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A State-Level Analysis of Okun's Law*

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Abstract

Okun's law is an empirical relationship that measures the correlation between the deviation of the unemployment rate from its natural rate and the deviation of output growth from its potential. In this paper, we estimate Okun's coefficients for each U.S. state and examine the potential factors that explain the heterogeneity of the estimated Okun relationships. We find that indicators of more flexible labor markets (higher levels of education achievement in the population, lower rate of unionization, and a higher share of non-manufacturing employment) are important determinants of the differences in Okun's coefficient across states. Finally, we show that Okun's relationship is not stable across specifications, which can lead to inaccurate estimates of the potential determinants of Okun's coefficient.

[JEL codes: C32, E32, R11]

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1 Introduction

Okun's law is an empirical relationship that measures the correlation between the deviation of the unemployment rate from its natural rate and the deviation of output growth from its potential. Okun [1962] used data on the quarter-to-quarter growth rate of the real gross national product (GNP) and the quarter-to-quarter difference in the unemployment rate from 1947 to 1960. He estimated that if real GNP growth were held at zero, the unemployment rate would grow 0.3 percentage points, on average, from one quarter to the next. In addition, for each 1-percentage-point increase in real GNP growth, the unemployment rate would decrease 0.3 percentage points. Economists call this latter number Okun's coefficient and the empirical relationship is dubbed Okun's law. It is important to note that, although subsequent studies have attempted to develop theories explaining the existence of Okun's law, the original manifestation was a purely statistical relationship. Nonetheless, it has been used in policy making, in classrooms, and in the media.

While Okun originally used U.S. data, the relationship has been estimated across many countries and the estimated coefficient has been found to vary across countries (see Paldam [1987], Kaufman [1988], Moosa [1997], Lee [2000], Freeman [2001]). Many of these papers attribute the regional differences in Okun's coefficient to regional differences in employment protection and minimum wage laws, the power of trade unions, and demographics; however, most of these papers do not test for the significance of these determinants. While different samples, estimation techniques, and filtering methods may lead to different point estimates of the coefficient, the relationship has remained fairly robust [Ball et al., 2013].

More recently, the relationship has been estimated for various regional groupings within a country. While most of the literature has found significant regional disparities in Okun's coefficient (i.e., in the Czech Republic and Slovakia [Durech et al., 2014], Canada [Adanu, 2005], and France [Binet and Facchini, 2013]), some countries were not found to have significant regional variation (e.g., Spain [Villaverde and Maza, 2009] and Greece [Apergis and Rezitis, 2003]). Another strand of literature has used regional-level data and exploited spatial relationships to estimate the relationship at a national level [Kosfeld and Dreger, 2006, Kangasharju et al., 2012]. For the United States, Okun's relationship has been estimated at a state-level for selective states [Blackley, 1991] and larger regional groups [Freeman, 2000] with mixed results on regional differences.

In this paper we first estimate Okun's relationship for each U.S. state, and then we examine the potential factors that explain the differences across the estimated Okun's relationships. We consider indicators of labor market flexibility and demographic characteristics, which have been indicated as possible determinants of variation in the macro literature. The dependent variable in the regression is Okun's coefficient estimated as the correlation of the transitory component of output and the transitory component of the unemployment rate, for each state. Our results illustrate that indicators of labor market flexibility have a significant effect. In particular, we find that union membership, education, and industry concentration are statistically significant. Similar to previous papers, we find that the estimates of Okun's coefficient are sensitive to the estimation methodology [Lee, 2000, Prachowny, 1993]. We find that small differences in the estimated Okun's coefficient can lead to large differences in the magnitudes of the regional determinants.

The balance of the paper is organized as follows: Section 2 describes the model that we use to estimate the Okun coefficient. We employ an unobserved components decomposition that allows us to estimate both the time-varying potential output and the time-varying natural rate of unemployment. Section 3 describes the methods and data we use for the estimation. Section 4 discusses the heterogeneity in the estimated Okun's coefficients across states. Section 5 outlines the results from the cross-sectional regressions to determine the sources of the heterogeneity in the Okun's coefficients. Section 6 checks the robustness of our results to differences in the state-level data, the specification of Okun's law, and changes in the cross sectional variables over time. Section 7 summarizes and offers some concluding remarks.

2 The Empirical Model

Our objective is to measure cross-regional variability in the response of local output to local unemployment. To do this, we first outline the methods of previous studies for estimating the response using national-level data. Okun's law is an relationship that measures the correlation between the deviation of the unemployment rate from its natural rate and the deviation of output growth from its potential. When Okun introduced this concept in 1962, he was interested in the relation between (national) potential output and the natural rate of (national) unemployment. Okun [1962] originally estimated deviations in the unemployment rate as the dependent variable and deviations in output as the independent variable. Since it is common to assume that other shocks affect output but not unemployment, we prefer to treat output deviations as the dependent variable.[1] The relationship can be specified in deviations from potential and the natural rate, respectively:

$$Y_t - Y_t^* = \alpha + \beta\left(u_t - u_t^*\right) + \omega_t, \tag{1}$$

where Y_t is period$-t$ log real output, Y_t^* is log potential output, u_t^* is the natural rate of unemployment, u_t is the unemployment rate, and ω_t is a zero-mean i.i.d. innovation. The intercept term α represents the expected growth rate of output at a stable unemployment rate and the coefficient β represents how a one-percentage-point increase in the unemployment rate affects the output growth rate—the so-called Okun's coefficient. Potential output and the natural rate of unemployment are unobserved and estimating them can be problematic. Thus, Okun [1962] estimated the relationship in differences, assuming a *constant potential output* and a *constant natural rate*:

$$\Delta Y_t = \alpha + \beta \Delta u_t + \omega_t^{\dagger}. \tag{2}$$

If Y_t^* and u_t^* are constant, it is straightforward to recover (2) from (1). However, if potential output and the natural rate are believed to be time-varying, (2) will return biased estimates of Okun's coefficient.[2]

If one believes that Y_t^* and u_t^* are time-varying, Okun's coefficient should be estimated from a model in levels. One method used to estimate (1) is to obtain Y_t^* and u_t^* through prefiltering techniques (e.g., the Hodrick and Prescott [1997] filter, for hereafter HP-filter). The HP-filter and some band pass filters, however, can introduce spurious cycles into the resulting data. The results are also sensitive to the sample period and have poor end-of-sample properties. A second method uses third-party (e.g., Congressional Budget Office) estimates of Y_t^* and u_t^*.[3] In either case, the

[1] This alternative identification, however, does not allow us to simply take the inverse of our coefficient [Plosser and Schwert, 1979] to compare with the original Okun [1962] results.

[2] Nelson and Plosser [1982] found evidence that most U.S. time series data are not well identified by a deterministic, linear trend. While there are many filtering methods that revolve around the belief of a smoothed, variable potential output, Orphanides and Norden [2002] find that the estimates are unreliable at the end of the sample. Additionally, Perry et al. [1970] and Adams and Coe [1990] find that the natural rate of unemployment varies over time, which may be due to changes in demographics, the unemployment insurance, relative minimum wages, and other factors of labor market rigidities (such as unionization rates).

[3] Using third party estimates of the natural rate and potential output can be problematic if they already assume an Okun-type relationship—i.e., the third party data may assume the result.

estimates of potential and the natural rate are often treated as *known quantities*, meaning that the coefficients associated with the estimation of (1) may be more uncertain than reported.

In this paper, we opt to estimate (1) using the unobserved components (UC) framework, which allows for time variation in both Y_t^* and u_t^*.[4] In addition, we are interested in both the trend and cyclical behavior of the unemployment rate and output in N different states. Let Y_{nt} and u_{nt} represent state n's period$-t$ level of log of output and the unemployment rate, respectively. We assume that each series can be decomposed into an unobserved permanent component, Y_{nt}^* or u_{nt}^*, and an unobserved transitory component, c_{nt}^i, where $i = \{y, u\}$. The bivariate system for state n can then be written as

$$\begin{bmatrix} Y_{nt} \\ u_{nt} \end{bmatrix} = \begin{bmatrix} Y_{nt}^* \\ u_{nt}^* \end{bmatrix} + \begin{bmatrix} c_{nt}^y \\ c_{nt}^u \end{bmatrix}, \tag{3}$$

where each series is the simple sum of its two components. In this model, we assume log output and the unemployment rate are both I(1) series.[5]

To identify the two latent components, we must specify how they evolve. We assume the permanent component follows a unit root process with constant drift, μ_n^i:

$$Y_{nt}^* = \mu_n^y + Y_{nt-1}^* + \eta_{nt}^y \tag{4}$$

$$u_{nt}^* = \mu_n^u + u_{nt-1}^* + \eta_{nt}^u \tag{5}$$

and the transitory component follows a stationary autoregressive process

[4] Unlike the HP-filter, the UC can be generalized to allow for multiple series and correlation between the innovations to the components. While the UC framework still suffers from the poor end-of-sample properties, it loses less data than other methods, such as some band pass filters. Compared to some other filtering techniques, the correlated UC model uses autoregressive processes rather than trigonometric functions to describe the cyclical components, which does not force the cycle into a wave shape *a priori*. Additionally, the UC method can be modified to allow for the Okun's coefficient, the potential output, and the natural rate of unemployment to all be estimated in one step.

