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Topics

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Business cycle dynamics across the US states

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. We analyze this issue within a system of economies and show that leading (or lagging behind) is a feature that does not occur at random across the economies. In addition, we investigate the economic drivers that could explain this behavior. To do so, we employ data for 48 conterminous US states between 1990 and 2009.

Keywords: Business cycles; Lead/lag structure; Synchronization.

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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, Carlino and Sill 2001; Carlino and DeFina 2004; Crone 2005; Owyang, Piger, and Wall 2005; Partridge and Rickman 2005; Beckworth 2010). If this feature was due to a random mechanism, such that states on some occasions tend to anticipate and on others 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 systematically lead (or lag behind), the mechanism is no more random. Were that 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. To do so, we generalize the existing literature on synchronization by associating the study of this feature with an explanation of the economic factors behind the systematically different timings of business cycles.

As far as synchronization is concerned, a well-known model has been proposed by Imbs (2004) and then adopted by a number of authors (Xing and Abbott 2007; Inklaar, Jong-A-Pin, and de Haan 2008; Schiavo 2008; Fidrmuc, Iwatsubo, and Ikeda 2010; Dées and Zorell 2011). The model allows analyzing 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, and focusing only on its main variables, the model consists of a system of 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, Sørensen, and Yosha (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.

Working along these lines, we develop a four-equation econometric model that explains not just the degree of synchronization among US states cycles but also the economic reasons why some of them do anticipate others. In particular, results show that the lead/lag structure is not random; rather, it is explained directly by the degree of synchronization among US states' business cycles and the extent of specialization in high-tech industries and indirectly by trade flows and financial integration. In addition, we find evidence of a possible circular relationship between the degree of synchronization and a general index of sectoral specialization.

The analysis is structured as follows. Section 2 studies the degree of synchronization characterizing the US states in recent decades, identifies the states who lead and those who lag behind and then analyses the persistence of the observed pattern over a set of sub-periods. The economic explanation of the lead/lag structure among the states' cycles is provided in Section 3 where the model is outlined and estimated over the period 1990–2009. Section 4 concludes.

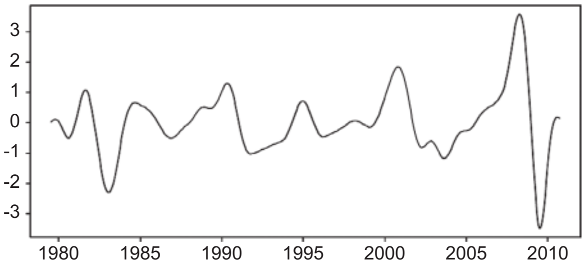

Figure 1 US Business Cycle (1979:7–2010:10).

2 An overview of synchronization and Lead/Lag behavior

2.1 Synchronization among state business cycles

In this section we describe the evolution of the degree of synchronization among US states' cycles. In order to do so, we first of all estimate the business cycles of the US and its 48 contiguous states using the monthly coincident index[1] for the broader 1979:7–2010:10 period.[2] To each series we apply a Baxter-King (Baxter and King 1999) filter that allows extracting directly the cyclical movements whose periodicity is within a certain range.[3] The outcome is shown in Figure 1.

In order to evaluate the degree of synchronization at each point in time, we compute rolling window cross-correlations between the cycle of the US and the cycle of each state; then, we take the average of these correlations within each window thus obtaining an average measure of cycle synchronization within the US at a point in time (corresponding to the mid-point of the window). We set the window length of 120 months which is a period long enough to capture

1 The coincident index is a macroeconomic indicator that summarizes in a single variable the current economic conditions of a state. It includes four main elements: non-farm payroll employment, average hours worked in manufacturing, unemployment rate, and wage and salary disbursements. Coincident index data are obtained from the website of the Federal Reserve Bank of Philadelphia.

2 As will be clarified in Section 3, the regression analysis covers a shorter period due to data availability problems for most variables introduced in the model.

3 Baxter and King (1999) 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, the applied filter passes through components of time series with fluctuations between 18 and 96 months while removing higher and lower frequencies.

