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RESEARCH PAPER

Analyzing Unemployment Rates Convergence across the US States: New Evidence Using Quantile Unit Root Test

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Abstract
This paper is to study the stochastic convergence toward cross-average across 50 US states over the period from 1976–2018. To the end, we apply the quantile unit root test and several conventional linear and nonlinear unit root tests. While conventional unit root tests reject the stochastic convergence hypothesis for most of the states, we have found results in favor of stochastic convergence for 41 out of 50 states using the quantile unit root tests. In addition, our results indicated that the states exhibited different stochastic behaviors in various quantiles. In the states, which have had an unemployment rate less than cross-average in the boom period, negative shocks to the unemployment rate have had long-lasting effects, and shocks are divergent from the cross-average unemployment rate. But in a recessionary period of economics, positive shocks to the unemployment rate result in convergence toward cross-average, but have transitory effects and disappear in the short run.
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Introduction

Unemployment is one of the basic variables in most macroeconomic theories, and a key indicator that represents the economic state. Over time, as the economy fluctuates between recessionary and expansionary periods, we can see high rates of unemployment in the periods of recession and low rates in times of expansion. The different behavior of unemployment rate across states/regions has been a considerable area of the theoretical and empirical literature. One important direction of this literature is the stochastic properties of the unemployment rate series. To the end, researchers have tested two properties including the unemployment rates stationary and convergence unemployment across states/regions.

About the stationary of unemployment rate series, the theoretical literature has prepared different predictions. Based on the natural rate theory (pioneered by Phelps, 1967; 1968; Friedman, 1968), unemployment fluctuates around the natural rate but converges toward it in the long run. This equilibrium level (natural rate) depends on the fundamentals of the economy e.g. labor productivity, technological change, real interest rate, real exchange rate, energy prices, and demographical and geographical factors. In contrast, the hysteresis effect (pioneered by Blanchard and Summers, 1986), human-capital effects (Blanchard, 1991), Sociological factors (Lindbeck, 1995), and family insurance and political response (Blanchard and Katz, 1997) imply that the current values of unemployment depend highly on their past values. Therefore, sustained high unemployment will gradually raise the natural rate.

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From a seminal paper of Blanchard and Katz (1992), in addition to examining the unemployment rates stationary, some researchers studied the evolution of regional disparities in unemployment rates within a country (e.g. Carmeci and Mauro, 2002; Bayer and Juben, 2007; Reis Gomes and Gomes da Silva, 2009; Cuestas et al., 2015). As noted by Blanchard and Katz (1992), while regional labor markets adjust toward their equilibrium, in the long run, the disparities in their unemployment rates may reduce over time due to unemployed workers moving other regions to take jobs or capital flows into low-wage areas to take advantage of labor's lower costs. Moreover, Armstrong and Taylor (2000) demonstrated that if the speed of adjustment toward long-run equilibrium was slow, due to asymmetric effects of negative demand shocks among the regions, unemployment disparities might arise during an adjustment period. Marston (1985) proposed that due to factors, e.g. attractive weather, high wages, and high unemployment insurance, differences across regions would not necessarily converge to zero.

Analyzing the unemployment rate disparities has important political implications. As noted by Bayer and Juben (2007), if the unemployment disparities were often perceived as persistent, it would have two main messages: (1) the shocks to regional unemployment rates have various long-lasting effects. In this case, policy interventions are more likely to be effective in the long run. (2) There are stable equilibrium differentials among regional unemployment rates. Various studies indicate that policy interventions have only short-run effects, and are less likely to change this stable equilibrium.

