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Understanding the lead/lag structure among regional business cycles

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Abstract
The analysis of synchronization among regional or national business cycles has recently been attracting a growing interest within the economic literature. Far less attention has instead been devoted to a closely related issue: given a certain level of synchronization, some economies might be systematically ahead of others along the swings of the business cycle. In other words, there could be a lead/lag structure in which some economies systematically lead or lag behind others.
In the present paper we aim at providing a thorough analysis of the lead/lag structure among a system of regional economies. This task is achieved in two steps. First, we show that leading (or lagging behind) is a feature that does not occur at random across the economies. Second, we investigate the economic drivers that could explain such a behavior. To do so, we employ data for 48 conterminous US states between 1979 and 2010.

Keywords
Regional business cycles, lead/lag structure, synchronization

JEL Codes
R10, E32, O18, F40

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1 Introduction

It is rather well-known that business cycles across the US states are not synchronized with the national cycle and hence with each other (among others, Beckworth, 2010; Crone, 2005; Owyang *et* al., 2005; Partridge and Rickman, 2005; Carlino and DeFina, 2004; Carlino and Sill, 2001). If this feature was due to a random mechanism, such that states on some occasions tend to anticipate and on some others tend to follow the national business cycle, the important aspect to be studied would merely be the degree of synchronization. However, if business cycles of some states persistently anticipate (follow) the national cycle, then systematic leading (lagging behind) behaviors emerge and the mechanism is no more random. If that were the case, examining the degree of synchronization would fall short from providing an adequate account of the observed feature and the analysis would also need to explain why some regions do tend to start the business cycle before others. The aim of this paper is to explore whether such a persistent pattern can be found among the US states and, in case, to understand the reasons behind it.

Differently from synchronization, there is no commonly adopted measure for the lead/lag phenomenon in the literature. Therefore, for the sake of clarity, we think it might be useful to spell out right from the introductory section the type of variable we are going to use in the analysis. Let us suppose there are m turning points indexed in z ($z = 1, \ldots, m$) which characterize the national business cycle over a certain period of analysis. For each state i, we define a measure of its lead or lag behind behavior with respect to the nation as the average along z of the time (in months) with which i anticipates or follows the turning points of the national business cycle ($t_{i,z}$):

$$LL_i = \frac{\sum_{z=1}^{m} t_{i,z}}{m}$$

where, in particular, $t_{i,z} > 0$ when i anticipates the national economy and $t_{i,z} < 0$ when i follows. When the attention is shifted to the relationship between any two states i and j then the corresponding measure is

$$LL_{ij} = LL_i - LL_j \quad (1)$$

Intuitively, given that the national cycle is obviously the same, a positive (negative) value of LL_{ij} implies that i leads (lags behind) j by the corresponding number of months.

It is important to note that the information conveyed by the measure in (1) is actually twofold. On the one hand the absolute value of this measure tells us how much two states are far from being synchronized; on the other hand the sign of (1) tells us which of the two states leads and which instead lags behind. In fact, the first component of LL_{ij} conceptually coincides with the measure commonly employed in the empirical studies on the degree of synchronization among business cycles of different economic systems. In relation to this, a particularly well-known model has been proposed by Imbs (2004). This model allows to analyze the degree of synchronization by means of trade openness, financial integration and industrial specialization and their respective links. More specifically, in its cross-country application (Imbs, 2004; Xing and Abbott, 2007), and focusing only on its main variables, the model consists of a system of four simultaneous equations in which: bilateral business cycle correlation is explained by differences in industrial specialization, bilateral financial integration and trade flows; differences in specialization patterns depend on trade flows and financial integration; trade flows are explained by differences in specialization (and gravity-type variables); financial integration is simply proxied via measures of existing restrictions to financial flows. In a companion working paper (Imbs, 2003), the model is also employed within an intra-national framework using data on US states. In such a case, however, its structure is somewhat simplified: bilateral financial integration is calculated from an estimate of the state-specific index of risk-sharing proposed by Kalemli-Ozcan *et al*. (2003) and, given the lack of data on inter-state trade, trade flows are estimated via a gravity model. As a result, only two equations have to be estimated simultaneously.

One element that characterizes the model put forward by Imbs is the relationship between the dissimilarities in industry specialization and the lack of correlation between business cycles. Quite naturally, if two economies are differentiated in terms of the type of goods they produce, they will react differently to sector-specific shocks and their business cycles will become less correlated. A reduction in the correlation might also be observed in relation to an unanticipated monetary policy as different sectors will respond differently to this common shock. Evidence in support of these argumentations is indeed reported in a number of papers that analyze whether the US fits the criteria for being considered an optimal currency area by examining the way in which the states react to monetary policy shocks (Beckworth, 2010, Carlino and DeFina, 1998, 1999a, 1999b and 2004; Crone, 2006 and 2007; Kouparitsas, 2001; Owyang and Wall, 2004 and 2009).

The relationship between specialization and synchronization assumed in most of these studies is in fact a one-way relationship: i.e., from the degree of similarity in production patterns to the level of correlation between cycles. There is however recent evidence suggesting the possibility of a circular mechanism. More specifically, Beckworth (2010) observes that the smaller the correlation between a state's business cycle and the national one, the more asymmetric the state's response to a common monetary shock is likely to be. The interpretation of this result offered by the author is that monetary policy exacerbates states cycles that are not synchronized with the national economy in case there are no economic shock absorbers such as flexible wages and prices, factor mobility fiscal transfers and an adequate level of diversification in the production structure. Put it differently, if states differ in terms of their industrial structure their business cycles will not be synchronized. Then, any monetary policy action will lead the states to react differently according to their specific industrial structure. These reactions, in turn, take the form of asymmetric changes in the states' structures so to further decrease the level of synchronization of their cycles. To sum up, therefore, it seems plausible to suppose the existence of a circular mechanism that leads to a cumulative decline in the level of synchronization through a progressive differentiation of specialization patterns. Consequently, the first main difference between the analysis carried out in this paper and the one proposed by Imbs (2004) is indeed represented by the fact that we explicitly allow for a possible circular relationship between industry specialization and the degree of synchronization between states business cycles.

Still, we are not yet able to explain the second component of our target variable LL_{ij}, i.e. its sign, or, in other words, why do some states lead the national cycle and others lag behind. In order to explain this component we must again turn our attention to the differences in industry mix that characterize the economic structure of the states. However, what matters here is not a general measure of dissimilarities in specialization but, rather, the sectors in which specialization actually takes form. There are several indications in the literature about which sectors appear to be more responsive and thus have cycles that tend to lead the others. Among others, while Crone (2006) reports that states with a higher share of output in agriculture and construction lead the growth in the nation, Sill (1997) and Park and Hewings (2003) point to the manufacturing sector. According to the last two authors, this is due to the high sensitivity of manufacturing to changes in monetary policy and to technology developments. A similar point is made by Carlino and DeFina (2004) and by Irvine and Shuh (2005) who focus, in particular, on the durable goods industry. From a practical point of view, it is clearly impossible to consider explicitly the evolution of each of the possibly relevant sectors. Hence, a decision must be taken on which sector to focus upon. The broad indication arising from the just mentioned literature leads to think that the manufacturing sector could be an appropriate choice. However, this sector could be excessively heterogeneous in our view and we have therefore decided to focus our attention on the high-tech industries. A first motivation of this choice is that high-tech manufacturing products are purchased for investment by firms or consumers as durable goods which implies that purchasing decisions should be highly affected by general economic conditions (DeVol *et al.*, 1999) and, in particular, by changes in the interest rate. In addition, Bernanke and Kuttner (2005) show that stock market values of high-tech industries tend to be relatively more sensitive to unanticipated changes in monetary policies. Finally, from a different perspective, Moretti (2010) documents that the high-tech sector is characterized by a much larger local multiplier than manufacturing; this implies that, in case a shock hits, the effect on the local economy induced by the response of the high-tech sector is much stronger than the effect arising from manufacturing.

The relationships among the main variables of the model just outlined are shown in Figure 1. In this figure, in addition to the direction of the relationships we also report their expected signs, more details on which will be provided in Section 4. Given the simultaneity characterizing the evolution of several variables, following Imbs (2004) and Xing and Abbott (2007) the model will be estimated via the Three-Stage Least Squares Estimator.

(Figure 1 About Here)

The structure of the paper is as follows. Section 2 studies the degree of synchronization characterizing the US states in recent decades. Section 3 is first devoted to the identification of the states who lead and those who lag behind and then it analyses whether the observed pattern is persistent over a set of sub-periods. The economic explanation of the lead/lag structure among the states' cycles over the period 1990-2009 is then provided in Section 4 where the just outlined model is estimated. Section 5 concludes.

