Understanding U.S. regional cyclical comovement: How important are spillovers and common shocks?

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Introduction and summary

The holy grail of the study of business cycles is identifying the source of economic fluctuations that affect an economic region. For anyone participating in the quest, there are three paths. First, shocks might be region-specific, affecting only one region of a broader economy. An obvious example is a weather-related shock. Second, they might be common to all regions, such as a change in federal tax rates or monetary policy. Finally, they might initially be region-specific, originating in one region, but eventually spill over to another. The high level of business cycle comovement among U.S. regions suggests that region-specific shocks have a minor role in regional business cycles, leaving spillovers and common shocks playing the major parts in regional business cycles. Despite the growing literature on the subject of regional business cycles, the question of whether the high level of regional business cycle comovement is the outcome of spillovers of shocks from one region to another or common shocks remains unanswered.

The purpose of this article is to determine the extent to which fluctuations in regional economic activity are driven by common and region-specific shocks (including spillovers of shocks across regions). The scope of my analysis is limited to real quarterly per capita income data for the eight U.S. Department of Commerce, Bureau of Economic Analysis (BEA) regions,[1] covering the period from 1961:Q1 to 2000:Q4. I use these data to estimate a model of regional business cycles. This model allows me to decompose a region's cyclical innovations into a part that is common across regions and a residual component that is region-specific. At the same time, the model's structure is rich enough to allow me to formally test whether these region-specific shocks spill over to other regions with at least a lag of one quarter.

Using this framework, I find that spillovers of region-specific shocks across regions account for a statistically insignificant share of the business cycle variation of regional per capita income across the eight BEA regions, while common shocks account for a large and statistically significant share of the business cycle variation of regional income. Based on these findings, I conclude that the high degree of business cycle comovement across U.S. regions over the last 40 years reflects the fact that regions are influenced by common sources of disturbance, rather than any significant spillover of shocks across regions.

Given the different industry mix and strong interregional trade across U.S. regions, these results provide evidence against theories of the business cycle that suggest it owes to cyclical fluctuations being transmitted through trade or production linkages. At the same time, my findings support the notion that the U.S. is an optimum currency area, since they reveal that the BEA regions are largely subject to common sources of disturbance to which they have common responses, which suggests that a common monetary policy is the ideal choice for U.S. regions.

Business cycle properties of per capita U.S. regional income

The starting point for any business cycle analysis is the age-old problem of decomposing fluctuations of economic time series into trend and cycle components. There are many competing methods. I begin my analysis of regional cycles by applying a popular approach to trend/cycle decomposition known as a *band-pass filter*, which limits the cyclical component

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to that part of the time series occurring at frequencies of 18 months to eight years to real per capita income of U.S. regions.[2] I concentrate on these frequencies of the data since they are arguably of most interest to policymakers (especially those charged with formulating monetary policy). I construct real regional per capital income using the BEA's eight-region nominal quarterly personal income from 1961:Q1 to 2000:Q4, divided by the size of the regional population and deflated by the national Consumer Price Index.[3] With these cyclical components in hand, I can make a preliminary assessment of sources of disturbance to U.S. regions by simply calculating the correlation between regional business cycles. A high correlation implies common sources of disturbances and similar responses to disturbances across U.S. regions, while a low correlation indicates differences in the sources of disturbances and/or different responses to disturbances across U.S. regions.

Estimates reported in table 1, panel A indicate a high level of comovement across U.S. regions, with the contemporaneous correlation between regional and aggregate U.S. income (last row of table 1, panel A) ranging from 0.77 for the Southwest to 0.97 for the Southeast. A similar picture emerges for the interregional correlation statistics. Regions that are geographically close tend to have higher correlation coefficients than other regions. For example, the correlation between New England and Mideast business cycle fluctuations is 0.91, while the correlation between New England and Southwest business cycle fluctuations is 0.51.

Panel B of table 1 reports the correlation coefficients for leads and lags of regional income. The results along the diagonal from the top left corner of the first row to the bottom right of the last row reveal the persistence of regional fluctuations. Coefficients close to one indicate highly persistent cyclical fluctuations, while coefficients close to zero indicate very little persistence in regional fluctuations. Regional cycles are roughly as persistent as the aggregate cycle, with own-lag-correlation coefficients of between 0.90 and 0.94. The off-diagonal cells of this panel, in contrast, highlight whether one region's business cycle leads (or lags) that of the other regions. For instance, if the lead/lag coefficient for regions *i* and *j* exceeds their corresponding contemporaneous correlation coefficient in panel A, this implies that *i*'s business cycle leads *j*'s business cycle. The coefficients reported in panels A and B of table 1 do not reveal a strong lead/lag relationship for U.S.

TABLE 1

Regional business cycle comovement and persistence

A. Contemporaneous correlation

	Income at time *t*								
Income at time *t*	**New England**	**Mideast**	**Great Lakes**	**Plains**	**Southeast**	**Southwest**	**Rocky Mt.**	**Far West**	**U.S.**
New England	1.00	0.91	0.76	0.61	0.83	0.51	0.54	0.80	0.85
Mideast	0.91	1.00	0.82	0.68	0.90	0.67	0.66	0.89	0.93
Great Lakes	0.76	0.82	1.00	0.84	0.92	0.65	0.72	0.82	0.94
Plains	0.61	0.68	0.84	1.00	0.82	0.64	0.80	0.68	0.84
Southeast	0.83	0.90	0.92	0.82	1.00	0.75	0.82	0.85	0.97
Southwest	0.51	0.67	0.65	0.64	0.75	1.00	0.77	0.71	0.77
Rocky Mountains	0.54	0.66	0.72	0.80	0.82	0.77	1.00	0.68	0.80
Far West	0.80	0.89	0.82	0.68	0.85	0.71	0.68	1.00	0.92
U.S.	0.85	0.93	0.94	0.84	0.97	0.77	0.80	0.92	1.00