In the empirical studies, the methodologies developed to examine the income convergence hypothesis, i.e. absolute convergence, conditional convergence, catching-up hypothesis, deterministic convergence, and stochastic convergence, are used to examine the unemployment rate convergence across regions or countries. Absolute convergence hypothesis (conditional convergence hypothesis) refers to the same (different) steady state(s) of the unemployment rate across regions. The stochastic convergence hypothesis is related to unemployment stochastic properties and the degree of shock persistence in the unemployment rate. According to Ranjbar et al. (2018), three methodologies i.e. cross-sectional approach, distribution approach (sigma convergence), and time-series approach will be employed to examine the above-mentioned hypotheses. In the cross-sectional approach (beta convergence), the unemployment rate growth is regressed on initial unemployment rates, and a negative (partial) correlation between the two variables is interpreted as evidence of the absolute (conditional) convergence. In the sigma convergence, dynamics of unemployment rates dispersion across regions are analyzed over time, and the dispersion decreasing is interpreted as sigma convergence. In the convergence debate, the beta convergence and sigma convergence are necessary and the sufficient conditions of convergence, respectively. To examine the stochastic convergence hypothesis, the stationary properties of relative unemployment series (the unemployment rate of a region to the base region) are examined using univariate panel unit root and/or stationary tests, and the rejection of unit root in the relative unemployment rates series is interpreted as evidence in favor of stochastic convergence hypothesis.

Using the above-mentioned methodologies, we tested the unemployment rate convergence across countries and regions of the US, UK, Germany, Brazil, and Italy, and found contradictory results. Martin (1997) found that the shocks had transitory effects on UK's regional unemployment rates, but the long-run unemployment rates differed across the region. Decressin and Fatas (1995), Obstfeld and Peri (1998), and Baddeley et al. (1998) tested the evolution of regional unemployment rates in Europe and concluded that the unemployment disparity across the countries was persistent as an equilibrium phenomenon. In contrast, using a novel unit root test that allowed for structural breaks and non-normal errors, Kristic et al. (2018) found results that confirmed the stochastic convergence of the majority of euro area countries. However, their results indicated that euro area membership was not a sufficient condition for stochastic convergence. Bayer and Juben (2007) examined the convergence hypothesis across unemployment rates of west Germany's different regions and found evidence in favor of both convergence and quick adjustment to an equilibrium distribution of regional unemployment rates. Employing a distributional dynamics approach, Beyer and Stemmer (2016) found a convergence pattern among European countries over the period 1996–2007 and a polarization over the period from 2007–2013. Reis Gomes and Gomes da Silva (2009) examined the stochastic convergence hypothesis across the unemployment rate of 6 Brazilian metropolitan areas and found convergence in 5 out of 6 areas.

Various studies, e.g. Song and Wu (1997), León-Ledesma (2002), Dreger and Reimers (2009), Romero-Avila and Usabiaga (2007), Sephton (2012), and Bahmani-Oskooee et al. (2018) examined the stochastic properties of unemployment in the US states and found mixed results on their stochastic behaviors. While Song and Wu (1997) and León-Ledesma (2002) found evidence in favor of the natural rate hypothesis, Romero-Avila and Usabiaga (2007), and Sephton (2012) observed a high degree persistence of unemployment in US state. Moreover, using the quantile-type unit root test, Bahmani-Oskooee et al. (2018) found evidence in favor of stationarity for 33 out of 52 US states with different behaviors across quantiles.

Few studies tested the convergence hypothesis across unemployment rates in US states. Rowthorn and Glyn (2006) found that the shocks had permanent effects on the unemployment rates disparities in the US regions. Partridge and Rickman (1997) found that the US labor market was more flexible, possessing higher rates of labor mobility and fewer government mandates, but there was still persistent dispersion in unemployment rates in US states. They indicated that larger proportions of the college-educated labor force greatly reduced the equilibrium unemployment rate in the state, and in contrast, international immigration increased unemployment.

As seen, the empirical literature on the US states disparity is very scarce. To the end, in this paper, we are going to examine the stochastic convergence across US states using quantile unit root tests. So, (1) we can control for asymmetric behavior of unemployment over the business cycle in the sense that it increases more quickly than it decreases. The test allows for different speeds of adjustment at the unemployment rate's various quantiles. (2) to capture the asymmetric behavior, there is no need to make a special assumption regarding the functional form of nonlinearities. (3) Due to the fundamentals' shifts, the unemployment natural rates may change permanently. Quantile regression allows for errors misspecification related to non-normality and the presence of outliers e.g. financial crisis or world wars.

