Natural Unemployment Rates for Sub-National Regions:
Estimates for U.S. States

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Abstract

This paper decomposes unemployment rates in 48 U.S. states into components associated with business cycles, industry shocks, structural effects due to policies and demographics, and an unexplained residual. The analysis is based on econometric estimates of the correlates of state-level unemployment in a panel sample. The results suggest that national business cycles have been the main source of fluctuations over time in state unemployment rates. There are strong differences across states in both the general level of unemployment due to "natural" factors and variations in cyclical sensitivity.

I have had the privilege of working on this research with two extraordinary students. The original research was undertaken in collaboration with Kevin Gallagher and extension and updating of the model were done with Xian Ng, both under the collaborative research program sponsored by Reed College. I am grateful for Kevin and Xian's central contributions to this work and to Jon Rork for providing selected data from his state-data archive. Responsibility for all shortcomings lies with the author.

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1. Introduction

This paper decomposes unemployment rates in the U.S. states into components associated with business cycles, industry shocks, structural effects due to policies and demographics, and an unexplained residual. The decomposition is based on econometric estimates of the correlates of unemployment in a panel sample. The results suggest that national business cycles have been the main source of fluctuations over time in a state's unemployment rate. There are strong differences across states in both the general level of unemployment due to "natural" factors and variations in cyclical sensitivity. Some of the differences are associated with differences in measurable state characteristics.

2. Natural Unemployment Rate and Related Concepts

Macroeconomists commonly separate the aggregate unemployment rate into two components: a natural rate that reflects microeconomic characteristics of the labor market and a cyclical component capturing the effects of aggregate economic fluctuations. Milton Friedman (1968, 8) introduced the term "natural rate" to macroeconomics as "the level [of unemployment] that would be ground out by the Walrasian system of general equilibrium equation, provided there is (*sic*) imbedded in them the actual structural characteristics of the labor and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and labor availabilities, the costs of mobility, and so on."

Friedman (1968, 9) clarifies by saying "let me emphasize that by using the term 'natural' rate of unemployment, I do not mean to suggest that it is immutable and unchangeable. On the contrary, many of the market characteristics that determine its level are man-made and policy-made." This paper examines how unemployment is affected at the level of the U.S. state by several such man-made and policy-made variables, and in doing so estimates time series for a natural rate of unemployment for each state.

The decomposition of the national unemployment rate into natural and cyclical components underpins the use of countercyclical monetary and fiscal policy: policy stimulus is often recommended when cyclical unemployment is positive. Because state governments have no mechanism for independent monetary policy and do not often undertake fiscal policy, a state-level natural rate would not likely be used as a basis for countercyclical policy.

However, a second use of the aggregate decomposition—and one that is more useful at the state level—is to facilitate estimation of the impact of cyclical movements on such variables as government budgets and international balances, estimating the “cyclically adjusted” government budget surplus or trade surplus. Like the federal government (and perhaps even more so) state governments must assess the extent to which any budget shortfall is “structural” or cyclical. A structural deficit would require adjustment via tax and spending changes, while a deficit that is purely cyclical might reasonably be expected to correct itself as the business cycle returns to its mean state, allowing the use of “rainy-day funds” to cover temporary deficits. Evaluation of the current state unemployment rate relative to an estimated natural rate would help state governments discriminate between the two kinds of deficits and choose the appropriate means of balancing the short-run budget.

Figure 1 shows the U.S. national unemployment rate along with a “short-run” natural-rate series published by the Congressional Budget Office (CBO). While actual unemployment varies between 3 and 10 percent during the post-World-War-II sample, the natural rate is estimated to move between 5 percent and just over 6 percent. The gap between actual and natural unemployment is a measure of cyclical unemployment.

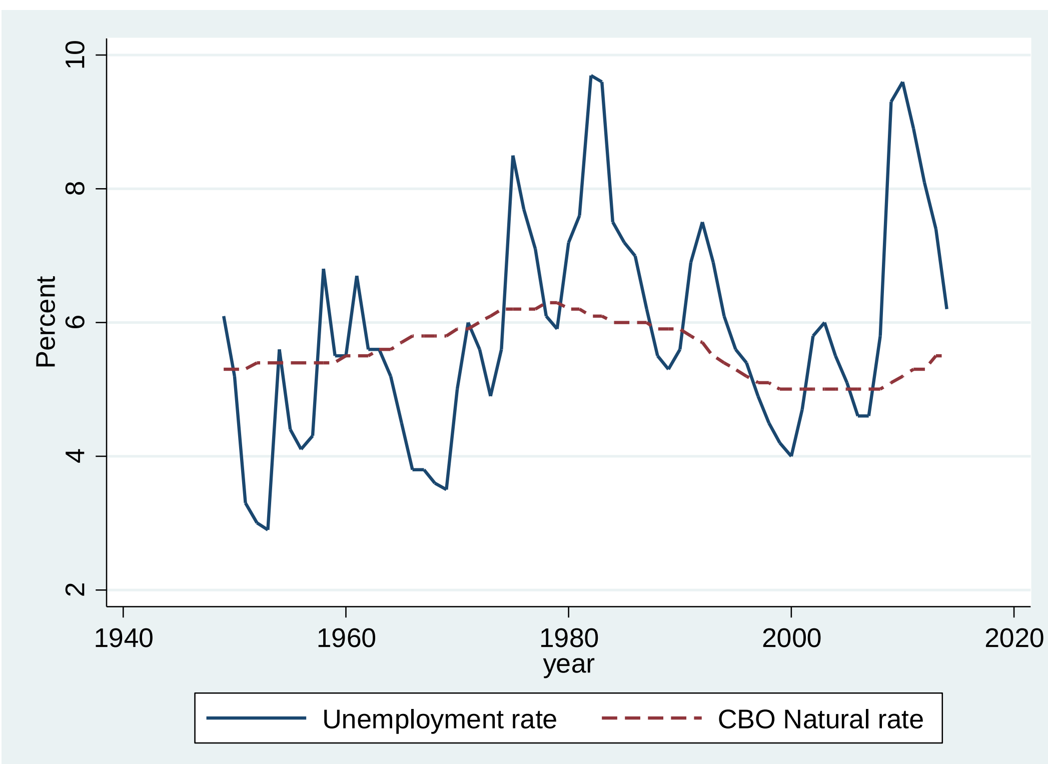


Figure 1. U.S. national unemployment series

Cyclical unemployment measures the position of the labor market relative to its estimated position of equilibrium. When the economy is producing below potential following a recession or a period of slow growth, we expect cyclical unemployment to be high; during output booms, cyclical unemployment will be low. This is shown for aggregate U.S. data by Figure 2, which shows the inverse co-movement in the CBO series for cyclical unemployment and the GDP gap.[1]