[5] The I(1) assumption for both variables is consistent with Sinclair [2009]. While conventional unit root tests do not reject the presence of a unit root in the U.S. unemployment rate, some researchers have preferred a stationary specification [e.g., Blanchard and Quah [1989]]. The stationarity assumption along with the assumption that one shock (i.e., demand shock) does not have a long-run effect, allows for identification of permanent and transitory shocks to the series. Differences in the specification of the unemployment rate can lead to different estimates of the permanent and transitory components (e.g., with the Beveridge-Nelson decomposition [Beveridge and Nelson, 1981].

$$c_{nt}^{i}=\phi_{n}^{i}\left(L\right)c_{nt-1}^{i}+\varepsilon_{nt}^{i}, \tag{6}$$

where $\phi_n^i(L)$ is a polynomial in the lag operator of at least order 2.[6] In the canonical unobserved components model, the innovations to components, η_{nt}^i and ε_{nt}^i, are assumed to be zero-mean i.i.d. and orthogonal (see Harvey [1985] and Clark [1987]). Recently, some models (see, for example, Morley et al. [2003] and Sinclair [2009]) have relaxed this assumption, arguing that unrestricted off-diagonal elements fit the data better. Without restrictions, however, the transitory component often looks like high frequency noise, leaving most of the series' dynamics relegated to the permanent component. As we intend to interpret the permanent component as the variable's trend and the transitory component as the series' cycle, we impose a set of identifying restrictions on the off-diagonal elements of (7). In particular, we impose a zero restriction on all off-diagonal elements, except for the covariance between the innovations of the transitory component of output and the transitory component of unemployment.

To illustrate, let $v_{nt}=\left[\eta_{nt}^{y},\eta_{nt}^{u},\varepsilon_{nt}^{y},\varepsilon_{nt}^{u}\right]'$ and $E_t\left[v_{nt}v_{nt}'\right]=\Omega_n$, where

$$\Omega_n=\begin{bmatrix}\sigma^2_{n\eta^y} & 0 & 0 & 0\\ 0 & \sigma^2_{n\eta^u} & 0 & 0\\ 0 & 0 & \sigma^2_{n\varepsilon^y} & \sigma_{n\varepsilon^y\varepsilon^u}\\ 0 & 0 & \sigma_{n\varepsilon^y\varepsilon^u} & \sigma^2_{n\varepsilon^u}\end{bmatrix}. \tag{7}$$

The on-diagonal elements represent the variances of each of the components, while the parameter $\sigma_{n\varepsilon^y\varepsilon^u}$ for each state allows for the estimation of a potential correlation across the temporary components. These restrictions impose that correlation between the state-level unemployment rate and output arises only through the transitory innovations, which is consistent with Okun's original interpretation.

The model (3) relates directly back to the original specification of Okun's law, (1), where the trend components are interpreted as a time-varying natural rate and a time-varying potential output. The cyclical components reflect these deviations discussed by Okun. To see this, we can write the relationship between each state's cyclical components as a VAR:

[6] Harvey [1985], Clark [1987], and Harvey and Jaeger [1993] suggest specifying the autogressive lags greater than or equal to 2 is necessary for the cycle to be periodic.

$$\begin{bmatrix} c_{nt}^{y} \\ c_{nt}^{u} \end{bmatrix} = \phi_n(L) \begin{bmatrix} c_{nt}^{y} \\ c_{nt}^{u} \end{bmatrix} + \begin{bmatrix} \varepsilon_{nt}^{y} \\ \varepsilon_{nt}^{u} \end{bmatrix} \tag{8}$$

and define $A_n \Sigma_n A_n' = E_t\left[e_{nt}^{p} e_{nt}^{p\prime}\right]$ as the upper right submatrix of Ω_n, where $e_{nt}^{p} = \left[\varepsilon_{nt}^{y}, \varepsilon_{nt}^{u}\right]'$, Σ_n is diagonal, and A_n^{-1} is upper triangular with unit diagonal. We can rewrite (8) in a "structural" form as:

$$A_n^{-1} \begin{bmatrix} c_{nt}^{y} \\ c_{nt}^{u} \end{bmatrix} = A_n^{-1} \phi_n(L) \begin{bmatrix} c_{nt}^{y} \\ c_{nt}^{u} \end{bmatrix} + \begin{bmatrix} e_{nt}^{y} \\ e_{nt}^{u} \end{bmatrix}, \tag{9}$$

where Okun's coefficient is measured by the inverse of the off-diagonal element of A_n^{-1}. At this stage, it is important to note that the description of Okun's law in our model requires an implicit Wold causal ordering for identification: We have imposed a recursive structure in the decomposition of Ω_n used to identify A_n^{-1}.

Since the model characterized by (3) – (7) treats each state separately, we are explicitly suppressing cross-state dynamics in both the trends and the cycles. It is entirely plausible—if not likely—that the states both grow together (i.e., have correlated trends) and experience coincident business cycles (i.e., have correlated cycles). The model does not rule these correlations out; *ex post* correlation of the individual components is still possible. The limitation of the model, however, is that it does not inform us about how (or whether) the shocks to the individual components might be correlated across states. Such a model, albeit interesting, would require simultaneous estimation of a model with $2N$ equations, which is infeasible given the relatively small number of observations available at the state-level.

3 Econometric Methodology

The following section outlines the estimation of the Okun coefficients, the latent state-level potential outputs and natural rates, and the methodology used to identify factors behind the cross-state heterogeneity of the estimated Okun coefficients. At the national level, output is measured as the quarterly real gross domestic product (GDP).[7] These data are available for the states, with the

[7]In his original paper, Okun [1962] used gross national product (GNP), which includes net foreign income. The BEA switched from GNP to GDP in 1991 under the belief that GDP more accurately represented the level of national

exception that output is measured by gross state product (GSP). The GSP data incorporates the first part of the BEA's 2013 comprehensive revision released in September 2013.[8] While state-level unemployment is available monthly, the GSP dataset is available only at an annual frequency. Therefore, for the state-level analysis, we estimate the restricted version of the correlated unobserved components model individually for each state using the annual GSP and the annual average of the unemployment rate from 1977-2012. Ideally, we would like to estimate this model with a higher frequency data, and we discuss our data limitations in Section 5.

3.1 Estimating the UC Model

In order to estimate the model outlined in the previous section, it is convenient to summarize it in its state-space representation. The measurement equation in the state space is

$$\begin{bmatrix} Y_{nt} \\ u_{nt} \end{bmatrix} = H\xi_{nt}, \tag{10}$$

where $\xi_{nt} = \left[Y^*_{nt}, u^*_{nt}, \widetilde{c}^{y\prime}_{nt}, \widetilde{c}^{u\prime}_{nt}\right]'$ is the state vector,

$$H = \begin{bmatrix} 1 & 0 & 1 & \mathbf{0}'_{p-1\times 1} & 0 & \mathbf{0}'_{p-1\times 1} \\ 0 & 1 & 0 & \mathbf{0}'_{p-1\times 1} & 1 & \mathbf{0}'_{p-1\times 1} \end{bmatrix},$$

$\mathbf{0}_{p-1\times 1}$ is an $p-1\times 1$ matrix of zeros, and the vector $\widetilde{c}^i_{nt} = \left[c^i_{nt}, c^i_{nt-1}, ..., c^i_{nt-p-1}\right]'$ contains both the current period and lagged values of the transitory component. Note that the the state space's measurement equation is independent of n, and simply acts to aggregate the two components.

Let $\widetilde{\phi}^i_n = \begin{bmatrix} \phi^i_{n1} & \cdots & \phi^i_{np} \end{bmatrix}$ represent the vector containing the coefficients in the pth order lag polynomial $\phi^i_n(L)$ and define

$$\Phi^i_n = \begin{bmatrix} \multicolumn{2}{c}{\widetilde{\phi}^i_n} \\ I_{p-1} & \mathbf{0}_{p-1\times 1} \end{bmatrix},$$

which is the companion matrix of the transitory components univariate VAR. The state equation is

production.

[8]For more information about the data revision, see `http://www.bea.gov/regional/docs/Info2013CompRev.cfm`.

$$\xi_{nt} = \mu_n + F_n \xi_{n,t-1} + v_{nt},$$

where

$$F = \begin{bmatrix} I_2 & \mathbf{0}_{2\times p} & \mathbf{0}_{2\times p} \\ \mathbf{0}_{p\times 2} & \Phi_n^y & \mathbf{0}_{p\times p} \\ \mathbf{0}_{p\times 2} & \mathbf{0}_{p\times p} & \Phi_n^u \end{bmatrix},$$

$\widetilde{v}_{nt} = \left[\eta_{nt}^y, \eta_{nt}^c, \varepsilon_{nt}^y, \mathbf{0}'_{p-1\times 1}, \varepsilon_{nt}^u, \mathbf{0}'_{p-1\times 1}\right]'$, and $\mu_n = \left[\mu_n^y, \mu_n^u, \mathbf{0}'_{2p\times 1}\right]'$ contains the drift coefficients.

