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Business cycle synchronization across U.S. states

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Abstract: We use wavelet analysis to conclude that individual U.S. states' business cycles are very well synchronized. We also find evidence of a strong and significant correlation between business cycle dissimilarities and the distance between each pair of states, consistent to gravity type mechanisms where distance affects trade. Trade, in turn, increases business cycle synchronization, while a higher degree of industry specialization is associated with a higher dissimilarity of the state cycle with the aggregate economy. Finally, there is evidence that business cycle dissimilarities have been decreasing with time, consistent with the previous findings coupled with the idea that information and communications technology make distances smaller.

Keywords: business cycle synchronization; continuous wavelet transform; trade.

JEL: E37; E52; R11.

1 Introduction

The introduction of the Euro caused a surge in the literature on optimal currency areas and, with it, a surge on the study of business cycle synchronization. This is so because synchronization of economic activity is commonly considered a necessary condition for the optimality of a single monetary policy – De Haan, Inklaar, and Jong-a-Pin (2008). The typical argument is that countries sharing the same currency, but with asymmetric business cycles, will incur costs associated

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with the monetary authority making decisions which benefit not all countries within the monetary union.¹ In this paper, using wavelet analysis and monthly state coincident indexes, we look at business cycle synchronization across U.S. states. We conclude that individual U.S. states' business cycles are very well synchronized, and that synchronization has been increasing over time.

Some contributions to the business cycle synchronization literature were brought about by the birth of the European Monetary Union in the 1990s. Frankel and Rose (1997) point out that increased trade in a common currency area could theoretically lead to more asynchronous business cycles, since regions may specialize in industries in which they have a comparative advantage [see also Krugman (1993)]. Still they believe that increased trade leads to more synchronous business cycles since common demand shocks prevail and intra-industry trade accounts for most of the trade.

Distance between trading partners and magnitude of trade was described as an inverse relationship by Tinbergen (1962). This leads us to infer that regions close to each other have a more synchronized business cycle, since trade intensity increases business cycle synchronization, as previously described by Imbs (2004), Baxter and Kouparitsas (2005) and Inklaar, Jong-A-Pin, and De Haan (2008).

Another strand of literature that tries to explain cyclical comovements between tradings partners is the literature on international real business cycles. Backus, Kehoe, and Kydland (1992) – see also Baxter and Crucini (1995), in a standard RBC model, extended to allow for free trade between two countries, concluded that following idiosyncratic shocks, the country with higher relative productivity shock should increase output while the other should decrease, suggesting negative cross-country correlations for economic activities. The puzzles introduced by this literature have proved to be highly robust to model specifications, at least when one considers productivity shocks to be the drivers of business cycles. If one considers that economic fluctuations are demand-driven then, as showed by Wen (2007), most of the puzzles disappear.

Previous work on business cycles on the U.S. state level include Owyang, Piger, and Wall (2005), who look at growth levels between states and finds that they differ greatly in the recession phase and in the expansion phase. The states also differ in the timing of switching between phases, indicating that states differ in the way that their business cycles are in sync with that of the aggregate

¹ Note, however, this implication is not automatic. If we think that the source of an asynchronous cycle is an optimal reaction to an idiosyncratic shock (either from the supply or the demand side) then there is no need for the monetary policy to intervene. In this paper, we will take a closer look at the U.S. and estimate how the individual states' business cycles are similar to the aggregate U.S. business cycle.

economy. Related with our paper, Magrini, Gerelimitto, and Duran (2013) investigate the determinants of the lead-lag behavior the business cycle between states. Guha and Banerji (1998/1999) find that the patterns of states' cyclical movement in employment differ significantly from the U.S. employment cycle. Those differences are explained by factors like industry diversification, difference in consumer sentiment and different fiscal policies. Kouparitsas (2001) identifies sources of common shocks and responses to those shocks for the eight Bureau of Economic Analysis regions of the U.S. He finds that five of them constitute a core region and three non-core. They differ significantly from each other in terms of sources of disturbances and responses to disturbances at business cycle frequencies.

