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We estimate trend unemployment rates for Ohio, Pennsylvania, Kentucky, and West Virginia, states that span parts of the Fourth District of the Federal Reserve System. Our estimated unemployment rate trend for the District as a whole stood at 5.7 percent in 2020:Q1 compared to a 4.7 percent observed unemployment rate within the District, implying a tight labor market by historical standards.

JEL Classification: E32, E24, D21, J6, R1.

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1 Introduction

This note describes our method for estimating the trend unemployment rate in the Fourth District of the Federal Reserve System, which consists of Ohio, western Pennsylvania, eastern Kentucky, and the northern panhandle of West Virginia. Our approach is based on Tasci [2012] and posits that the trend unemployment rate is determined by trends in the rates of labor market flows into and out of unemployment.

We estimate that the unemployment rate trend for the Fourth District was 5.7 percent in 2020Q1, one percentage point above the District's actual unemployment rate. Following a slow but gradual recovery after the Great Recession, labor markets seemed very tight across the District states just before the COVID-19 outbreak hit US labor markets. We hope to update our estimates regularly to reflect ongoing developments in the region's labor markets.

2 Defining the Unemployment Rate Trend

Tasci [2012] developed a method for estimating the trend rate of unemployment for the United States based on transition rates between labor market statuses. In this paper we implement this method at the state level. We will focus on the four states that are partially or fully within the Fourth Federal Reserve District which the Federal Reserve Bank of Cleveland serves.

Implementing this approach in the context of individual states presents challenges beyond those present at the national level. In addition to obtaining appropriate-frequency data at the state level, the most important is the treatment of migration and of labor market flows involving non-participation. Although at the national level it may be reasonable to abstract from these two types of flows, given the large movements of persons between states and differences in demographics across states, state-level models must take both migration and the not-in-the-labor-force status into account. This is our main contribution in this note.

In particular, although Tasci [2012] found it adequate for the US as a whole to work with just two statuses, employment and unemployment, at the state level one should define four statuses: employed within the state, unemployed within the state, out of the labor force within the state, and out of state. However, as a practical matter, there turns out to be little advantage to treating out of the labor force within the state and out of state as separate statuses. Accordingly, we define only three distinct labor force statuses: employed within the state (E), unemployed within the state (U), and the complement of these two states (Q), being the combination of out of the labor force within the state and out of state.

Let U, E, Q also denote the number of persons in each status w.r.t. a particular state. Then, for that state, we denote the gross flows between these three different labor market statuses by UE, UQ, EU, EQ, QE, and QU. The transition (hazard) rate from status x to y is indicated by $r^{xy}, x \in \{U, E\}$.

The equation of motion for unemployment is given by a simple equation

$$dU = E \cdot r^{EU} - U \cdot r^{UE} + QU - UQ$$

However, the quality of the available data does not support estimating separate trends for QU and UQ. Instead, we write the equation in terms of the net flow between these two statuses, defining netQU = QU - UQ.

Then

$$dU = E \cdot r^{EU} - U \cdot r^{UE} + netQU \tag{1}$$

Similarly, we define netQE = QE - EQ and write

$$\begin{aligned} dE &= U \cdot r^{UE} - E \cdot r^{EU} + QE - EQ \\ &= E \cdot r^{UE} - U \cdot r^{EU} + netQE \end{aligned} \tag{2}$$

Therefore, letting u denote the unemployment rate,

$$\begin{aligned} du &= \frac{(1-u) \cdot dU - u \cdot dE}{(U+E)} \\ &= \frac{(1-u) \cdot (E \cdot r^{EU} - U \cdot r^{UE} + netQU) - u \cdot (U \cdot r^{UE} - E \cdot r^{EU} + netQE)}{U+E} \\ &= (1-u) \cdot r^{EU} - u \cdot r^{UE} + (1-u)\frac{netQU}{U+E} - u\frac{netQE}{U+E} \end{aligned} \tag{3}$$

In a spirit similar to scaling EU flows by E and UE flows by U to generate hazard rates, we can treat $s^{QU} = \frac{netQU}{U+E}$ and $s^{QE} = \frac{netQE}{U+E}$ as the quantities of interest where Q is involved. Call these the scaled net flows between {E,U} and Q. Thus,

$$du = (1-u) \cdot r^{EU} - u \cdot r^{UE} + (1-u) \cdot s^{QU} + u \cdot s^{QE} \tag{4}$$

Equation (4) is at the heart of our approach and determines the dynamics of the unemployment rate within a state. The flow rates in (4) usually fluctuate over the business cycle. Following Tasci [2012], we will estimate the underlying trends for these flow rates to obtain an estimate of the trend unemployment rate that would prevail in the absence of cyclical shocks. Denote the trend flow rates and trend scaled net flows, to be estimated below, by bars. Setting du=0 yields a steady-state unemployment rate implied by the trend flows

$$u^* = \frac{\overline{r^{UE}} + \overline{s^{QU}}}{\overline{r^{EU}} + \overline{r^{UE}} + \overline{s^{QU}} + \overline{s^{QE}}} \tag{5}$$

This implied steady-state unemployment rate, u^*, is our estimate of the trend unemployment rate for each state.