B. Lead / lag correlation

	Income at time *t*+1								
Income at time *t*	**New England**	**Mideast**	**Great Lakes**	**Plains**	**Southeast**	**Southwest**	**Rocky Mt.**	**Far West**	**U.S.**
New England	0.94	0.84	0.73	0.58	0.77	0.40	0.43	0.71	0.78
Mideast	0.87	0.93	0.78	0.63	0.84	0.54	0.55	0.80	0.86
Great Lakes	0.70	0.75	0.94	0.75	0.84	0.52	0.60	0.71	0.85
Plains	0.56	0.65	0.80	0.90	0.75	0.52	0.70	0.59	0.77
Southeast	0.79	0.84	0.88	0.78	0.93	0.61	0.71	0.76	0.90
Southwest	0.54	0.68	0.68	0.65	0.76	0.92	0.72	0.71	0.78
Rocky Mountains	0.56	0.67	0.73	0.78	0.80	0.70	0.92	0.64	0.79
Far West	0.79	0.86	0.84	0.68	0.83	0.60	0.62	0.94	0.89
U.S.	0.82	0.88	0.91	0.79	0.91	0.65	0.70	0.83	0.93

Note: Regional and aggregate income data filtered using the quarterly business cycle band-pass filter described in Baxter and King (1999).
Source: Author's calculations using data from the BEA.

regional business cycles at one quarter, since there are only a couple of cases where a lead/lag correlation exceeds the corresponding contemporaneous correlation. The lead/lag relationship is somewhat weaker at longer horizons of two to four quarters. Overall, these results suggest that U.S. regions have common sources of innovation and similar responses to these disturbances or strong spillovers of shocks across regions that occur at business cycle frequencies. An obvious weakness of this simple approach is that it does not allow for a comparison of the sources of disturbances or responses to disturbances across regions.

A structural model of U.S. regional economic fluctuations

One way of overcoming the limitations of the simple correlation analysis is to use a structural model of the trend and cycle. With appropriate parameter restrictions, a structural model can identify common and region-specific sources of innovation, and identify the shape of responses to common shocks and region-specific shocks. I follow the *unobserved components* (UC) approach of Watson (1986) in decomposing U.S. regional per capita income fluctuations into their trend and cycle components. Unlike the band-pass filter, this approach requires assumptions about the data-generating process. For example, in his analysis of the cyclical characteristics of U.S. aggregate output, Watson modeled the trend of the log of output as a *random walk with drift* and the cyclical component as a *stationary second-order autoregression*. Watson's approach explicitly assumes that the current log of output depends on the most recent past observation plus some random component and a constant term. The constant term, typically called drift, measures the underlying trend growth rate. That is, in the absence of random fluctuations, trend output grows at a rate equal to the drift term. In contrast, positive random fluctuations lead to trend growth in excess of the drift, while negative random fluctuations cause the trend to grow by less than the drift. Using this method, Watson generated a cyclical component for U.S. aggregate output with peaks and troughs that closely match those reported by the National Bureau of Economic Research's (NBER) Business Cycle Dating Committee. Elsewhere, I have shown that this method generates a cyclical component for U.S. aggregate output that closely matches that generated by a band-pass filter.[4]

Unobserved components model

Following Watson's approach, I assume that log per capita income for region i at time t, y_{it}, is composed of a trend τ_{it} and cyclical c_{it} component,

$$1)\quad y_{it} = \tau_{it} + c_{it}, \qquad \text{for } i = 1, \ldots, 8.$$

The trend is assumed to be a unit root with drift,

$$2)\quad \tau_{it} = \delta_{it} + \tau_{it-1} + \mu_{it}, \qquad \text{for } i = 1, \ldots, 8,$$

where the drift term, δ_{it}, measures the trend growth rate of per capita income in region i at time t; μ_{it} is the innovation to the trend of region i's per capita income at time t, which is distributed as an independent normal random variable with mean zero and variance $\sigma^2_{\mu i}$; and the μ_{it}s are assumed to be orthogonal for all t. In this setting, trend output grows at the rate of the drift term in the absence of random fluctuations. Positive shocks lead to trend growth above the drift, and negative shocks lead to trend growth below the drift. Elsewhere, I have shown that the trend growth rate of U.S. aggregate output has changed over time, so I extend Watson's model by allowing the drift to vary over time according to predetermined break points. I consider three periods that are widely considered by empirical researchers, such as Gordon (2000), to be periods in which the trend growth rate of productivity changed significantly: the productivity slowdown era from 1972:Q3 to 1995:Q4; the new economy era from 1996:Q1 to 2000:Q4; and the pre-productivity slowdown era from 1961:Q1 to 1972:Q2.