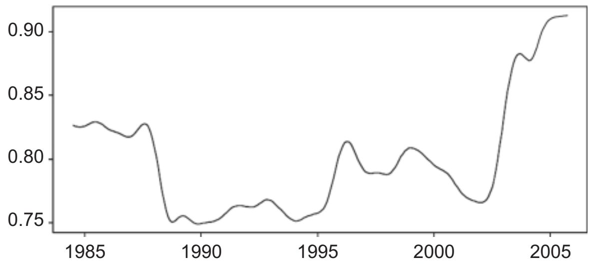

Figure 2 Degree of Synchronization within the US.

the complete business cycles (peak-to-peak or trough-to-trough). The evolution of this measure of synchronization is reported in Figure 2 in which we note that the degree of synchronization among US states cycles clearly decreases towards the end of the 1980s, reaching a minimum at the beginning of the 1990s. After some moderate fluctuations, we finally observe a sudden and sizeable jump in the degree of synchronization after 2003.

2.2 Who leads and who lags behind?

Having reported that the degree of synchronization among state cycles varies in an appreciable way over the analyzed time-span, we now investigate whether there are states that permanently lead or lag behind others along the swings of the business cycle. To do so, we need to identify which states lead and which lag behind at given points in time – as well as their geographical distribution within the US – and then to evaluate whether the observed pattern is actually persistent over time.

In general, leading and lagging behind states are identified through a comparison between the timing of the turning points of the US cycle and those characterizing the cycle of each state. Operatively, we initially detect the turning points in each business cycle by 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 we use monthly data, we impose that a phase must be at least 6 months long and a cycle must last at least 15 months.[4]

4 Table A1 in the Appendix reports, 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.

Next, state by state, we calculate the median lead or lag with respect to the US turning points. These values are reported in Table 1 where we can notice that the state that most clearly leads the US cycle is Montana (3 months ahead of the US cycle), followed by Maine, Rhode Island, Massachusetts, Washington, Idaho and Nevada (2 months ahead of the US cycle). The states which are instead lagging behind most substantially are Louisiana, Texas and Wyoming (3 months behind the US cycle) and Oklahoma (2 months behind the US cycle).

Figure 3 reports the geographical distribution of leads and lags, where states with the brightest color are those that lead the most while states that lag behind most substantially are the darkest. 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).

Table 1 Median leads and lags with respect to the US cycle.

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

Figure 3 Geographical distribution of leads and lags (1979:7–2010:10).
Note: The range between maximum lag and maximum lead is divided into 5 equisized intervals.

2.3 Persistence of leads and lags

Having documented that over the entire period of analysis some states tend to anticipate the national business cycle and some others to follow it, we now study whether the pattern is actually persistent over different sub-periods. In details, we divide the overall time-span into the following four, non-overlapping sub-periods running from trough to trough of the aggregate business cycle (as identified by NBER): 1980:7–1982:11; 1982:11–1991:3; 1991:3–2001:11; 2001:11–2009:7. Then, for each of these sub-periods, we show the geographical distribution of leads and lags. In particular, we consider a state as "leading" if its median lead/lag with respect to the US turning points is within the interval $(0.5, \infty)$ and as "lagging behind" if its median lead/lag is within $(-0.5, -\infty)$.[5] The geographical distribution of leads and lags is displayed in Figure 4 where, as before, the brightest color denotes leaders while the darkest indicates states that lag behind. Despite some obvious variations across periods, we observe that the states that we previously identified as leading (lagging behind) the others tend to maintain this attribute also in the different sub-periods. Overall, therefore, these maps suggest that the location of leads and lags is not purely random but possibly displays a systematic behavior.

To investigate this issue further, in Table 2 we count the number of states that switch from leading (+) to lagging behind (−) (or *vice versa*) across consecutive periods. We note that, on average, only about 6 states out of 48 switch their behavior across each couple of consecutive periods thus implying that approximately 88% 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

5 A detailed table with median lead/lag values for all the States and all sub-periods is provided in the Appendix (Table A2).