3 Estimating Trend Labor Force Flows

Following Tasci [2012], we assume that labor market flow rates have both cyclical and trend components, where the cyclical components are identified through the cyclical component of the aggregate economic activity and trend components are independent across flows and follow different random walk processes. In Tasci [2012], aggregate economic activity is measured by real GDP. In this paper, we use a measure of state economic activity (see section 4.1) at the quarterly frequency, denoted by Y_t for time period t. We assume that Y_t has a transitory cyclical component, y_t, and a trend component, $\overline{y}_t$. Following a standard approach for modeling aggregate output, we assume that the trend component has potentially a stochastic growth rate, g_t (Clark [1987] and Clark [1989]).

Similarly, each of the flow rates that determine the steady-state unemployment rate in equation (5) is assumed to follow transitory cyclical components that depend on the cyclical component of the output. This is in part motivated by the fact that unemployment inflows and outflows have very clear cyclical patterns (Elsby et al. [2009], Fujita and Ramey [2009], and Tasci [2012]). Thus we assume that r_t^{UE}, r_t^{EU}, s_t^{QE}, and s_t^{QU} will have cyclical components that depend on contemporaneous cyclical components of the output, y_t, as well as its lags. Finally, we assume that all of these flow rates have random walk trends, which constitute the key elements for estimating the u^*. More formally, we can write down a state-space representation for the flow rates and aggregate output as

$$\begin{bmatrix} Y_t \\ r_t^{UE} \\ r_t^{EU} \\ s_t^{QE} \\ s_t^{QU} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \rho_1 & \rho_2 & \rho_3 & 0 & 1 & 0 & 0 & 0 \\ 0 & \theta_1 & \theta_2 & \theta_3 & 0 & 0 & 1 & 0 & 0 \\ 0 & \alpha_1 & \alpha_2 & \alpha_3 & 0 & 0 & 0 & 1 & 0 \\ 0 & \beta_1 & \beta_2 & \beta_3 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \overline{y}_t \\ y_t \\ y_{t-1} \\ y_{t-2} \\ g_t \\ \overline{r_t^{UE}} \\ \overline{r_t^{EU}} \\ \overline{s_t^{QE}} \\ \overline{s_t^{QU}} \end{bmatrix} + \begin{bmatrix} 0 \\ \epsilon_t^{uec} \\ \epsilon_t^{euc} \\ \epsilon_t^{qec} \\ \epsilon_t^{quc} \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} \overline{y}_t \\ y_t \\ y_{t-1} \\ y_{t-2} \\ g_t \\ \overline{r_t^{UE}} \\ \overline{r_t^{EU}} \\ \overline{s_t^{QE}} \\ \overline{s_t^{QU}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \overline{y}_{t-1} \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ g_{t-1} \\ \overline{r_{t-1}^{UE}} \\ \overline{r_{t-1}^{EU}} \\ \overline{s_{t-1}^{QE}} \\ \overline{s_{t-1}^{QU}} \end{bmatrix} + \begin{bmatrix} \epsilon_t^{yn} \\ \epsilon_t^{yc} \\ 0 \\ 0 \\ \epsilon_t^{g} \\ \epsilon_t^{uen} \\ \epsilon_t^{eun} \\ \epsilon_t^{qen} \\ \epsilon_t^{qun} \end{bmatrix} \tag{7}$$

where (6) is the measurement equation and (7) is the transition equation. We assume that all the shocks are independent white-noise processes and are not serially correlated over time. Our objective is to estimate the unobserved trends: $\overline{r_t^{UE}}$, $\overline{r_t^{EU}}$, $\overline{s_t^{QE}}$, and $\overline{s_t^{QU}}$ and evaluate u^* in equation (5) for each state in the Fourth District. We estimate the empirical model described in equations (6) - (7) via maximum likelihood using the Kalman filter, as in Tasci [2012].

An important computational challenge for the estimation is the large number of parameters to be estimated, given that our data start in 1979 and are at the quarterly frequency. As of Q1 in 2020, this gives us 165 observations per state for 25 parameters and leads to non-convergence in the absence of further parameter restrictions. Thus, depending on the shape of the log-likelihood, we need to impose some restrictions to be able to estimate the model in equations (6) - (7) with maximum likelihood. In practice, we find that for each state, a few of the trend components usually are required to follow a linear trend to obtain identification and convergence. We also formally test for each state whether s^{QE} and s^{QU} have any cyclical variation, i.e., that α and β are non-zero. This test provides parsimony when we can afford it. Among the Fourth District states, for Ohio and Kentucky we cannot reject the null that α_i's and β_i's are all zero, and constrain them to be so in the final estimation. In contrast, the models for Pennsylvania and West Virginia allow for cyclical variation in these two flows.