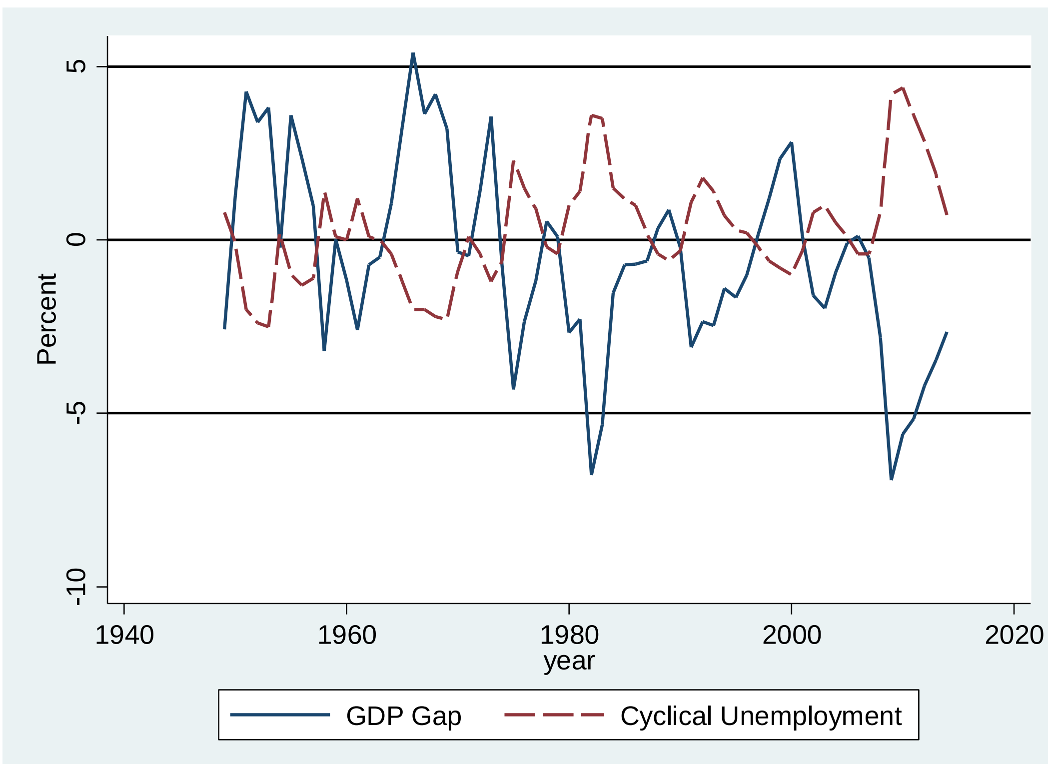


Figure 2. U.S. cyclical unemployment and output gap

[1] It is not surprising to note this strong, negative correlation between two cyclical series published by the same organization. The GDP gap is used by the CBO as a component in the calculation of cyclical unemployment. A regression of CBO cyclical unemployment on CBO GDP gap yields an R^2 of 0.89.

This paper uses the CBO measure of the GDP gap shown in Figure 2 as the basic indicator of the aggregate U.S. business cycle. It is constructed by comparing actual real GDP to their estimate of potential output, which is based on a Solow growth-accounting exercise examining long-run movements in capital and labor inputs and in productivity.

3. Approaches to the natural rate and related literature

An empirically facile, but economically uninformative, way to estimate a natural rate of unemployment is to use time-series methods to filter out cyclical fluctuations in the unemployment rate series. Depending on the movements in the series, a linear trend, a Hodrick and Prescott (1997) flexible trend, or a Baxter and King (1999) band-pass filter could be used to extract the de-trended or cyclical component of unemployment. These trend-based methods have the advantage of simplicity and may be suitable for historical analysis. However, policymakers seeking information about the current natural rate are, by definition, at the far endpoint of the available sample, where trend methods are often unreliable (or, in the case of the band-pass filter, unusable). Moreover, these methods yield no information about what policies or conditions might cause changes in the natural rate.

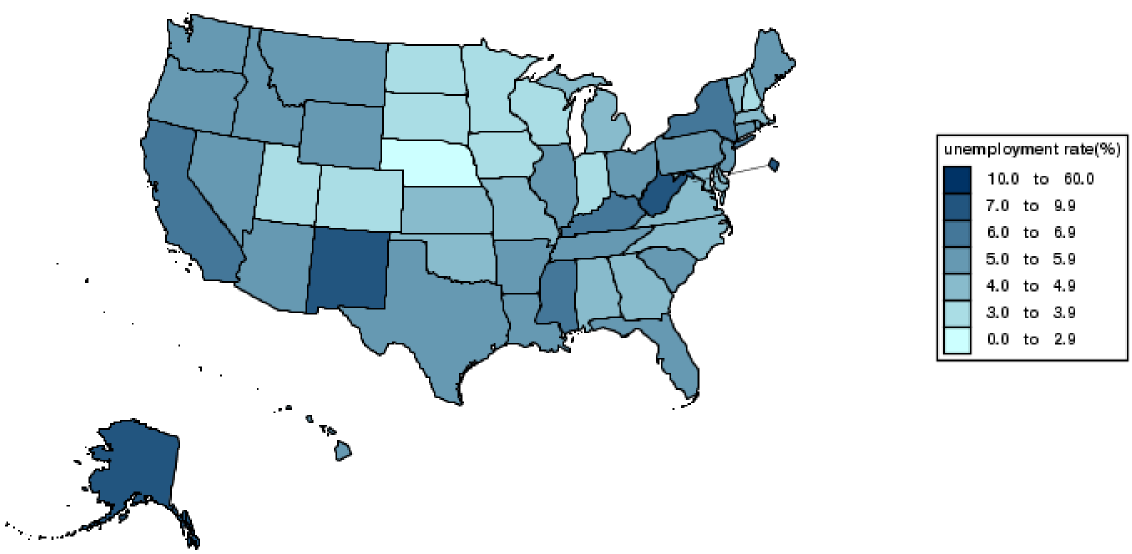
An alternative method, adopted here, is a structural decomposition of the unemployment rate into components attributable to national business cycles, state demographics, state-level labor-market policies, the industry composition of the state's employment base, and an unexplained residual. This not only provides an estimate of the state-level natural and cyclical unemployment components over time, but can also use the panel sample to yield insights about the effects of various structural variables and policies on unemployment.