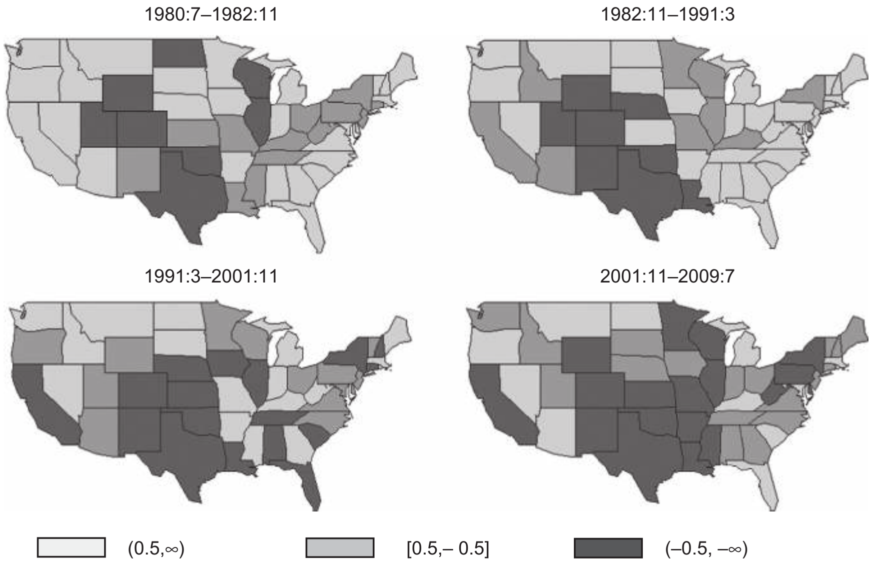

Figure 4 Geographical distribution of leads/lags during sub-periods.

Table 2 States switching from leading (lagging) to lagging (leading) behavior across consecutive sub-periods.

Initial period	Following period	Switching states
1980:7–1982:11	1982:11–1991:3	2
1982:11–1991:3	1991:3–2001:11	9
1991:3–2001:11	2001:11–2009:7	8
Mean		6

hierarchical structure 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 next section.

3 Why do some states lead others?

3.1 A generalization of the model by Imbs

The relationships that characterize the model through which we try to provide an account of the lead/lag phenomenon are synoptically represented in Figure 5.

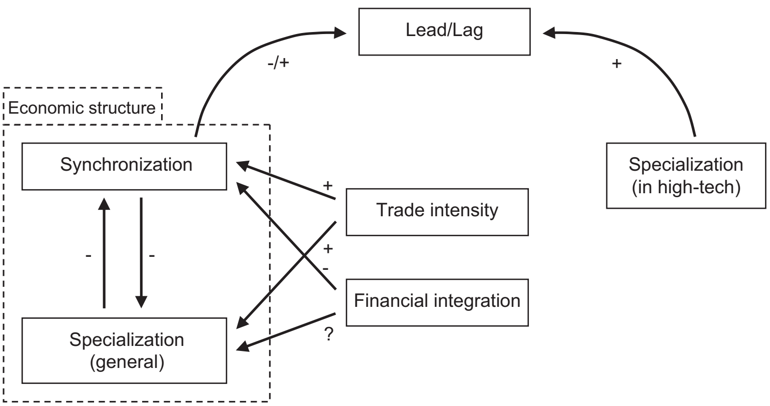

Figure 5 Relationships between the main variables of the model.

Our explanation clearly builds on the analysis by Imbs (2003, 2004) with respect to the relationship between business cycle synchronization, trade intensity and financial integration. The main element of departure is represented by the attempt to explain explicitly the lead/lag phenomenon for which there is no commonly adopted measure in the literature. Therefore, we concentrate here on the type of variable we use in the analysis to represent the lead/lag phenomenon as well as on the description of the relationships that shape its behavior. Let us suppose there are m turning points, indexed in k ($k=1, ..., m$), which characterize the national business cycle over a certain period of analysis. For each state i, we measure the amount of time the state leads or lags behind the nation as the average (along k) of the number of months with which i's turning points anticipate or follow the corresponding turning points of the national business cycle ($t_{i,k}$):

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

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

$$LL_{ij} = LL_i - LL_j \tag{1}$$

Intuitively, given that the national cycle is obviously the same for the two economies, 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 any 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. To explain the first informative component of LL_{ij} we directly draw on the setting developed by Imbs which features a 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 states react to monetary policy shocks (Carlino and DeFina 1998, 1999a,b, 2004; Kouparitsas 2001; Owyang and Wall 2004, 2009; Crone 2006, 2007; Beckworth 2010).

It should be emphasized, however, that the relationship between specialization and synchronization assumed in most of these studies is in fact a one-way relationship: from the degree of similarity in production patterns to the level of correlation between cycles. On the other hand, recent evidence suggests 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 when 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 them 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 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.

As for the second informative component of our target variable LL_{ij}, i.e., its sign (or, in other words, the reason why some states lead the national cycle and others lag behind), once again we focus our attention to the differences in industry mix that characterize the economic structure of the states. Differently from before, 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 manufacturing could be an appropriate choice. In our view, however, this sector is excessively heterogeneous and we have therefore decided to focus our attention on high-tech industries. A first motivation for 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.