Finally, we aggregate the individual states' estimates into an estimate for the District by weighting each state by its contemporaneous share of Fourth District employment. This weighting puts almost 70 percent weight on Ohio's estimates, around 20 percent on Pennsylvania, and slightly more than 10 percent on Kentucky and West Virginia combined. This weighting is evident in Figure 1, where we show actual unemployment rates in individual District states along with the representative District unemployment rate. Throughout the sample period, the District's unemployment rate lies close to Ohio's.

4 Data

For a national model as in Tasci [2012], long time series of the necessary data for the US are readily available from published sources. (See section 3.1 there.) At the state level, the process is more involved, and requires several assumptions. In this section we describe our data and how we obtain the necessary flow rates for each state.

4.1 Output

As measures of overall economic activity in each state, $Y_{s,t}$, we use the state coincident indexes (SCI) produced by the Federal Reserve Bank of Philadelphia.[1] In principle, gross domestic product by state (www.bea.gov/regional) may be preferable. However, those data are available on a consistent quarterly basis only since 2005. GDP by state is available on an annual basis much farther back, and at the annual frequency the SCI follows GDP fairly closely.

4.2 Stocks of employment and unemployment

For the stocks of employment (E) and unemployment (U) we use data published by the US Bureau of Labor Statistics' Local Area Unemployment Statistics program. These estimates are derived from models that improve upon direct estimates from the Current Population Survey (CPS), partly by combining the CPS data with data from other sources. They are considered to be superior to estimates that would be calculated directly from the CPS.

4.3 Internal flows

We calculate the monthly transition rates for each of the six conventional flows among employment, unemployment, and not in the labor force within each state from matched CPS micro data, using longitudinal weights and the matching algorithm described in Nekarda [2009].[2] We multiply these transition rates by the previous month's published (nsa) stocks to obtain levels of each flow for persons who have neither migrated across state lines nor moved into or out of scope for the CPS.[3] Call these flows EU^{nm}, EN^{nm}, UE^{nm}, UN^{nm}, NE^{nm}, and NU^{nm}.

[1] www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/.

[2] A few months cannot be matched using public data, and a few cells in smaller states have no observations. We fill in these missing cells from both causes by linear interpolation of seasonally adjusted data.

[3] The levels of flows from the matched data themselves would naturally understate the true levels because not all observations match.

4.4 External flows

We sum the appropriate flow levels from above to obtain estimates of the net change in E and U for non-migrants. Call these $\Delta X^{nm}, X = E, U$. We calculate the total (non-migrant plus migrant) change in each stock from the published values, $\Delta X, X = E, U$. The difference between these is our estimate of the net migration into each status in the state, $\Delta X^m, X = E, U$. This also includes net movements between out-of-scope and in-scope, such as turning age 16 and dying.[4]

4.5 Net QE and QU flows

At this point we combine the NX, XN, and ΔX^m flows into the netQE and netQU flows described above:

$$\begin{aligned} netQU &= NU^{nm} - UN^{nm} + \Delta U^m \\ netQE &= NE^{nm} - EN^{nm} + \Delta E^m \end{aligned} \tag{8}$$

Thus we have estimates of the levels of the four flows EU^{nm}, UE^{nm}, $netQE$ and $netQU$, which we aggregate from monthly to quarterly sums, and seasonally adjust.

We convert the EU and UE flows (suppressing the superscripts henceforth) to hazard rates. For the denominators we use the 3-month average of employment and unemployment, respectively, offset (lagged) one month relative to the calendar quarter in order to better match the risk set for the transitions. Similarly, we scale the netQE and netQU flows by the offset 3-month average of labor force in the state. These estimates provide us with what the state-space model in section (3) demands.

5 Estimation Results

Our estimation sample starts in 1979Q1 and ends in 2020Q1. The effects of the COVID-19 outbreak and the related state-level stay-at-home orders are mostly absent from the data; hence, our estimates reflect little of the recent labor market developments.

Our method provides us with individual trend estimates for each flow rate and the unemployment rate (u^*) for each state. We present the estimated trends along with the corresponding actual measures in Figures 2 through 5. For each of the states, the actual unemployment rate was near or below the estimated trend rate in 2020:Q1.

[4] In principle, one could separately measure in-migration and out-migration into each labor force status, but the available data are both lower frequency and beset by inadequately small sample sizes.

