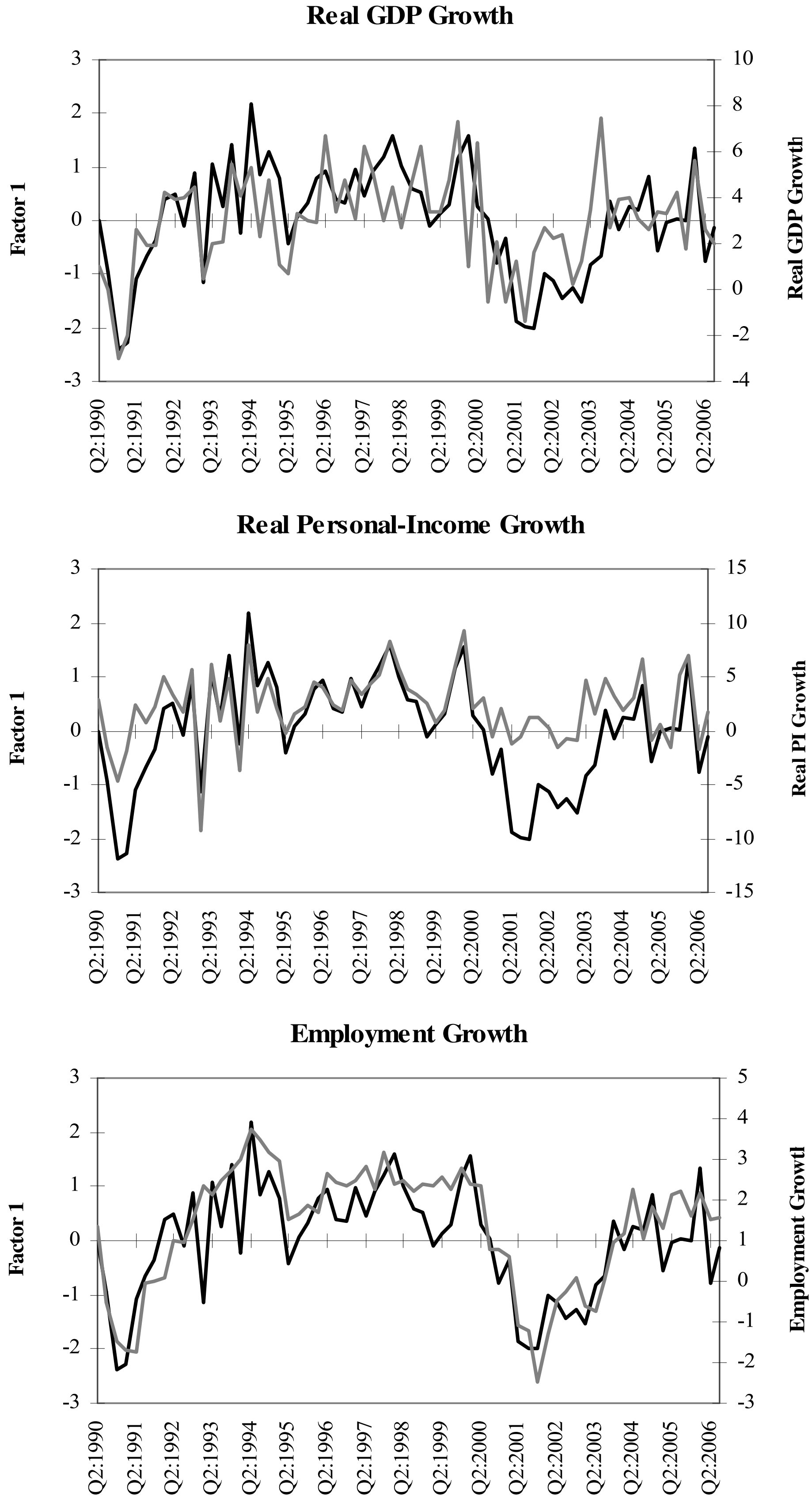
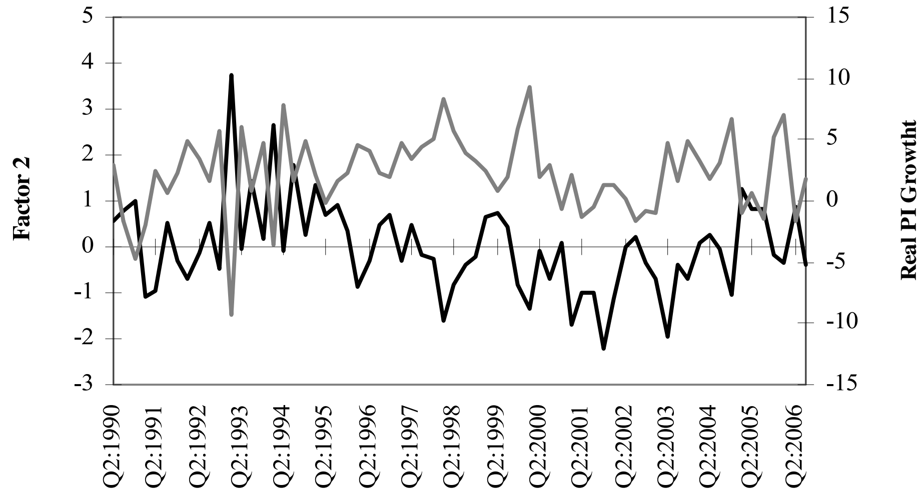