To study this issue, we rely on wavelet based measure of business cycle synchronization. Wavelet analysis is particularly well-suited to study business cycle synchronization. This is so, because with wavelets one can estimate the spectral characteristics of a time-series as a function of time, revealing how the different periodic components of a particular time-series evolve over time. Rua (2010) was probably the first author to rely on wavelet analysis to measure comovements between different regions in the time-frequency space and in recent work, the same author highlights the usefulness of the methodology in uncovering regional and state-level heterogeneity in economic activity – Rua and Lopes (2015). We will follow the procedure proposed by Aguiar-Conraria and Soares (2011) – also applied by Aguiar-Conraria, Martins and Soares (2013) and Aguiar-Conraria, Magalhães and Soares (2013) – to compare the wavelet spectra of two regions. By doing so, we test if the contribution of cycles at each frequency is similar, if this contribution happens at the same time or not, and, finally, if the ups and downs of each cycle occur simultaneously.

We also look at how much the distance between states can explain business cycle synchronization. Tinbergen (1962) originally proposed that bilateral trade between countries had a strong gravity-type mechanism, i.e. that trade flows between two countries were “proportional to the gross national products of those countries and inversely proportional to the distance between them.” High trade flows between states due to close proximity to each other causes their economies to integrate, and, therefore, may cause their business cycles to synchronize.² If this is correct then states far away from the economic core will be less synchronized with the national business cycle than those close to it.

Our results show that U.S. states' business cycles are well synchronized with the national business cycles, with only a few exceptions. Furthermore, we show

² Assuming that intra-industry trade dominates trade in final goods. Otherwise, the two regions will specialize according to their respective comparative advantages, and their business cycles may diverge from each other.

that synchronization increased in the most recent half of the sample. The results also show that there is a significant positive correlation between business cycle dissimilitude and distance between each pair of states. In other words, the closer the states are geographically the more synchronized their business cycles are. Also, we find a strong and significant association between a state's degree of industry specialization and its dissimilitude with the aggregate cycle, which is robust to subsample analysis.

2 Data

The monthly state coincident indexes published by the Federal Reserve Bank of Philadelphia will serve as data for our analysis. An alternative would be to use the gross state product published by the Bureau of Economic Analysis of the U.S. Department of Commerce, but those are annual numbers, which would imply significantly fewer observations.

The coincident index uses four state-level variables to summarize current economic conditions in each U.S. state. The variables are non-farm payroll employment, average hours worked in manufacturing, the unemployment rate, and wage and salary disbursements deflated by the consumer price index. Such an index was constructed by Stock and Watson (1989) using a Kalman filter to estimate a latent dynamic factor for the national economy, with the common factor designated as the coincident index. The methodology was then used by Crone and Clayton-Matthews (2005) to construct a coincident index for each of the 50 U.S. states. The index is constructed to mimic GDP.

We focus on business cycle frequencies. Data is filtered using the Baxter and King bandpass filter after taking logs. The time span is from 1979:07 to 2013:12 for a total of 414 observations for each state – after filtering we are left with 390 observations.

3 Methodology

Wavelet analysis performs the estimation of the spectral characteristics of a time-series as a function of time, revealing how the different periodic components of a particular time-series evolve over time. While in spectral analysis we break down a time-series into sines and cosines of different frequencies and infinite duration in time, the wavelet transform expands the time-series into shifted and scaled versions of a function that has limited spectral band and limited duration in time.

Apart from some technical details, for a function to qualify for being a wavelet it must have zero mean (implying that it has to wiggle up and down) and be well-localized in time (e.g. have compact support or, at least, fast decay), behaving like a small wave that loses its strength as it moves away from the center, hence the term choice wavelet. It is this property that allows, contrary to the Fourier transform, for an effective localization in both time and frequency.

Complex analytic wavelets are ideal to study oscillations. We use the most popular wavelet with these characteristics, the Morlet wavelet.³ Given a time series $x(t)$, its continuous wavelet transform (CWT) with respect to the wavelet is a function of two variables, $W_x(\tau, s)$:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \bar{\varphi}\left(\frac{t-\tau}{s}\right) dt$$

where the bar denotes complex conjugation, s is a scaling or dilation factor that controls the width of the wavelet and τ is a translation parameter controlling the location of the wavelet. With our wavelet choice, there is an inverse relation between wavelet scales and frequencies, $f \approx 1/s$, greatly simplifying the interpretation of the empirical results.