Transition rates from U to E, r^{UE}, exhibit significant procyclicality, rising during expansions and sharply declining during contractions. The flip side of this transition rate, r^{EU}, exhibits a countercyclical pattern and a secular decline in three of the four states. The flows that involve the composite labor market status, Q, on average are very small in magnitude in comparison to r^{UE} and r^{EU} – unsurprising since they are net flows. The estimated trend lines, as well as the average levels for S^{QE} and s^{QU} indicate that, on net, these flows pushed the trend unemployment rate up in each state, and arguably pushed the observed unemployment rate up as well.

Figure 6 plots the estimated u^* for each state over time along with the weighted average of the individual states in the Fourth District. Three of the four District states have at least recently declining trend unemployment rates, with Kentucky being the exception. The estimated District u^* stood at 5.7 percent at the end of our sample, a full percentage point above the corresponding District unemployment rate (Figure 7). Hence, the labor market in the Fourth District looked tight just before the COVID-19 pandemic hit the US labor market.

6 Conclusion

In this paper we present a method of estimating trend unemployment rates at the state level and present estimates of those trends for the four states in the Fourth Federal Reserve District. The estimates indicate that labor markets were quite tight in the Fourth District before the COVID-19 pandemic walloped labor markets throughout the US. We hope to make updated estimates regularly available on the Federal Reserve Bank of Cleveland's website to aid in assessing economic conditions in the District.

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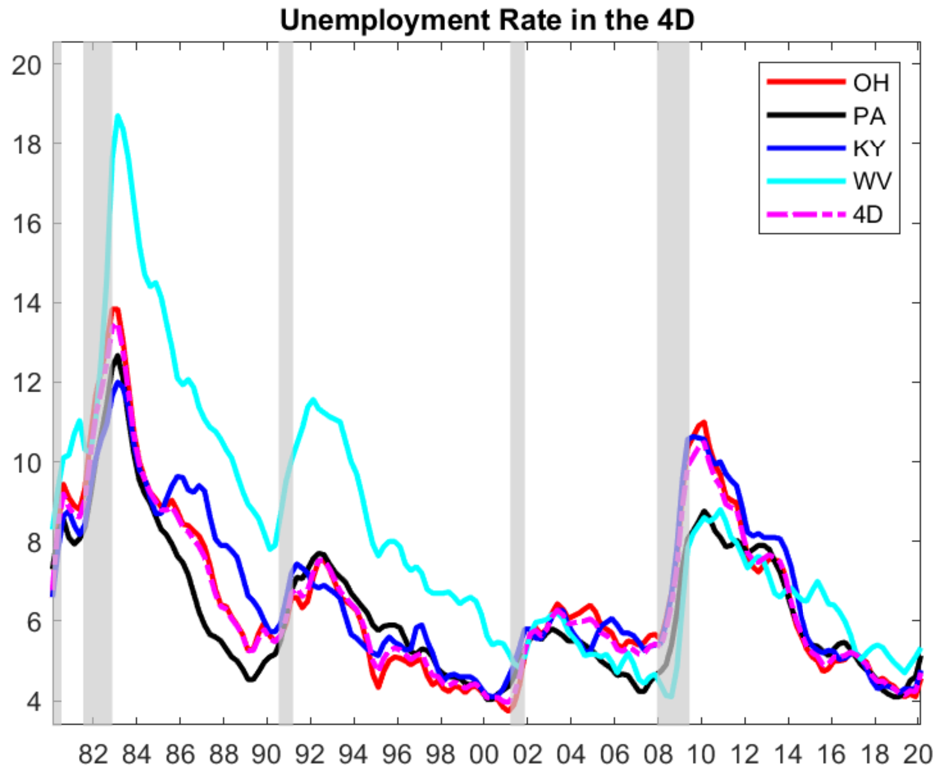

Figure 1: Unemployment Rate for the States in the Fourth District. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics.