Previous work on sub-national unemployment has followed both paths. Groenewold and Hagger (2003) use a VAR to represent a simple, state-level macroeconomic model for Australia and extract a natural-rate series using identifying restrictions on the effects of shocks on natural unemployment. Partridge and Rickman (1997) use U.S. state data to estimate a structural model similar to that pursued here, but do not construct natural-rate estimates. Other related work includes Blackley (1989), Clemente, Lanaspa, and Montanes (2005), Dixon and Shepherd (2011), and Elhorst (2003). A related literature has used panel unit-root tests to examine the stationarity of unemployment rates among states in the U.S. and Australia. See, for example, Song and Wu (1997), Nissan and Carter (2001), Smyth (2003), Romero-Avila and Usabiaga (2007), and Sephton (2009).

4. Modeling State Unemployment

As shown in the two panels of Figure 3, which depict state unemployment rates in the boom year of 1996 and the recession year of 2010, not only do unemployment rates vary considerably across states at any point in time, but their response to the business cycle also varies. Broadly speaking, the west-central states (many of which are heavily agricultural) saw smaller increases in unemployment in 2010 than coastal and southern states. The differential response among states with differing industrial structure suggests that industrial composition may affect not just the level of unemployment in a state, but also its cyclical variation. I model this below by decomposing industry-level employment growth into trend, cyclical, and shock components and allowing each of these to affect state unemployment separately.

Unemployment rates by State, seasonally adjusted, December 1996



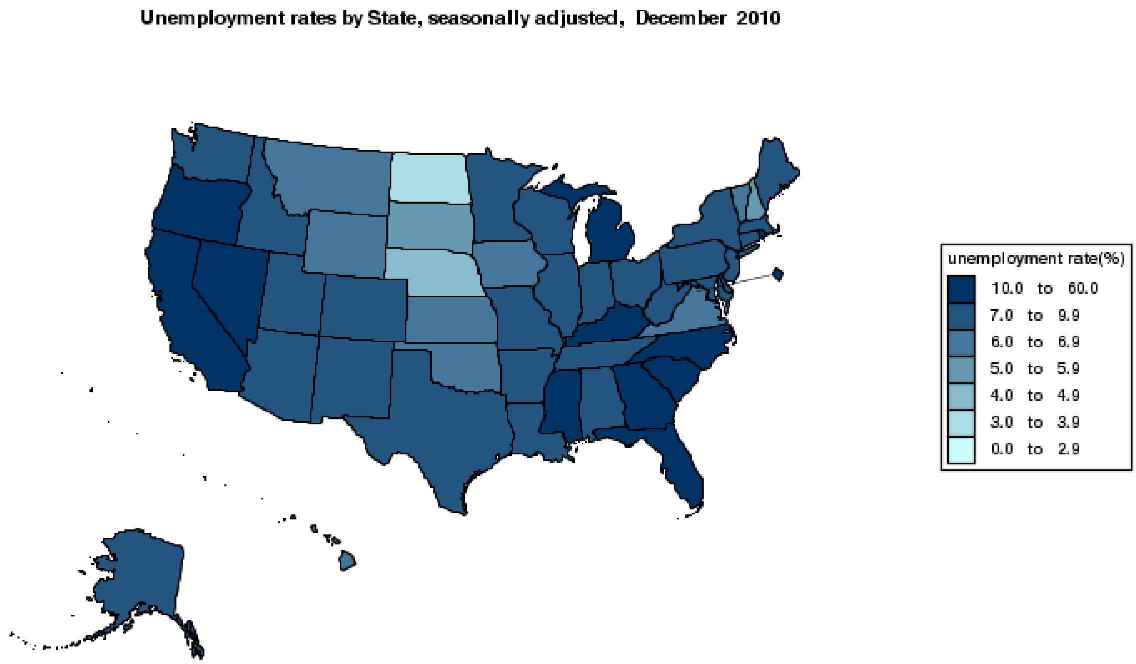


Figure 3. U.S. state unemployment rates, 1996 and 2010

Below I model the effects on state unemployment of five components:

- Industry composition of state employment (which itself has trend, cyclical, and residual components),
- Demographic characteristics of the state, including the age structure of the population, educational attainment, the extent of urbanization, and the importance of labor unions,
- Labor-market policies of the state, including minimum-wage laws and tax rates,
- National business cycles, and a
- Residual, unexplained component.

From this model, the five components can be aggregated into a cyclical component (including the direct business-cycle effect and the effect operating through industry cyclical changes), the "natural rate" component (including the effects of demographic and policy variables), plus the industry-shock and residual. Since by definition we do not know the source of the residual fluctuations, it is difficult to know whether they would be better characterized as part of the natural rate or cyclical unemployment, hence I maintain the residual as a separate category.

To estimate the effect of industry composition on state unemployment, I first estimate a simple model of national industry employment growth separately for each industry. The industry taxonomy is based on the 2012 NAICS, which breaks down economic activity into 20 industry categories, as described in Appendix A. The model includes a trend and the current and two lagged values of the national GDP gap variable as a cyclical measure, as in equation (1), where *i* indexes industries and *t* indexes time.

$$\ln E_{i,t} - \ln E_{i,t-1} = \alpha_{0,i} + \alpha_{1,i} t + \beta_{0,i} GAP_t + \beta_{1,i} GAP_{t-1} + \beta_{2,i} GAP_{t-2} + \varepsilon_{i,t} \tag{1}$$

Based on estimates of equation (1), time series for the trend, cyclical, and shock components of each industry's employment growth at the national level are extracted as:

$$\begin{aligned} G_{i,t}^{trend} &\equiv \hat{\alpha}_{0,i} + \hat{\alpha}_{1,i} t, \\ G_{i,t}^{cycle} &\equiv \hat{\beta}_{0,i} GAP_t + \hat{\beta}_{1,i} GAP_{t-1} + \hat{\beta}_{2,i} GAP_{t-2}, \\ G_{i,t}^{shock} &\equiv \hat{\varepsilon}_{i,t}. \end{aligned} \tag{2}$$