Based on the discussion in the previous section, the model we estimate consists of four simultaneous equations:

$$\begin{cases} LL_{ij} = \alpha_0 + \alpha_1 \rho_{ij} + \alpha_2 DL_{ij} + \alpha_3 \left(\rho_{ij} \cdot DL_{ij}\right) + \alpha_4 HT_{ij} + \varepsilon_{ij} \\ \rho_{ij} = \delta_0 + \delta_1 S_{ij} + \delta_2 \hat{T}_{ij} + \delta_3 \hat{F}_{ij} + \boldsymbol{\delta} \mathbf{V}_{ij}^{\rho} + \eta_{ij} \\ S_{ij} = \gamma_0 + \gamma_1 \rho_{ij} + \gamma_2 \hat{T}_{ij} + \gamma_3 \hat{F}_{ij} + \boldsymbol{\gamma} \mathbf{V}_{ij}^{s} + \upsilon_{ij} \\ HT_{ij} = \beta_0 + \boldsymbol{\beta} \mathbf{V}_{ij}^{HT} + \xi_{ij} \end{cases} \tag{2}$$

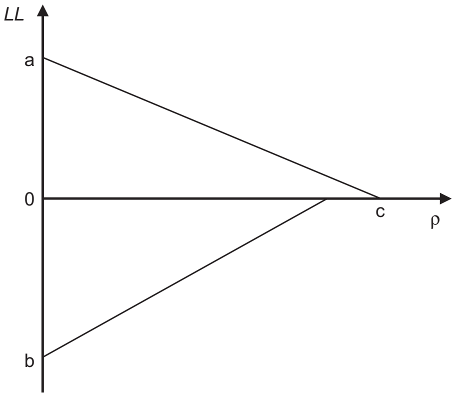

Figure 6 Relationship between *LL* and ρ.
Notes: Based on the coefficients reported in the first equation of the system, the slope is $\alpha_1+\alpha_3$ (<0) in the positive section of the codomain and α_1 (>0) in the negative one. In addition: $a=\alpha_0+\alpha_2$ (>0), $b=\alpha_0$ (<0), $c=-(\alpha_0+\alpha_2)/(\alpha_1+\alpha_3)$ (>0).

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 6, 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.[6]

The second equation in (2) models the determinants of the degree of synchronization. In particular, synchronization depends on the differential level of sectoral specialization (S_{ij}), on a measure of bilateral trade intensity $\left(\hat{T}_{ij}\right)$ and on the level of financial integration $\left(\hat{F}_{ij}\right)$ between the states. As anticipated, the explanation of the relationships between these variables and synchronization borrows from the literature adopting a simultaneous equation approach (Imbs 2003, 2004; Xing and Abbott 2007; Dées and Zorell 2011).[7] In particular, S_{ij} is likely

6 We do not impose any restriction on these coefficients in the estimation and subsequently check that the estimated values are compatible with the signs reported in Figure 5.
7 There is also a branch of the literature that studies directly the role of trade and financial integration on the degree of synchronization by estimating a single equation model and allowing

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 standard international macroeconomic theories (Obstfeld 1994; Heathcote and Perri 2004; Kalemli-Ozcan, Papaioannou, and Peydró 2009) financial integration should weaken the degree of synchronization among business cycles.

Finally, as for the effect of trade flows on synchronization levels, it must be noted that the sign of δ_2 is potentially ambiguous being, as acknowledged by Frankel and Rose in their seminal paper (Frankel and Rose 1998), the net effect from two contrasting forces arising from inter- and intra-industry trade. While the original four-equation system developed by Imbs would allow disentangling these two components, the lack of data on inter-state trade and the need to estimate trade flows from a gravity model do not make this possible here. However, on the one hand Van Biesebroeck (2010) shows that most manufacturing trade among US states is intra-industry; on the other hand, Fidrmuc (2004) emphasizes that the commonly reported positive relationship between trade and synchronization must be actually attributed to intra-industry trade. As a consequence, in our setting we expect to ascertain a positive role for trade flows on the degree of synchronization among business cycles.

Through the third equation the circularity between synchronization levels and differences in specialization patterns takes form. Here, based on the dynamics explained in the previous 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 specialization levels: while the sign of the first relationship is expected to be positive, the sign of the second is ambiguous.[8]

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 three equation-specific vectors of instruments $\mathbf{V}^{\rho}$, $\mathbf{V}^{S}$ and $\mathbf{V}^{HT}$ and by a fourth vector containing instruments that are common

for endogeneity via instrumental variables (among many other, Abbott et al. 2008; Baxter and Kouparitsas 2005; Inklaar et al. 2008; Kalemli-Ozcan et al. 2009; Kose et al. 2003; Otto et al. 2001).