I also build on Watson's approach by assuming the cyclical component is made up of two parts, a common cycle across regions, x_{nt}, and a regional cycle, x_{it}. I permit regions to have different sensitivity to the common component governed by a parameter γ_i:

$$3)\quad c_{it} = \gamma_i x_{nt} + x_{it}.$$

Under this assumption, regions that do not have a region-specific cycle x_{it} would have income y_{it} that was directly proportional to the common component x_{nt} and their business cycles would be perfectly correlated. The dynamics of the common component x_{nt} follow Watson's specification for the U.S. aggregate cycle of a stationary second-order autoregression:

$$4)\quad x_{nt} = \rho_1 x_{nt-1} + \rho_2 x_{nt-2} + \varepsilon_{nt},$$

where ρ_1 and ρ_2 are scalar coefficients and ε_{nt} is the innovation to the common cyclical component at time t, which is distributed as an independent normal random variable with mean zero and variance σ^2_n. For ease of exposition, I allow $X_t = [x_{1t}, x_{2t}, \ldots, x_{8t}]'$. I assume that the dynamics of the regional cycles follow a first-order vector autoregression:

$$5)\quad X_t = \Phi X_{t-1} + \varepsilon_t,$$

where Φ is an 8×8 matrix of coefficients and $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{8t}]'$ is the vector of innovations to the regional cycle, which is distributed as an independent normal random vector with a zero mean vector and covariance matrix Λ. I identify the region-specific cyclical innovations by limiting the analysis to the case where shocks to x_{it} do not affect x_{jt}, for all $i \neq j$, at time t. In other words, the covariance matrix of regional innovations Λ is assumed to be a diagonal. In this case, the extent of spillovers of cyclical shocks from one region to another is indicated by the off-diagonal elements of the coefficient matrix, Φ. Details of the estimation strategy are provided in box 1.

Results

With the estimated model in hand, I present two sets of results. The first set focuses on measures of U.S. and regional business cycles. The second set concentrates on answering the question of whether the strong pattern of regional cyclical comovement is due to common shocks or spillovers. For completeness, I report all model parameters in tables 2 to 5. I discuss previous approaches to modeling regional income fluctuations in box 2.

Measuring business cycles

The mainstream academic view of business cycles emphasizes that they consist of expansions at about the same time in many economic activities/regions, followed by similarly general contractions. In other words, the U.S. business cycle can be measured by common cyclical fluctuations in regional activity, while variation in regional activity that is not explained by the common cycle serves to highlight region-specific sources of disturbance.

U.S business cycle

Figure 1 (on page 35) plots the common cyclical component of per capita income across U.S. regions

BOX 1

Estimation strategy

The model described by equations 1 to 5 is a variant of Watson and Engle's (1983) general dynamic multiple indicator-multiple cause (DYMIMIC) model. This framework allows unobserved variables to be dynamic in nature, as well as being associated with observed variables. DYMIMIC models are typically estimated using maximum likelihood. In this setting, the likelihood function is evaluated using the Kalman filter on the model's state space representation.[1]

One of the requirements of maximum likelihood is that the data used in the estimation must be stationary. Augmented Dickey-Fuller unit root tests applied to the log-levels and log-first-differences of real per capita income for the eight BEA regions suggest that the null of a unit root cannot be rejected for any of the level data series at the 5 percent level of significance. However, the null of a unit root is rejected for the first-difference data at the same level of significance. In light of this, I specify and estimate the model using the log-first-differences of real per capita regional income.

Under this transformation of the data, the state space representation of the model is described by the following measurement equation:

$$\Delta Y_t = \begin{bmatrix} \delta_{61:1,72:2} & \delta_{72:3,95:4} & \delta_{96:1,02:4} \end{bmatrix} \begin{bmatrix} D_{61:1,72:2} \\ D_{72:3,95:4} \\ D_{96:1,02:4} \end{bmatrix} +$$

$$\begin{bmatrix} \gamma & I_{8\times 8} \end{bmatrix} \begin{bmatrix} \Delta x_{nt} \\ \Delta X_t \end{bmatrix} + \mu_t \,,$$

and transition equation:

$$\begin{bmatrix} x_{nt} \\ X_t \end{bmatrix} = \begin{bmatrix} \rho_1 & 0 \\ 0 & \Phi \end{bmatrix} \begin{bmatrix} x_{nt-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} \rho_2 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_{nt-2} \\ X_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{nt} \\ \varepsilon_t \end{bmatrix},$$

where $Y_t = [y_{1t}, y_{2t}, \ldots, y_{8t}]'$; $\delta_{t1,t2} = [\delta_{1t1,t2}, \delta_{2t1,t2} \ldots, \delta_{8t1,t2}]'$; $D_{t1,t2}$ is one for $t1 \leq t \leq t2$ and zero for all other t; $\gamma = [\gamma_1, \gamma_2, \ldots, \gamma_8]'$; $\mu_t = [\mu_{1t}, \mu_{2t}, \ldots, \mu_{8t}]'$; $I_{8\times 8}$ is an 8×8 identity matrix and $\Delta z_t = z_t - z_{t-1}$.

Identification of the model's parameters requires two additional restrictions on the parameter space. First, the vector governing the sensitivity to the common income component γ is identified by normalizing one γ_i to unity. I use the Southeast as the benchmark region, largely because the volatility of fluctuations of the quarterly growth rates of Southeast income is the same as that of aggregate U.S. income. Second, all innovations are assumed to be orthogonal.

[1]I estimate my DYMIMIC model using the recursive EM algorithm described by Watson and Engle (1983). To avoid local optimization problems, I examined a wide range of starting values and imposed severe convergence criteria on the parameter space of 1×10^{-7}. Standard errors of the parameters are estimated using a standard gradient search algorithm to evaluate the matrix of second derivatives of the likelihood function at the EM parameter estimates.