2 Synchronization among state business cycles

First of all, we estimate the business cycles for the US and its 48 contiguous states using the monthly coincident index between 1979:7 and 2010:10. The coincident index is a macroeconomic indicator that summarizes the current economic conditions of a state in a single variable. It includes four main elements: non-farm payroll employment, average hours worked in manufacturing, unemployment rate and wage and salary disbursements.[1]

To each series we apply a Baxter-King (Baxter and King, 1999) filter that allows to extract directly the cyclical movements in the economic series whose periodicity is within a certain range. In particular, Baxter and King propose a band-pass filter, based on Burns and Mitchell's (1946) definition of a business-cycle, designed to remove low and high frequencies from the data. As recommended by Baxter and King, the filter passes through components of time series with fluctuations between 18 and 96 months while removing higher and lower frequencies.

In addition, to identify the cycle we also use the Hodrick-Prescott (Hodrick and Prescott, 1997) de-trended (quarterly) per capita real personal income net of transfers between 1969:1 and 2008:4 (from paper 1) for US and 48 States.[2]

[1] Coincident indexes are obtained from Federal Reserve Bank of Philadelphia.

[2] The term below explains the Hodrick-Prescott deviation cycle estimation procedure. Let y_t represent income at time t and λ a trend smoothness parameter. Given a properly chosen λ, there is a trend τ_t minimising

The outcome of the two filtering procedures is shown respectively in Figures 2 and 3. Allowing for a different degree of smoothing characterizing the two techniques, the cyclical movements identified appear highly consistent.

(Figure 2 and 3 About Here)

In order to evaluate the degree of synchronization at each point in time, we compute the rolling window cross-correlations between each state and US cycle and then take the average of these correlations for each window which gives an average value of synchronization within the US for the time instant corresponding to the mid-point of the window. We set the window length of 120 months which is a period long enough to capture the complete business cycles (peak-to-peak or trough-to-trough).

(Figures 4 and 5 About Here)

Figure 4 and 5 report the evolution of synchronization respectively for coincident index and personal income cycles. We firstly concentrate on the latter as the covered time-span is broader. We note that the degree of synchronization among US states cycles clearly decreases from the 1970s (0.92 on average) until 1990 (reaching a value as low as 0.74) and, after a rebound, appears to be rather stationary (around a value of 0.80). As a consequence, timing differences across states' business cycles have became more relevant in recent years compared to the 1970s.

The implications from the evolution of synchronization for coincident index cycles (Figure 4) are consistent with those just highlighted as far as the overlapping period (approximately, 1985-2003) is concerned. After 2003, we observe a sudden jump in synchronization which is obviously not observable in Figure 5.

$$\min \sum_{t=1}^{T} \left(y_t - \tau_t \right)^2 + \lambda \sum_{t=2}^{T-1} \left[\left(\tau_{t+1} - \tau_t \right) - \left(\tau_t - \tau_{t-1} \right) \right]^2$$

the first component of which represents deviations of income from trend while the second determines the smoothness of the trend. The trend gets smoother trend as λ increases; here, following what is commonly done in the literature we set λ=1600.

3 Identifying who leads and who lags behind

In the previous Section we concluded that timing differences across state cycles appear to have increased in recent years with respect to the '70s and '80s. Now, we investigate whether there are states that permanently lead others along the swings of the business cycle. To do so, we first need to identify which states lead and which instead lag behind, as well as their geographical distribution within the US. This will be done using two alternative approaches, one based on dynamic cross-correlations, the second on turning points. Finally, we will evaluate whether the observed pattern is actually persistent over the time period under analysis.

3.1 Dynamic Cross-Correlation Approach

The first approach we employ is a widely used methodology that allows to identify the economies that lead or lag behind by calculating the dynamic cross-correlations among the cycles of the economic units (Park and Hewings, 2003).

In details, for each state *i* we calculate the dynamic correlations between its cycle and the US national cycle:

$$\rho_{i,\tau} = corr\left(C_{US,t}, C_{i,t+\tau}\right) \tag{2}$$

where $C_{\bullet,t}$ stands for the cycle component obtained via filtering and τ ranges between –8 and +8 (months). Then, we identify the value of τ such that $\rho_{i,\tau}$ is maximized. So, for instance, if the correlation in (2) is maximized when $\tau = 2$ ($\tau = -2$) this means the cycle of state *i* leads (lags behind) the US cycle by 2 months. Table 1 summarizes the results obtained applying this methodology to the Baxter-King filtered coincident index cycles of the 48 coterminous states between 1979:7 and 2010:10.

(Table 1 About Here)

The state that most clearly leads the US cycle is Montana (3 months ahead of the US cycle), followed by Rhode Island, South Carolina, Oregon, Florida, Idaho, Indiana and Maine (2 months ahead of the US cycle). The states which are instead lagging behind most substantially are Wyoming (4 months behind the US cycle), and Texas, Oklahoma and Louisiana (3 months behind the US cycle).

(Figure 6 About Here)

Figure 6 displays the geographical distribution of leading and lagging behind states. Areas with the brightest color represent the states that lead the most while darkest areas represent the states that lag behind most substantially. We can easily observe that the states that most consistently lag behind are located in the West South Central Census Division (Louisiana, Oklahoma and Texas) and in part of the Mountain Division (Colorado, Utah, New Mexico and Wyoming). On the other hand, a large part of the leading states are located in the Pacific (Oregon, Washington), in the Midwest (Indiana, Michigan) and in the South Atlantic (Florida, South Carolina) Divisions.

3.2 Turning Points Approach

Another possible approach for the identification of leading and lagging behind states is through a comparison between the timing of the turning points of the US cycle and those characterizing the cycle of each state.

Operatively, first of all we detect the turning points in each business cycle applying the Bry-Boschan (Bry and Boschan, 1971) algorithm to the Baxter-King filtered monthly coincident index series. The algorithm detects a set of local minima and maxima in the series and then imposes several restrictions on the phase and cycle lengths to ensure an adequate duration. In particular, since our data is monthly, we impose that a phase must be at least 6 months long and a cycle must last at least 15 months. Table 2 summarizes, for each state and for each turning point of the US business cycle, the number of months by which a state leads or lags behind due to differences in timing of cycle swings.

(Table 2 About Here)

Then, state by state, we calculate the median lead or lag with respect to the US turning points. These values are reported in Table 3. Similarly to the results obtained with the previous approach, the most leading state is Montana (3 months ahead of the US cycle); then, we find Maine, Rhode Island, Massachusetts, Washington, Idaho and Nevada (2 months ahead of the US cycle). Yet again, the most lagging states are Louisiana, Texas and Wyoming (3 months behind the US cycle) and Oklahoma (2 months behind the US cycle).

(Table 3 About Here)

Figure 7 reports the geographical distribution of leads and lags. In general, lagging states are located in the Southwest Central Census Division (Texas, Oklahoma, Louisiana) while leading ones can be found in the New England (Maine, Rhode Island, Massachusetts), Mountain (Montana, Idaho) and Pacific Divisions (Washington, Nevada).

(Figure 7 About Here)

Overall, the geographical positioning of leads and lags is consistent across the two approaches since the darkest and brightest areas of Figures 6 and 7 mostly overlap.

3.3 Persistence of Leads and Lags

Having seen that over the entire period of analysis some states tend to anticipate the national business cycle and some others to follow it, we now want to understand whether the pattern is actually persistent over different sub-periods.

In details, we divide the overall time-span into the following five, non-overlapping sub-periods: 1979:7-1985:9; 1985:10-1991:12; 1992:1-1998:3; 1998:4-2004:6; 2004:7-2010:10. Then, for each of these sub-periods we repeat the analysis carried out in the previous Sections; results are shown in Tables 4 and 5.

(Tables 4 and 5 About Here)

For each sub-periods, we also display the geographical distribution of leads and lags calculated using both the dynamic cross-correlations approach (Figure 8) and the turning points approach (Figure 9).

(Figures 8 and 9 About Here)

Similarly to what previously seen, areas with the brightest color represent states that lead the most while darkest areas represent the states that lag behind most substantially. We can therefore observe that the geographical location of leads and lags does not change much over time, with the only exception of the 1992-1998 period in Figure 9. Overall, these maps suggest that location of leads and lags is not purely random but possibly displays a systematic behavior.

To investigate this issue further, in Table 6 we count the number of states that switch from leading (+) to lagging (–) (or *vice versa*) across consecutive periods. Based on the cross-correlations approach, on average, only about 6 states out of 48 switch their behavior across each couple of consecutive periods. This figure increases to approximately 17 when we resort to the turning points approach. The difference in the results coming from the two approaches is most probably due to the fact that, in calculating leads and lags, the cross-correlations approach makes reference to a time window; consequently, its outcome is characterized by a lower degree of variability with respect to that obtained through the turning point approach which, instead, works turning point-by-turning point.