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

to all equations. More specifically, identification of the system at least requires a difference between $\mathbf{V}^{\rho}$ and $\mathbf{V}^{S}$. As for the fourth vector, this contains additional exogenous variables which are not of interest, but are included fundamentally to avoid misspecification and omitted variable bias. These variables are used only in the first stage as instruments for the endogenous ones. A detailed account of all four vectors will be offered in the following section.

3.2 Data

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 are forced to concentrate our analysis on the period that follows 1990.[9]

The main dependent variable, LL_{ij}, is calculated for all pairs of 48 conterminous states according to Eq. (1). In particular, as in Section 2, we applied the Baxter-King band-pass filter on the monthly coincident index for the national economy in order to identify the cycle. The set of turning points, k, is then derived using the Bry-Boschan algorithm on the filtered coincident index data. For each state i, the indicator $t_{i,k}$ is calculated as the average along k of the time (in months) with which i anticipates or follows the turning points of the national business cycle ($t_{i,k}$).

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:

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

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.[10] 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.

9 Table A3 in the Appendix provides a detailed description of the variables and data sources.

10 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 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).[11] In addition, bilateral financial integration is calculated from an estimate of the state-specific index of risk-sharing proposed by Kalemli-Ozcan, Sørensen, and Yosha (2003). Specifically, the state-specific index of risk sharing θ_i is obtained by estimating

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

where GSP stands for the per capita gross state product while DY is the disposable income per capita.[12] Then, the measure of cross-state financial integration between i and j is

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

Pairwise 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 was previously done in the literature adopting this framework. The first set, $\mathbf{V}^{\rho}$, includes pairwise products of the natural logarithm of GSP and differences in crude oil production (expressed in absolute value); the second set, $\mathbf{V}^{S}$, employed in the explanation of the differences in specialization, includes the pairwise differences (expressed in absolute value) and products of GSP (in logs).

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 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, 1980) and high-skill workers tend to have a relatively higher average income, it might be plausible to think that

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

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

12 Both GSP and DY have been detrended using the Hodrick-Prescott (Hodrick and Prescott 1997) filter.

high-tech jobs tend to move towards areas characterized by a relatively higher supply of this type of amenities. Evidence in support to this link between amenities and high-tech employment is reported by Partridge et al. (2008). We therefore include a variable that measures 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. Our expectation is that this variable should be positively associated with high-tech employment. Then, we include a second 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. In addition, similarly to the explanation of the discrepancies in the two states' industrial structures, we include the pairwise difference of GSP per capita (in logs) as a proxy of other factor endowment differences and wealth gaps as suggested by Artis and Okubo (2011) and we expect it to exert a positive influence on the degree of specialization in high-tech.

Finally, we introduce a further set of exogenous regressors common to all equations. In particular, these are the distance between state capitals and the pairwise differences in population, in the states' share of agriculture employment and in the states' share of public sector employment.

4 Results

Table 3 reports the results from the Three-Stage Least-Squares (TSLS) estimation of the system in Eq. (2) 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.[13]

As expected, the coefficient of high-tech is positive. The magnitude of the coefficient implies that an increase of one percentage point in the differential level of specialization in high-tech for the representative state leads to an increase in the *LL* variable of approximately 8 days.

Also the estimated relationship between LL_{ij} and ρ_{ij} is in accordance with expectations and, in particular, with the representation in Figure 6. More in detail, the relationship is negative ($\alpha_1+\alpha_3=-4.15$) when LL_{ij} is positive, which implies that the lead decreases as the degree of synchronization increases, and becomes positive ($\alpha_1=5.23$) when LL_{ij} is negative. We can now calculate the impact of a change in the degree of synchronization by distinguishing the effect accruing to

13 Estimates are obtained using the *reg3* command in Stata 12.

Table 3 Three-Stage Least-Squares regression results.