BOX 2

Previous approaches to modeling regional income fluctuations

The most closely related study is Carlino and Defina (1995), hereafter CD.[1] They use a structural model to estimate the effects of region-specific spillovers of real per capita income of the eight BEA regions that is virtually identical to the one described by equations 1 to 5. However they deviate along one significant dimension, using observed data rather than unobserved components to decompose regional output into its trend and cycle parts. In particular, they assume that the common cyclical component of regional per capita income is proportional to log U.S. per capita income, which allows them to simply estimate the region-specific cycle as the difference between log per capita regional income and log U.S. per capita income. To see the implications of this assumption, it is important to note that log U.S. per capita income is well approximated by a weighted sum of the log per capita regional income, where the weights are equal to the share of regional per capita income in aggregate per capita income sy_i. In terms of my notation, CD assume:

$$x_t = \sum_i sy_i y_{it}.$$

In the context of both models this implies:

$$x_t = \sum_i sy_i (\gamma_i x_t + x_{it}).$$

CD also assume that regional sensitivity to the common cyclical component is the same across regions (that is, $\gamma_i = 1$ for all i), which according to my analysis cannot be rejected at typical levels of statistical significance (see table 2). However, this restriction implies that the share-weighted sum of the regional cyclical components at all dates is zero:

$$x_t = \sum_i sy_i (x_t + x_{it}) = x_t + \sum_i sy_i x_{it} \text{ , or}$$

$$\sum_i sy_i x_{it} = 0 \text{ ,}$$

which is clearly rejected by my and CD's analyses, since a failure to reject this assumption would mean that the regional cyclical components were collinear, thereby making it impossible to identify the spillover matrix Φ in equation 5. In other words, CD's model is misspecified, because their simplifying assumption that the common cycle is explained by observed fluctuations in aggregate income is not consistent with the rest of the model. My unobserved component model overcomes this weakness, since the common and region-specific components are by design consistent with all aspects of the model.

[1]See Carlino and DeFina (1998) for an extensive literature review of empirical studies of regional business cycles. From a methodological standpoint, Rissman (1999) is the most closely related study to mine. Her unobserved components model of regional fluctuations, which is estimated using regional employment data, differs significantly from the model of this article along a number of dimensions that make direct comparison of the estimated coefficients impossible. Despite these differences, her analysis delivers similar conclusions to this article with regard to the sources of innovation in regional activity. In particular, she finds, as I do, that fluctuations in regional activity are largely driven by common sources of innovation.

(expressed as a percentage deviation from the Southeast's trend), against the NBER's business cycle peaks and troughs. I find, just as Watson did with U.S. aggregate income, that the UC approach generates a measure of the U.S. business cycle that has turning points that closely match those of the NBER.

According to this figure, the U.S. economy has been operating below its trend for most of the 1990s, which on first glance is difficult to reconcile with the fact that U.S. output grew strongly in the mid- to late 1990s. This counterintuitive finding is resolved by the fact that the UC model attributes much of the strong growth in income over the second half of the 1990s to an increase in the trend growth rate of regional per capita income (see table 3). One interpretation of these results is that the U.S. experienced a permanent rather than a temporary increase in its productivity growth rate in the 1990s.

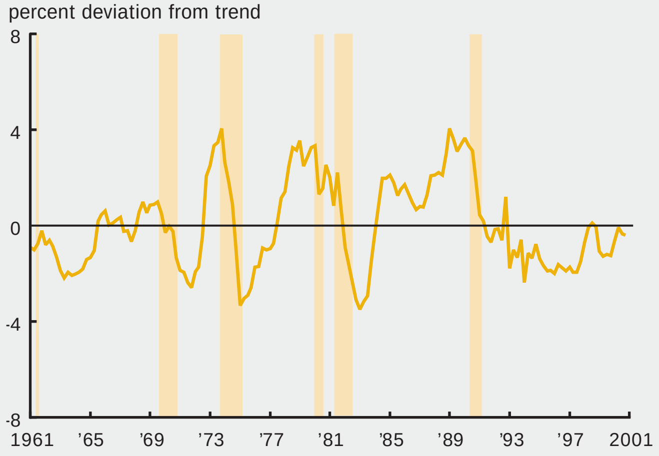
Table 2 reports the differences in regional sensitivity to the U.S. business cycle captured by the γ_is in equation 3. As discussed in box 1, γ_i for the Southeast is normalized to 1. The point estimates of these coefficients indicate that the Plains is the only region that is more sensitive than the Southeast. The Great Lakes has roughly the same sensitivity to the U.S. business cycle as the Southeast, while all the other regions are less sensitive than the Southeast. However, a formal statistical test cannot reject the hypothesis that the γ_i values are equal to one, suggesting that differences in regional sensitivity to the U.S. business cycle are not statistically significant.

Regional cycles

Figure 2, in contrast, highlights differences in the cyclical fluctuations of U.S. regions by plotting the region-specific cycles (expressed as a percentage

FIGURE 1

U.S. business cycle



Note: Shaded areas indicate recessions as defined by the National Bureau of Economic Research,
Source: Author's calculations based on BEA data.

deviation from the region's trend). According to this figure, the Southeast has the weakest region-specific cycle, suggesting that its cyclical behavior is largely explained by movements in the common cyclical component. This reflects the fact that the Southeast has an industrial structure that is virtually identical to that of total U.S. income (see table 6 on page 40). The remaining seven regions fall into two distinct groups.

The first comprises regions, the Southwest, Rocky Mountains, and Plains, that devote a disproportionate share of their industrial activity to the production of commodities. Region-specific cycles of this group are dominated by fluctuations in commodity prices that are to a large extent exogenous to the region. For example, the oil-intensive Southwest's idiosyncratic cycle clearly reflects the large oil price movements of the 1970s and early 1980s, while the mineral-intensive Rocky Mountains' region-specific fluctuations are influenced by movements in prices of oil substitutes over this same period. The idiosyncratic cycle of the Plains, in contrast, takes on the highly volatile pattern of agricultural prices, including the boom that occurred in 1973.