The major advantage of using a complex-valued wavelet is that we can compute the phase of the wavelet transform of each series and thus obtain information about the possible delays of the oscillations of the two series as a function of time and frequency, by computing the phases and the phase difference. The phase is given by $\tan^{-1}(\Im(W_x(\tau, s))/\Re(W_x(\tau, s)))$ and the phase difference by $\tan^{-1}(\Im(W_{xy}(\tau, s))/\Re(W_{xy}(\tau, s)))$, where, for a given complex number z , $\Re(z)$ and $\Im(z)$ denote, respectively, its real part and imaginary part. A phase-difference of zero indicates that the time series move together at the specified frequency; a phase-difference between 0 and $\pi/2$ (0 and $-\pi/2$) indicates that the series move in-phase, with x (y) leading y (x), while if the phase-difference is between $\pi/2$ and π ($-\pi$ and $-\pi/2$), then variables are out-of-phase with y (x) that is leading.

In this paper, we will use the measure of the dissimilarities between the wavelet transform of two time-series proposed by Aguiar-Conraria and Soares (2011). We use the singular value decomposition (SVD) of a matrix to focus on the common high power time-frequency regions.

For that purpose, given two wavelet spectral matrices $W_x(\tau, s)$ and $W_y(\tau, s)$, let $Q_{x,y} = W_x(\tau, s)W_y^H(\tau, s)$, be their covariance matrix, where W_y^H is the conjugate transpose of W_y . After applying SVD to $Q_{x,y}$, the first extracted components

³ The reader is referred to Aguiar-Conraria and Soares (2014) for technicalities about the optimal properties of such wavelet.

correspond to the most important common patterns between the wavelet spectra. With those, we construct leading patterns and leading vectors. Using just a few of these, say K , one can approximately reconstruct the original spectral matrices.

Then, to define a distance between the two wavelet transforms, we compute the following distance:

$$\text{dist}(W_x, W_y) = \frac{\sum_{k=1}^K \sigma_k^2 [d(\mathbf{l}_x^k, \mathbf{l}_y^k) + d(\mathbf{u}_x^k, \mathbf{u}_y^k)]}{\sum_{k=1}^K \sigma_k^2}$$

In the above formula, $\mathbf{l}_x^k$ and $\mathbf{l}_y^k$ are the leading patterns, $\mathbf{u}_x^k$ and $\mathbf{u}_y^k$ the singular vectors and σ_k the singular values. We compute the distance between two vectors by measuring the angle between each pair of corresponding segments, defined by the consecutive points of the two vectors, and take the mean of these values.

The above distance is computed for each pair of regions and, with this information, we can then fill a matrix of distances. The closer to zero our measure of distance is, the more similar are the wavelet transforms of $x(t)$ and $y(t)$.

4 Results

In Figure 1, we see the results of the wavelet spectra dissimilarity calculation for each state vis-à-vis the national aggregate.⁴ The states with the lowest dissimilarity, i.e. those that are the most in sync with the national business cycle, are Pennsylvania, Illinois, Colorado, Ohio and Maryland. The most dissimilar are Alaska, North Dakota, Wyoming, Louisiana and Hawaii.

The darker a state is, the tighter it is synchronized. We can see a pattern, the states right in the middle of the country, stretching from Oklahoma all the way up to North Dakota, are not too tightly synchronized. Possible explanations might include relatively low population numbers and therefore low economic activity which does not weigh heavily in the aggregate cycle or different economic structures with a relatively higher weight on agriculture and oil production. We see as well that Alaska is the least synchronized state, which may as well be explained by a heavy reliance on oil production as well as the distance between it and the contiguous 48 states. Hawaii is also relatively loosely synchronized, which matches our hypothesis that states far away from other states have high business cycle dissimilarity.

⁴ Estimates are normalized to the state with the highest value.

Figure 1: U.S. states' business cycle dissimilitudes.

In Figure 2, we see the business cycle synchronization significance levels. Black indicates significance at the 1% level (meaning that we reject the null of no synchronization), dark gray 5%, light gray 10% and white indicating insignificance. There are only four states out of 50 which are out-of-sync with the national business cycle in the U.S. Just for comparison, Aguiar-Conraria and Soares (2011) with the same methodology, but using a different economic activity measure (a monthly industrial production index), found that six out of 13 Euro Zone countries were out of sync, a much higher proportion.