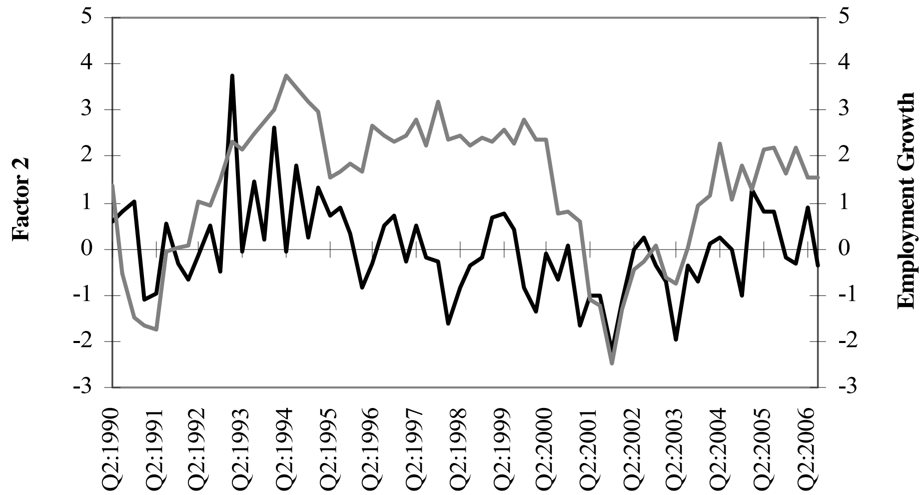
Figure 3. Aggregate Covariates of the Second Factor

(Factor in black and covariate in gray)