The remainder of this paper is organized as follows. Section 2 briefly reviews the stochastic convergence and quantile unit root test. In Section 3, data are discussed, and Section 4 provides the results. Section 5 concludes the paper.

Methodology

Stochastic Convergence Hypothesis

The stochastic convergence is related to the stationary behavior of unemployment rates. The phenomenon is developed by Carlino and Mills (1993), Bernard and Durlauf (1995), Evans and Karras (1996a), and Li and Papell (1999) to compare the convergence hypothesis for per capita income of a country with a benchmark country. In this paper, the benchmark country consists of the cross-average US states. Thus, unemployment rates of state i ($U_{i,t}$) will converge toward the cross-average of the unemployment rate ($U_{AV,t+n}$) if and only if:

$$\lim_{n\to\infty}(U_{i,t+n} - \rho U_{AV,t+n} \,|\xi_t) = 0 \qquad (1)$$

where ξ_t is the information set at time t. $U_{i,t+n}$ and $U_{AV,t+n}$ are in logs form. Due to the different fundamentals across states, we expect $\rho \neq 0$, and thus, a permanent difference across unemployment rates of US states. But if the gap between unemployment rates of states i and of cross-average decrease over time, and the null hypothesis of unit root is rejected for relative unemployment rate series $(U_{i,t+n}/U_{AV,t+n})$, there will be evidence in favor of convergence unemployment rates of states i toward unemployment rates of cross-average. As noted in the previous section, to examine the unit root hypothesis, we use the quantile unit root test by Koenker and Xiao (2004).

Quantile Unit Root Test

We assume that the relative unemployment rate (RU) is generated as:

$$RU_t = \beta_0 + +\xi_t \tag{2}$$

where RU_t is the logarithm of relative unemployment rates. We define the demean version of RU as $\overline{RU}$. To examine the null hypothesis of a unit root in τth conditional quantile of $\overline{RU}$, We should specify and estimate the following quantile regression:

$$\psi_{\overline{RU}_t}(\tau|\overline{RU}_{t-1}) = \pi_0(\tau) + \pi_1(\tau)\overline{RU}_{t-1} + \sum_{p=1}^{p=l} \pi_{1+p}(\tau)\Delta\overline{RU}_{t-p} + \vartheta_t \tag{3}$$

where $\psi_{\overline{RU}_t}(\tau|\overline{RU}_{t-1})$ is τth quantile of $\overline{RU}_t$ conditional on the past information set, and $\overline{RU}_{t-1}.\pi_0(\tau)$ is τth conditional quantile of ϑ_t. We set maximum lags at 19 and selected optimum lags (p^*) by the Akaike's Information Criterion (AIC). Following Koenker and Xiao (2004), we estimated $\pi_0(\tau)$, $\pi_1(\tau)$, $\pi_2(\tau)$, …, $\pi_{p+1}(\tau)$ by minimizing the sum of asymmetrically weighted absolute deviations:

$$min \sum_{t=1}^{n} \left(\tau - I\left(\overline{RU}_t < \pi_0(\tau) + \pi_1(\tau)\overline{RU}_{t-1} + \sum_{p^*=1}^{p^*=l} \pi_{1+p^*}(\tau)\Delta\overline{RU}_{t-p^*} \right) \right) \Bigg| \overline{RU}_t - \pi_0(\tau) + \pi_1(\tau)\overline{RU}_{t-1} + \sum_{p^*=1}^{p^*=l} \pi_{1+p^*}(\tau)\Delta\overline{RU}_{t-p^*} \Bigg| \tag{4}$$

where I=1 if $\overline{RU}_t < (\pi_0(\tau) + \pi_1(\tau)\overline{RU}_{t-1} + \sum_{p^*=1}^{p^*=l} \pi_{1+p^*}(\tau)\Delta\overline{RU}_{t-p^*})$ and I=0, otherwise. To examine the stochastic properties of $\overline{RU}_t$ within the τth quantile, Koenker and Xiao (2004) suggest the following *t ratio* statistic:

$$t_n(\tau_i) = \frac{\hat{f}(F^{-1}(\tau_i))}{\sqrt{\tau_i(1-\tau_i)}} (\chi'_{-1} G_W \chi_{-1})^{1/2} (\widehat{\pi_1}(\tau_i) - 1) \tag{5}$$