Variables	Coefficients		s.e.
Dependent variable: *LL*			
Constant	−5.9384[a]		0.6929
HT	28.2762[a]		8.6322
DL	10.6560[a]		1.1435
ρ	5.2595[a]		0.8879
ρ·*DL*	−9.4122[a]		1.4528
R^2		0.6354	
Dependent variable: ρ			
Constant	0.9988[a]		0.0641
S	−0.6699[a]		0.1196
$\hat{T}$	0.0110[a]		0.0044
$\hat{F}$	−0.0856[a]		0.0163
ln GSP product	0.0044[a]		0.0015
Oil	−0.0002[a]		0.0000
R^2		0.1098	
Dependent variable: *S*			
Constant	0.5316[a]		0.0701
ρ	−0.2519[a]		0.0721
$\hat{T}$	−0.0115[a]		0.0030
$\hat{F}$	−0.0683[a]		0.0099
ln GSP product	−0.0024[a]		0.0009
ln GSP gap	0.0284[a]		0.0063
R^2		0.1473	
Dependent variable: *HT*			
Constant	0.0003		0.0003
Amenity	0.0024[a]		0.0002
Mining	−0.1672[a]		0.0161
ln GSPpc difference	0.0110[a]		0.0026
R^2		0.2024	

Notes: Significance levels: [a]=1%, [b]=5%, [c]=10%.
Endogenous variables: *LL*, *HT*, *S*, ρ·*DL*, ρ.

a "representative leading" [14] state from that to a "representative lagging behind" state. In this case, an increase in the level of synchronization of one percentage point determines a reduction of about 1 day (30 h) in the lead of the "representative leading" state and a decrease of about 1.5 days (38 h) in the lag of the "representative lagging behind" state.

14 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.

All signs in the second equation are in accordance to the theoretical predictions summarized in Sections 3.1–3.2. The effect of specialization on ρ has a negative sign, implying that more dissimilar industrial structures result in lower synchronization. In addition, the level of synchronization is affected positively by trade flows and negatively by financial integration. As for the latter result, it must be noted that most empirical analyses tend to report estimates with the opposite sign. To our knowledge, the only two studies that find a negative relationship between synchronization and financial integration are Garcia-Herrero and Ruiz (2008) and Kalemli-Ozcan, Papaioannou and Peydró (2009); the latter also suggests that the positive association reported in most analyses arises because global shocks and country-pair factor effects are not allowed for. Finally, couples of states with higher GSP and lower differences in crude oil production tend to display more synchronized business cycles.

Interestingly, the estimated coefficients for the third equation confirm the possibility of a circular relationship between synchronization and differences in specialization patterns. The coefficient of ρ is significant and its negative sign is clearly in line with the negative sign characterizing 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. Financial integration reduces differentiation in industrial specialization and, contrary to expectations, the same is true for trade flows. Yet, it must be noted that the latter results is in line with what reported by Imbs (2003, 2004) who also shows that the sign reverses if a different measure of trade is employed, an alternative that however cannot be pursued here given that no data are available on direct trade flows between US states. In addition, pairs of richer states as well as pairs of states with lower GSP gaps tend to have more similar economic structures.

Finally, *HT* equation estimates indicate that natural amenities and differences in the log of per capita GDP play a positive role in favoring the relative concentration of high-tech jobs while, as expected, mining tends to discourage it.

4.1 Sensitivity analysis

In this section we check the soundness of our results. We start this by estimating the model equation-by-equation using Ordinary Least-Squares (OLS). Results are reported in Table 4 where we can note that, 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.

However, a few important remarks must be made. First, the sign of the coefficient of *HT*, α_4, in the first equation is reversed with respect to the TSLS estimate

Table 4 Equation-by-equation Ordinary Least-Squares regression results.

Variables	Coefficients		s.e.
Dependent variable: *LL*			
Constant	−5.0341[a]		0.3079
HT	−19.4412[a]		3.6182
DL	10.1466[a]		0.4265
ρ	4.0543[a]		0.3895
ρ·*DL*	−8.7373[a]		0.5342
R^2		0.6905	
Dependent variable: ρ			
Constant	0.8606[a]		0.0533
S	−0.2693[a]		0.0457
$\hat{T}$	0.0183[a]		0.0039
$\hat{F}$	−0.0608[a]		0.0149
ln GSP product	0.0059[a]		0.0015
Oil	−0.0003[a]		0.0000
R^2		0.1677	
Dependent variable: *S*			
Constant	0.3931[a]		0.0356
ρ	−0.0988[a]		0.0183
$\hat{T}$	−0.0156[a]		0.0024
$\hat{F}$	−0.0606[a]		0.0094
ln GSP product	−0.0028[a]		0.0009
ln GSP gap	0.0362[a]		0.0062
R^2		0.1975	
Dependent variable: *HT*			
Constant	0.0004		0.0003
Amenity	0.0024[a]		0.0002
Mining	−0.1758[a]		0.0162
ln GSPpc difference	0.0161[a]		0.0027
R^2		0.2055	

Notes: Significance levels: [a]=1%, [b]=5%, [c]=10%.

and is thus in contrast with the theoretical predictions. Then, if we concentrate on the potential circularity between ρ and S (second and third equation of the system), we observe that OLS clearly reduces the absolute value of the estimated coefficients compared to TSLS; this fact is 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 potential circularity between ρ and S was allowed for. Intuitively, this result appears to support the appropriateness of the specification introduced in this analysis.