Let β_n^* represent the Okun coefficient for state n. Following Sinclair [2009], β_n^* can be estimated directly from the covariance matrix Ω_n[9], or alternatively from the $\widetilde{\Omega}_n = E_t\left[\widetilde{v}_{nt}\widetilde{v}'_{nt}\right]$, as

$$\beta_n^* = \frac{\sigma_{n\varepsilon^y\varepsilon^u}}{\sigma_{n\varepsilon^u}^2}, \tag{11}$$

which is analogous to the VAR with a Cholesky decomposition interpretation, (9). This can be seen explicitly, if we define the off-diagonal element of the matrix, A_n, as $a_{n,12}$; then, Okun's coefficient is

$$a_{n,12} = \frac{\mathrm{Cov}(\varepsilon_{nt}^y, \varepsilon_{nt}^u)}{\mathrm{Var}(\varepsilon_{nt}^u)} = \frac{\sigma_{n\varepsilon^y\varepsilon^u}}{\sigma_{n\varepsilon^u}^2} = \beta_n^*. \tag{12}$$

Once the model is in state-space form, the parameters can be estimated from the data using maximum likelihood and the components are estimated using the Kalman filter with a two period start [Harvey, 1989]. Results in the following sections are generated using a smoothed filter.

3.2 Estimating the Factors Behind Cross-State Heterogeneity

To identify the factors that explain the cross-state differences in the estimated Okun relationships, we regress the estimated Okun coefficients on a set of independent state-level variables. Because the dependent variable is estimated on a state-by-state basis, the sampling uncertainty is unlikely to be constant across states. Therefore, the errors in the regression will be heteroskedastic and ordinary

[9] This assumes the autoregressive coefficients are the same for the GSP and the unemployment rate for each state.

least squares estimates will be inefficient. To address the heteroskedasticity in our regression, we have to account both for the estimation error in the regression and for the added variation because of the sampling uncertainty in the dependent variable. Hanushek [1974] first addressed this problem by decomposing the total variation into the sampling uncertainty of the dependent variable and the variation in the residuals to estimate a feasible generalized least squares model.[10]

Following Hanushek [1974] and Lewis and Linzer [2005], we construct a two-stage feasible generalized least squares estimator (`2FGLS`), where the dependent variable β_n is not directly observable but, instead, we observe an estimate

$$\beta_n^* = \beta_n + \vartheta_n, \tag{13}$$

where ϑ_n is a zero-mean sampling error with variance ς_n^2. The objective is to estimate

$$\beta_n = x_n' \delta + \epsilon_n, \tag{14}$$

where $\epsilon_n \sim N\left(0, \sigma_\beta^2\right)$ is the i.i.d. error that would obtain if β_n were known. As β_n is assumed to be observed with sampling error, we can only estimate (14) as:

$$\beta_n^* = x_n' \delta + \nu_n, \tag{15}$$

where $\nu_n = \vartheta_n + \epsilon_n$. Estimates of β_n^* and ς_n^2 are provided by the UC procedure described earlier. Clearly, even though ϵ_n is assumed to be homoskedastic, ν_n need not be. Assuming that the β_n^*s are independent across n, that is $\mathrm{Cov}(\vartheta_l, \vartheta_m) = 0$ for $l \neq m$, we can use a two-step process to estimate σ_β^2. First, let $\mathbf{v} = (\nu_1, \ldots, \nu_N)$ and define $\mathbf{\Omega} = \mathrm{E}(\mathbf{v}\mathbf{v}')$. Then write $\mathbf{\Omega} = \sigma_\beta^2 \mathbf{I} + \mathbf{G}$, where $\mathbf{G} = \mathrm{diag}(\varsigma_1^2, \ldots, \varsigma_N^2)$. Let $\hat{\nu}_n$ denote the residuals from a first-step ordinary least squares estimation of the regression in (15). Now let $\mathbf{X}$ denote the $N \times (K+1)$ data matrix, which includes a constant. Then, an unbiased estimator for σ_β^2 is given by:[11]

[10] Hornstein and Greene [2012] illustrate a similar approach, based on Saxonhouse [1976], that estimates a weighted least squares procedure in which the observations are weighted by the inverse of the standard error of the dependent variable, ignoring the estimation error in the regression. Lewis and Linzer [2005] notes that this approach is appropriate only when the share of the total variation in the regression residual due to the sampling uncertainty in the dependent variable is large.

[11] Lewis and Linzer [2005] warns that $\hat{\sigma}_\beta^2$ can be negative in small samples, in which case it can be set to zero.

$$\hat{\sigma}_\beta^2 = \frac{\sum_n \hat{\nu}_n^2 - \sum_n \varsigma_n^2 + \mathrm{tr}\left((\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{G}\mathbf{X} \right)}{N-K}. \tag{16}$$

The second-step estimation of the regression in (15) can be carried out applying weighted least squares. The weights, ϖ_n, are constructed by replacing σ_β^2 with its estimate $\hat{\sigma}_\beta^2$ calculated using the estimates of the dependent variable and its variance, β_n^* and ς_n^2, provided by the UC procedure:

$$\varpi_n = \frac{1}{\sqrt{\hat{\sigma}_\beta^2 + \varsigma_n^2}}.$$

The weighted least squares estimation yields efficient estimates of the regression parameter, δ.

4 Results

In this section, we first estimate the model, $(3)-(7)$, using national-level data and compute Okun's coefficient. This serves as a baseline for comparison with the extant literature and a benchmark for the following state-level estimation. We then describe the results of the state-level estimations. To facilitate comparison, we restrict the national-level sample to be identical to our state-level sample. Finally, we will consider the determinants of the Okun coefficient by examining the cross-state variation. In the interest of brevity, we will refer to the permanent components of output and the unemployment rate as potential output and the natural unemployment rate, respectively. We will also occasionally refer to the transitory components of output and the unemployment rate as cyclical output or the output gap and the cyclical unemployment rate.[12]

4.1 National Results

[Figure 1 about here.]

The top panel of Figure 1 shows potential output and the transitory component of U.S. GDP estimated from the sample period of 1977-2012.[13] The potential output has an essentially constant

[12] Note that our notion of the potential output does not refer to the maximum capacity of output but rather the level of output consistent with unemployment at the natural rate.

[13] The estimated Okun's coefficient is robust to the inclusion of a structural break in GDP in 1996 [Bai and Perron, 2003] (i.e., -2.049 with the structural break and -2.033 without). Therefore, we present the results without structural breaks for consistency and comparison with the state-level results.

upward trend over the sample period. The transitory component of GDP does not exhibit the typical business cycle fluctuations due to the lower frequency data; however, cyclical output does fall during NBER recessions (shaded areas in the figures), turning negative for three of the four recessions during the sample period.[14]

The bottom panel of Figure 1 shows the natural rate of unemployment and the transitory component of the unemployment rate for the same period. The natural rate of unemployment falls steadily since the early 1980s. Cyclical unemployment does exhibit cycle fluctuations, rising after the onset of an NBER recession. Characteristic of the recent jobless recoveries, cyclical unemployment remains elevated even after the end of the NBER recessions.

The textbook version of Okun's law argues that a one percent decrease in the unemployment rate is associated with a 2-percentage-point increase in the output gap Abel et al. [2013]. Recent studies have obtained similar values for Okun's coefficient: Lee [2000] found Okun's coefficient for the U.S. to be between -2.09 to -1.84, depending on the estimation technique and Daly et al. [2014] estimated Okun's coefficient to be -2.25. Our estimate of Okun's coefficient over this time period is -2.03, consistent with most of the extant literature.

4.2 State-Level Results

The decompositions for the state-level data are qualitatively similar to those obtained using national-level data. In particular, most of the states have a nearly constant upward trend in potential GSP, albeit with different levels and trend growth rates across states, and a slight downward trend in the natural rate of unemployment after 1980. While both potential GSP and the natural rate have similar shapes for most states, there is a variety of regional cyclical variation. Since the states are smaller economic units than the nation, the transitory components are less smooth. In particular, the timings and depths of the downturns vary across states. In some cases, states do not experience downturns coincident with the nation at all. Moreover, there are some regional patterns. For example, states in the Northeast display more cyclicality that most other states, while states in the Midwest are weakly cyclical, not having experienced much of a transitory downturn in the 1991

[14] Fernald [2014] estimates that potential output has dropped since 2013, which is consistent with the later decision by the CBO [February 2014] to revise their projections of potential output downward. A recent report by the CBO [February 2015] predicts that while actual output is projected to grow from 2020 to 2025, it is expected to grow at the same rate as potential output.

and 2001 recessions.[15]

While most states follow the same tendencies of the national level data there are two types of deviations from the downward sloping unemployment trend. Notably, there are five states (specifically Indiana, Kansas, North Carolina, Rhode Island, and Oregon) that have an upward (albeit small) unemployment trend across the sample. Also, Washington, Wisconsin, Nevada, and Georgia have a more variable trend, which is consistent with the theory that the natural rate of unemployment is flexible.[16] Some additional analysis was done on a selection of states to test structural breaks in the trend using the Bai and Perron [2003] multiple break point test. While some states were found to have a structural break, including the break did not change the estimate of Okun's coefficient. Additionally, the breaks vary by states, which is consistent with previous literature finding heterogeneous business cycle dynamics across states [Owyang et al., 2005, 2009]. Therefore, for the sake of uniformity, the reported results do not include breaks.