There are many possible explanations to why the U.S. has more similar business cycles than the euro area. The euro has only existed since 1999 while the dollar has existed for more than a 100 years, giving the U.S. states a longer time to converge. Fiscal policy may also explain the difference – the federal budget in the US is over 30% of GDP but in the EU is around 1%. Industry specialization may also play a role, with U.S. states possibly less specialized, and therefore more diversified, than Eurozone countries, which results in more synchronized business cycles.⁵

⁵ Clark and van Wincoop (2001) look at all these factors, as well as bilateral trade, and find that the relatively lower level of trade between European countries explains to a large extent why U.S. Census regions are more synchronized than European countries.

Figure 2: Significance of business cycle synchronization of U.S. states.

It is also interesting to test how synchronization evolved across time. To do so, when computing the distance between the wavelet transform matrices of two states we divide the matrix into two parts. Our results show a strong increase in business cycle synchronization, with distance decreasing in 1124 out of 1275 pairwise distances. The average pairwise dissimilarity between states decreased 18%.

The first part corresponds to the first half of the sample (until the first quarter of 1997) and the second part correspond to the most recent half of the sample (from April 1997 onwards), coinciding with the generalization of the internet (it was in 1997 that, for the first time, at least one third of the American adults used the internet). Note that by the time of the internet revolution several authors declared the death of distance – e.g Frances Cairncross (1997) argued that the importance of distance in how businesses are conducted was fading thanks to the new information and communication technologies.

4.1 Spatial correlation

The gravity equation explains, among other things, how distance between regions affects trade. It is one of the most robust findings in trade economics

(Anderson and van Wincoop 2003), so it is safe to assume that all else being equal, regions close to one another trade more than regions that are far away from each other.

Theoretically though, more trade does not necessarily lead to more synchronized business cycles. Krugman (1993) argues that increased trade leads to more specialization between the trading partners, as they specialize in the sectors of the economy they have a comparative advantage in. A specialized region is more vulnerable to shifts in tastes. When such a shift happens the region faces large and erratic changes in exports. If a shift in taste results in an export boom for a specialized region, then that boom is also reinforced by investment inflows. These accompanying capital movements serve to increase the difference in growth rates between booming regions and non-booming. All-in-all, greater trade integration will lead to divergence in economic structure and growth rates of regions.

One could also argue that geographical proximity, by reducing the cost of labor relocation, increases labor mobility which would reduce business cycle synchronization.

Frankel and Rose (1997), using 30 years of data for 20 industrialized countries, find that countries with closer trade links actually have a more tightly correlated business cycle, which is the opposite of what is expected based on Krugman's (1993). They argue that most trade is actually intra-industry, i.e. trade is *within* rather than between industries. Greater trade intensity may also increase the covariance of country-specific aggregate shocks. Aggregate demand shocks affecting one country can spill over easily to its trading partners, since e.g. a positive demand shock can increase demand for both domestic and foreign output. Another channel where trade can increase business cycle synchronization is when it induces a more rapid spread of productivity shocks. Coe and Helpman (1995) argue this point, where a country's total factor productivity does not only depend on domestic but also on foreign R&D capital, and that this foreign productivity effect is stronger the more the domestic economy is open to foreign trade. In other words, trade acts as a transmission mechanism for shocks to spread more strongly across borders, whether it be demand or productivity shocks. These results are confirmed in Imbs (2004), Frankel and Rose (1998) and Inklaar, Jong-A-Pin, and De Haan (2008) who find significant effects of trade in accounting for business cycle correlation.

In Table 1, we see the Spearman rank correlation coefficient between states' dissimilarity and physical distance between state capitals, along with their significance.⁶ We find that in an overwhelming amount of cases, there is a positive

⁶ Estimates of surface distance between state capitals were taken from <http://www.geobytes.com/CityDistanceTool.htm>.

Table 1: Distance vs. states’ business cycle dissimilarities.