(Table 6 About Here)

Anyway, only about 6 to 17 states switch their lead/lag behavior across consecutive periods, which corresponds to about 13% to 33% of the considered states. Put it differently, we can conclude that between 67%-87% of the states tend to exhibit a time-consistent leading/lagging behavior. One may therefore argue that state business cycles in the US tend to display a hierarchical nature so that fluctuations in the aggregate economy are in actual facts propagated by leading states and then spread out to the others as a wave that sweeps along the nation. Trying to understand the economic reasons behind this behavior is the focus of the next Section.

4 Why do some states lead others?

4.1 The Estimated Model

Following the discussion in the introductory section, the model we estimate consists of four simultaneous equations:

$$\begin{cases} LL_{ij} = \alpha_0 + \alpha_1\rho_{ij} + \alpha_2 DL_{ij} + \alpha_3\left(\rho_{ij}\cdot DL_{ij}\right) + \alpha_4 HT_{ij} + \varepsilon_{ij} \\ \rho_{ij} = \delta_0 + \delta_1 S_{ij} + \delta_2\hat{T}_{ij} + \delta_3\hat{F}_{ij} + \boldsymbol{\delta}\mathbf{V}^{\rho}_{ij} + \eta_{ij} \\ S_{ij} = \gamma_0 + \gamma_1\rho_{ij} + \gamma_2\hat{T}_{ij} + \gamma_3\hat{F}_{ij} + \boldsymbol{\gamma}\mathbf{V}^{S}_{ij} + \upsilon_{ij} \\ HT_{ij} = \beta_0 + \boldsymbol{\beta}\mathbf{V}^{HT}_{ij} + \xi_{ij} \end{cases} \tag{3}$$

The first equation explains the lead/lag relationship between the cycles of states *i* and *j* (LL_{ij}) in terms of its two fundamental components. The first component, the time that separates the cycles of state *i* and *j*, is introduced directly by means of the degree of synchronization between the business cycles of *i* and *j* (ρ_{ij}). The second component, i.e. which cycle leads the other, is captured by the bilateral differences in employment shares in high-tech industries. We must recall that LL_{ij} actually takes on both positive and negative values and, in principle, as depicted in Figure 10, the relationship between this variable and the degree of synchronization should be negative when LL_{ij} is positive (implying that the time that separates the cycles decreases as their degree of synchronization increases) and positive in the opposite case. In order to capture this, the first equation also includes a dummy variable for the leading state (DL_{ij}), taking value 1 when *i* leads *j*, and an interaction term between this dummy and the synchronization variable.[3]

The second equation in (3) models the determinants of the degree of synchronization. In particular, synchronization depends on the differential level of sectoral specialization

[3] We do not impose any restriction on these coefficients in the estimation and then check that the estimated values are compatible with the signs implied by Figure 1.

(S_{ij}), on a measure of bilateral trade intensity ($\hat{T}_{ij}$) and on the level of financial integration ($\hat{F}_{ij}$) between the states. The explanation of the relationships between these variables and synchronization borrows from Imbs (2004). In particular, S_{ij} is likely to affect synchronization of the cycles directly in a negative fashion: the degree of synchronization between the cycles of *i* and *j* should increase as the discrepancies in their economic structures decrease given that they should react in a more similar fashion to any shock. Following the implications coming from a variety of theoretical models (see Imbs, 2001 for an account of the related literature), intense bilateral trade flows tend to be associated with higher synchronization levels. Finally, financial integration should weaken the degree of synchronization among business cycles according to standard international macroeconomic theories (Obstfeld, 1994; Heathcote and Perri, 2006; Kalemli-Ozcan *et al*., 2009).

Through the third equation the circularity between synchronization levels and differences in specialization patterns takes form. Here, based on the dynamics explained in the introductory section, we expect a negative relationship between these two variables. In addition, in line with Imbs (2004), also trade flows and financial integration are considered as possible determinants of the correlation among cycles: while the sign of the first relationship is expected to be positive, the sign of the second is ambiguous.[4]

The intensity with which state economies specialize in high-tech industries is explained in the fourth equation through a set of exogenous variables that act as instruments ($\mathbf{V}^{HT}$). The rationale for this is that the level of specialization in high-tech is quite likely to be endogenous in the first equation.

Given the simultaneity characterizing the evolution of these variables, the model is estimated via the Three-Stage Least Squares Estimator. The identification of the system is guaranteed by the three vectors of instruments $\mathbf{V}^{\rho}$, $\mathbf{V}^{S}$ and $\mathbf{V}^{HT}$ a detailed account of which will be offered in the following section.

4 See Imbs (2004) for details on the sign of these relationships.

4.2 Data

As shown in Section 2, timing differences across state business cycles appear to have increased significantly after 1990. For this reason, and given the well-known difficulties that the move from the Standard Industrial Classification (SIC) to the North American Industrial Classification System (NAICS) poses for the construction of many of our variables, we concentrate our analysis on the period that follows 1990.

The main dependent variable, LL_{ij}, is calculated for all pairs of 48 coterminous states according to equation (1). In particular, in order to identify the cycle we applied the Baxter-King band-pass filter on the monthly coincident index for the national economy. The set of turning points, z, is derived using the Bry-Boschan algorithm on the filtered coincident index data. For each state i, the indicator $t_{i,z}$ is calculated as the average along z of the time (in months) with which i anticipates or follows the turning points of the national business cycle ($t_{i,z}$).

The degree of synchronization among state business cycles, ρ_{ij}, is simply the bilateral correlation among the Baxter-King cycles of states i and j. The industrial dissimilarity index is computed in the following way:

$$S_{ij} = \frac{1}{T} \sum_{t} \sum_{n=1}^{N} \left| s_{n,i,t} - s_{n,j,t} \right|$$

where $s_{n,i,t}$ is the employment share of industry n in total employment, in state i at time t, and S_{ij} is the time average of the discrepancies in the two states' industrial structures.[5] This variable reaches a maximum of 2 when the industrial structures of two states are totally different and a minimum of 0 when structures are identical.

[5] The N industries that have been used are: agriculture, mining, utilities, construction, manufacturing, wholesale trade, retail trade, transportation, information, finance and insurance, real estate, rental and leasing, professional, scientific and technical services, management of companies and services, administrative services, educational services, health care and social assistance, arts, entertainment, recreation services, accommodation and food services, other services except government and government sector.

As we anticipated, given the lack of data on inter-state trade, trade flows $\hat{T}$ are obtained via a gravity model along the lines of Imbs (2003).[6] In addition, bilateral financial integration is calculated from an estimate of the state-specific index of risk-sharing proposed by Kalemli-Ozcan *et al*. (2002). Specifically, the state-specific index of risk sharing θ_i is obtained by estimating

$$\ln \mathrm{GSP}_{i,t} - \ln \mathrm{DY}_{i,t} = c + \theta_i \, \mathrm{GSP}_{i,t} + e_{i,t}$$

where GSP stands for the per capita gross state product while DY is the disposable income per capita (both detrended using the Hodrick-Prescott filter). Then, the measure of cross-state financial integration between *i* and *j* is

$$\hat{F}_{ij} = \hat{\theta}_i + \hat{\theta}_j$$

Bilateral differences in the degree of specialization in high-tech production are calculated as the time average of yearly bilateral differences across states in the relevance of the high-tech sector:

$$HT_{ij} = \frac{1}{T} \sum_t \left(HT_{i,t} - HT_{j,t} \right)$$

where $HT_{i,t}$ is the share of employment in high-tech industries in state *i* at time *t*.

As already mentioned, to guarantee the identification of the system three instrument sets, $\mathbf{V}^{\rho}$, $\mathbf{V}^{S}$ and $\mathbf{V}^{HT}$, enter the model. The variables featuring in the first two sets are in line with what previously done in the literature adopting this framework. The first set, $\mathbf{V}^{\rho}$, includes the pairwise product of GSP per capita and difference in crude oil productions (expressed in absolute value); the second set, $\mathbf{V}^{S}$, employed in the explanation of the differences in specialization, includes the natural logarithm of distance between state capitals, the pairwise difference (expressed in absolute value) and product of GSP per capita.