We highlight a few of the interesting cross-state characteristics in the components; the full set of states is available upon request. Figure 2 shows the components of GSP and unemployment for two states (Connecticut and New Mexico) separated both by geography, demographics, and economic characteristics (including population growth, labor force participation rates, and share of non-manufacturing employment, among others). See Table 2 for the complete list of variables included in the analysis. Both states have upward trending potential GSPs and downward trending natural rates, with New Mexico's natural rate falling faster. Their cycles, on the hand, appear very different. Connecticut has downturns in its GSP gap and upticks in its cyclical unemployment around the same time as NBER recessions. New Mexico's cyclical unemployment rises a number of times—more than those associated with NBER recessions; on the other hand, New Mexico's GSP gap exhibits much lower frequency movements.

[Figure 2 about here.]

Next, in Figure 3, we consider two states that are geographically proximate—Iowa and Missouri—but have slight differences in industrial compositions. (Iowa had a larger share of manufacturing

[15] These results are consistent with previous research which finds the timing and magnitude of a state's business cycle may not coincide with the national dynamics [Owyang et al., 2005], and states' business cycles exhibit heterogeneity [Owyang et al., 2009].

[16] See Perry et al. [1970] and Adams and Coe [1990] who note that the natural rate of unemployment may be changing over time due to changes in the labor market (i.e., demographics, prevalence of unions, and unemployment insurance).

employment in 2010, 13.6%, compared with 9.2% in Missouri.) As with most other states, both of these states exhibit growth in potential GSP and a decline in the natural rate over the sample period. The cyclical features of their unemployment rates are also broadly similar. The business cycle experiences of each state's GSP, however, differ substantially. In particular, Missouri has larger lower frequency fluctuations in its GSP. This suggests that even states within the same region can have heterogeneous business cycle experiences.

[Figure 3 about here.]

[Table 1 about here.]

The first of our main results centers on the state-level heterogeneity in the interaction between the cyclical components of the two series—the so-called Okun coefficient. Table 1 contains the estimated Okun coefficients by state; for ease of analysis, Figure 4 contains the same information in the form of a map, where darker shades are associated with larger (in absolute value) Okun coefficients. The estimated Okun coefficients vary by state with the coefficient being in the range of -4.378 (North Dakota) to -1.254 (Colorado).[17] While the range of values may seem large, most of the states fall within the range of -1.5 to -3.[18] Although [Freeman, 2000] did not find regional variation in the Okun coefficients, it could be that the level of aggregation (eight regions) masked heterogeneous differences. Research has shown that some information is lost when heterogeneous groups or individuals are aggregated, which can cause an estimation bias [Zellner, 1962, Goodfriend, 1992].

[Figure 4 about here.]

Figure 4 reveals some regional patterns. States in the Mideast region generally have lower (in absolute value) Okun coefficients. States that border with Canada have a higher coefficient in absolute value. Alternatively, the Southeast tends to have larger coefficients on average. The next section will investigate these differences across states.

[17] Louisiana has by far the smallest Okun's coefficient in absolute value (-0.368). This estimate may be an outlier and influenced by the aftermath of Hurricane Katrina.

[18] While Blackley [1991] did not estimate Okun's coefficient for all states, he found coefficients ranging from -1.7 to -6.8.

5 Explaining the Heterogeneity in the State-Level Okun coefficients

Previous studies have documented the variation of Okun's coefficient across countries and shown that cross-country heterogeneity in the coefficients can be associated with differences in production, labor participation, and regulations [Kaufman, 1988, Moosa, 1997, Ball et al., 2013]. These factors could also be the cause of heterogeneity in the U.S. state-level Okun coefficients. In this section, we will formally investigate some possible causes for Okun's law to vary by state.

5.1 Determinants of Okun's Coefficient

In searching for potential determinants of the cross-state heterogeneity in Okun's coefficient, we consider indicators of labor market flexibility and demographic characteristics. Greater flexibility in labor markets should lead to less responsiveness of the unemployment rate to the business cycle (i.e., changes in output). For example, a more rigid labor market can be identified as having more employee protection, meaning that it would be harder for an employer to fire an employee.[19] This increased employee protection may delay the hiring and firing practices of employers [Hopenhayn and Rogerson, 1993]. In this case, an increase in the unemployment rate will have a larger (negative) effect on output than it would in a more flexible labor market environment because the rigid labor market magnifies the effect on output through other mechanisms, such as decreased productivity and a reduction of hours worked.

[Table 2 about here.]

Higher labor market rigidity or lower labor market flexibility might be characterized by (1) higher unionization rates, (2) higher employment concentration in a small number of industries, or (3) lower levels of education. We include the percentage of the workforce in 1970 who are union members, the employment share in non-manufacturing industries in 1970, and the share of the population in 1970 with a college education. Summary statistics are listed in Table 2 along with their 2010 counterparts for comparison. The covariates vary over the course of our time sample;

[19] For a comparison of the determinants of labor market rigidities in Europe and the U.S., see Nickell [1997].

however, in the baseline regressions, we use the beginning of the sample for estimation as we believe the results should be more sensitive to the initial conditions of the labor force.

Similarly, demographic variables representing higher availability of the labor input would obviate the need for more flexible labor markets to generate large changes in output from relatively small changes in the unemployment rate. For example, a higher rate of population growth would be consistent with a higher absolute value of Okun's coefficient.

5.2 Results

[Table 3 about here.]

The first column of Table 3 presents our baseline estimation results using the Okun's coefficients from the UC model in the two-step procedure described earlier, which provides the correct standard errors of the estimated coefficients. We find that a higher degree of unionization is associated with a statistically significantly higher magnitude of Okun's coefficient. This finding is consistent in the cross country literature, which finds that higher union density and coverage increases unemployment and decreases labor supply ([Nickell, 1997, Blanchard and Summers, 1986]), which increases the labor market rigidity. While there is some debate whether the U.S. employment is becoming more concentrated or deconcentrated over time (see [Desmet and Fafchamps, 2006, Chatterjee and Carlino, 2001]), the link between growth and productivity at the country level is also mixed (see [Baldwin and Martin, 2004, Gardiner et al., 2010]). We find that a higher concentration of employment in non-manufacturing industries is associated with a statistically significantly higher magnitude of Okun's coefficient. This is consistent with the interpretation that an increase in employment concentration leads to more labor market rigidity.

Education, measured by the share of state population with a college degree, has a statistically significant effect. The positive sign of the estimated coefficient indicates that higher levels of education are associated with *smaller* magnitudes of Okun's coefficient. This effect has the largest magnitude in our regression at 10.67. This means that a 1% increase in the share of the state population with a college education in 1970 will lead to a decrease (in magnitude) of the Okun's coefficient of 0.11. Our finding is consistent with the interpretation of higher education being an indicator of more flexible labor markets, which is consistent with international comparisons Barro and Lee [1993].

While population growth was not statistically significant in our sample, the negative sign of the coefficient is consistent with previous studies ([Blackley, 1991, Kennedy, 2009]). The interpretation is that population growth represent a higher availability of the labor input in the state's production function, which is consistent with the Okun relationship necessitating relatively small changes in the unemployment rate to bring about large changes in output: that is, a larger magnitude of the Okun's coefficient.

Additionally, we have included two indicators of the labor force that have been found to be significant in previous studies (e.g. Blackley [1991]): the share of young people in the labor force and the share of women in the labor force, both at their 1970 values. The inclusion of the youth (under 25 years old) employed share of the labor force is motivated by previous research that has found that younger members of the labor force are less attached to the labor market than their older peers Lynch [1983, 1989]. This weak attachment has been documented by higher levels of unemployment due to more frequent spells and longer duration of unemployment [Clark and Summers, 1982]. These findings connect to Okun's law by Owyang and Sekhposyan [2012] and Zanin [2014] who find that the Okun's coefficient can vary by the age of the unemployed population. Specifically, by restricting the unemployment rate to only include participants 20 years and older, Owyang and Sekhposyan [2012] found that the unemployment rate of this group was less sensitive to changes in output growth. The interpretation would be that higher levels of youth participants in the labor market would lead to less flexible labor markets, suggesting a higher magnitude of Okun's coefficient, and an expected negative sign. Therefore, while the variable was not statistically significant in our sample, the coefficient has the expected sign.

Finally, the share of women in the labor force has been found to be associated with less flexible labor markets in previous studies ([Blackley, 1991, Kennedy, 2009]) because women have been found to have a longer duration of unemployment [Darby et al., 1985]. However, more recent research has found a dramatic increase in the returns of college education for women [He, 2011], which has led to an increase in college enrollment by women and increased labor force participation. Additionally, Lazear and Spletzer [2012] find that the changes in the gender composition of the work force (i.e., increase in female labor force participation) cannot explain the changes in the unemployment rate. Therefore, there is some conflict over the expected sign of the coefficient of the share of the females in the labor force. Indeed, our coefficient is not statistically significant, and the sign of the coefficient varies across ordinarily least squares and two-stage least squares estimation methods.