In equation (5), χ_{-1} is the vector of the lagged dependent variable ($\overline{RU}_{t-1}$), and G_z is the projection matrix onto the space orthogonal to $W = (1, \Delta\overline{RU}_{t-1}, \dots, \Delta\overline{RU}_{t-p^*})$. To obtain a consistent estimator of $\hat{f}(F^{-1}(\tau_i))$, Koenker and Xiao (2004) suggest the equation(6):

$$\hat{f}\big(F^{-1}(\tau_i)\big) = \frac{(\tau_i - \tau_{i-1})}{W'\big(\varrho(\tau_i) - \varrho(\tau_{i-1})\big)} \tag{6}$$

where $\varrho(\tau_i) = (\pi_0(\tau_i), \pi_1(\tau_i), \pi_2(\tau_i), \ldots, \pi_{1+p^*}(\tau_i))$ and $\tau_i \in [\underline{d}, \overline{d}]$. In this paper, we set $\underline{d} = 0.1$ and $\overline{d} = 0.9$. Koenker and Xiao (2004) recommend the following quantile Kolmogorov–Smirnov (QKS) test statistics to examine the unit root hypothesis over a range of quantiles:

$$QKS = \sup_{\tau_i \in [\underline{d}, \overline{d}]} |t_n(\tau)| \tag{7}$$

The limiting distributions of $t_n(\tau_i)$ and QKS test statistics are nonstandard, and depend on the nuisance parameters. Hence, we use Koenker and Xiao's (2004) re-sampling procedures to drive the exact critical values.

Data Description

We collected the monthly seasonally adjusted unemployment rates of 50 US states over the period from 1976:1 to 2018:6. There were provided the average unemployment rate for the states over the decades 1970s, 1980s, …, 2010s. The statistical data are described in Table 1. Results of average unemployment rates over each decade in panel A indicate that North Dakota, Nebraska, and South Dakota had experienced unemployment rates less than cross-average minus 1 standard deviation over all decades, but Iowa, Vermont, New Hampshire, Hawaii, Utah, and Kansas had experienced unemployment rate less than cross-average minus 1 standard deviation over most of the decades. In contrast, Mississippi, Michigan, California, and Alaska have experienced the highest unemployment rates over most of the decades. Over the decade 2010s, Georgia, Illinois, Rhode Island, and Nevada have been experiencing an unemployment rate from 7% to 9%. Over the period 1976–2018, some states, i.e. Delaware, Louisiana, New York (States), Ohio, West Virginia, Alabama, and Alaska experienced high unemployment rates about 8%–12% over the decades 1970s and 1980s, but over the later decades, they succeeded to reduce unemployment rates to 6%–7%.

Statistical properties of unemployment rates of states over the period 1976–2018 in panel B indicate that the highest median is related to Alaska, Michigan, West Virginia, Mississippi, California, Louisiana, Alabama, New Mexico, and Washington, by a tolerance between 6.7%-7.5%, and the lowest median is related to Nebraska, South Dakota, North Dakota, New Hampshire, Iowa, Vermont, and Kansas by a tolerance between 3.2%–4.5%. West Virginia, Michigan, Alabama, Ohio, Nevada, Illinois, and Louisiana have experienced the highest unemployment rates about 1.1%–18.8%, and in contrast, Hawaii, Virginia, Connecticut, New Hampshire, Nebraska, Iowa, South Dakota, Utah, Minnesota, North Dakota, and Wyoming have experienced the lowest unemployment rates about 2%–2.5%.

The p-values of Jarque–Bera statistics indicate that the unemployment rates of all states except New Mexico exhibit non-normal distribution, which is strong evidence to use the quantile approach of Koenker and Xiao (2004).