Due to its novelty, the last set, $\mathbf{V}^{HT}$, deserves a few words of motivation. Here, the general aim is to introduce variables which are as exogenous as possible and, at the same time, able to provide an explanation to the differential development of high-tech

[6] Here we adopt the original coefficients estimated by Imbs (2003) so that inter-state trade between *i* and *j* is:

$$\hat{T}_{ij} = -1.355 \ln\left(\mathrm{distance}_{ij}\right) + 1.057 \ln\left(\mathrm{GDP}_i \cdot \mathrm{GDP}_j\right) - 0.635 \ln\left(\mathrm{Pop}_i \cdot \mathrm{Pop}_j\right) - 29.834$$

sectors across states. A possible set of candidates stems from the literature on amenity migration within the US. Since (natural) amenities are considered a normal or superior good (Graves, 1979 and 1980) and high-skill workers tend to have a relatively higher average income it might be plausible to think that high-tech jobs tend to move towards areas characterized by a relatively higher supply of the type of amenities. Evidence in support to this link between amenities and high-tech employment is reported by Partridge *et al*. (2008). However, the work by Dorfman *et al*. (2008) seems to suggest that this link should be qualified better as they find little evidence that high-skill workers drive amenity migration towards rural areas. To try to accommodate both suggestions we introduce two variables: the first measures the bilateral differences in natural amenities using the natural amenity index for each state provided by the Economic Research Service of the United States Department of Agriculture; the second is the pairwise differences in the states' share of employment in agriculture. Based on the suggestions from the just cited works, our expectation is that the first variable should be positively associated with high-tech employment, while the opposite should hold for the second. Then we include a further variable related to old resource-based industries, in the form of pairwise differences in the states' share of employment in mining activities; given the impact of these activities on landscape, skills and on the availability of land, we expect this variable to have a negative influence on the ability of the region to attract high-tech jobs. Finally, as in the explanation of the discrepancies in the two states' industrial structures, we include the pairwise difference of GSP per capita.

4.3 Results

Table 7 reports the results from the Three-Stage Least-Squares (TSLS) estimation of the system in equation (3) from which we can immediately notice that, with the only exception of the constant term in the *HT* equation, all coefficients are significant at the 1% level or better.

(Table 7 About Here)

As expected, the coefficient of high-tech is positive. To evaluate the impact of this variable on *LL* we consider the "representative leading"[7] state and calculate the corresponding predicted lead (approximately 42 days); similarly, we calculate the predicted lag (approximately 56 days) for the "representative lagging behind" state. Then, we consider an increase of one standard deviation in the mean value of *HT* of the "representative leading" state and, analogously, a decrease of one standard deviation in the mean value of *HT* for the "representative lagging behind" state. As a result, we obtain that the "representative leading" state increases its lead by approximately 7.5 days while the lag of the "representative lagging behind" state grows by 8.1 days.

Also the estimated relationship between LL_{ij} and ρ_{ij} is in accordance with expectations and, in particular, with the representation in Figure 10. More in detail, the relationship is negative ($\alpha_1+\alpha_3=-5.36$) when LL_{ij} is positive, which implies that the lead decreases as the degree of synchronization increases, and becomes positive ($\alpha_1=4.63$) when LL_{ij} is negative. With the same logic described above, we can calculate the impact of a change in the degree of synchronization: a one standard deviation increase in the degree of synchronization for a "representative leading" state determines a reduction of about 1 day in the predicted lead; a one standard deviation reduction in the degree of synchronization for a "representative lagging behind" state determines an increase of about 1 day in the predicted lag.

All signs in the second equation are in accordance to the theoretical predictions summarized in Sections 4.1-4.2. The effect of specialization on ρ has a negative sign, implying that more dissimilar industrial structures result in lower levels of synchronization. In addition, the level of synchronization is affected positively by trade flows and negatively by financial integration. Finally, couples of states with higher GSP and lower differences in crude oil production tend to display more synchronized business cycles.

[7] By "representative leading" state we mean the hypothetical state for which all independent variables take on their sample mean value conditional on the dummy *DL* being equal to 1. A similar concept applies for the "representative lagging behind" state with the only difference that the dummy *DL* is equal to 0.

Estimates for the third equation confirm the possibility of a circular relationship between synchronization levels and differences in specialization patterns. The coefficient of ρ is significant and its negative sign is clearly in line with the negative sign on the link between *S* and ρ in the second equation. Specifically, the smaller the correlation between state business cycles and the more asymmetric their industrial structures. Trade flows induce differentiation in industrial specialization while financial integration has the opposite effect. In addition, pairs of richer states as well as pairs of states with lower GSP gaps and lower physical distance tend to have more similar economic structures.

Finally, estimates for the *HT* equation suggest that natural amenities play a positive role in favoring the relative concentration of high-tech jobs while, as expected, all other variables tend to discourage it.

Table 8 reports equation-by-equation estimates using Ordinary Least-Squares (OLS). Similarly to the TSLS estimation, all coefficients are significant at the 1% level with, again, the only exception of the constant term in the *HT* equation.

(Table 8 About Here)

However, two important remarks must be made. First, the sign of coefficient of *HT*, α_4, in the first equation is reversed with respect to the TSLS estimate and is thus in contrast with the theoretical predictions. Second, concentrating now on the second and third equations of the system and, in particular, on the potential circularity between ρ and S, we observe that, compared to TSLS, OLS clearly diminish the absolute value of the estimated coefficients possibly due to a bias arising from neglected endogeneity. Moreover, it should be noted that the strong significance levels of δ_1 and γ_1 in the OLS estimates was also found in the TSLS estimates where the possible circularity between ρ and S was allowed for. Intuitively, this result appears to support the appropriateness of the specification introduced in this analysis.

5 Conclusions

This paper analyzes the possibility that some economies might be systematically ahead of others along the swings of the business cycle and tries to find out the economic reasons why this may happen. To do so we concentrate on the business cycle fluctuations of the 48 coterminous US states between 1979 and 2010.

First of all, we have observed that timing differences across state cycles have recently become more evident. Furthermore, we have reported evidence suggesting the existence of a lead/lag structure whereby some states are systematically ahead of others (and, clearly, others are systematically behind) along the swings of the business cycle.

The core of our analysis is the development of a multiple equation econometric model to explain not only the degree of synchronization that might exist among regional cycles but also the economic reasons why some state cycles do anticipate others. In particular, due to the presence of simultaneous relationships among featured variables the model is estimated via Three-Stage Least-Squares. This strategy also allows us to accommodate an hypothesized circular mechanism between the degree of synchronization and the dissimilarities in industrial structures. Our estimates show that the lead/lag structure is significantly explained by the degree of synchronization and, indirectly, by trade flows and financial integration. In addition, specialization, and particularly specialization in the high-tech sector, plays an important role in predicting whether a state leads or lags behind another.

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Figures

Figure 1 Relationships between the main variables of the model

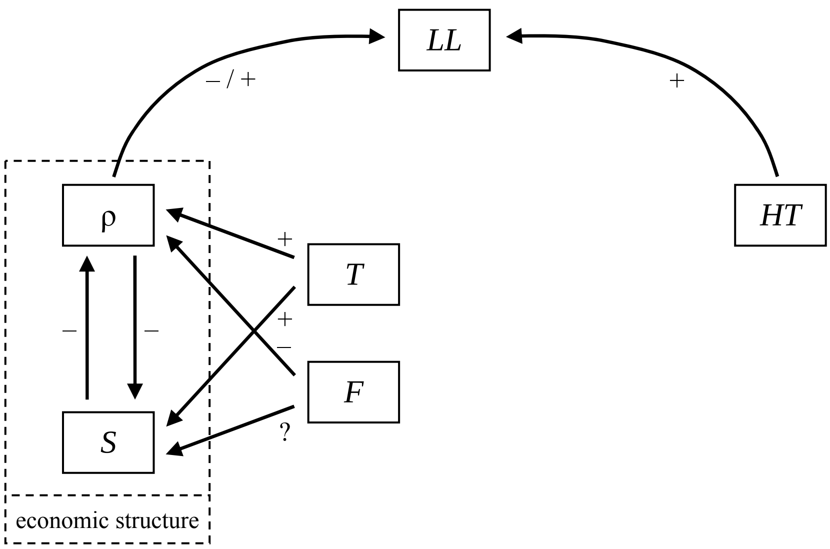


Figure 2 US Business Cycle (1979:7-2010:10)
Baxter-King filtered coincident index

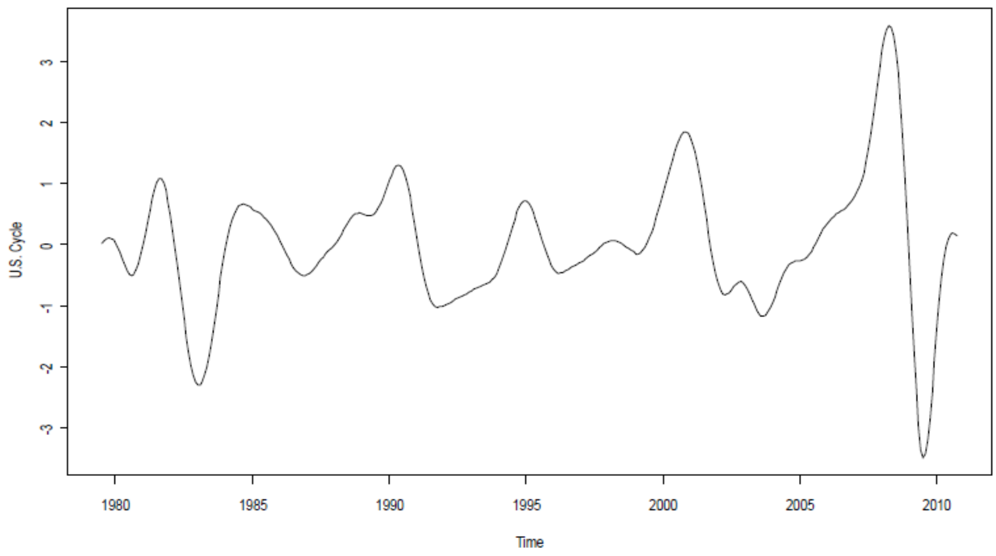


Figure 3 US Business Cycle (1969:Q1-2008:Q4)
Hodrick-Prescott filtered personal income