Then, we have carried out the Hausman (1978) test to investigate whether the OLS should actually be preferred to the TSLS (Table 5). The results of this test

Table 5 Hausman test on the equation-by-equation OLS regression.

Hausman test	χ^2_{12}	p-level
H0: OLS is consistent	274.12	0.0000

strongly indicate that the TSLS leads to a more appropriate model specification than OLS.

A further check of the robustness of our results is obtained by employing Fishers's z-transformations of the bilateral correlation coefficients, ρ_{ij}. As suggested by Otto et al. (2001), Inklaar, Jong-A-Pin and de Haan (2008) and Artis and Okubo (2011), since the correlation coefficient is bounded at –1 and 1, unless the variance of the error term is sufficiently small, reliable inference is complicated as the error term loses its normality properties. The transformation

$$z_{ij} = \frac{1}{2}\ln\left(\frac{1+\rho_{ij}}{1-\rho_{ij}}\right)$$

thus maps the [–1,1] variation into the real line and should ensure valid inference.

Results of the TSLS estimate using z_{ij} are reported in Table 6. Since the variable z is a non-linear transformation of bilateral correlations, a meaningful comparison with results in Table 3 must concentrate on signs and statistical significance levels of the estimated coefficients. Under this perspective, we note that exactly the same message is conveyed by the two sets of estimates and we can therefore maintain that the transformation of the correlation variable is unnecessary in order to provide reliable inference.

5 Conclusion

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

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

The core of our analysis was the development of a multiple equation econometric model to explain not only the degree of synchronization that might exist among

Table 6 Three-Stage Least-Squares regression results Fisher *z*-transformation.

Variables	Coefficients		s.e.
Dependent variable: *LL*			
Constant	−4.8327[a]		0.4244
HT	22.2439[a]		8.5493
DL	8.9490[a]		0.7367
z	2.6559[a]		0.3758
z·DL	−4.9625[a]		0.6429
R^2		0.6200	
Dependent variable: ρ			
Constant	1.6429[a]		0.1475
S	−1.8957[a]		0.2736
$\hat{T}$	0.0483[a]		0.0102
$\hat{F}$	−0.1086[a]		0.0376
ln GSP product	0.0126[a]		0.0035
Oil	−0.0007[a]		0.0000
R^2		0.1841	
Dependent variable: *S*			
Constant	0.4265[a]		0.0479
z	−0.0885[a]		0.0281
$\hat{T}$	−0.0100[a]		0.0035
$\hat{F}$	−0.0565[a]		0.0093
ln GSP product	−0.0024[a]		0.0009
ln GSP gap	0.0278[a]		0.0066
R^2		0.1875	
Dependent variable: *HT*			
Constant	0.0003		0.0002
Amenity	0.0024[a]		0.0002
Mining	−0.1658[a]		0.0161
ln GSPpc difference	0.0126[a]		0.0027
R^2		0.2038	

Notes: Significance levels: [a]=1%, [b]=5%, [c]=10%.
Endogenous variables: *LL*, *HT*, *S*, z·*DL*, z.

regional cycles but also the economic reasons behind persistent differences in timing of state cycles. In particular, due to the presence of simultaneous relationships among featured variables the model was estimated via Three-Stage Least-Squares. This strategy also allowed us to accommodate an hypothesized circular mechanism between the degree of synchronization and the dissimilarities in industrial structures. Our estimates showed 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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6 Appendix

Table A1 Leads and lags with respect to US turning points.

Turning points (T)/(P)	1980 Aug (T)	1981 Sep (P)	1983 Feb (T)	1984 Sep (P)	1986 Dec (T)	1990 May (P)	1991 Oct (T)	1994 Dec (P)	1996 Mar (T)	1998 Feb (P)	1999 Feb (T)	2000 Nov (P)	2003 Sep (T)	2008 Apr (P)	2009 Jul (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	2	0
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	−1	0
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	5	1
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	6	0
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	1	−2
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	−4	−3
Maine	1	3	1	1	11	15	4	−2	−2	14	2	5	2	0	−2
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	0	1
Minnesota	1	1	1	−1	6	0	1	−11	−11	0	0	0	−2	−2	−1
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	−1	0