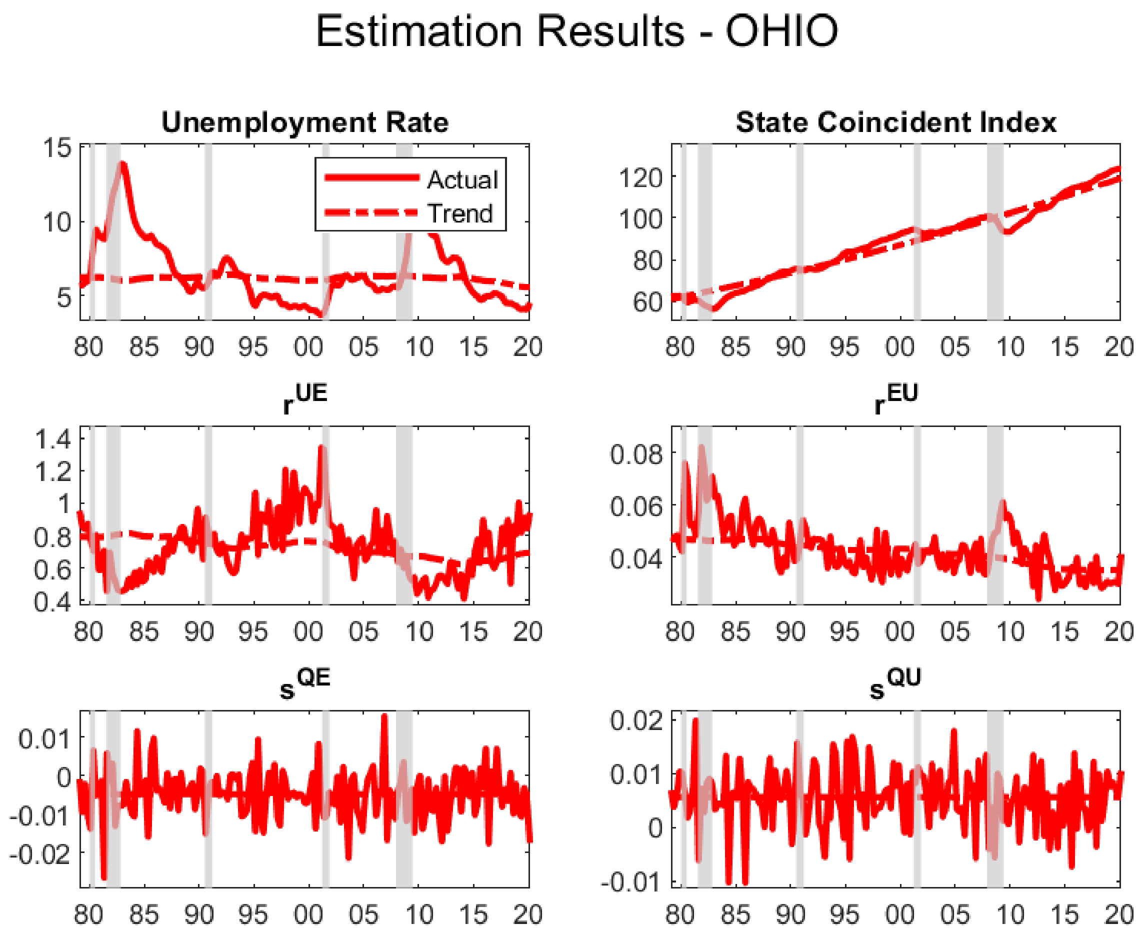

Figure 2: Estimated Trends for Ohio as of 2020Q1. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics, FRB Philadelphia and authors' calculations.