State	ρ_s	State	ρ_s	State	ρ_s	State	ρ_s
AL	0.28**	AK	−0.11	AZ	0.24*	AR	0.20
CA	0.22	CO	−0.10	CT	0.69***	DE	0.44***
FL	0.08	GA	0.10	HI	0.40***	ID	0.23
IL	0.15	IN	0.44***	IA	0.14	KS	0.33**
KY	0.50***	LA	0.10	ME	0.78***	MD	0.57***
MA	0.52***	MI	0.50***	MN	0.10	MS	0.31**
MO	0.11	MT	−0.11	NE	0.12	NV	−0.12
NH	0.71***	NJ	0.59***	NM	0.18	NY	0.54***
NC	0.58***	ND	0.34**	OH	0.49***	OK	0.07
OR	0.15	PA	0.39***	RI	0.66***	SC	0.48***
SD	0.40***	TN	0.48***	TX	0.20	UT	0.07
VT	0.67***	VA	0.43***	WA	−0.04	WV	0.33**
WI	0.51***	WY	0.15				

***<0.01; **<0.05; *<0.10.

correlation between distance and dissimilarity with the business cycle. For over half of the cases, the significance was at least on the 5% level. This indicates that the further states are away from each other, the more dissimilar they will be from each other. As we have seen, there are theories that imply (or at least suggest) that more geographical proximity leads to less business cycle synchronization and theories that suggest the opposite. The results described in Table 1 support the latter hypothesis.

4.2 Regression analysis

Having looked at trade as a potential factor in explaining business cycle synchronization, we can also look at other factors. The single biggest factor that comes into mind is the level of industry specialization. As we have seen, Krugman (1993) argued that increased specialization decreases synchronization. However, this depends on the nature of the source of business cycles. If the main sources are aggregate shocks and there is high complementarity between specialized states, then the effect may actually be the opposite.

If specialized states have a more idiosyncratic business cycle, we should see a positive relationship between specialization and business cycle dissimilarity. To test this hypothesis, we regress business cycle dissimilarity on a measure of specialization, along with other controls.

4.2.1 Specialization index

Krugman specialization index, as originally seen in Krugman (1991), measures how the industrial structure in a given state is different from the aggregate industrial structure. It takes a value from 0 to 2 where 0 is identical industrial structure to the aggregate, and 2 is complete dissimilarity. The index for state i , is defined as $K_i(t) = \sum_k \text{abs}(v_i^k(t) - \bar{v}_i^k)$ where v_i^k is industry k 's share in total industrial output of state i , and $\bar{v}_i^k$ is the national benchmark.

Using data from the Bureau of Economic Analysis, we get a measure of how specialized a state is in terms of its industrial structure. From Table 2 we get a significant and positive relationship between dissimilitude with the national cycle and the specialization index, which agrees with Krugman's prediction. This comes as no surprise, since states with a low index have a more diversified industrial structure, and are therefore more resistant to idiosyncratic sectoral shocks, compared to more specialized states. Diversified states also resemble the aggregate industrial structure more so than the less diversified states, so they should have more similar business cycles.

4.2.2 Controls

In Table 2 we control for factors which might affect both the dissimilarity and the specialization index, and see whether the results are robust.⁷ First we control for state's weight in the aggregate GDP for the U.S. We see from Figure 1 that some of the least populated states are also some of the most dissimilar in terms of the national business cycle. A possible explanation for that is that lowly populated states weigh too little in the aggregate cycle. State weights might also affect the specialization index, since big states are more likely to be more diversified and thus have a comparatively less specialized industrial structure. We find the coefficient to be insignificant.

The regression contains a dummy variable which takes on the value 1 if a state contains the headquarters of a Federal Reserve district. We include it to test if Federal Reserve district presidents use their influence on the FOMC to get

⁷ Since we are dealing with variables that change over time, while the dissimilarity coefficient summarizes in a single value business cycle synchronization for 1979–2013, we will use an average of the variables over that period. Due to data restrictions and different industry classifications however, we must limit the average for the specialization index to the years 1979–2008, federal expenditures to 1981–2005, and oil production to 1997–2011. The estimates are however robust for different time frames for which data is available.

Table 2: Explaining business cycle dissimilarity.

Variables	Coefficient (std. err.)
Intercept	0.163*** (0.048)
Specialization index	0.141*** (0.050)
State weights	−0.681 (0.443)
Fed district HQ dummy	−0.001 (0.024)
Fed expenditure	0.163 (0.191)
Oil and gas extraction	0.989*** (0.274)
N	50
Adjusted R^2	0.523

***<0.01; **<0.05; *<0.10.

preferential monetary policy for their state, which should make that specific state more synchronized with the aggregate business cycle. The dummy might also affect the specialization index, since district headquarters are usually located in major metropolitan areas, and are as such less specialized due to industry diversification. We find the dummy not to be significant.