To compute the industry-based trend, cyclical, and shock variables that are relevant to any particular state *s*, I compute the weighted average of the industry growth components using the previous year's employment share of each industry in state *s* ($E_{s,i,t-1} / E_{s,t-1}$) as weights:

$$\begin{aligned} g_{s,t}^{trend} &\equiv \sum_i \frac{E_{s,i,t-1}}{E_{s,t-1}} G_{i,t}^{trend}, \\ g_{s,t}^{cycle} &\equiv \sum_i \frac{E_{s,i,t-1}}{E_{s,t-1}} G_{i,t}^{cycle}, \\ g_{s,t}^{shock} &\equiv \sum_i \frac{E_{s,i,t-1}}{E_{s,t-1}} G_{i,t}^{shock}. \end{aligned} \tag{3}$$

The state unemployment regression estimated below includes the g^{trend}, g^{cycle}, and g^{shock} variables as regressors; their effects represent the influence of industry composition on state unemployment. Faster growth in employment in industries important to a state (due to any of the three *g* variables) is expected to lower the state's unemployment rate, so we expect negative coefficients on these three variables. The trend component is considered to be part of a state's natural rate of unemployment arising from ongoing (non-cyclical) industry effects at the state level. The cyclical component is part of the state's cyclical unemployment. The effect of the industry shock is neither natural nor cyclical, but is an identifiable component of the residual variation in state unemployment. It is retained as a separate category.

Davis and Haltiwanger (1992) demonstrated that "gross flows" of job creation and job destruction convey information that is relevant to unemployment beyond what is contained in the corresponding net employment changes. National gross flow data are now published at the industry level through the Job Openings and Labor Turnover Survey (JOLTS) of the Bureau of Labor Statistics. However, these data are only available back to 2000, which would nearly halve the size of the sample.

Although gross flows are not pursued here, I do break out the industry-employment-growth variables shown in equation (3) into industries with positive net national employment growth and industries with negative growth. For each of the employment-growth components in (3), separate variables for (net) growing industries and (net) shrinking industries are created, as shown in equation (4) for the "cycle" component:

$$
\begin{aligned}
g_{s,t}^{cycle,+} &\equiv \sum_i \frac{E_{s,i,t-1}}{E_{s,t-1}} G_{i,t}^{cycle} \times I\left(G_{i,t}^{cycle} > 0\right), \\
g_{s,t}^{cycle,-} &\equiv \sum_i \frac{E_{s,i,t-1}}{E_{s,t-1}} G_{i,t}^{cycle} \times I\left(G_{i,t}^{cycle} \le 0\right),
\end{aligned} \tag{4}
$$

where I is the indicator function that takes on the value one if the logical condition that is its argument is true and zero if it is false. There are corresponding definitions for the industry trend and industry shock variables separated by industries whose national trend or shock components were positive or negative: $g_{s,t}^{trend,+}$, $g_{s,t}^{trend,-}$, $g_{s,t}^{shock,+}$, and $g_{s,t}^{shock,-}$.

In the unemployment regressions below, the positive and negative parts of each of the three component effects of industry-weighted employment growth are entered separately, making a total of six industry-employment-growth variables in the regression. For the cyclical variables shown in equation (4), $g_{s,t}^{cycle,+}$ would measure the effect in the state of industries in which national employment is expanding due to the business cycle whereas $g_{s,t}^{cycle,-}$ measures the effect of industries who cyclical component is contracting at the national level.

The demographic variables in the model (with predicted effect) are the following:

- Percentage of the state's population in the 18–24 age group (positive effect because younger workers are more often unemployed)

- Percentage of the state's population in the 25–64 age group (negative effect because this is the "prime working age" population)
- Percentage of the state's population with at least high-school education (negative)
- Percentage of the state's population with college education (negative)
- Percentage of workers in the public sector who belong to a union (positive)
- Percentage of workers in the private sector who belong to a union (positive)

The effects of these variables are considered to be part of the natural unemployment rate.

Three policy variables are included:

- Real minimum wage: the higher of the federal or state legal minimum (positive)[2]
- Sales-tax rate (positive)
- Highest individual marginal income-tax rate (positive)

These variables, similarly, are included in natural unemployment.

Finally, to capture the general effect of business cycles on state unemployment, the current and one lagged value of the national GDP gap (in percentage) is included. These variables are expected to have a negative sign because unemployment in general is strongly countercyclical. The total business-cycle effect on state unemployment is the sum of the direct effects of the national GDP gap and the indirect effects from the cycle components (positive and negative) of industry employment growth.

5. Sample and Estimation Methods

The sample comprises the 48 contiguous states (omitting Alaska, Hawaii, and the District of Columbia, which are highly idiosyncratic) over 23 years from 1991 to 2013. This gives a total of 1,104 observations in the panel. The variables that require lags are available prior to 1990, so the presence of the lagged GDP gap and the previous year's state-level industry employment weights does not reduce the estimation sample size—all regressions use the full 1,104 observations.

A variety of estimation methods might be employed for this model beyond pooled ordinary least squares. Error terms of observations corresponding to individual states are

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[2] Due to the absence of state-specific price indexes over most of the sample, the nominal state minimum wage is deflated by the national Consumer Price Index. This accounts for inflation over time, but not for interstate price differences. An alternative measure—the state nominal minimum wage divided by the average hourly wage of manufacturing production workers in the state—yielded similar results, and was compromised by the non-availability of data for several sample years.

likely correlated. This leads to biased standard errors and inefficient coefficients. The former can be corrected by the use of clustered standard error estimates. To achieve more efficient estimators I also included specifications with a first-order autoregressive error across the time dimension.

Fixed-effects and random-effects estimators are standard for panel-data models such as this one. Random-effects estimators are likely to be biased here because the state-level error components are quite likely correlated with the state characteristics included in the equation.[3] Because some explanatory variables vary mostly across states rather than over time, state dummies are likely to be strongly collinear with them, making it difficult to estimate their coefficients in a fixed-effects model. Thus, estimates both with and without fixed effects are of interest and are presented below. An alternative to state fixed effects is to include regional dummy variables for the nine Census regions of the United States. This allows cross-regional effects to be "dummied out" by the fixed effects but leaves intra-regional, cross-state variation in the sample to facilitate identification of the explanatory variables.

Fixed-effects estimation effectively allows each state to have a distinct intercept term. Using the fixed-effects estimates to construct the state-level natural rate series, as I do, assumes that this cross-state variation in intercepts reflects differences in natural unemployment across states that are not captured in the demographic and policy variables.