Overall, these results are broadly consistent with the international literature on Okun's law, indicating that there is a similar variation across states as there is across countries. We find that the statistically significant determinants of Okun's coefficient at the state level are union membership, education, and industry concentration. Many of these characteristics have been identified as possible cross-country variation in the literature; although, not tested directly Paldam [1987], Kaufman [1988], Moosa [1997], Lee [2000], Freeman [2001]. Since regional demographic and industrial differences within a country can lead to similar variation seen across countries, Okun's law may not be ideal for monetary policy for two reasons. One is because there are many different determinants can change the relationship between output and unemployment, as noted by Altig et al. [1997] and estimated directly in this paper. Another is because monetary policy will have a heterogeneous effect within a country.

In the next section, we analyze the consistency of these results to other estimation techniques of Okun's coefficient and the changes in the determinants over time.

6 Robustness Checks

In this section, we discuss the consistency of these results to (1) alternative data sources for estimating the Okun's coefficient, (2) other specifications of Okun's regression and (3) the changes over time in the variables that influence Okun's coefficient.

6.1 Other Data Sources

One issue with the current data sources used in this paper, is that annual frequency is not ideal when considering business cycle dynamics. While state-level unemployment rates are available at a monthly frequency, the bottleneck is a higher frequency measure for state-level output. Therefore, we also estimate the model using state personal income (SPI) which is available quarterly from the Bureau of Economic Analysis (BEA), as a proxy for GSP, and estimated the model again using an interpolated series from SPI and GSP.[20] This allows us to expand our data set from 1976Q1

[20]The data used to calculate quarterly gross state product are annual real gross state product and quarterly real personal income by state from the Bureau of Economic Analysis (BEA). Both data series are in millions of chained

to 2012:Q4 and increase the number time series observations per state from 36 to 148. However, as others have noted [von Kerczek and Lopez, 2012, Wolfers, 2014], SPI is a noisy series, which affected the precision of the estimated components, and our econometric method was unable to produce reasonable business cycles.

While the quality of the SPI series may be a justification for our inconsistent measurement, it could also be due to our model specification. A drawback of the unobserved components model is that model validation is dependent on the appropriateness of the assumptions about the true data generating process (DGP). In this paper, we describe the permanent components as a random walk with drift and the cyclical components as an autoregressive process of order two. However, while this model has a general framework [Harvey, 1985, Morley et al., 2003, Sinclair, 2009], it might not capture the true DGP of personal income for all states. Therefore, in order to appropriately estimate a UC model, we would have to allow for more model variations by state. However, the goal of this paper was not a modeling exercise, but to identify and explain the cyclical dynamics between unemployment, and identify state level factors to account for this variation.

6.2 Alternative Specifications

We compare our restricted, bivariate UC version of the Okun's coefficient to other specifications of Okun's law: a differenced model and another identification of deviations from potential measure. The first approach from (2) estimates the changes of the differenced version of Okun's law, implicitly assuming a constant potential and a constant natural rate. If there is an unobservable trend in output and unemployment, differencing the data will remove the constant trend. While this specification is econometrically straightforward to estimate and does not require estimation of potential output and the natural rate of unemployment, there are some disadvantages. First, the defined cyclical components may not have some of the desired properties of cycles (i.e., cycles may not be mean zero). Additionally, if the trends are not deterministic, then this could lead to biased estimates of the Okun's coefficient.

Another approach is to estimate a deterministic trend and take the residual of that as the cyclical

2009 U.S. dollars. Quarterly real GSP is obtained by interpolating annual real GSP on quarterly personal income using proportional Denton interpolation. The initial output from the Denton interpolation is the level of gross state product added by quarter, in other words, the sum of four quarters yields the annual gross state product. This output is multiplied by 4 to obtain an annualized level of GSP. The final quarterly GSP data are thus annualized real gross state product in millions of chained 2009 U.S. dollars component. This would then lead to a two-step estimation process, where the trend component can be specified as polynomial:

$$\tau_{nt}^{i} = \alpha_0 + \Sigma_j \alpha_j t^j.$$

In this case, τ_{nt}^{i} is the trend component where $i = \{y, u\}$. The cyclical component—also called the gap—is the residual. Okun's coefficient is then computed from these gap estimates. Similar to our original model specification, we allow the trend estimates to vary by states and estimate the previous equation under the assumption that $j = 1$ (i.e., a linear deterministic trend). While this method requires an additional step compared to the UC model and the differenced model, it can still be easily computed. However, this method, similar to the differenced specification, is susceptible to spurious correlations due to misspecification of the trend [Mocan and Topyan, 1993].

[Figure 5 about here.]

[Figure 6 about here.]

Figure 5 and 6 show the estimated coefficients visually by states. Similar to the previous map, the Okun's coefficient varies by state with the differenced specification leading to coefficients ranging from -3.61 to -0.40, and the gap estimation with a linear trend specification leading to coefficients ranging from -4.65 to 1.25. Interestingly, the linear trend gap specification found that two of the states, North Dakota and Alaska, had positive Okun coefficients. Another important characteristic is that the coefficients vary by specification, which is consistent to previous research [Lee, 2000, Prachowny, 1993]. However, for some states the estimates are not stable across techniques. For example, Georgia's Okun's coefficient was -2.00 and -4.65 from the differenced and linear trend technique, respectively. Perhaps this is not surprising as the different specifications imply drastically different evolutionary processes for the underlying trends.

Table 3 shows the estimation results of determinants of the state-level Okun's coefficient using all specifications of estimating the Okun's coefficients. Column (1) displays the results using the UC specification of the Okun's coefficient, column (2) presents the results using the differenced specification from equation (2), and column (3) shows the results using the linear trend specification of the Okun's coefficients.

The table demonstrates that the determinants of Okun's coefficient vary depending on the specification used in estimating the coefficients. Interestingly, none of the coefficients are significant for all specifications. The significant determinants of the differenced Okun's coefficient are union membership, the share of the labor force that is female, and the employment share of non-manufacturing industries, while the linear trend found only the share of the labor force that is female as statistically significant under the `2SFGLS` estimation method. We conclude that Okun's coefficient can vary based on the specification, which can also lead to inaccurate estimation of the determinants of the coefficient. These alternative models differ in the way the trend is specified, where the linear trend and first difference models assume that the trends are deterministic. The UC specification allows for a more robust estimation as it allows for the trend to be stochastic and, in a sense, nests the other two models.[21]

6.3 Changes in the Determinants of Okun's Coefficient

[Table 4 about here.]

Section 5 identifies possible determinants of the Okun's coefficient using data from 1970, prior to the start of the sample. While exploring how the initial conditions affect the estimated Okun coefficient has been the standard for this type of analysis [Blackley, 1991, Kennedy, 2009], it would also be interesting to examine the effect of the change of the regressors across the sample on the Okun's coefficient estimates. Table 4 shows the results when we differenced the regressors (values of 2010 minus the values of 1970). While the `OLS` model using the Okun's coefficients from the UC estimation shows marginal significance of the difference of the share of females in the labor force and the difference of the share of employment in non-manufacturing industries, these results do not hold under the `2SFGLS` model. However, the signs are in the expected direction with a negative coefficient, suggesting that Okun's coefficient increases in magnitude with an increase in the determinant over the estimation period.

Similar to the previous section, the estimated coefficients of the determinants of Okun's coefficient vary depending on the method for estimating Okun's law. Additionally, some of the regressors

[21] This table also suggests that the *magnitudes* of the effects can also vary by specification. The linear trend specification of Okun's coefficient, the coefficient of the female labor force is much larger in magnitude in the linear trend specification than in the other two specifications.

display a unreasonably large effect depending on the estimation method, which could be an indicator of spurious correlation in Okun's coefficient.

7 Conclusions

In this paper we estimate the Okun coefficients for each U.S. state and find that it varies by state with some regional patterns present. Then we examine the potential factors that explain the differences across states of the estimated Okun's relationships, taking into account primarily indicators of labor market flexibility and demographic characteristics. Our results illustrate that indicators of labor market flexibility have the expected direction of effect. In particular, education attainment, measured by the share of the state population with a college degree, has a statistically significant effect. The positive sign of the estimated coefficient indicates that higher levels of education are associated with smaller magnitudes of Okun's coefficient. We also find that a higher rate of union membership and a higher concentration of employment in non-manufacturing industries are both associated with a higher magnitude of the Okun's coefficient. Finally, we show that the estimated Okun's coefficients are not stable across estimation techniques, which can lead to inaccurate estimates of the potential determinants of Okun's coefficient.

The usefulness of Okun's law for monetary policy depends on its stability and ability for broad inference. These results highlight the fact that national level policy, such as monetary policy, can have heterogenous effects within the U.S. for two reasons. One is because the relationship between output and the unemployment rate varies across states and shows some regional patterns. Therefore, monetary policy will have a different effect on output and the unemployment rate due to the variation of the Okun's coefficients. Another reason is because, as this paper has shown, there are many demographic and industrial differences that can change the regional relationship between output and unemployment. As regional demographic and industrial patterns change, this will also lead to a change in the Okun's coefficient.