We also control for federal expenditures in each state. Expenditures like farm subsidies and military spending might affect both business cycle dissimilarity and the specialization index, but including it yields an insignificant estimate.

Finally, we control for oil and gas extraction, as a fraction of gross state product, to see if the relationship between business cycle dissimilarity and specialization is not simply characterized by the oil producing sector. We see from Figure 1 that some of the biggest oil producing states like Alaska, North-Dakota and Oklahoma,⁸ are also some of the least synchronized with the aggregate business cycle. Controlling for oil production does however not change the point estimate for the specialization index in any significant way, and we also find the oil extraction itself is significant at the 1% level and positive, meaning that a higher reliance on the oil producing sector increases dissimilarity with the aggregate business cycle.

Having previously observed that synchronization increases over time, we split up the regression period into pre and post 1997 (see Table 3 below), in order to check the robustness of our previous findings. We find that the point estimate for the specialization index is smaller in the post 1997 period compared to the

⁸ Texas and California, being the biggest and 3rd biggest producers of oil, respectively, are relatively synchronized. This is probably due to the fact that they are by themselves two of the largest economies in the U.S., and are therefore comparatively diversified and thus the oil producing sector does not dominate the states' economy, like in Alaska and North-Dakota.

Table 3: Explaining business cycle dissimilarity, pre and post 1997.

Variables	Coefficient Pre 1997 (std. err.)	Coefficient Post 1997 (std. err.)
Intercept	0.179*** (0.060)	0.092 (0.055)
Specialization index	0.115* (0.062)	0.107* (0.057)
State weights	−0.294 (0.552)	−0.546 (0.506)
Fed district HQ dummy	−0.006 (0.030)	−0.012 (0.028)
Fed expenditure	−0.013 (0.238)	0.175 (0.218)
Oil and gas extraction	0.529 (0.342)	1.892*** (0.313)
N	50	50
Adjusted R^2	0.170	0.600

***<0.01; **<0.05; *<0.10.

whole period in Table 2, but the difference is not statistically different. Overall the conclusions are robust to the sub-sample analysis. The only change is that the coefficient for oil and gas extraction is not significant in the first half of the sample.

5 Conclusion

Using the coincident index of economic activity for each of the 50 states and the U.S. aggregate, we calculate the continuous wavelet transform and use that to get an estimate of business cycle dissimilarities. A low value for the dissimilitude between a pair of states, or between a state and the national aggregate, indicates that they have a similar contribution of their business cycles to total variance, the respective contribution to total variance happens at the same time, and the oscillations of each business cycle happens simultaneously. The results show that the states furthest away from the coasts are the least synchronized with the aggregate U.S. business cycle. Alaska and Hawaii show this trend clearly, but it also shows up in the central region of the U.S., stretching from Oklahoma to North-Dakota. It is also noteworthy that there is strong evidence the business cycles between states are becoming more synchronized with time.

We get a strong and significant correlation between distance and business cycle dissimilarities between states, which is argued to be due to effects of increased trade intensity when regions are closer to each other, as predicted in the gravity model. Theoretically, increased trade might cause regions to specialize and therefore have a less synchronized business cycle, but as seen in Frankel and Rose (1998), Imbs (2004) and Inklaar, Jong-A-Pin, and De Haan (2008), we find this not

to be the case. Greater trade intensity can affect business cycle synchronization in various ways, but the literature mostly asserts that it acts as a transmission mechanism for shocks, whether they be demand or productivity shocks.

We estimate a simple regression to look at the relationship between business cycle dissimilarities and industry specialization. We find a significant positive relationship between the two, meaning that states that have a high measure of specialization are more dissimilar to the national business cycle. States that rate low on the specialization index have a more diversified industrial structure and are less vulnerable to idiosyncratic sectoral shocks, which makes their business cycles more similar to the national business cycle. These results are robust even when controlling for states' weight in U.S. GDP, federal expenditures, whether a state contains a Federal Reserve district headquarters and whether the state is a major oil producer.

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