Panel data invite the inclusion of year dummies (time fixed effects) in addition to state or regional effects. However, a key variable of this analysis—the national GDP gap—varies only over time, so it would be collinear with the year dummies and its effect could not be estimated. Thus, no year dummies are included.

Finally, I assume that the variables in the regression can be modeled as stationary. Conventional unit-root tests have low power when the time-series dimension of the sample is short, which can lead to spurious rejection of the stationarity hypothesis. Song and Wu (1997) find that U.S. state unemployment rates are stationary over an earlier sample period using the panel-data unit root tests of Levin, Lin, and Chu (2002). Applying this test to a 1976–2013 sample yields ambiguous results: rejection of the presence of a unit root depends on the number of lags included in the augmented Dickey-Fuller specification.

6. Results

[3] A Hausman test rejects the consistency of the random-effects estimator for this model.

Table 1 presents the estimation results. Column (1) contains OLS pooled-sample estimates with state-level clustered standard errors. Column (2) repeats this analysis including regional dummy variables (whose coefficients are not reported). Column (3) is the state fixed-effects model. Column (4) assumes a first-order autoregressive process for the error. I will focus on the results in the right-hand three columns.

Structural and policy variables

Among the structural and policy variables, the signs of the estimated coefficients are mostly consistent with the predictions of basic labor-market theory, though the statistical significance of the results often varies across estimation methods.

The effect of the real minimum wage is negligible, of the opposite sign than expected, and totally without statistical significance.

Higher tax rates tend to raise state unemployment slightly, but the effect is not statistically significant in some specifications. The sales-tax rate seems to have a larger association with unemployment than the income-tax rate, which is surprising because the latter might be expected to have a more direct impact on labor markets. Even the largest estimated tax coefficients indicates a small effect, though. An increase of more than 6 percentage points in the tax rate would be required to raise natural unemployment in the state by one percentage point.

As expected, states with larger young populations (16–24) tend to have higher unemployment rates, this effect is highly significant in the fixed-effects models. The effect of the prime-working-age (25–64) population share is negative, as expected, but loses statistical significance in the autoregressive model. Age shares change very slowly over time, which may explain why including the autoregressive error component reduces the magnitude and significance of their estimated coefficients.

Higher levels of college education lower unemployment, as expected, and are strongly significant in the fixed-effects models. However, the magnitude of the estimated coefficients is tiny. High-school education does not seem to matter once fixed-effects are introduced to model cross-state differentials, though it does have the predicted negative effect when dummy variables are used at the regional level instead of the state level.

The estimates for private-sector unionization rates vary across estimation methods. The positive and significant result for the model with regional dummies conforms to the predictions of theory; the negative result for the fixed-effects model does not. But in all cases the magnitude of the estimated coefficient is small. Public-sector unionization seems to have no effect at all.

GDP gap

The national GDP gap has a strong, negative effect on state unemployment in all econometric specifications. In all cases, the lagged effect is stronger than the current effect, which supports the conventional assessment of unemployment as a lagging indicator.

Across specifications, the sum of the coefficients is approximately –0.5, which implies an "Okun's Law" coefficient of approximately –2; a 2% increase in GDP (relative to natural GDP) is required to reduce unemployment by one percentage point. Of course, the GDP gap variables are only part of the overall cyclical effect in this model, alongside the cyclical component of weighted industry employment growth.

Industry-composition effects

As discussed above, there are three industry-composition components—industry trend, industry cycles, and industry shocks—and each of the variables is separated into an aggregate for industries for which the component is positive and an aggregate for industries with a negative value for the component. Thus there are six industry-composition variables in the equation: trend growth in industries with positive trend, trend growth in industries with negative trend, cyclical employment growth in industries with positive cyclical component, cyclical employment growth in industries with negative cyclical component, positive industry employment shocks, and negative industry employment shocks.

All six industry employment-growth variables should have negative signs; more positive (or less negative) employment growth in the state's industries from any source should lower state unemployment. The effect of the negative-employment-growth variables measures the impact of industries that are currently in a declining phase in the U.S. overall and may be associated with rising unemployment due to job destruction. The positive-employment-growth variables measure the effect of industries that are growing in the United States, and may reflect lower unemployment due to job creation. Thus, the relative magnitude of these coefficients could provide a useful but rough measure of the relative importance of job destruction and job creation in determining state unemployment rates.

With only one exception (the positive cyclical component only in the regressions without fixed effects), all of the coefficients have the expected negative sign. All three of the job-destruction variables are statistically significant in the regional-dummy and fixed-effects regressions, though only the cyclical component is significant with the autoregressive error. Among the job-creation variables, only the shock component is consistently large and significant.

The variation across econometric methods suggests that these results must be interpreted cautiously. But taken at face value, they suggest that states suffer high unemployment as a result of cyclical reductions in employment (at the national level) in their main industries. But the largest impact of positive employment comes not from cyclical expansion but from non-cyclical, non-trend (national) shocks to employment in their main industries. The coefficients on the industry trend variables are often large in absolute value, but the standard errors are also much larger than those of the other components. Ongoing trend declines in industry employment have an extremely large estimated effect in some models but are insignificant in others, making it impossible to interpret the results clearly.

The model allows us to test whether the response of state unemployment to positive and negative industry-growth components is symmetric. If the response is the same, then the coefficients of the positive and negative components should be identical. The final row of Table 1 shows that the symmetry hypothesis is strongly rejected in all models. Expanding and contracting industries do not seem to have symmetric effects on state unemployment.

Although it is not shown in the table, interaction terms between the state dummies (fixed-effects) and the GDP gap variables are statistically significant, suggesting that there are cross-state differences in the cyclical sensitivity of unemployment apart from the differences measured by the industry-cyclical variable. This enhanced model is used in the next section to construct state-level estimates of the natural rate of unemployment. The coefficients on the other variables of the model are very similar to those reported in Table 1 and of course the coefficients reported in the table for the GDP gap variables are averages of the individual state coefficients.