Table 1. Data Description

Panel A: Average unemployment rate over					Panel B: Data description						
1970s	**1980s**	**1990s**	**2000s**	**2010s**	**Median**	**Maximum**	**Minimum**	**Skewness**	**Kurtosis**	**Jarque-Bera statistics**	**Probability**
6.894	9.948	6.054	5.655	7.106	6.750	15.500	3.700	1.090	4.010	122.653	0.000
9.319	9.546	7.475	6.964	7.135	7.500	11.200	6.300	0.724	2.249	56.556	0.000
7.256	6.840	5.560	5.444	7.223	5.900	11.500	3.600	0.954	3.229	78.501	0.000
6.456	8.470	5.805	5.536	6.098	6.300	10.300	3.600	0.291	2.227	19.889	0.000
7.710	7.191	7.353	6.418	8.158	6.900	12.300	4.200	0.769	2.824	50.960	0.000
5.608	6.468	4.443	4.873	5.675	5.400	8.900	2.600	0.253	2.386	13.444	0.001
6.660	4.814	5.375	4.748	6.888	5.300	9.800	2.200	0.432	2.675	18.103	0.000
7.971	5.708	4.672	4.390	6.069	4.900	9.800	3.000	0.516	1.961	45.600	0.000
7.485	6.386	5.912	5.145	6.983	5.800	11.300	3.100	0.731	2.979	45.449	0.000
6.481	6.361	5.112	5.299	7.465	5.600	10.600	3.400	1.061	3.504	101.129	0.000
7.602	4.833	4.977	4.020	4.576	4.900	10.200	2.000	0.354	2.787	11.585	0.003
5.652	7.671	5.534	5.028	5.659	5.600	10.200	2.900	0.455	2.702	19.500	0.000
6.077	8.636	5.857	6.086	7.554	6.400	13.100	4.100	0.834	3.149	59.526	0.000
5.967	8.223	4.636	5.454	6.568	5.500	12.600	2.900	0.866	2.976	63.785	0.000
3.983	6.461	3.653	4.122	4.407	4.200	9.100	2.400	1.041	3.507	97.590	0.000
3.619	4.974	4.228	4.897	5.017	4.500	7.300	2.900	0.766	3.432	53.876	0.000
5.225	8.907	5.707	6.033	7.013	5.900	12.000	4.000	0.811	2.574	59.710	0.000
6.794	10.228	6.734	5.708	6.559	6.800	13.100	4.100	1.045	3.390	96.147	0.000
7.531	6.068	5.903	4.886	5.725	5.400	9.000	2.700	0.170	1.774	34.382	0.000
6.050	5.604	5.176	4.340	5.882	5.000	8.500	3.300	0.480	2.167	34.315	0.000
7.263	4.988	5.650	5.054	5.741	5.300	10.300	2.600	0.444	2.393	24.564	0.000
8.096	10.742	6.112	7.173	7.702	7.300	16.500	3.200	0.769	3.183	50.962	0.000
4.794	5.899	4.048	4.678	4.847	4.650	8.900	2.500	0.788	3.394	56.132	0.000
6.629	9.759	6.540	6.618	7.650	6.950	12.800	4.500	0.698	2.538	45.935	0.000
5.502	7.142	5.118	5.579	6.238	5.750	10.600	3.100	0.797	3.377	56.987	0.000
5.788	7.315	5.798	4.673	5.254	5.600	8.800	2.900	0.301	2.399	15.361	0.000
3.204	4.498	2.646	3.533	3.591	3.200	6.300	2.300	0.884	3.104	66.636	0.000
6.225	7.062	5.344	5.500	8.850	5.850	13.700	3.800	1.269	3.893	153.915	0.000
4.740	4.099	4.774	3.933	4.272	4.050	7.400	2.200	0.548	2.313	35.541	0.000
8.494	6.021	6.148	5.228	7.156	6.000	10.700	3.600	0.501	2.178	35.656	0.000
7.204	8.213	6.607	5.176	6.877	6.700	10.500	3.700	0.111	3.008	1.054	0.590
8.567	6.635	6.587	5.558	6.653	6.400	10.300	4.000	0.319	2.139	24.374	0.000
5.344	6.038	4.435	5.908	7.319	5.350	11.400	3.000	1.089	3.454	105.085	0.000
4.119	5.174	3.620	3.373	3.018	3.700	6.200	2.500	0.610	2.420	38.781	0.000
6.396	8.822	5.473	6.020	6.700	6.100	14.000	3.700	1.176	4.086	142.624	0.000
4.394	6.426	4.998	4.437	5.085	4.900	8.900	2.900	0.583	2.757	30.177	0.000