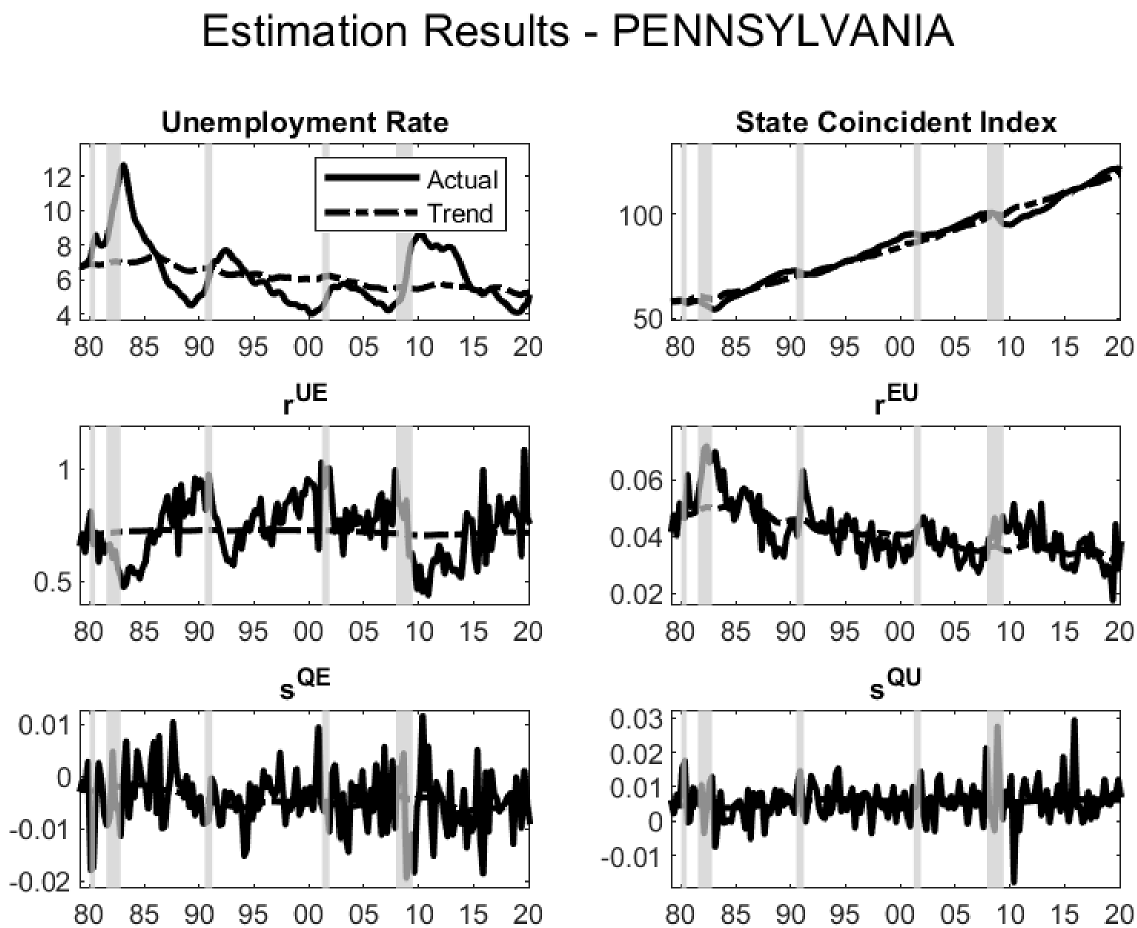

Figure 3: Estimated Trends for Pennsylvania as of 2020Q1. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics, FRB Philadelphia and authors' calculations.

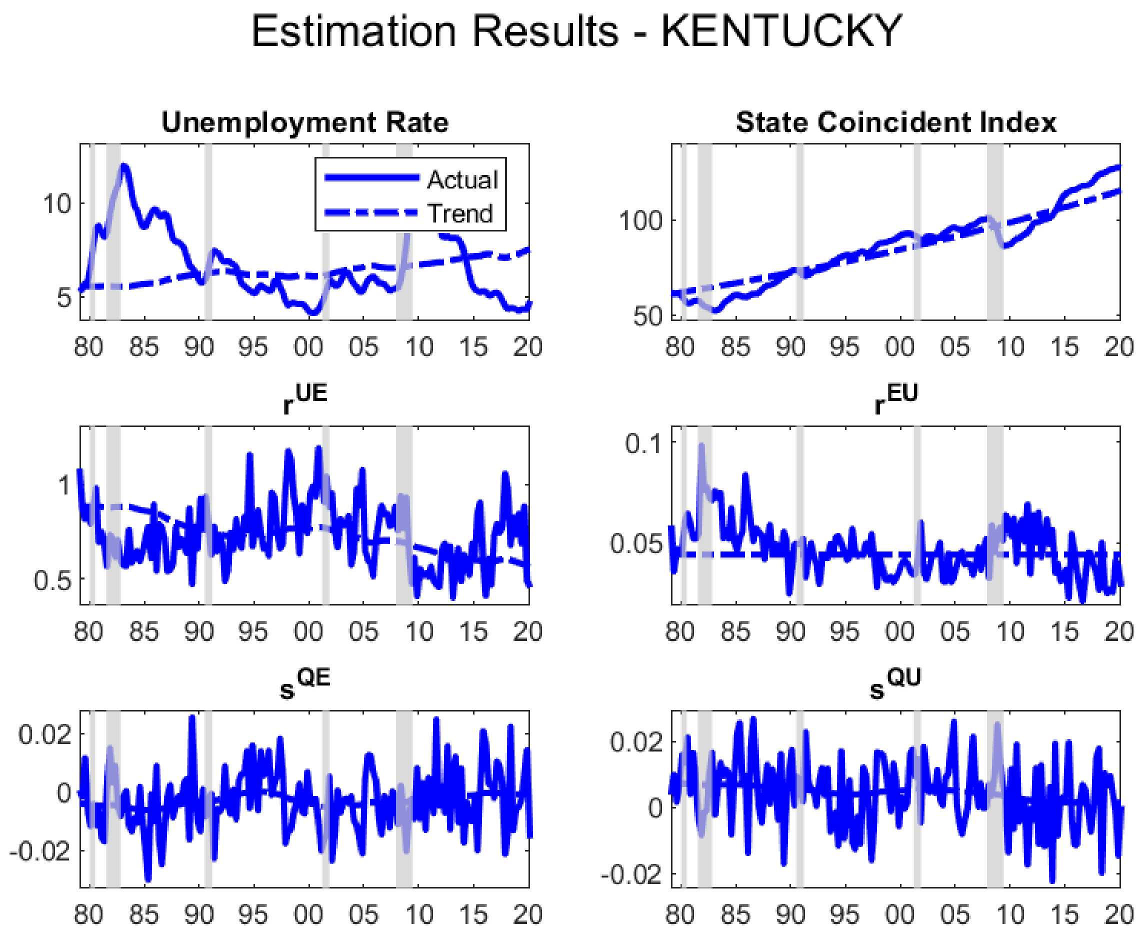

Figure 4: Estimated Trends for Kentucky as of 2020Q1. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics, FRB Philadelphia and authors' calculations.