Region-specific cycles of the remaining regions appear to be heavily influenced by the creation and destruction of productive inputs in response to economic slowdowns, changes in defense spending, and technical innovation. Two examples clearly stand out in figure 2, the Rust Belt era of the Great Lakes and the Massachusetts Economic Miracle episode of New England.

The Great Lakes' Rust Belt era began with a strong downturn in regional activity in the late 1970s and ended with a regional recovery in the early 1990s. There is a widely held view that because it had developed much earlier than that of other regions, manufacturing technology in the Great Lakes was of an earlier vintage and relatively less efficient. As a result, the Great Lakes' manufacturing sector experienced a relatively larger decline in demand for its products following the economic slowdown

TABLE 2

Sensitivity to common cycle

Region	Coefficient (γ_i)	Standard error	t-statistic (γ_i = 1)
New England	0.93	0.16	–0.43
Mideast	0.90	0.11	–0.92
Great Lakes	0.99	0.16	–0.04
Plains	1.10	0.20	0.51
Southeast	1.00		
Southwest	0.81	0.16	–1.18
Rocky Mountains	0.82	0.12	–1.47
Far West	0.80	0.15	–1.32

Note: γ_i indicates the parameter for regional sensitivity.
Source: Author's calculations using data from the BEA.

TABLE 3

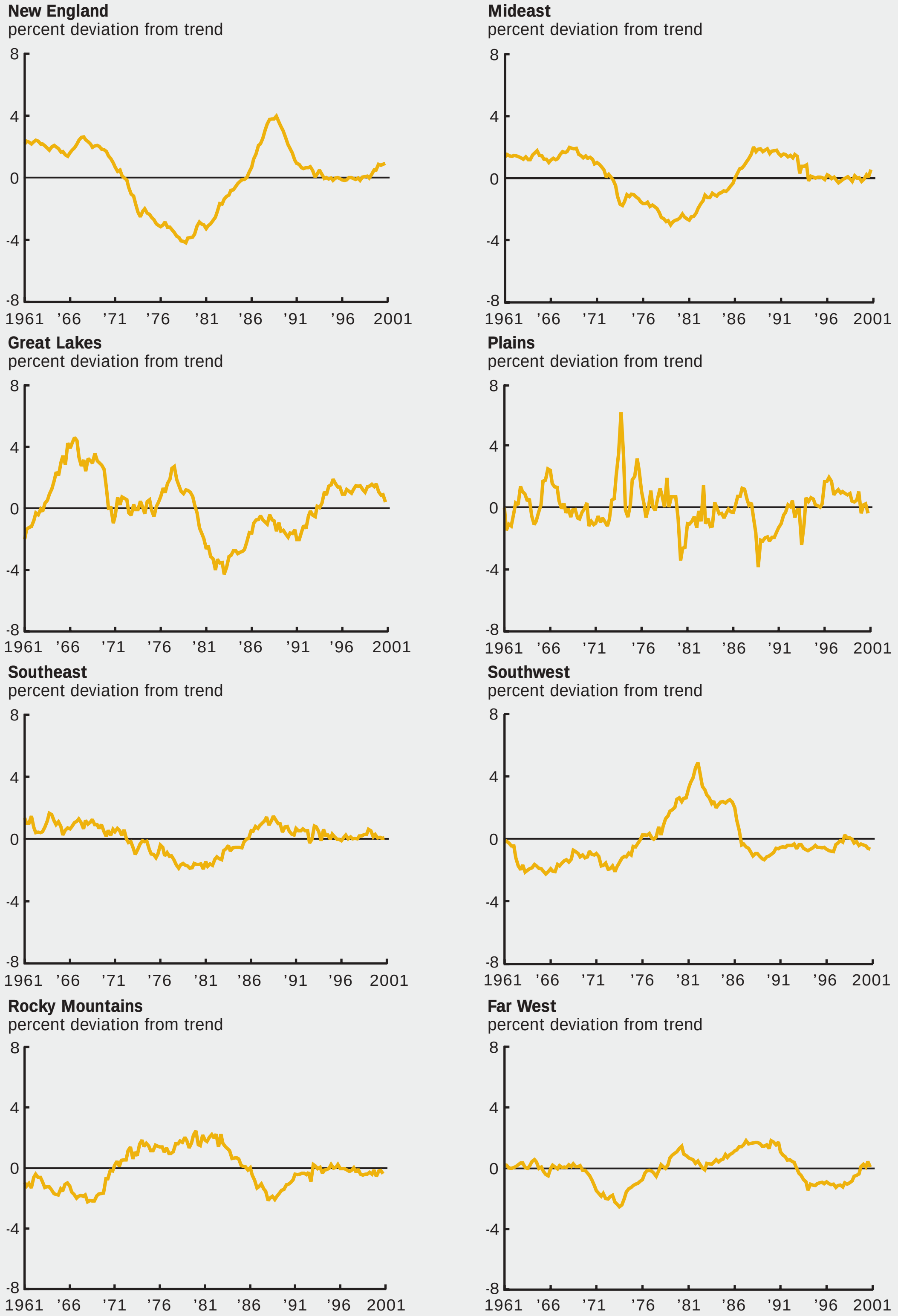
Trend parameters

Region	δ_{it} 1961–72	δ_{it} 1973–95	δ_{it} 1996–2001	$\sigma_{\mu i}$
New England	3.36	2.42	3.35	0.02
Mideast	3.21	2.16	2.84	0.01
Great Lakes	2.78	1.95	2.47	0.02
Plains	3.42	2.06	2.94	0.01
Southeast	4.46	2.43	2.27	0.00
Southwest	3.75	1.98	3.13	0.03
Rocky Mountains	2.80	2.03	3.49	0.01
Far West	3.01	1.65	2.98	0.05

Notes: δ_{it} is the drift term. $\sigma_{\mu i}$ is the standard deviation of the innovation to the regional trend.
Source: Author's calculations using data from the BEA.