(**Table A1** Continued)

Turning points (T)/(P)	1980 Aug (T)	1981 Sep (P)	1983 Feb (T)	1984 Sep (P)	1986 Dec (T)	1990 May (P)	1991 Oct (T)	1994 Dec (P)	1996 Mar (T)	1998 Feb (P)	1999 Feb (T)	2000 Nov (P)	2003 Sep (T)	2008 Apr (P)	2009 Jul (T)
Montana	1	3	6	3	−7	18	7	2	5	−5	−2	5	−1	5	1
Nebraska	0	2	1	−2	−2	−3	−19	3	−10	−5	−1	−8	4	0	−1
Nevada	2	1	1	3	8	0	−18	4	6	13	11	−2	16	1	0
New Hampshire	1	2	3	5	18	16	4	−1	−8	−2	−3	−1	12	0	−1
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	0	1
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	−3	−2
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	10	−1
South Carolina	2	3	3	4	14	−1	1	−4	−8	−5	−1	4	0	2	1
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	−3	−2
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	0	−1
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	−2	−1
Wisconsin	−2	−2	−1	3	−3	0	1	0	1	−2	−2	5	4	−4	−2
Wyoming	1	−3	−3	−15	−3	−3	−14	2	−2	3	2	−12	7	−4	−3

Table A2 Median leads and lags with respect to US cycle in sub-periods.

Lead/Lag	1980:7–1982:11	1982:11–1991:3	1991:3–2001–11	2001:11–2009:7
Alabama	1	1.5	−1.5	0
Arizona	1.5	−0.5	0	1
Arkansas	1.5	2	1.5	−1
California	1.5	−0.5	−6.5	−1
Colorado	−2.5	−1.5	−1	−1
Connecticut	0.5	7.5	−3	0
Delaware	4.5	0.5	1	−1
Florida	2	1	−3	1
Georgia	3	1	1	−0.5
Idaho	2	0	2.5	0
Illinois	−2	−0.5	−3.5	−1
Indiana	1.5	3	1.5	0
Iowa	1	3	−1	0
Kansas	0.5	2	−3	−1
Kentucky	−0.5	0.5	1	1
Louisiana	0	−1.5	−4	−3
Maine	2	6	3	0
Maryland	6	1.5	0.5	1
Massachusetts	5.5	3.5	1.5	1
Michigan	1	2	1	1
Minnesota	1	0.5	0	−2
Mississippi	0.5	1	3	−2
Missouri	0.5	−0.5	5.5	−1
Montana	2	4.5	3.5	1
Nebraska	1	−2	−6.5	0
Nevada	1.5	2	5	1
New Hampshire	1.5	10.5	−1.5	0
New Jersey	0.5	3	−0.5	0
New Mexico	0.5	−2.5	−2.5	−1
New York	0	0.5	−1	−1
North Carolina	1	3.5	0.5	−0.5
North Dakota	−2	4	1	1
Ohio	0.5	1	−0.5	0
Oklahoma	−3	−2	−1.5	−2
Oregon	2.5	4.5	0	1
Pennsylvania	0.5	2.5	0	−1
Rhode Island	3	1	−1	10
South Carolina	2.5	3.5	−2.5	1
South Dakota	1	1	4.5	0
Tennessee	0.5	3	−2	0
Texas	−2	−3	−3.5	−2
Utah	−2	−2.5	0.5	0
Vermont	1	4.5	−0.5	0
Virginia	7	2.5	0.5	0
Washington	3	3	2	0
West Virginia	−0.5	1.5	1.5	−1
Wisconsin	−2	−0.5	0.5	−2
Wyoming	−1	−3	0	−3

Table A3 Variables and data sources.

Variable	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 340,000 "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	See text
F	Cross-state financial integration	See text
Amenity	Pairwise differences across states in the natural amenity index	Economic Research Service; US Dept. 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
Public	Time average of yearly pairwise differences across states in the share of public sector employment over total employment	US Bureau of Economic Analysis

(**Table A3** Continued)

Variable	Definition	Data source
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	
Pop difference	Time average of yearly pairwise differences across states in population	US Bureau of Economic Analysis
ln GSPpc difference	Time average of yearly pairwise differences across states in log Gross State Product (GSP) per capita	US Bureau of Economic Analysis
ln GSP gap	Time average of yearly pairwise differences (in absolute terms) across states in log GSP	US Bureau of Economic Analysis
ln GSP product	Time average of yearly pairwise products across states in log GSP	US Bureau of Economic Analysis

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