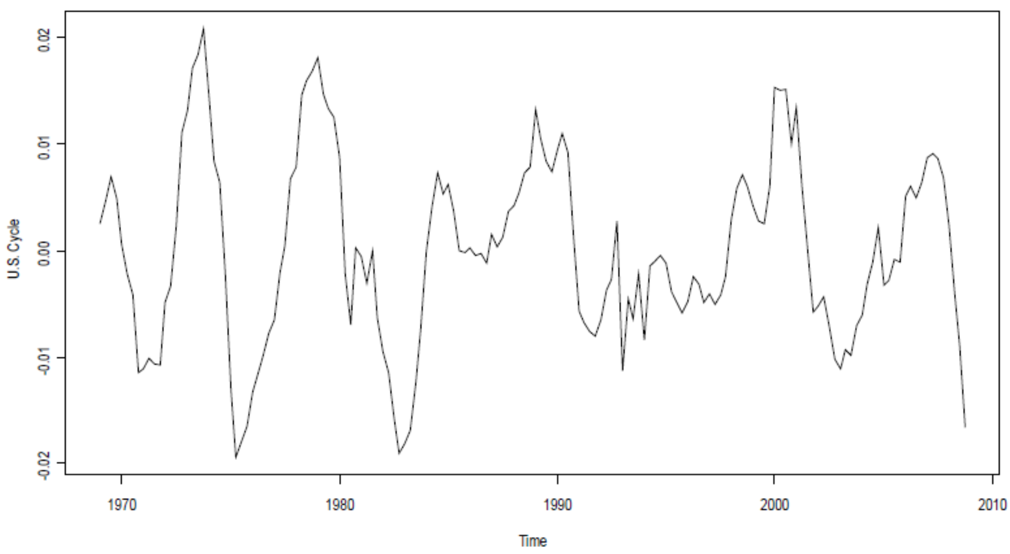


Figure 4 Degree of Synchronization within the US (coincident index cycles)

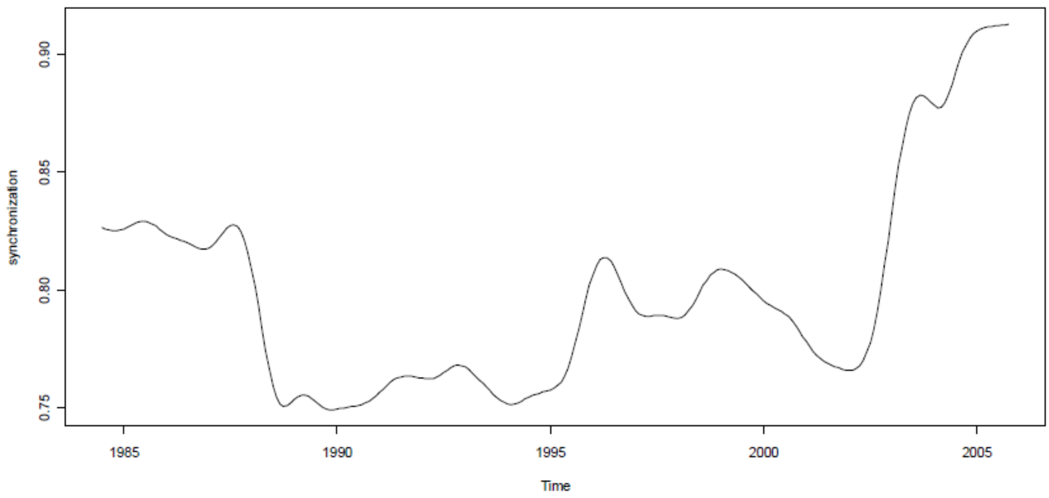
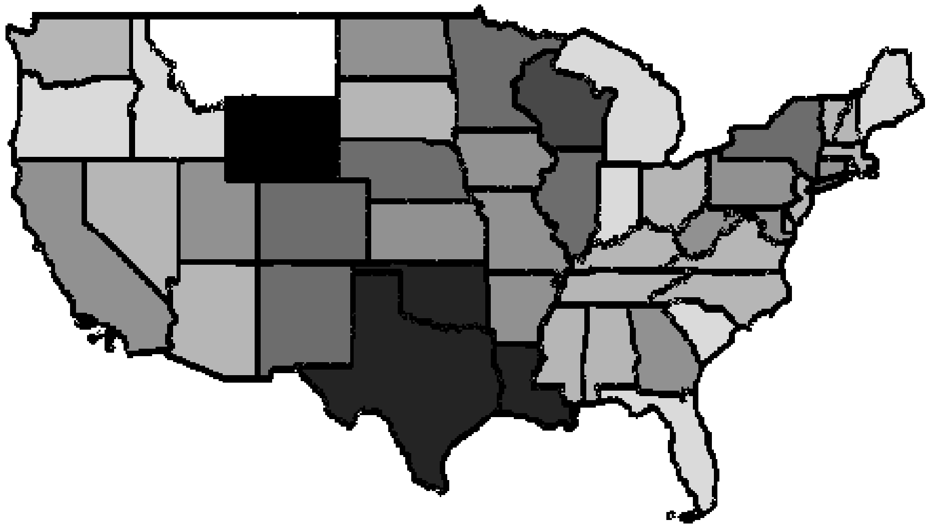


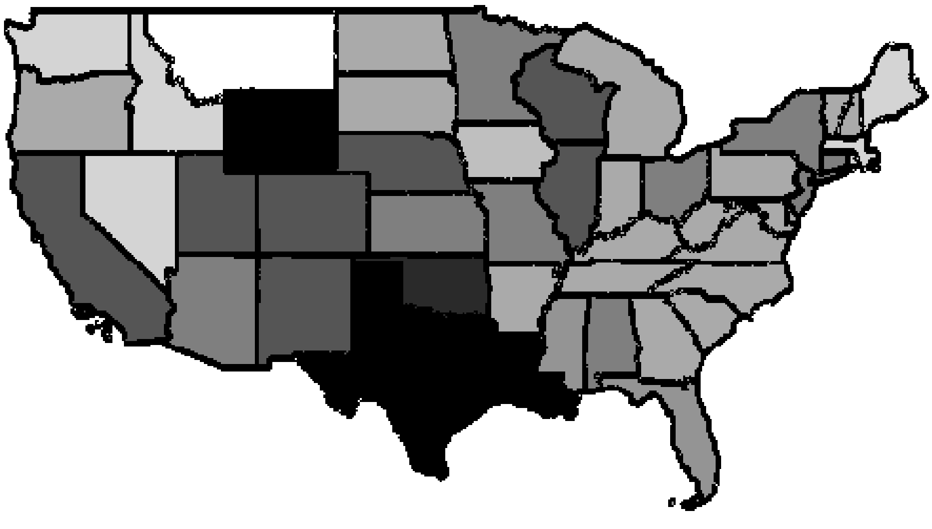
Figure 5 Degree of Synchronization within the US (personal income cycles)

Figure 6 Geographical distribution of leads and lags, 1979-2010
Cross-Correlation Approach