FIGURE 2

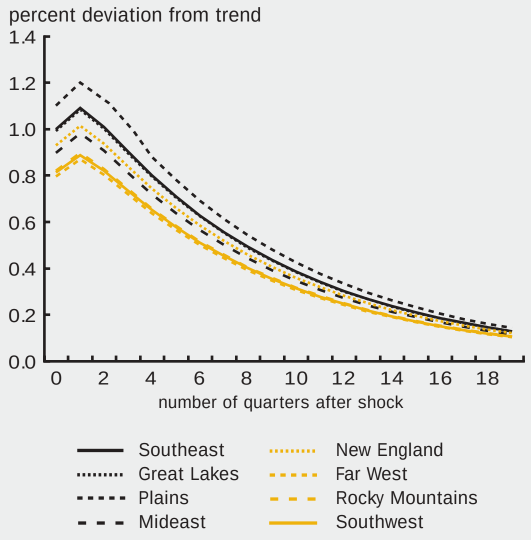
Region-specific cycles



Source: Author's calculations based on BEA data.

FIGURE 3

Response of regional income to common shock



caused by the oil price shocks, since a significant portion of its market share was lost to regions with newer plants. Ultimately, the downturn drove out a significant share of the older plants in the region and paved the way for plants with relatively more efficient technologies to gain market share during the recovery from the recession of the early 1990s.

The Massachusetts Economic Miracle describes the unexpected hi-tech boom of the late 1970s that more than offset the decline in activity brought about by the rapid erosion of New England's manufacturing sector that started in the early 1970s. The era came to an end in the 1980s as New England's hi-tech sector eventually lost its competitive advantage to other regions, such as the Far West, and the end of the Cold War brought about a dramatic decrease in demand for the region's defense-related products. The Far West's regional cycle shows that the region was affected by the same cuts in defense spending that led to the downturn in New England.

Finally, the Mideast's idiosyncratic cycle also reflects the erosion of its industrial sector that started in the early 1970s. In contrast, the Mideast's region-specific cycle improved because of a growing demand for financial services. That trend has persisted since the mid-1980s, leaving the Northeast overall with the largest regional share of activity in finance, insurance, and real estate (FIRE) in table 6. (For a more detailed discussion of these events, see Kouparitsas, 2002).

Common shocks versus spillovers

I assess the source of high comovement of U.S. regional business cycles along two dimensions. First, by studying the cyclical impulse response functions generated by the vector autoregression (VAR) described by equation 5, I assess whether cyclical shocks that originate in one region have a significant effect on the cycles of other regions and at what horizon. Second, I determine the importance of common and region-specific disturbances by decomposing the variance of regional output at business cycle frequencies by source of innovation.

Impulse response functions

Figure 3 describes in detail the way that the eight BEA regions respond over time to a common cyclical shock, normalized to 1 percent of Southeast per capita income. The response of the Southeast is dictated by the coefficients of the second-order autoregressive model reported in table 4. The responses of the other regions reflect differences in the regional sensitivity to common cyclical innovations as reported in table 2.

Figure 4 describe how the level of per capita income (expressed as a percentage deviation from trend) in all eight BEA regions responds over time to an innovation that originates in one of the regions. All shocks are normalized to 1 percent of the per capita income of the region in which the shock originates. For ease of exposition I do not report confidence intervals in this figure; instead I report in the text the few cases where the impulse response functions are significant.[5]

According to my parameter estimates, the Southeast is the only case where shocks that originate in that region have a statistically significant effect on the income of other regions, namely New England and the Mideast. Elsewhere, shocks that originate in one region have a significant positive effect on their own per capita income, but not on the income of other regions. These regions can be divided into two groups according to the persistence of the response to their region-specific income shocks. New England, Great Lakes,