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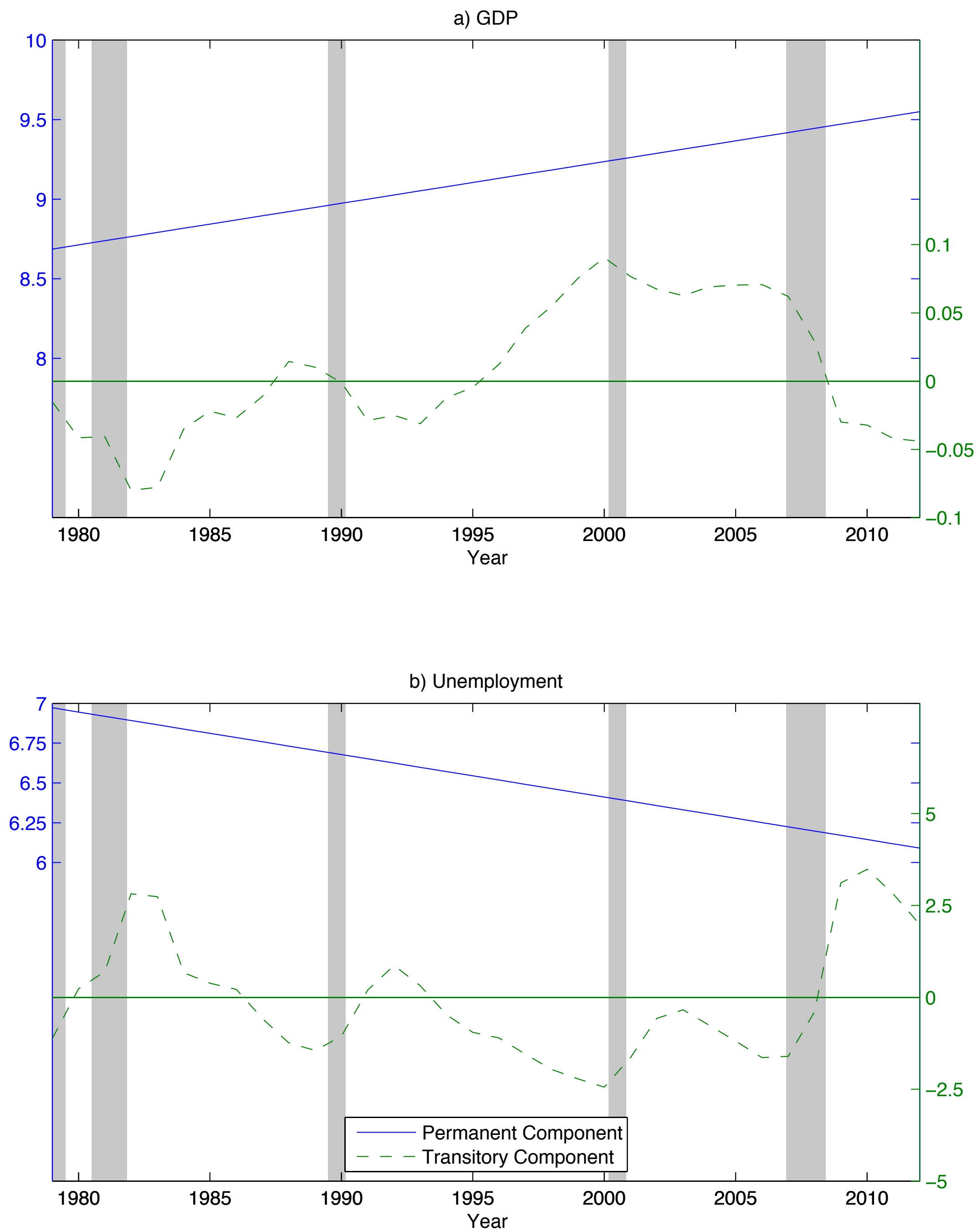
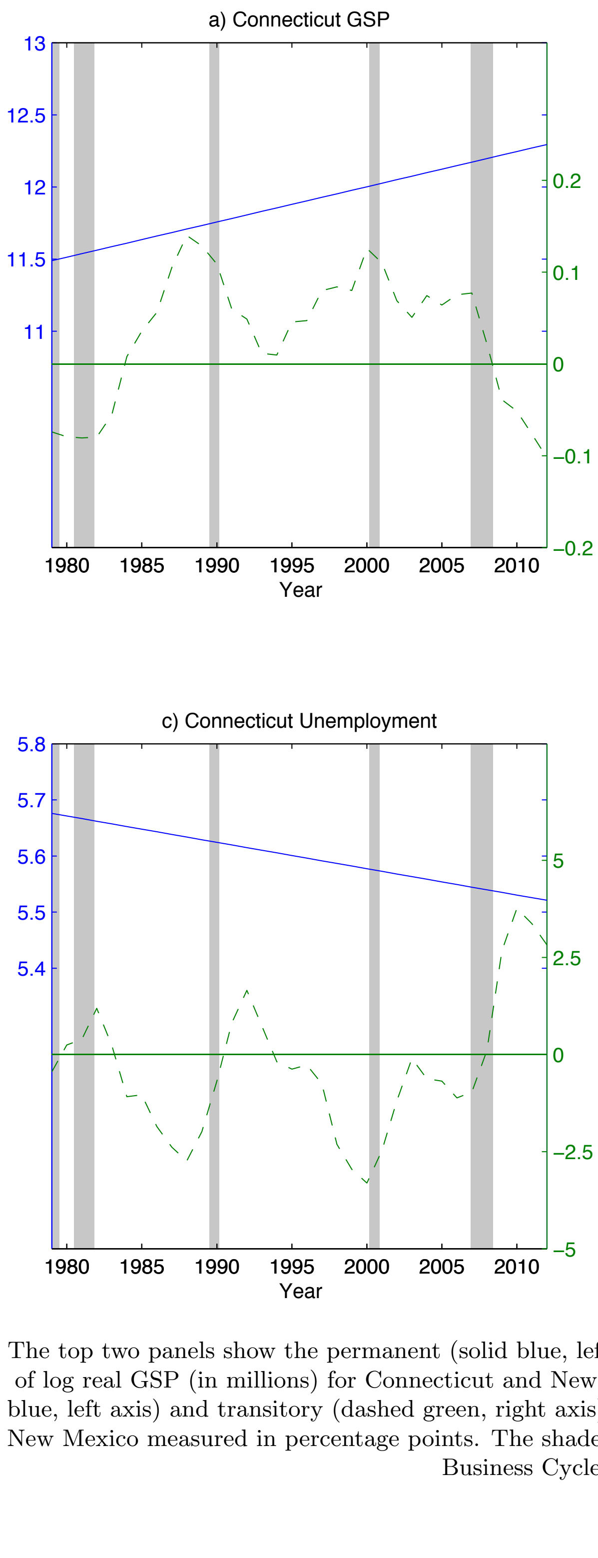
List of Figures