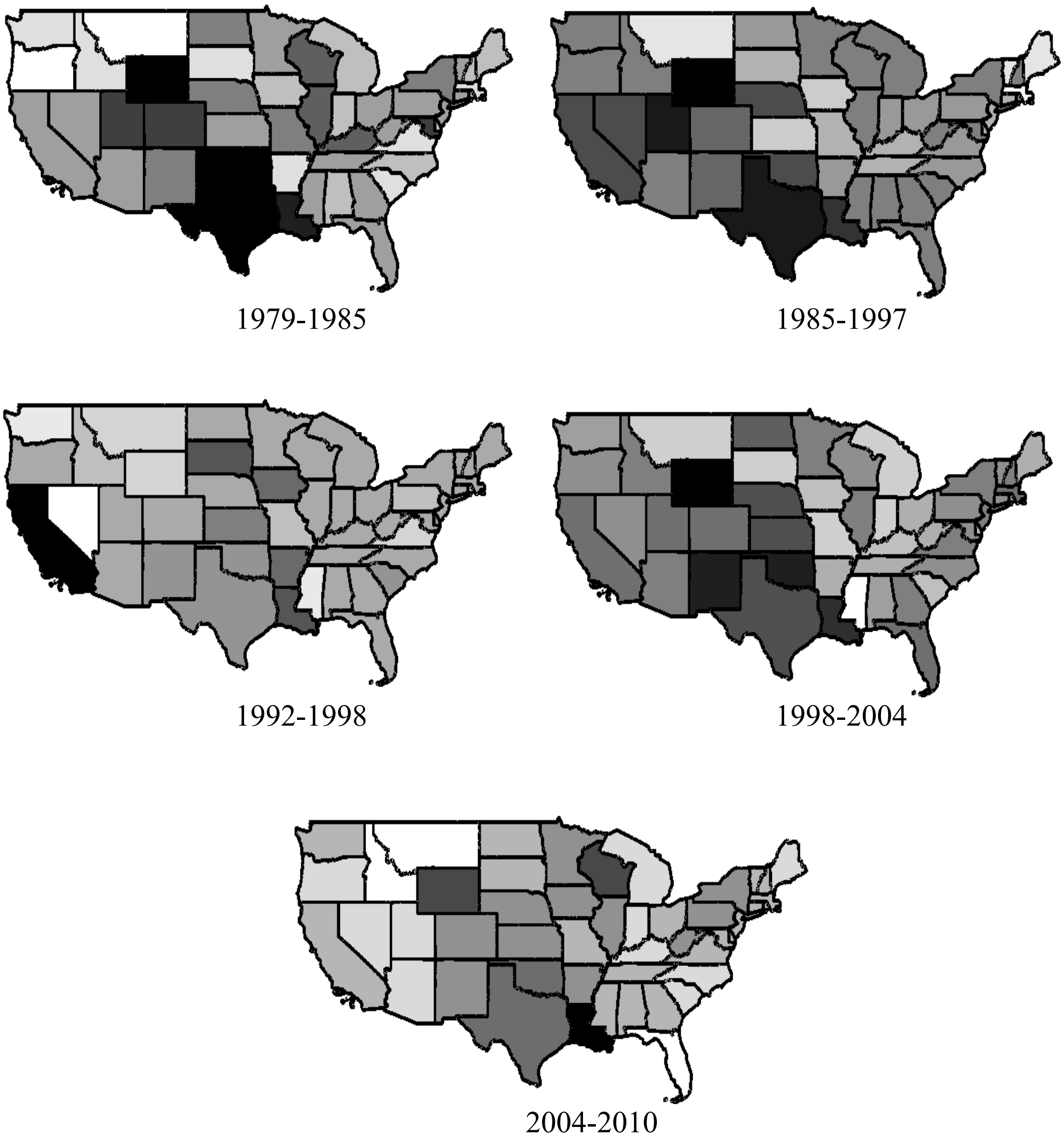
Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads

Figure 7 Geographical distribution of leads and lags, 1979-2010
Turning Points Approach



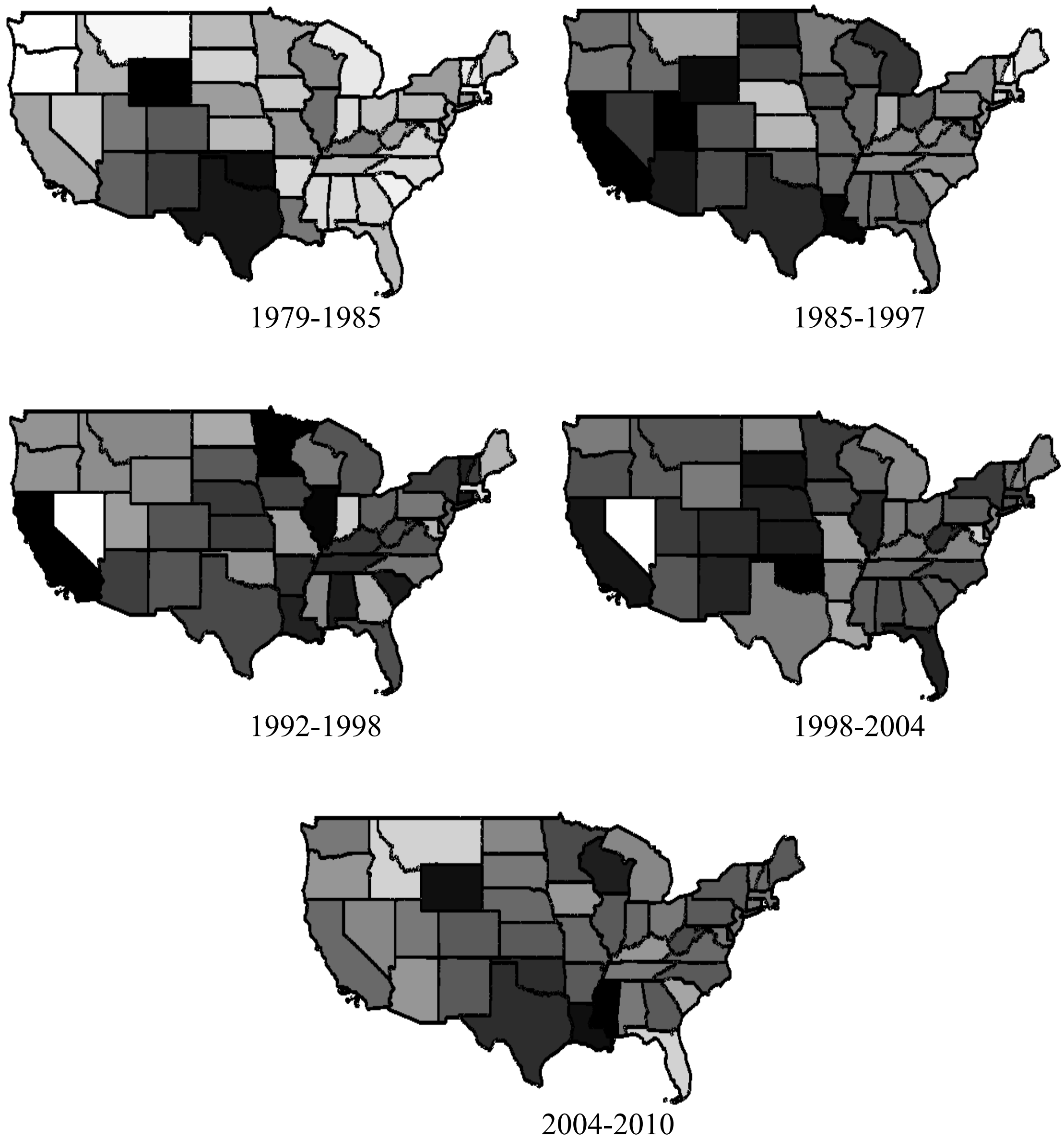
Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads

Figure 8 Geographical distribution of leads/lags during sub-periods (Cross-Correlation Approach)



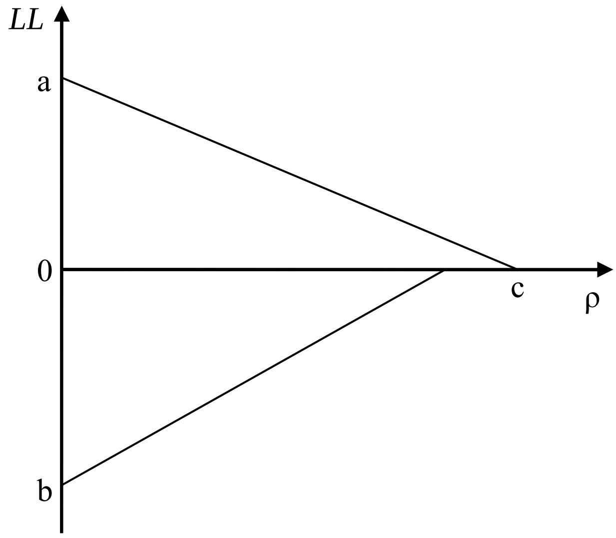
Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads

Figure 9 Geographical distribution of leads/lags during sub-periods (Turning points Approach)



Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads

Figure 10 Relationship between *LL* and ρ



Notes: Based on the coefficients reported in the first equation of the system, the slope is $\alpha_1+\alpha_3$ (<0) in the positive section of the codomain and α_1 (>0) in the negative one. In addition:
$a = \alpha_0 + \alpha_2\,(>0)$, $b = \alpha_0\,(<0)$, $c = -\dfrac{\alpha_0 + \alpha_2}{\alpha_1 + \alpha_3}(>0)$.