TABLE 4

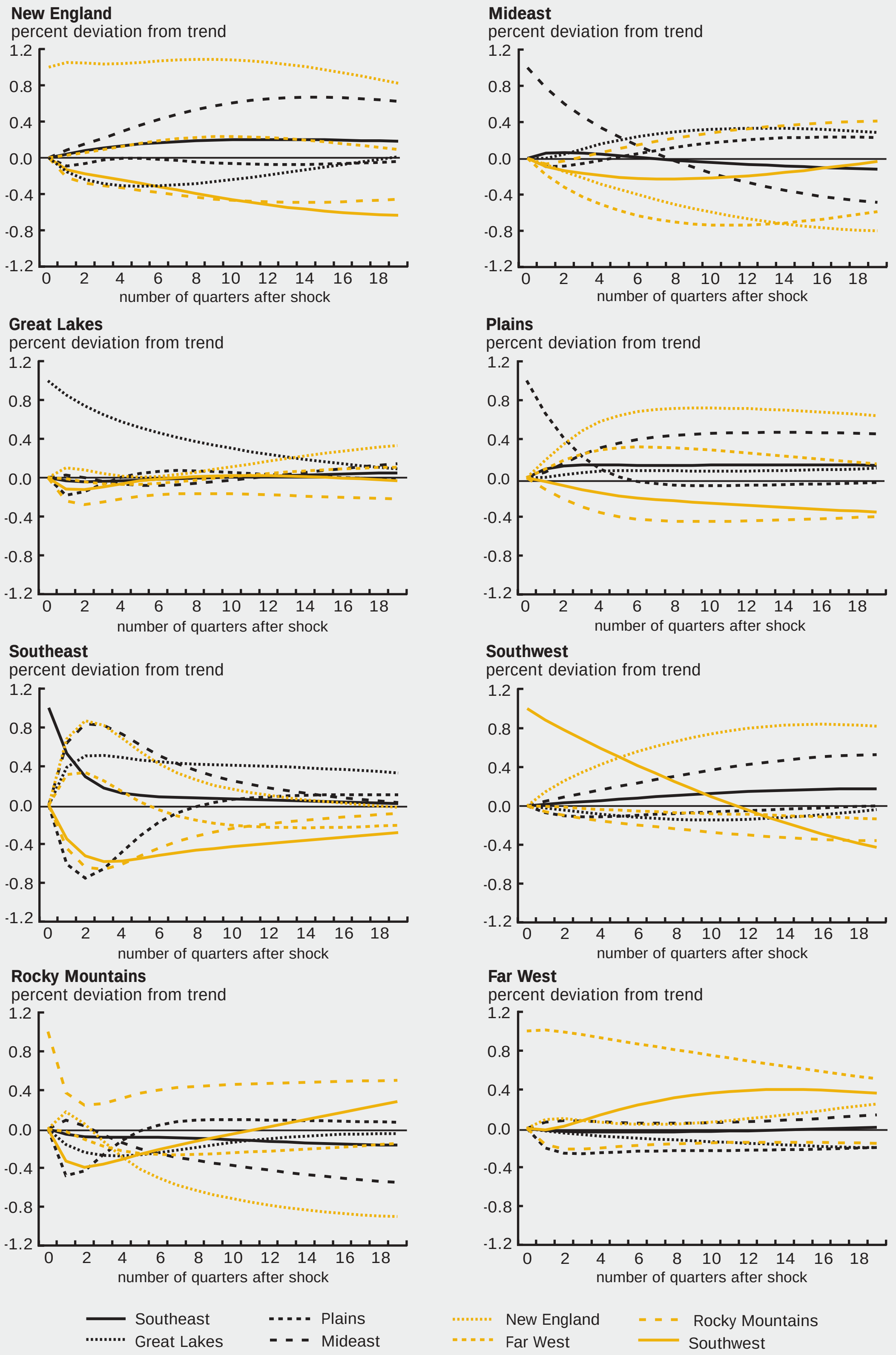
Common cycle parameters

Coefficient	Value
ρ_1	1.09
ρ_2	–0.18
σ_n	0.73

Notes: ρ_1 and ρ_2 are the autoregressive coefficients. σ_n is the standard deviation of the innovation of the common cycle.
Source: Author's calculations using data from the BEA.

FIGURE 4

Responses of regional income to region-specific shocks



Southwest, and Far West have persistent responses to their region-specific income shocks that are statistically significant five to seven quarters after the shock date, while shocks originating in the Mideast, Plains, and Rocky Mountains die out one to two quarters after the shock date.

Returning to the Southeast case in figure 4, note that the response functions of the Southeast and New England are statistically significant two quarters after the shock, while the Mideast response is significant for four quarters after the shock. According to this figure, a 1 percent shock to the Southeast's per capita income causes per capita income of New England and the Mideast to rise by 0.7 percent in the following quarter and an additional 0.2 percent in the subsequent quarter. The confidence interval surrounding these point estimates ranges from 0.2 percent to 1.5 percent, which implies that the spillovers from the Southeast are potentially significant from an economic standpoint. However, note that a typical Southeast shock from 1961:Q1 to 2000:Q4 had a standard deviation of 0.25 percent (see the column labeled $\sigma_{\varepsilon i}$ in table 5), which suggests that spillovers from the Southeast to the Northeast were probably not an economically significant source of innovation over this period.[6]

Variance decomposition at business cycle frequencies

Table 7 ties together the sources of, sizes of, and responses to disturbances by decomposing the variance of regional output at business cycle frequencies.[7] Each column breaks down the variance of regional income by source of shock. For example, the first number in the first column reveals that innovations to the common cyclical component account for a statistically significant 56 percent business cycle fluctuations in New England per capita income. The next number in that column reveals that 5 percent of New England's business cycle variation is explained by shocks that originate in New England, although this is not statistically different from zero at typical levels of significance. Moving down the column uncovers the influence of shocks that originate in other regions. In all cases, the estimates are not statistically different from zero. Overall, the results suggest that spillovers of shocks from other regions are not a statistically significant source of business cycle variation for the New England region.

The remaining columns tell a similar story for the other seven U.S. regions, with a large (statistically significant) share of their business cycle fluctuations explained by the common component. The only other statistically significant sources of business cycle variation in these regions are innovations that originate in the region. For example, region-specific shocks explain almost 30 percent of the business cycle variation of per capita income of the Plains and Southwest, which is not surprising given that they derive a disproportionately large share of their income from commodities, whose price fluctuations are largely exogenous to the U.S. On the other hand, region-specific shocks account for an insignificant share of the business cycle variation of per capita income in the Southeast, which reflects the fact that their industrial composition is virtually identical to that of aggregate U.S. income.