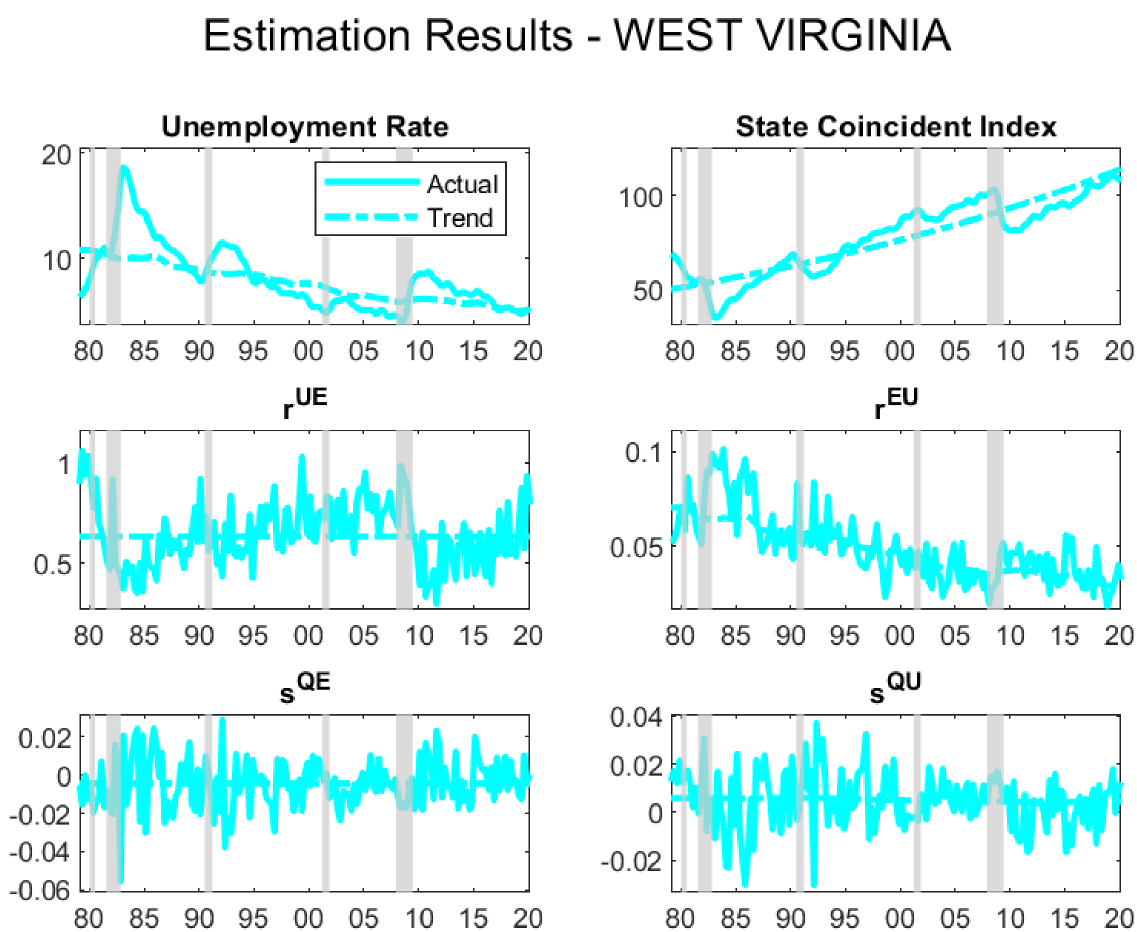

Figure 5: Estimated Trends for West Virginia as of 2020Q1. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics, FRB Philadelphia and authors' calculations.