Table 1. Regression Results

		(1) OLS	(2) OLS with Regional Dummies	(3) State Fixed Effects	(4) State Fixed Effects AR(1) Error
Natural/Structural Factors	Industry emp. growth trend, positive	– 1.065***	– 0.793**	– 0.424	– 0.268
		(0.316)	(0.319)	(0.420)	(0.429)
	Industry emp. growth trend, negative	– 0.363	– 2.209***	– 4.038***	– 0.855
		(0.716)	(0.655)	(0.803)	(0.634)
	Real minimum wage	0.169	– 0.0951	– 0.0932	– 0.0181
		(0.146)	(0.0989)	(0.0794)	(0.0572)
	Sales-tax rate, %	0.0448	0.0935**	0.160	0.130*
		(0.0640)	(0.0361)	(0.147)	(0.0738)
	Top individual income-tax rate, %	– 0.00368	0.0169	0.155**	0.0394
		(0.0393)	(0.0221)	(0.0625)	(0.0381)
	Percent in 18–24 age group	0.0546	– 0.0334	0.482***	0.253***
		(0.149)	(0.107)	(0.111)	(0.0869)
	Percent in 25–64 age group	0.0529	– 0.0408	– 0.306***	– 0.0462
		(0.0654)	(0.0679)	(0.104)	(0.0612)
	Percent with at least high school education	– 0.157***	– 0.123***	0.0124	0.00526
		(0.0249)	(0.0248)	(0.0378)	(0.0135)
	Percent with at least some college	– 0.00888	0.00275	– 0.101***	– 0.0260**
		(0.0191)	(0.0187)	(0.0260)	(0.0127)
	Union membership, public sector, %	0.0111	0.0101	– 0.0117	– 0.000848
		(0.00675)	(0.0119)	(0.0144)	(0.00564)
	Union membership, private sector, %	0.0794**	0.0965**	– 0.0214	– 0.0408*
		(0.0306)	(0.0420)	(0.0494)	(0.0212)
Cyclical Factors	Current U.S. GDP gap, %	– 0.124***	– 0.0780**	– 0.000665	– 0.150***
		(0.0356)	(0.0294)	(0.0299)	(0.0268)
	Lagged U.S. GDP gap, %	– 0.394***	– 0.407***	– 0.420***	– 0.328***
		(0.0337)	(0.0237)	(0.0251)	(0.0171)
	Industry emp. growth cycle, positive	0.194	0.0217	– 0.0607	– 0.00746
		(0.126)	(0.0931)	(0.0866)	(0.0516)
	Industry emp. growth cycle, negative	– 0.453***	– 0.486***	– 0.543***	– 0.320***
		(0.0731)	(0.0504)	(0.0491)	(0.0335)
	Industry emp. growth shock, positive	0.0454	– 0.180	– 0.252**	– 0.252***
		(0.147)	(0.111)	(0.101)	(0.0658)
	Industry emp. growth shock, negative	– 0.109*	– 0.180***	– 0.241***	– 0.0429
		(0.0604)	(0.0416)	(0.0419)	(0.0375)
	Observations	1,104	1,104	1,104	1,056
	R-squared	0.686	0.751	0.783	
	AR(1) coefficient				0.794
	F statistic for symmetry test	12.88***	14.09***	23.44***	16.06***

7. Natural-Rate Estimates

We use the estimates of the enhanced version of column (4) of Table 1 (augmented by interaction variables between the state dummies and the GDP gap variables as discussed above) to decompose each state's unemployment rate time series into four components:

- Natural unemployment rate is the predicted level of the state unemployment rate if the GDP gap, the cyclical components of weighted industry employment growth ($g_{i,t}^{cycle+}$ and $g_{i,t}^{cycle-}$), industry shock variables, and the residual are all zero.
- Estimated cyclical unemployment is the estimated effect of the four cyclical variables: the current and lagged GDP gap plus the cyclical components of weighted industry employment growth ($g_{i,t}^{cycle+}$ and $g_{i,t}^{cycle-}$).
- The industry-shock component is the effect of the shock components of weighted industry employment growth ($g_{i.t}^{shock+}$ and $g_{i.t}^{shock-}$).
- The unexplained residual is the residual of the unemployment rate equation.

The four components taken together sum to the state's actual unemployment rate.

The estimates suggest a tendency for natural unemployment to vary relatively little over time within a state. Figure 4 shows the decomposition of the unemployment rate over time for Oregon, my home state. Oregon's major industries include electronics, forestry, agriculture, and apparel. The natural unemployment rate has gradually and very slightly increased since 1992 from about 5.8% to 6.0%. Most of the variation in Oregon unemployment rate has been associated with national business cycles and the idiosyncratic equation residual, with a miniscule contribution from industry shocks. The serial correlation in the residual component is apparent. As expected, the large increase in unemployment after 2008 is entirely explained by the national business cycle.

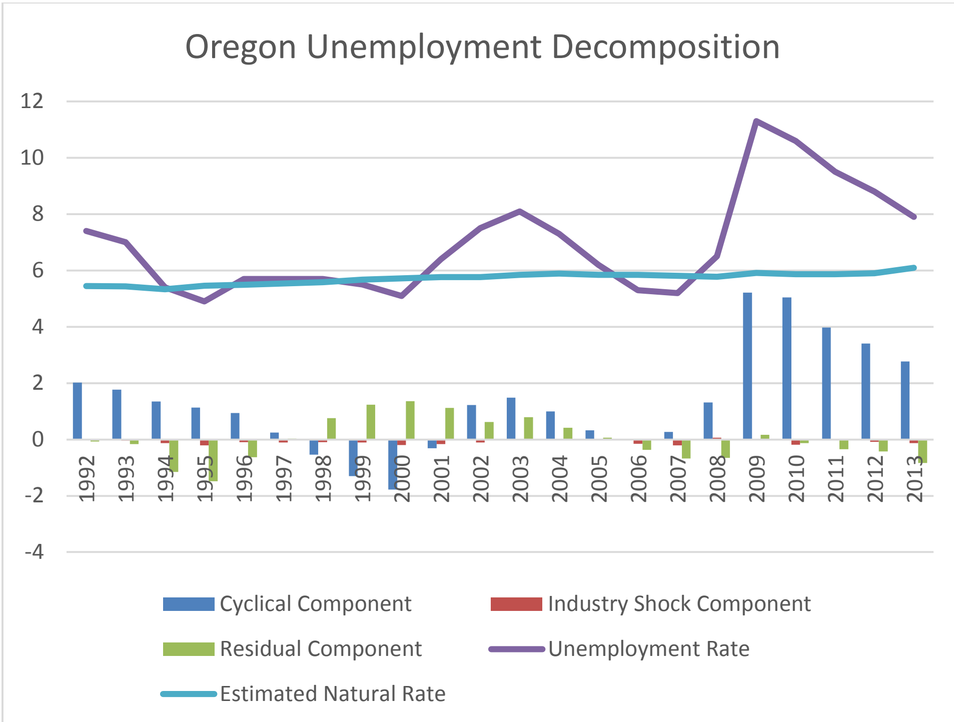

Figure 4. Oregon unemployment rate decomposition

Figure 5 shows a corresponding diagram for the state of Nebraska, an agricultural state in the Midwest. Nebraska has experienced far smaller fluctuations in unemployment around a lower mean, with the estimated natural rate rising from around 2.9% to about 3.3% through the sample. Nebraska experienced no substantial business cycle until 2009 and 2010. Even then, the "Great Recession" raised Nebraska's unemployment rate by less than 2 percentage points, compared with the roughly 5 points seen in Figure 4 for Oregon.