Figure 1: U.S. GDP and Unemployment Components



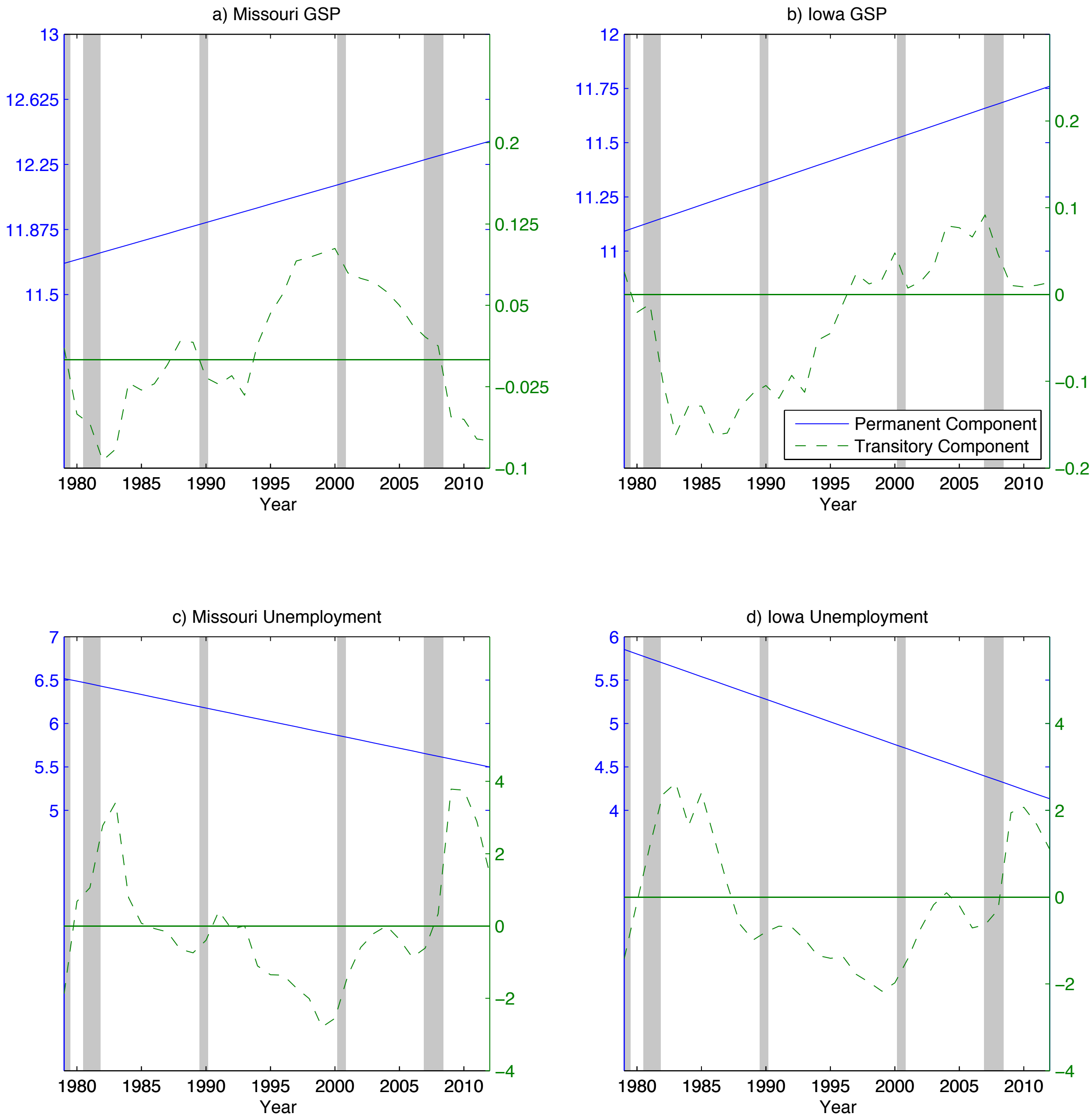
The top panel shows the permanent (solid blue, left axis) and transitory (dashed green, right axis) components of log real GDP (in billions). The bottom panel shows the permanent (solid blue, left axis) and transitory (dashed green, right axis) components of the unemployment rate measured in percentage points. The shaded areas are recessions as defined by the NBER Business Cycle Dating Committee.

Figure 2: Output and Unemployment Components of CT and NM



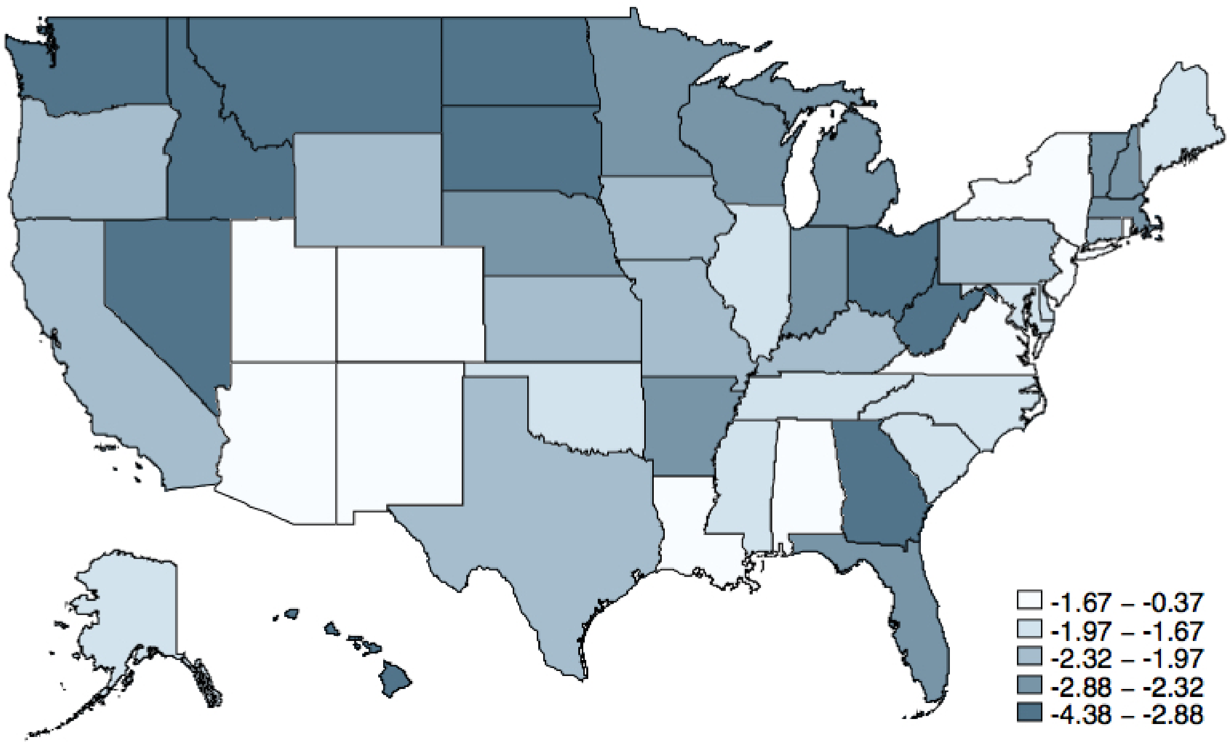
The top two panels show the permanent (solid blue, left axis) and transitory (dashed green, right axis) components of log real GSP (in millions) for Connecticut and New Mexico. The bottom two panels show the permanent (solid blue, left axis) and transitory (dashed green, right axis) components of the unemployment rate for Connecticut and New Mexico measured in percentage points. The shaded areas are U.S. national recessions as defined by the NBER Business Cycle Dating Committee.

Figure 3: Output and Unemployment Components of MO and IA



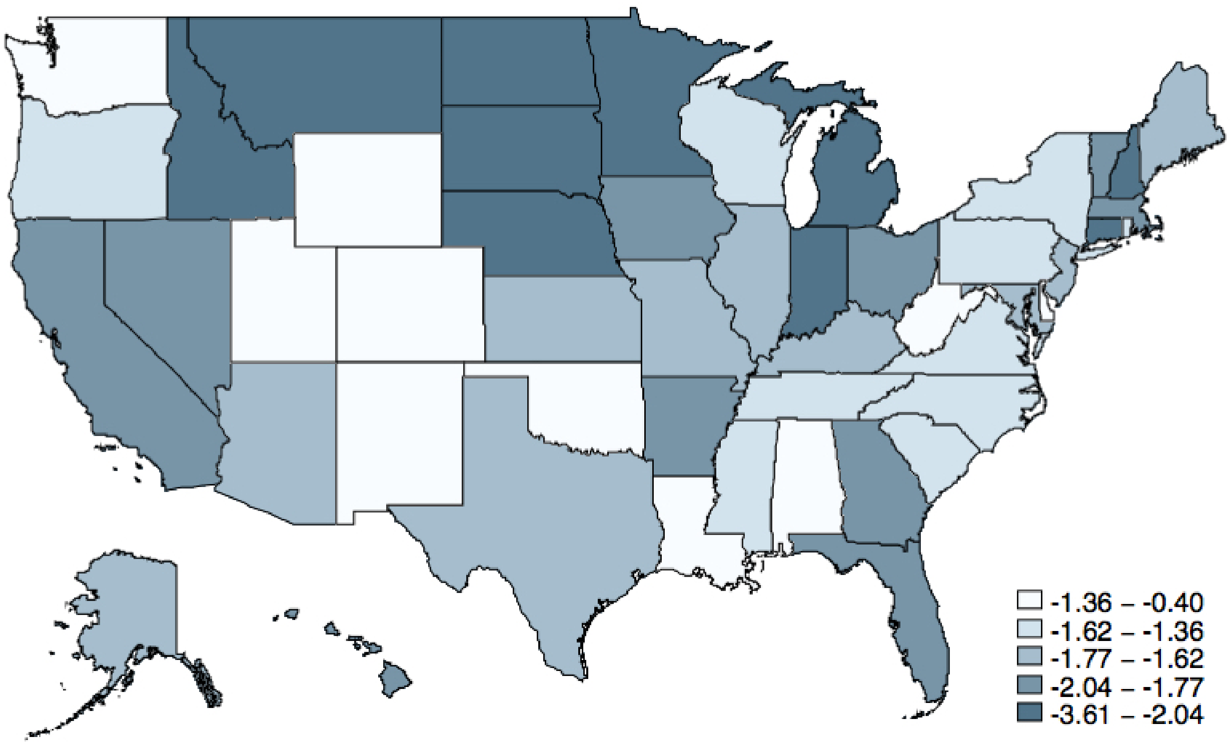
The top two panels show the permanent (solid blue, left axis) and transitory (dashed green, right axis) components of log real GSP (in millions) for Missouri and Iowa. The bottom two panels show the permanent (solid blue, left axis) and transitory (dashed green, right axis) components of the unemployment rate for Missouri and Iowa measured in percentage points. The shaded areas are U.S. national recessions as defined by the NBER Business Cycle Dating Committee.