Conclusion

This article develops an empirical model to study the sources of business cycle variation of the eight U.S. BEA regions. Using unobserved component modeling techniques, I identify both common and region-specific sources of innovation in U.S. regional per capita income data. I show that spillovers of region-specific shocks to other regions account for a statistically insignificant share of the business cycle variation of

TABLE 5

Regional cycle parameters

Region	Φ New England	Φ Mideast	Φ Great Lakes	Φ Plains	Φ Southeast	Φ Southwest	Φ Rocky Mountains	Φ Far West	$\sigma_{\varepsilon i}$
New England	1.05	–0.07	0.10	0.18	0.68	0.14	0.18	0.09	0.22
Mideast	0.09	0.77	0.03	0.06	0.64	0.05	0.09	0.06	0.36
Great Lakes	–0.15	0.00	0.85	0.00	0.39	–0.02	–0.16	–0.03	0.43
Plains	–0.09	–0.10	–0.18	0.67	–0.61	–0.07	–0.48	–0.20	0.75
Southeast	0.04	0.05	–0.03	0.09	0.53	0.02	–0.06	–0.02	0.25
Southwest	–0.13	–0.10	–0.12	–0.04	–0.35	0.88	–0.33	–0.02	0.46
Rocky Mountains	–0.21	–0.06	–0.24	–0.12	–0.44	–0.06	0.37	–0.17	0.51
Far West	0.03	–0.19	–0.01	0.09	0.31	–0.01	–0.03	1.01	0.38

Notes: Φ indicates the 8 × 8 coefficient matrix. $\sigma_{\varepsilon i}$ is the standard deviation of the innovation to the region-specific cycle.
Source: Author's calculations using data from the BEA.

TABLE 6

Percent of regional gross state product accounted for by major industry

Region	Agriculture	Mining	Construction	Manufac-turing	Transport. & public util.	Trade	FIRE	Service	Govt.
New England	1.03	0.08	4.62	23.81	7.04	16.11	18.73	17.88	10.68
Mideast	0.77	0.35	4.20	17.66	9.06	15.92	20.41	18.48	13.14
Great Lakes	1.94	0.86	3.69	28.55	9.07	16.16	14.40	14.76	10.58
Plains	5.90	1.53	4.05	20.13	10.43	17.20	14.02	14.49	12.25
Southeast	2.15	4.09	4.80	19.73	9.54	16.96	14.35	13.71	14.67
Southwest	1.77	12.98	5.36	13.14	9.72	16.39	14.71	13.57	12.36
Rocky Mountains	2.88	8.07	5.48	11.91	11.09	15.81	15.12	14.49	15.16
Far West	2.29	2.79	4.63	15.37	8.25	16.75	18.48	17.79	13.65
U.S.	2.04	3.26	4.49	19.38	9.13	16.46	16.54	15.81	12.89

Note: FIRE is finance, insurance, and real estate.
Source: Author's calculations based on BEA data.

TABLE 7

Variance decomposition of U.S. regional income at business cycle frequencies

	Percentage of total variation due to innovation							
Source of innovation	New England	Mideast	Great Lakes	Plains	Southeast	Southwest	Rocky Mountains	Far West
Common	56*	66*	76*	62*	94*	55*	71*	60*
New England	5	1	1	0	0	0	1	0
Mideast	2	14*	1	0	0	1	1	6
Great Lakes	1	1	16*	1	0	1	2	0
Plains	18	7	0	28*	1	2	11	7
Southeast	5	6	2	3	4	3	5	2
Southwest	5	2	1	0	0	29*	1	0
Rocky Mountains	8	3	3	5	0	7	8	2
Far West	0	0	0	1	0	2	1	21*
Total, all shocks	100	100	100	100	100	100	100	100

Note: Numbers in columns may not total due to rounding. * indicates significance at the 5 percent level.
Source: Author's calculations using data from the BEA.

regional per capita income across the eight BEA regions, while common shocks account for a large and statistically significant share of the business cycle variation of regional income. Overall, these findings suggest that the high degree of business cycle comovement across U.S. regions reflects the fact that the regions are influenced by common sources of disturbance, rather than any significant spillover of shocks across regions. Given the different industry mix and strong interregional trade across U.S. regions, this is evidence against theories of the business cycle that suggest it owes to cyclical fluctuations being transmitted through trade or production linkages.

The findings of this article also have implications for the choice of regional monetary policy. In particular, the techniques developed here can be used to address the question of whether a set of regions (or countries) meets Mundell's (1961) criteria for an optimum currency area, by showing that the importance of common sources of innovation in the test region is the same as that of a well-functioning currency union, such as the U.S. For example, one could test whether the European Monetary Union (EMU) was an optimum currency area by repeating the analysis of this article for the EMU countries, then testing to see if the common component across EMU countries is as important a source of variation as it is for U.S. BEA regions.[8]

NOTES

[1]A complete listing of the regions is available at www.bea.gov/bea/regional/docs/regions.htm.

[2]See Baxter and King (1999) for details.

[3]Gross state product (GSP) is an alternative measure of regional activity. The main drawback of GSP is that it is collected annually, which makes it less able to pick business cycle turning points with any precision.

[4]See Kouparitsas (1999) for details.

[5]Confidence intervals are calculated by Monte Carlo methods. Following Hamilton (1994) section 11.7, I randomly draw from the estimated distribution of the model's parameters. For each draw of parameters I generate an impulse response function. I repeat this process 10,000 times. At each lag I calculate the 500th lowest and 9,500th highest value across all 10,000 simulated response functions. These boundaries form the 90 percent confidence interval. If the zero line lies within this interval the impulse response is deemed to be not significantly different from zero at that lag.

[6]I leave a careful examination of the other impulse responses to the reader.

[7]I do this by way of a linear filter that allows me to map from the covariance of the first-difference of regional per capita income to the covariance of the business cycle components of per capita regional income. The mapping is carried using standard spectral/Fourier analysis tools. While, the precise form of the liner filter is, $G(L)=\frac{BP_{6,32}(L)}{1-L}$, where $BP_{6,32}(L)$ is the Baxter-King approximate business cycle band-pass filter for quarterly data; and L is the lag operator (that is, $Lz_t = z_{t-1}$).

[8]See Kouparitsas (2001) for an extended discussion of regional business cycles in the context of optimum currency area criteria.

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