Figure 6 describes the unemployment decomposition for California, America's largest and perhaps most industrially diverse state. Unlike Oregon and Nebraska, California suffered high cyclical unemployment in the early 1990s due to its high cyclical sensitivity and its industry composition. The dot-com boom of the late 1990s was associated with strongly negative cyclical unemployment, which then reversed after the bust in the early 2000s. The estimated natural rate for California fluctuates between 6% and 6.5%. California was also hit strongly by the Great Recession, with cyclical factors raising the unemployment rate almost 6 percentage points above the natural rate in 2010.

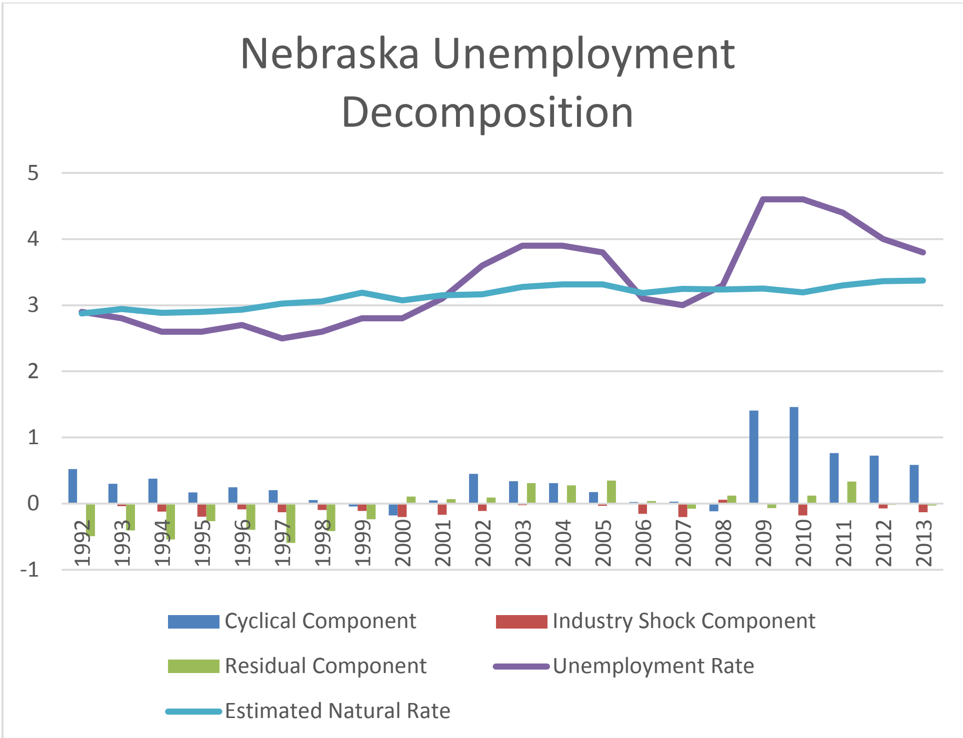

Figure 5. Nebraska unemployment rate decomposition

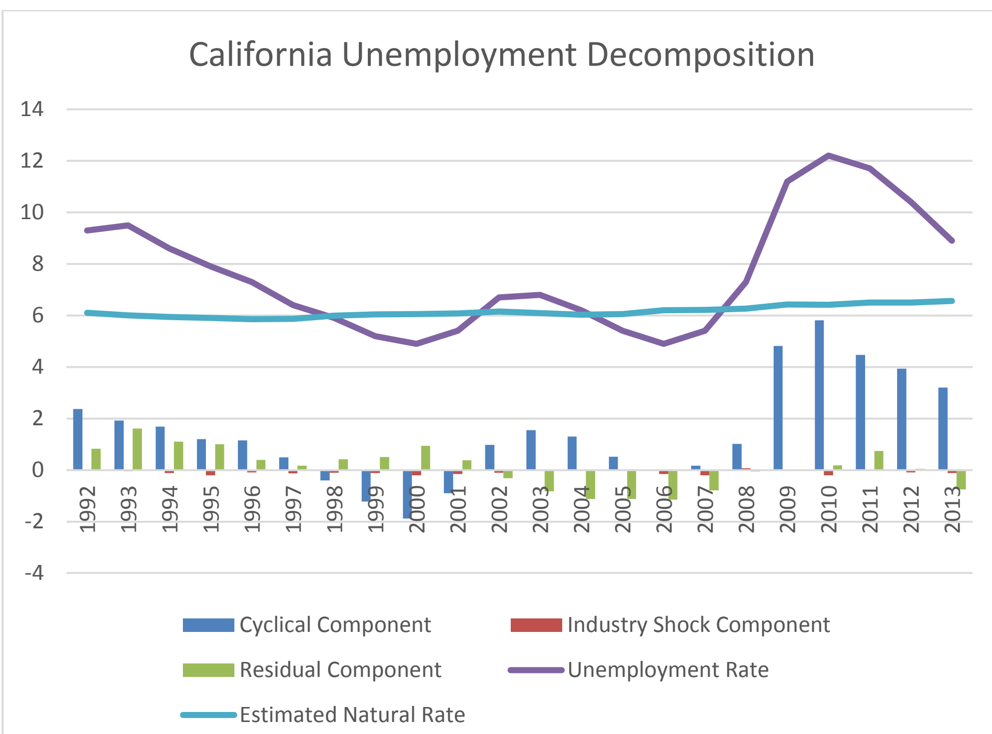

Figure 6. California unemployment rate decomposition

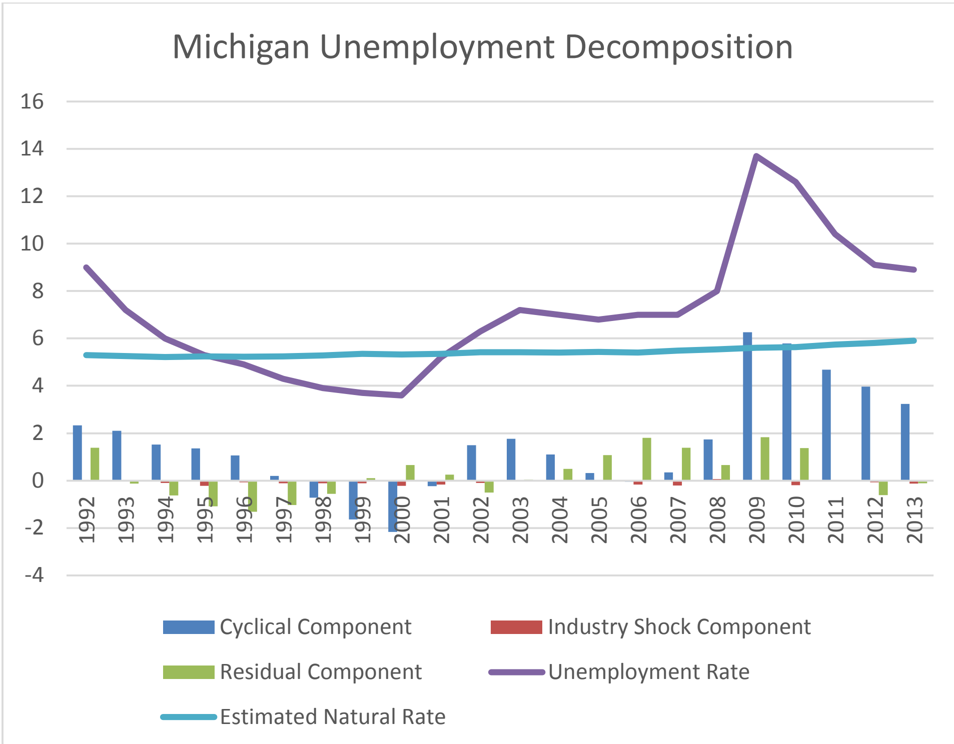

Figure 7. Michigan unemployment rate decomposition

Finally, Figure 7 shows the decomposition for Michigan, the historical home of the U.S. auto industry and a state whose heavy reliance on manufacturing has always led to a strong cycle in economic activity. Indeed, the pattern for Michigan is similar to that of California, with a boom in the late 1990s following high unemployment at the beginning of the decade and a severe recession in 2009–10. The natural rate in Michigan is estimated to have risen slowly from 5.7% to 6%.

8. Discussion

The state unemployment decompositions suggest several tentative conclusions. First, most of the fluctuation in state unemployment rates is correlated with the national business cycle or the unexplained residual. Neither of these is surprising. Unemployment on the national level is highly cyclical (Okun's Law) and the results mirror this at the state level. The flip side of this result is that natural unemployment rates as estimated in this model vary considerably across states, but do not seem to vary much over time during the 1992–2013 period.

A second result that is clearly demonstrated in the state-decomposition figures is that the residual of the state unemployment regression seems strongly cyclical. This autocorrelation is reflected by the large coefficient on the lagged residual in columns (6) and (7) of Table 1. Should we consider this residual to be part of natural unemployment or cyclical unemployment? By definition, it is a residual, so we do not know. But its cyclical pattern suggests the possibility of a state-level business cycle that is not being picked up by either the national GDP gap variable or the cyclical movements in state-employment-weighted industry growth. Further exploration of the residual and its autocorrelation might allow these movements to be understood as natural or cyclical.

A somewhat surprising result is the small magnitude of the effects of industry-employment shocks in the figures. This variable has strong statistical significance and a substantial coefficient (for positive shocks) in Table 1, but does not seem to drive large movements in state unemployment.