Empirical Results

To study the stochastic convergence toward cross-average over the period 1976–2018, first, we examine the null hypothesis of unit root with four conventional linear unit root tests including Augmented Dickey and Fuller (1979) (ADF), Elliott et al. (1996) (DF-GLS), Ng and Perron (2001), Phillips and Perron (1988) (PP), and Ng–Perron (2001), and two nonlinear unit root tests namely Kapetanios et al. (2003) and Sollis (2009). To decide the null hypothesis of unit root, the test statistics to the critical values are compared at 5% for all unit root tests.

According to the linear unit root tests, the null hypothesis of unit root is rejected for unemployment rates series of 17, 8, 12, and 2 using ADF, DF-GLS, PP, and NP unit root tests, respectively. Results of nonlinear unit root tests indicate that the null hypothesis of unit root is rejected for 18 and 22 unemployment rates series using KSS and Sollis (2009) unit root tests, respectively. These results are shown in Table 2.

As can be seen in Table 2, according to conventional linear and non-linear unit root tests, the stochastic convergence hypothesis is rejected for more than half of the unemployment rates series. This result is in line with existing literature which emphasizes on low power of the above-mentioned tests when the relative unemployment rates series is highly persistent and exhibits a clear sign of non-normal distribution.

Table 2. Conventional Unit Root Tests Results

States	Panel A: linear unit root test				Panel B: non-linear unit root test	
	ADF	**PP**	**DF-GLS**	**NP**	**KSS**	**Sollis (2009)**
Alabama	-2.496	-2.643	-1.124	-3.399	-1.882	5.073
Alaska	-3.423*	-2.501	-1.412	-2.142	-2.285	4.991*
Arizona	-3.492*	-3.623*	-0.984	-3.326	-2.341	4.899*
Arkansas	-3.085*	-2.368	-2.741*	-9.938*	-2.493	5.252
California	-2.552	-1.578	-2.397*	-4.541	-2.645	5.357
Colorado	-2.589	-2.454	-2.206*	-7.546	-3.09*	4.97*
Connecticut	-2.369	-2.123	-1.245	-1.879	-2.69	4.935
Delaware	-2.63	-2.235	-1.697	-5.707	-1.452	5.24
Florida	-3.188*	-2.616	-1.192	-1.964	-2.949*	5.085
Georgia	-2.08	-2.628	-1.25	-5.781	-5.677*	5.222*
Hawaii	-2.459	-2.03	-0.834	-0.344	-2.406	4.771
Idaho	-2.287	-2.237	-1.2	-2.49	-6.142*	5.17*
Illinois	-2.914*	-3.414*	-0.65	-2.954	-3.181*	5.046*
Indiana	-1.827	-2.006	-1.514	-6.546	-2.163	5.216
Iowa	-2.614	-2.14	-1.149	-1.422	-2.701	5.216*
Kansas	-1.886	-1.968	-0.328	-0.823	-2.127	5.085
Kentucky	-3.727*	-2.988*	-0.279	-0.784	-2.595	5.288
Louisiana	-2.227	-3.072*	-1.01	-5.05	-4.333*	5.173*
Maine	-2.452	-1.923	-0.95	-1.204	-3.405*	4.955*
Maryland	-1.792	-1.739	-1.804	-7.397	-1.544	4.749
Massachusetts	-2.699	-2.501	-1.049	-1.333	-2.091	5.221
Michigan	-2.046	-1.726	-1.898	-5.047	-3.308*	5.194*
Minnesota	-3.23*	-2.803	-3.06*	-14.287*	-2.894	5.145
Mississippi	-3.595*	-3.114*	-1.011	-1.999	-8.149*	4.917*
Missouri	-3.046*	-3.574*	-1.401	-6.031	-3.728*	4.814*
Montana	-2.332	-2.465	-1.371	-4.969	-2.57	4.844*
Nebraska	-2.134	-1.919	-0.826	-1.27	-2.424	5.092
Nevada	-2.331	-2.021	-1.701	-4.697	-1.701	5.265*
New Hampshire	-3.644*	-2.497	-1.828	-4.217	-2.437	5.238
New Jersey	-2.593	-2.099	-0.898	-1.477	-1.599	5.06
New Mexico	-3.032*	-1.793	-2.548*	-5.252	-3.147*	4.895*
New York (States)	-2.671	-2.335	-1.044	-1.682	-2.695	4.946