Figure 4: Variation of Okun's Law by State



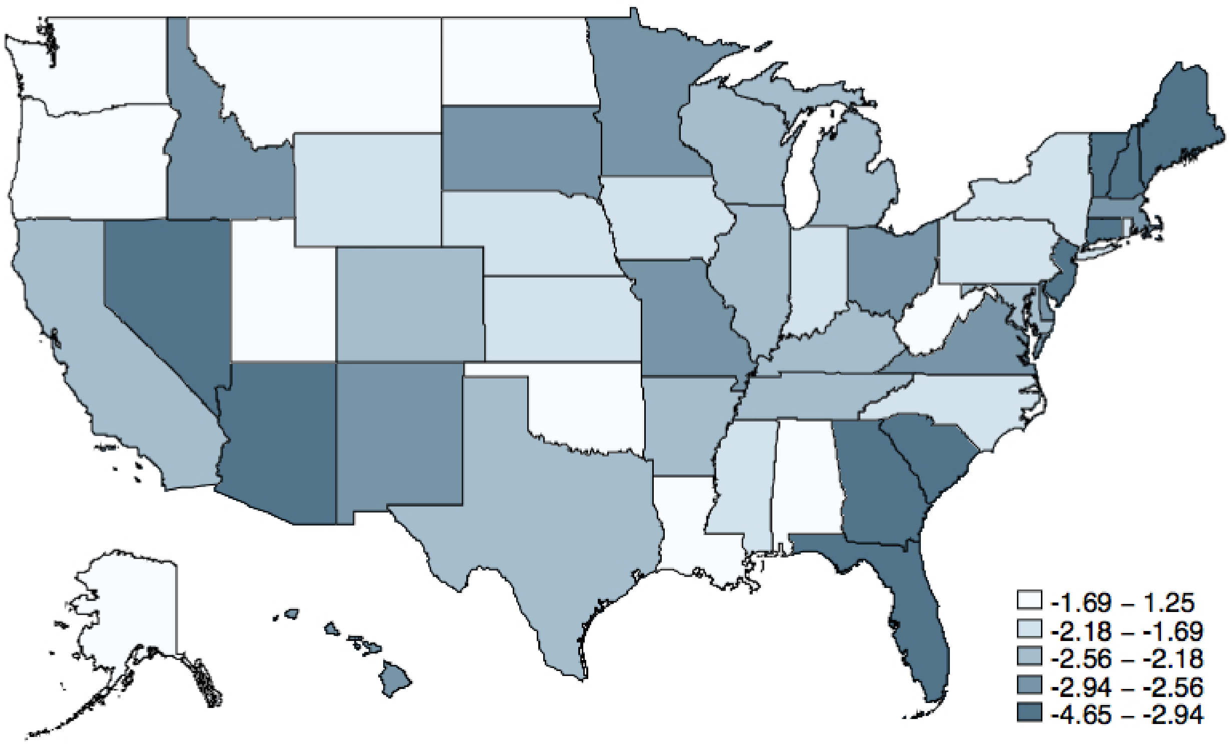
The map shows magnitude of the Okun's coefficient in the baseline unobserved components model specification.

Figure 5: Variation in Okun's Law (Difference Specification)



The map shows magnitude of the Okun's coefficient in the differences specification.

Figure 6: Variation in Okun's Law (Linear Trend Specification)



The map shows magnitude of the Okun's coefficient in the linear trend specification.

List of Tables

Table 1: Okun's Coefficients

State	Okun's Coefficient	Std. Dev.	State	Okun's Coefficient	Std. Dev.
Alabama	-1.45	0.18	Montana	-3.18	0.63
Alaska	-1.70	1.64	Nebraska	-2.33	0.70
Arizona	-1.61	0.37	Nevada	-3.69	0.56
Arkansas	-2.57	0.49	New Hampshire	-2.82	0.46
California	-2.12	0.21	New Jersey	-1.60	0.22
Colorado	-1.25	0.23	New Mexico	-1.49	0.77
Connecticut	-2.10	0.36	New York	-1.64	0.38
Delaware	-1.71	0.72	North Carolina	-1.79	0.23
Florida	-2.38	0.17	North Dakota	-4.38	1.85
Georgia	-3.70	0.77	Ohio	-2.96	0.97
Hawaii	-3.10	0.69	Oklahoma	-1.96	0.30
Idaho	-3.08	0.56	Oregon	-2.31	0.45
Illinois	-1.87	0.18	Pennsylvania	-2.07	0.21
Indiana	-2.44	0.23	Rhode Island	-1.31	0.25
Iowa	-2.26	0.87	South Carolina	-1.73	0.15
Kansas	-2.06	0.33	South Dakota	-3.31	0.80
Kentucky	-2.16	0.30	Tennessee	-1.85	0.26
Louisiana	-0.37	0.36	Texas	-1.98	0.33
Maine	-1.79	0.28	Utah	-1.59	0.31
Maryland	-1.79	0.27	Vermont	-2.50	0.31
Massachusetts	-2.41	0.25	Virginia	-1.55	0.29
Michigan	-2.57	0.25	Washington	-4.36	0.80
Minnesota	-2.47	0.41	West Virginia	-3.66	0.95
Mississippi	-1.74	0.25	Wisconsin	-2.41	0.32
Missouri	-2.26	0.24	Wyoming	-2.05	0.52
United States	-2.03	0.17			

The table shows the estimated Okun's coefficient and its standard deviation for the baseline unobserved components specification.

Table 2: Summary Statistics: Cross-State Covariates

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Labor Market Flexibility Indicators				
Union membership 1970	0.25	0.09	0.09	0.42
Union membership 2010	0.11	0.06	0.03	0.24
Labor force: share age<25 1970	0.22	0.02	0.18	0.29
Labor force: share age<25 2010	0.13	0.01	0.11	0.18
Labor force: share female 1970	0.38	0.02	0.33	0.41
Labor force: share female 2010	0.48	0.01	0.45	0.51
Employment share nonmanufacturing 1970	0.53	0.05	0.38	0.70
Employment share nonmanufacturing 2010	0.68	0.05	0.55	0.76
Demographic Indicators				
Population: compound avg. growth 1970-2010	0.01	0.01	0.00	0.04
Population: share education college 1970	0.11	0.02	0.07	0.15
Population: share education college 2010	0.28	0.05	0.18	0.39
Observations = 50				

All regressors are shares in decimals (0.01 is 1.0%).

Population data are from the Census Bureau.

Labor force indicators are from the Bureau of Labor Statistics.

Union membership data are from Hirsch et al. [2001].

Industry employment data are from County Business Patterns.

Table 3: Determinants of Variation in Okun's Coefficient

	(1) uc	(2) dif	(3) lin
Union membership 1970	-3.03**	-1.76**	-0.12
	(1.20)	(0.70)	(1.83)
Labor force: share age<25 1970	-7.28	-5.12	11.61
	(5.53)	(3.21)	(8.47)
Labor force: share female 1970	-2.60	-10.07***	-25.55***
	(6.09)	(3.36)	(9.06)
Pop. share college educ. 1970	10.67**	3.44	0.21
	(4.56)	(2.73)	(7.19)
Pop. comp. avg. growth 1970-2010	-13.47	2.57	-29.27
	(13.00)	(7.49)	(19.22)
Emp. share nonmanufac 1970	-4.65**	-2.81**	-1.57
	(2.13)	(1.22)	(3.13)
Constant	2.66	4.81***	6.05
	(3.16)	(1.61)	(4.53)
Observations	50	50	50
$\overline{R}^2$	0.21	0.12	0.23
F	3.19	2.15	3.46
$\hat{\sigma}^2$	0.18	-0.05	0.66
χ^2	15.48	17.71	14.62

This table reports the coefficients for the 2-stage-feasible-least-squares regressions of the state-level Okun's coefficient on the cross-state covariates. The columns correspond to (1) the baseline unobserved components, (2) the differences, and (3) the linear trend specifications. Standard errors are in parentheses. The * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 4: Determinants of Variation in Okun's Coefficient: Changing Determinants

Differenced variables	(1) uc	(2) dif	(3) lin
Union membership	2.82	2.15**	-2.76
	(1.78)	(0.89)	(2.76)
Labor force: share age <25	10.80	5.00	-10.43
	(7.60)	(3.71)	(10.33)
Labor force: share female	-11.14	3.35	-5.19
	(8.78)	(4.46)	(12.71)
Pop. share college educ.	-2.38	3.22**	-8.35*
	(2.99)	(1.53)	(4.56)
Pop. comp avg. growth 1970-2010	-13.94	-0.98	-60.20***
	(15.53)	(8.11)	(22.52)
Emp. share nonmanufac	2.94	0.95	-6.36**
	(2.12)	(1.13)	(3.00)
Constant	0.44	-0.86	0.043
	(1.39)	(0.72)	(2.07)
Observations	50	50	50
$\overline{R^2}$	0.12	0.06	0.21
F	2.12	1.51	3.10
$\widehat{\sigma}^2$	0.24	-0.04	0.69
χ^2	8.76	12.90	15.77

This table reports the coefficients for the 2-stage-feasible-least-squares regressions of the state-level Okun's coefficient on the *differences* in the cross-state covariates. The columns correspond to (1) the baseline unobserved components, (2) the differences, and (3) the linear trend specifications. Standard errors are in parentheses. The * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.