Several extensions of this work may be useful. Data are available on wages at the state level, and the recent publication of state purchasing-power-parity price indexes will make it possible to construct state-level time series for real wages. Wages and unemployment must be considered jointly dependent variables, so including real wages in the model would necessitate careful consideration of variables that might serve as exogenous instruments. Modeling the joint behavior of state real wages and unemployment could be a productive extension.

Inter-state migration should also have a joint relationship with unemployment. High (low) unemployment should lead to out- (in-) migration, while the migration itself would affect the unemployment rate in a stabilizing direction. Data on inter-state migration are sparse, making it doubtful that this extension could be successfully pursued.

The industry effects modeled here emphasize differences in state labor demand; expanding industries will tend to lower unemployment where they have a strong effect on state-level labor demand. A similar analysis could be conducted using state-level variation in the occupation composition of the labor force. Strong national growth in the demand for specific occupations (perhaps due to biased technological change) should lower unemployment in states with many workers in those trades. Occupation data are available at the state level, but only from 1998. Although the sample is short, it may be feasible to extend the present model to include occupational effects alongside industry effects.

Another extension of interest would be to estimate a state-level Phillips curve. This would involve examining the association at the state level between cyclical unemployment and inflation.

Finally, it is likely that bordering states have correlated unemployment shocks. Including spatial lags or correcting for spatial autocorrelation may be a useful extension of the model's econometric methodology.

9. Conclusion

This paper explores the effect of national business cycles on state-level unemployment. The results suggest that unemployment at the state level is strongly cyclical, both through the general effects of the national GDP gap and through the state's industry composition.

The estimated natural rate of unemployment is rather stable over time, but varies widely across states. Some of the variation is due to differences in state income and sales tax rates and in the proportion of young working-age people in the state. Other demographic variables have weaker effects that are not consistently statistically significant across estimation methods.

National non-cyclical shocks to the industries that are important in a state have the expected effect on state unemployment and are strongly statistically significant, but their effects seem small in comparison with the effects of business cycles.

Appendix A. NAICS Industry Categories

11	Agriculture, Forestry, Fishing, and Hunting
21	Mining, Quarrying, and Oil and Gas Extractions
22	Utilities
23	Construction
31– 33	Manufacturing
42	Wholesale Trade
44– 45	Retail Trade
48– 49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
92	Public Administration

Source: U.S. Census Bureau

https://www.census.gov/cgi– bin/sssd/naics/naicsrch?chart=2012

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