Real Personal-Income Growth



Employment Growth



Commodity-Price Inflation

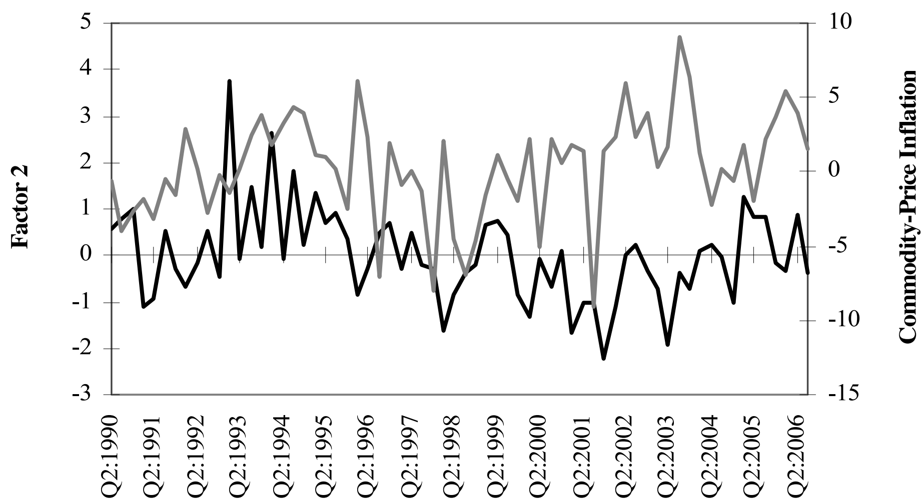
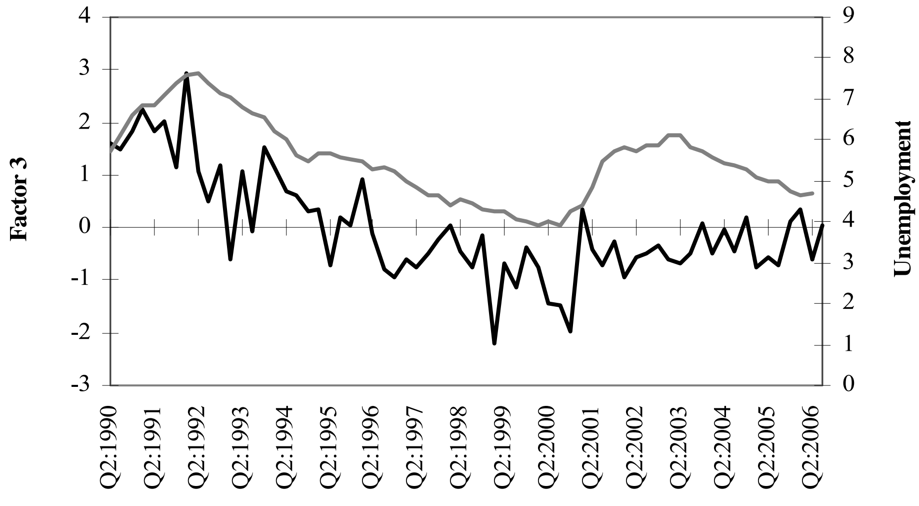
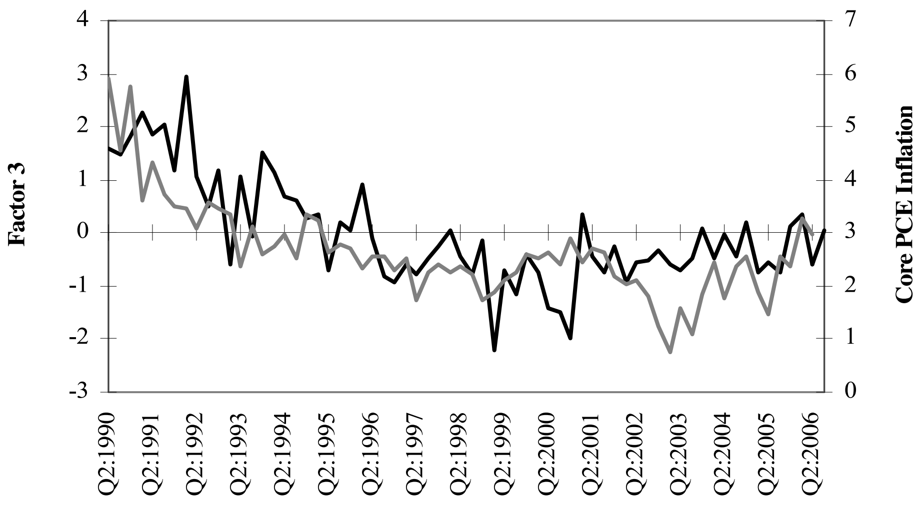