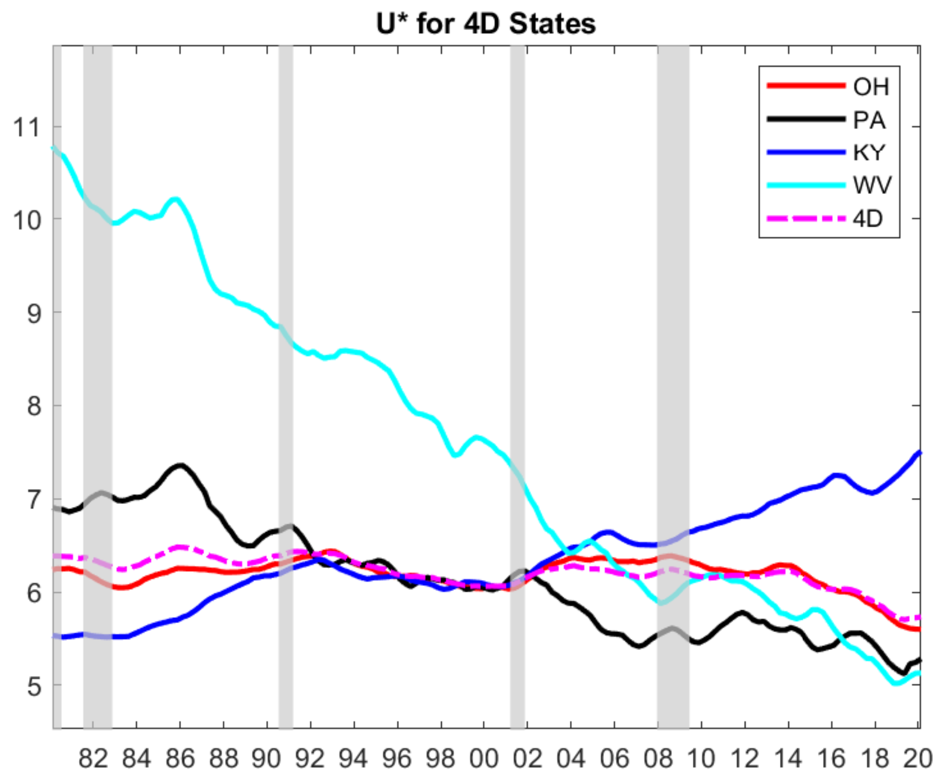

Figure 6: Estimated Unemployment Trend for the States in the Fourth District as of 2020Q1. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics and authors' calculations.

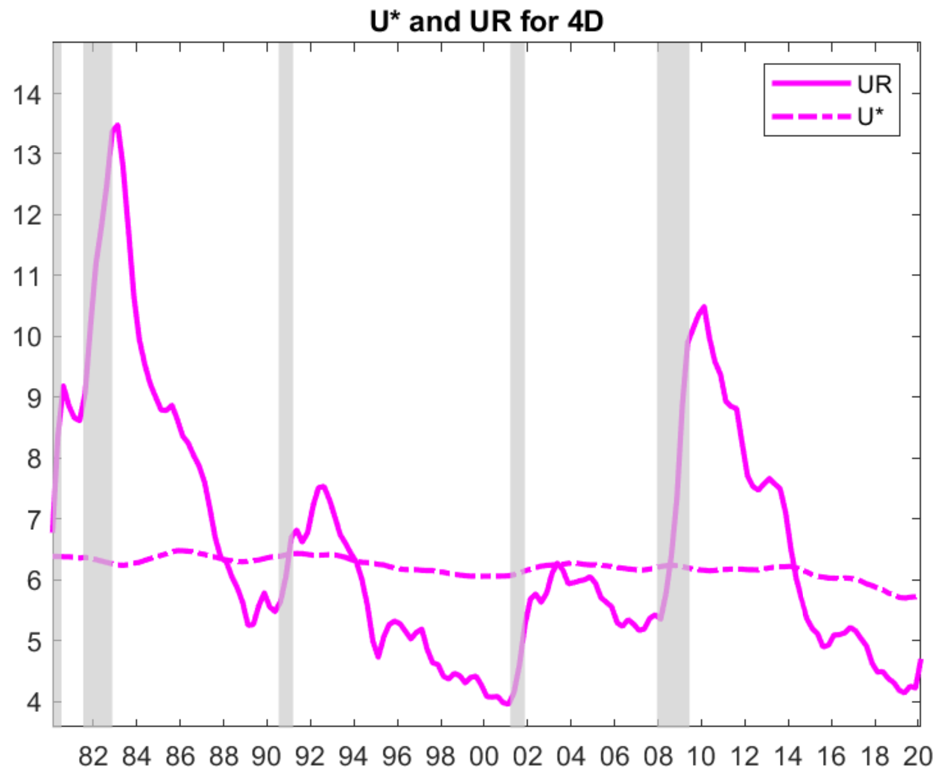

Figure 7: Estimated Unemployment Trend for the Fourth District as of 2020Q1 and the District Unemployment Rate. Both series are weighted averages of the relevant variable for individual states. Shaded areas indicate US recessions. Source: Bureau of Labor Statistics and authors' calculations.