Tables

Table 1 Lead/lag of the states with respect to the U.S. cycle
Dynamic Cross-Correlations Approach, 1979-2010

States	Lead (+)/Lag(–)	States	Lead (+)/Lag(–)
Alabama	1	Nebraska	–1
Arizona	1	Nevada	1
Arkansas	0	New Hampshire	1
California	0	New Jersey	1
Colorado	–1	New Mexico	–1
Connecticut	0	New York	–1
Delaware	1	North Carolina	1
Florida	2	North Dakota	0
Georgia	0	Ohio	1
Idaho	2	Oklahoma	–3
Illinois	–1	Oregon	2
Indiana	2	Pennsylvania	0
Iowa	0	Rhode Island	2
Kansas	0	South Carolina	2
Kentucky	1	South Dakota	1
Louisiana	–3	Tennessee	1
Maine	2	Texas	–3
Maryland	0	Utah	0
Massachusetts	1	Vermont	1
Michigan	2	Virginia	1
Minnesota	–1	Washington	1
Mississippi	1	West Virginia	0
Missouri	0	Wisconsin	–2
Montana	3	Wyoming	–4

Table 2 Lead/Lag of state turning points with respect to US turning points

US turning points (T)/(P)	80-08 (T)	81-09 (P)	83-02 (T)	84-09 (P)	86-12 (T)	90-05 (P)	91-10 (T)	94-12 (P)	96-03 (T)	98-02 (P)	99-02 (T)	00-11 (P)	03-09 (T)	07-09 (P)	08-04 (T)
Alabama	0	2	2	5	1	1	1	-2	-11	-4	-1	4	-2	0	0
Arizona	1	2	2	-12	0	-1	-16	0	-11	0	1	0	1	0	2
Arkansas	0	3	3	3	-2	1	3	-3	-10	0	3	3	2	-1	-1
California	1	2	1	-2	2	-2	-23	-10	-8	-4	-5	-1	-1	0	-1
Colorado	-2	-3	-2	-1	-2	-1	0	-1	-7	1	-4	-1	1	-1	-1
Connecticut	0	1	0	1	14	16	-2	1	-12	-6	-4	3	3	0	0
Delaware	2	7	-2	-6	7	3	1	-2	-7	12	6	1	0		-2
Florida		2	1	1	6	0	-2	1	-4	-5	-5	0	0	1	5
Georgia	2	4	1	1	1	0	0	1	7	0	1	1	0		-1
Idaho	1	3	5	-5	0	0	3	3	-6	6	2	2	-1	0	6
Illinois	-3	-1	0	-1	9	-3	-3	-3	-12	-6	-4	0	0	-1	-1
Indiana	1	2	2	4	1	15	2	-2	0	16	6	1	0	-2	1
Iowa	0	2	2	3	3	14	-19	-1	-12	3	3	-1	-1		1
Kansas	0	1	2	2	14	2	5	-1	-6	-4	-5	-2	1	-1	-1
Kentucky	-1	0	-1	-1	3	2	4	0	-10	-2	2	4	1	1	1
Louisiana	2	-2	-3	-1	-1	-2	-19	-4	-9	-3	-4	8	9	-3	-4
Maine	1	3	1	1	11	15	4	-2	-2	14	2	5	2	-2	0
Maryland		6	1	-2	2	3	-3	0	-1	11	12	1	5	-1	1
Massachusetts	5	6	2	0	5	15	3	15	6	-3	-3	0	2	-1	1
Michigan	0	2	3	6	-12	1	1	0	-9	2	1	6	2	1	0
Minnesota	1	1	1	-1	6	0	1	-11	-11	0	0	0	-2	-1	-2
Mississippi	0	1	2	6	-1	0	3	4	-12	10	3	0	0		-4
Missouri	0	1	-1	0	-3	2	4	2	-3	7	8	9	-5	0	-1
Montana	1	3	6	3	-7	18	7	2	5	-5	-2	5	-1	1	5
Nebraska	0	2	1	-2	-2	-3	-19	3	-10	-5	-1	-8	4	-1	0
Nevada	2	1	1	3	8	0	-18	4	6	13	11	-2	16	0	1
New Hampshire	1	2	3	5	18	16	4	-1	-8	-2	-3	-1	12	-1	0
New Jersey	0	1	1	2	10	4	-1	0	0	-3	-2	3	7	0	0
New Mexico	0	1	0	-13	-4	-1	0	-3	-6	2	-2	-4	1	-1	-1
New York	0	0	0	1	10	0	-1	-1	-10	0	0	-1	-1		-1
North Carolina	0	2	3	4	5	2	3	-1	-1	1	0	1	0		-1
North Dakota	-2	-2	2	7	6	0	-20	2	5	1	1	-6	14	1	0
Ohio	0	1	2	3	-3	0	3	-1	-3	-1	0	4	1	0	0
Oklahoma	-1	-5	-3	-9	-1	0	0	1	6	-3	-8	-4	2	-2	-3
Oregon	1	4	5	4	7	0	-1	-1	0	5	0	1	0	1	1
Pennsylvania	0	1	1	3	8	2	0	0	2	-3	-1	2	2	-1	-1
Rhode Island	2	4	2	0	-2	15	1	14	-9	-5	-3	2	15	-1	10
South Carolina	2	3	3	4	14	-1	1	-4	-8	-5	-1	4	0	1	2
South Dakota	0	2	3	3	-9	-1	5	-4	-7	5	4	9	1	0	0
Tennessee	0	1	1	3	3	4	3	-3	-8	-3	-1	3	1	0	0
Texas	-1	-3	-3	-10	-2	-3	-8	-2	-4	-3	-6	-2	1	-2	-3
Utah	-2	-2	-1	1	-8	-4	-11	8	-1	-1	2	2	0		0
Vermont	0	2	3	6	2	13	4	-4	-11	-1	0	1	6	0	0
Virginia		7	3	-4	7	2	0	1	1	-9	-6	1	3	-1	0
Washington	2	4	4	4	2	0	2	2	2	0	1	3	1	0	0
West Virginia	-1	0	1	2	10	-1	2	-2	-7	1	4	3	1	-1	-2
Wisconsin	-2	-2	-1	3	-3	0	1	0	1	-2	-2	5	4	-2	-4
Wyoming	1	-3	-3	-15	-3	-3	-14	2	-2	3	2	-12	7	-3	-4

Table 3 Median Lead/lag of the states with respect to the US cycle
Turning Points Approach, 1979-2010

States	Lead (+)/Lag(–)	States	Lead (+)/Lag(–)
Alabama	0	Nebraska	–1
Arizona	0	Nevada	2
Arkansas	1	New Hampshire	1
California	–1	New Jersey	0
Colorado	–1	New Mexico	–1
Connecticut	0	New York	0
Delaware	1	North Carolina	1
Florida	0.5	North Dakota	1
Georgia	1	Ohio	0
Idaho	2	Oklahoma	–2
Illinois	–1	Oregon	1
Indiana	1	Pennsylvania	1
Iowa	1.5	Rhode Island	2
Kansas	0	South Carolina	1
Kentucky	1	South Dakota	1
Louisiana	–3	Tennessee	1
Maine	2	Texas	–3
Maryland	1	Utah	–1
Massachusetts	2	Vermont	1
Michigan	1	Virginia	1
Minnesota	0	Washington	2
Mississippi	0.5	West Virginia	1
Missouri	0	Wisconsin	–1
Montana	3	Wyoming	–3

Table 4 Lead /lag of states with respect to U.S. cycle during sub-periods
Dynamic Cross-Correlations Approach

lead/lag	1979-1985	1985-1991	1992-1998	1998-2004	2004-2010
Alabama	2	0	0	2	0
Arizona	1	0	0	0	1
Arkansas	3	1	-3	3	-1
California	1	-2	-8	-1	0
Colorado	-2	-1	0	-1	-1
Connecticut	1	2	0	1	0
Delaware	2	2	-1	4	0
Florida	1	0	0	-1	2
Georgia	1	0	0	0	0
Idaho	3	0	1	0	2
Illinois	-1	0	0	0	-1
Indiana	2	1	0	5	1
Iowa	2	3	-3	4	-1
Kansas	1	3	-2	-3	-1
Kentucky	-1	2	0	4	1
Louisiana	-3	-3	-4	-5	-5
Maine	2	4	0	3	1
Maryland	-2	0	0	1	0
Massachusetts	3	5	0	-1	0
Michigan	2	0	0	5	1
Minnesota	1	0	0	0	-1
Mississippi	1	0	3	8	0
Missouri	0	2	1	5	0
Montana	4	4	2	5	2
Nebraska	0	-2	0	-3	-1
Nevada	1	-2	4	1	1
New Hampshire	2	6	0	0	0
New Jersey	1	2	0	0	0
New Mexico	0	-1	-1	-6	-1
New York	0	0	0	0	-1
North Carolina	2	1	0	1	1
North Dakota	0	1	0	-2	0
Ohio	1	1	0	3	0
Oklahoma	-4	-2	-1	-6	-2
Oregon	4	0	0	1	1
Pennsylvania	1	1	1	1	-1
Rhode Island	2	1	2	3	1
South Carolina	3	0	-1	4	1
South Dakota	3	2	-4	5	0
Tennessee	1	2	0	3	0
Texas	-4	-4	-1	-3	-2
Utah	-2	-4	0	-1	1
Vermont	1	4	0	1	0
Virginia	3	1	2	0	0
Washington	3	0	3	2	0
West Virginia	1	0	0	3	-1
Wisconsin	-1	0	0	1	-3
Wyoming	-4	-5	2	-8	-3
Mean	0.79	0.52	-0.172	0.79	-0.19