Figure 4. Aggregate Covariates of the Third Factor
(Factor in black and covariate in gray)

Unemployment Rate



Core PCE Inflation



Oil-Price Inflation

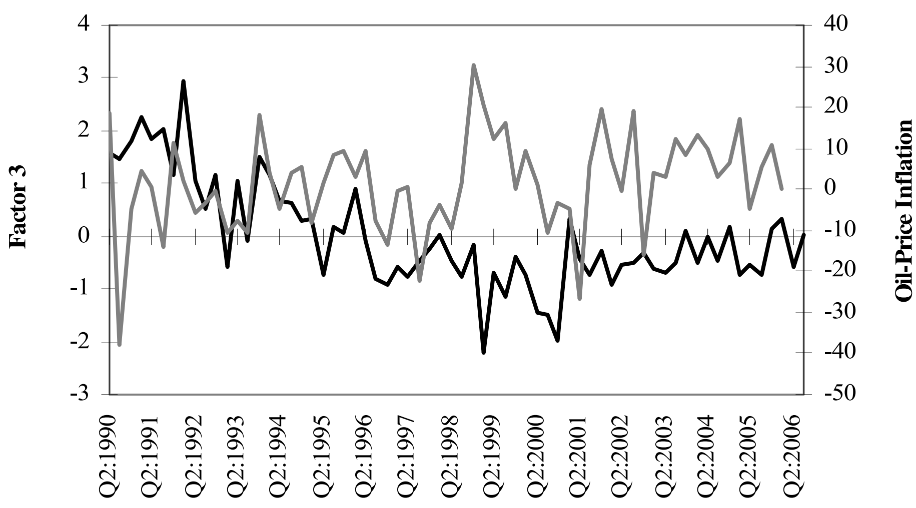


Figure 5. Business-Cycle Factor Loadings

Personal Income | Employment

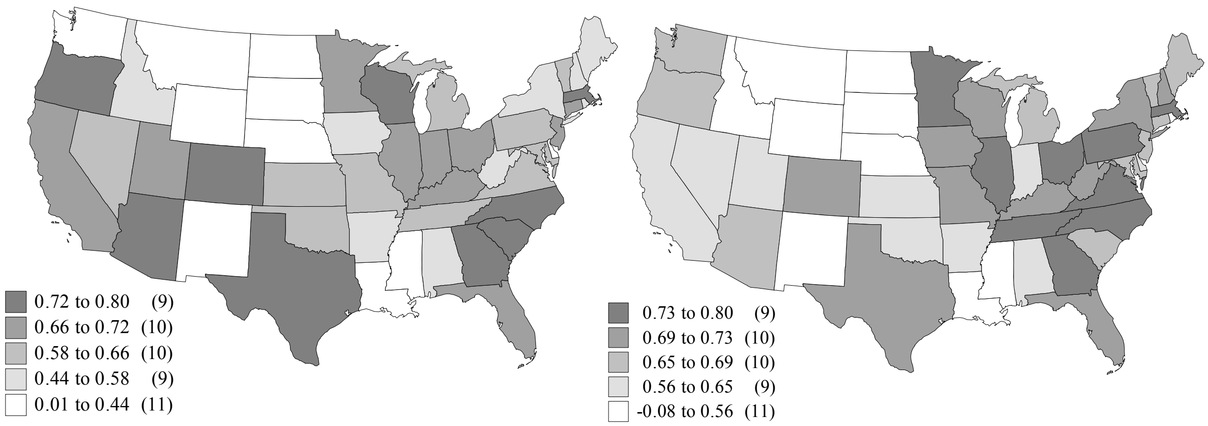


Figure 6. Dissonance Factor Loadings

Personal Income | Employment

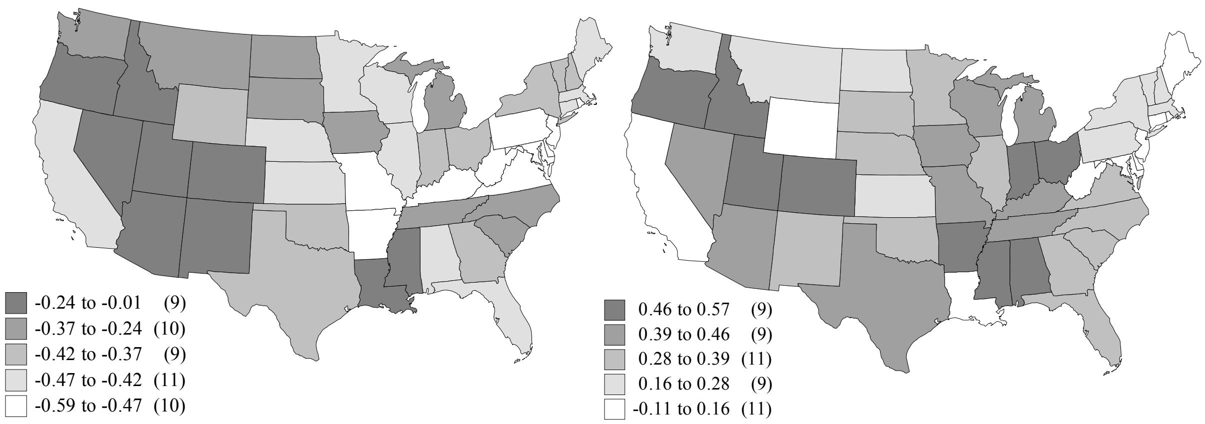


Figure 7. Nominal Returns Factor Loadings

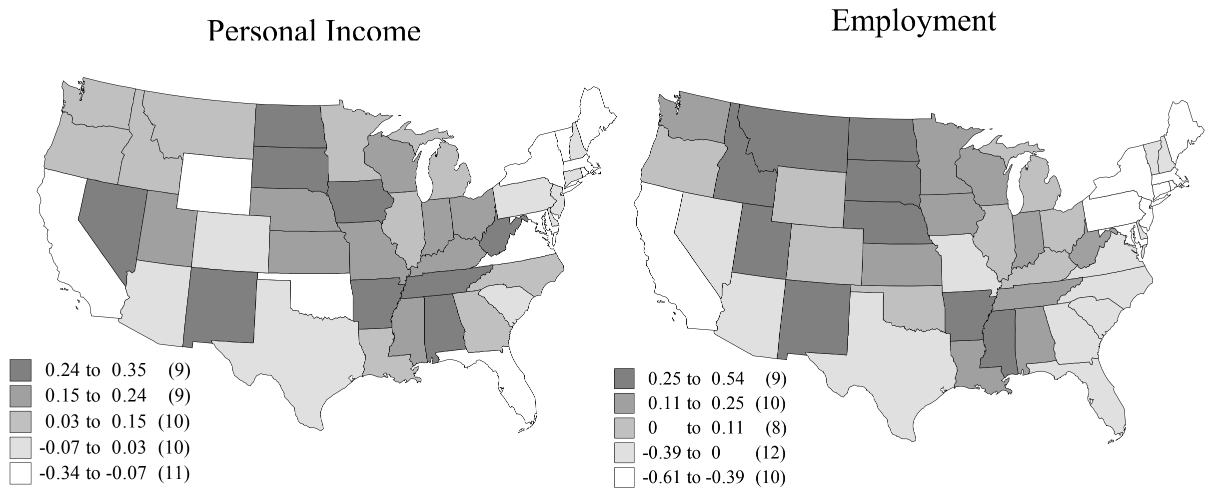


Figure 8. Goodness of Fit (R^2)