Table 5 Lead /lag of states with respect to US cycle during sub-periods
Turning Points Approach

lead/lag	1979-1985	1985-1991	1992-1998	1998-2004	2004-2010
Alabama	2.25	1	-5.67	0.33	0
Arizona	-1.75	-5.67	-3.67	0.67	1
Arkansas	2.25	0.67	-4.33	2.67	-1
California	0.5	-7.67	-7.33	-2.33	-0.5
Colorado	-2	-1	-2.33	-1.33	-1
Connecticut	0.5	9.33	-5.67	0.67	0
Delaware	0.25	3.67	1	2.33	-2
Florida	1.33	1.33	-2.67	-1.67	3
Georgia	2	0.33	2.67	0.67	-1
Idaho	1	1	1	1	3
Illinois	-1.25	1	-7	-1.33	-1
Indiana	2.25	6	4.67	2.33	-0.5
Iowa	1.75	-0.67	-3.33	0.33	1
Kansas	1.25	7	-3.67	-2	-1
Kentucky	-0.75	3	-4	2.33	1
Louisiana	-1	-7.33	-5.33	4.33	-3.5
Maine	1.5	10	3.33	3	-1
Maryland	1.67	0.67	3.33	6	0
Massachusetts	3.25	7.67	6	-0.33	0
Michigan	2.75	-3.33	-2.33	3	0.5
Minnesota	0.5	2.33	-7.33	-0.67	-1.5
Mississippi	2.25	0.67	0.67	1	-4
Missouri	0	1	2	4	-0.5
Montana	3.25	6	0.67	0.67	3
Nebraska	0.25	-8	-4	-1.67	-0.5
Nevada	1.75	-3.33	7.67	8.33	0.5
New Hampshire	2.75	12.67	-3.67	2.67	-0.5
New Jersey	1	4.33	-1	2.67	0
New Mexico	-3	-1.67	-2.33	-1.67	-1
New York	0.25	3	-3.67	-0.67	-1
North Carolina	2.25	3.33	-0.33	0.33	-1
North Dakota	1.25	-4.67	2.67	3	0.5
Ohio	1.5	0	-1.67	1.67	0
Oklahoma	-4.5	-0.33	1.33	-3.33	-2.5
Oregon	3.5	2	1.33	0.33	1
Pennsylvania	1.25	3.33	-0.33	1	-1
Rhode Island	2	4.67	0	4.67	4.5
South Carolina	3	4.67	-5.67	1	1.5
South Dakota	2	-1.67	-2	4.67	0
Tennessee	1.25	3.33	-4.67	1	0
Texas	-4.25	-4.33	-3	-2.33	-2.5
Utah	-1	-7.67	2	1.33	0
Vermont	2.75	6.33	-5.33	2.33	0
Virginia	2	3	-2.33	-0.67	-0.5
Washington	3.5	1.33	1.33	1.67	0
West Virginia	0.5	3.67	-2.67	2.67	-1.5
Wisconsin	-0.5	-0.67	-0.33	2.33	-3
Wyoming	-5	-6.67	1	-1	-3.5
Mean	0.8	1.12	-1.35	1.17	-0.34

Table 6 Number of states that switch from leading (lagging) to lagging (leading) behavior across consecutive sub-periods

		Number of switching states	
Initial period	Following period	Cross-Correlations Approach	Turning Points Approach
1979-1985	1985-1991	3	8
1985-1991	1992-1998	7	24
1992-1998	1998-2004	6	22
1998-2004	2004-2010	7	13
	Mean	5.75	16.75

Table 7 Three-Stage Least-Squares regression results

	Variables	Coefficients	s.e.
Dependent Variable: *LL*	constant	-5.3403^{***}	0.8172
	HT	38.0828^{***}	11.4080
	DL	10.9556^{***}	1.3599
	ρ	4.6319^{***}	1.0501
	ρ·*DL*	-9.9860^{***}	1.7366
	R-squared	0.6065	
Dependent Variable: ρ	constant	1.0121^{***}	0.0614
	S	-0.6578^{***}	0.1044
	$\hat{T}$	0.0121^{***}	0.0043
	$\hat{F}$	-0.0855^{***}	0.0161
	GSP product	0.0039^{***}	0.0015
	Oil	-0.0002^{***}	0.0000
	R-squared	0.1119	
Dependent Variable: *S*	constant	0.4883^{***}	0.0796
	ρ	-0.2760^{***}	0.0813
	$\hat{T}$	0.1123^{***}	0.0153
	$\hat{F}$	-0.0469^{***}	0.0106
	Distance	0.1689^{***}	0.0215
	GSP product	-0.0275^{***}	0.0034
	GSP difference	0.0149^{***}	0.0060
	R-squared	0.1785	
Dependent Variable: *HT*	constant	0.0001	0.0003
	Amenity	0.0022^{***}	0.0002
	Mining	-0.1970^{***}	0.0170
	Agriculture	-0.0478^{***}	0.0107
	GSP difference	-0.0041^{***}	0.0004
	R-squared	0.1827	

Notes: Significance levels: * = 10%, ** = 5% , *** = 1%
Endogenous variables: *LL*, *HT*, *S*, ρ·*DL*, ρ

Table 8 Equation-by-equation Ordinary Least-Squares regression results

	Variables	Coefficients	s.e.
Dependent Variable: *LL*	constant	-5.0341^{***}	0.3079
	HT	-19.4412^{***}	3.6183
	DL	10.1466^{***}	0.4265
	ρ	4.0543^{***}	0.3895
	ρ·*DL*	-8.7373^{***}	0.5342
	R-squared	0.6905	
Dependent Variable: ρ	constant	0.8633^{***}	0.0532
	S	-0.2692^{***}	0.0458
	$\hat{T}$	0.0184^{***}	0.0039
	$\hat{F}$	-0.0609^{***}	0.0149
	GSP product	0.0059^{***}	0.0015
	Oil	-0.0003^{***}	0.0000
	R-squared	0.1674	
Dependent Variable: *S*	constant	0.3072^{***}	0.0355
	ρ	-0.0880^{***}	0.0177
	$\hat{T}$	0.1277^{***}	0.0158
	$\hat{F}$	-0.0337^{***}	0.0095
	Distance	0.1971^{***}	0.0215
	GSP product	-0.0322^{***}	0.0033
	GSP difference	0.0217^{***}	0.0062
	R-squared	0.2539	
Dependent Variable: *HT*	constant	0.0003	0.0003
	Amenity	0.0023^{***}	0.0002
	Mining	-0.1950^{***}	0.0172
	Agriculture	-0.0427^{***}	0.0117
	GSP difference	-0.0022^{***}	0.0005
	R-squared	0.1974	

Notes: Significance levels: * = 10%, ** = 5% , *** = 1%

APPENDIX Variables and Data Sources

Variables	Definition	Data Source
LL	Average (along national turning points) of the number of months by which a state's business cycle anticipates or follows the national business cycle	
ρ	bilateral correlation among states' cycles. Cycles have been identified using the Baxter-King band-pass filter	
S	Time average of yearly pairwise differences across states in the industry mix: $S_{ij} = \frac{1}{T}\sum_t \sum_{n=1}^{N} \left\| s_{n,i,t} - s_{n,j,t} \right\|$ where $s_{n,i,t}$ is the employment share of industry *n* in total employment at time *t*	US Bureau of Economic Analysis
HT	Time average of yearly pairwise differences across states in the share of high technology sector employment over total employment; high-tech sector is proxied by NAICS 340000 "computer and electronic product manufacturing"	US Bureau of Economic Analysis
DL	Dummy variable which takes on a value of 1 if the first state of the pair is leading the second in terms of business cycle, 0 otherwise	
T	Bilateral trade intensity	Estimated as described in the text
F	Cross-state financial integration	Estimated as described in the text
Amenity	Pairwise differences across states in the natural amenity index	Economic Research Service; US Department of Agriculture
Agriculture	Time average of yearly pairwise differences across states in the share of agriculture employment over total employment	US Bureau of Economic Analysis
Mining	Time average of yearly pairwise differences across states in the share of mining employment over total employment	US Bureau of Economic Analysis
Oil	Pairwise differences across states in 2010 oil production (in million barrels)	US Energy Information Administration
Distance	Logarithm of Euclidean distance across states' capitals	
GSP difference	Time average of yearly pairwise differences across states in Gross State Product	US Bureau of Economic Analysis
GSP product	Time average of yearly pairwise products across states in Gross State Product	US Bureau of Economic Analysis