States	Panel A: linear unit root test				Panel B: non-linear unit root test	
	ADF	PP	DF-GLS	NP	KSS	Sollis (2009)
North Carolina	-1.95	-1.673	-1.84	-5.293	-2.512	4.856
North Dakota	-2.582	-2.434	-1.448	-1.947	-1.859	5.388
Ohio	-2.058	-2.396	-2.691*	-11.314*	-2.31	5.047
Oklahoma	-2.338	-2.175	-2.25*	-9.182*	-3.177*	5.012*
Oregon	-2.274	-2.608	-1.037	-5.566	-2.563	5.016
Pennsylvania	-3.074*	-2.16	-2.495*	-7.438	-2.612	4.986
Rhode Island	-2.519	-1.781	-2.395*	-6	-1.838	4.995
South Carolina	-1.849	-2.345	-1.855	-11.034*	-2.053	5.142
South Dakota	-3.934*	-2.837	-0.595	-0.596	-3.275*	4.9*
Tennessee	-2.993*	-3.062*	-1.25	-2.97	-2.22	5.255
Texas	-2.447	-1.838	-1.285	-1.882	-2.692	4.903
Utah	-3.135*	-2.547	-3.13*	-12.928*	-3.431*	5.152*
Vermont	-3.588*	-2.955*	-0.881	-0.503	-3.393*	5.066*
Virginia	-2.583	-2.781	-2.38*	-13.919*	-3.466*	5.083*
Washington	-3.148*	-2.687	-2.797*	-12.699*	-2.474	5.448
West Virginia	-1.738	-1.652	-1.21	-2.992	-2.288	5.374
Wisconsin	-2.648	-2.128	-1.916	-6.259	-4.279*	5.006*
Wyoming	-2.593	-2.036	-0.993	-1.961	-3.218*	5.031*

Note: (1) We determine optimum lag(s) for ADF, DF-GLS, PP, NG, KSS, and Sollis (2009) unit root tests based on the AIC information criteria. In the NG and PP tests, the bandwidth was selected by the Bartlett Kernel. (2) * denotes the null hypothesis of unit root is rejected at 5%.
Source: Research finding.

To address the low power of conventional unit root tests, a quantile unit root test was used. Results have been provided in Table 3. The optimum lags (p*) are indicated in the second column. The optimum lags have been selected using AIC information criteria. The number of optimum lags is between 2 and 19. So, for 9 out of 50 unemployment rate series, 19 lags are selected, while only for 1 series, 2 lags are chosen.

Table 3. Quantile Unit Root Test Results

States	Optimum lag(s)	QKS statistics	Critical values			P-values of $t_n(\tau_i)$								
			90%	95%	99%	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Alabama	19	3.937	3.106	3.295	3.663	1.000	0.960	0.730	0.310	0.170	0.030	0.080	0.000	0.000
Alaska	16	4.615	3.174	3.448	3.742	0.000	0.000	0.000	0.010	0.020	0.050	0.560	0.590	0.950
Arizona	7	4.395	3.078	3.437	3.981	0.250	0.240	0.050	0.070	0.060	0.010	0.000	0.000	0.000
Arkansas	13	2.843	3.097	3.366	3.750	0.080	0.500	0.280	0.500	0.270	0.390	0.050	0.020	0.010
California	13	2.429	3.093	3.233	3.701	0.640	0.270	0.470	0.510	0.560	0.490	0.150	0.080	0.070
Colorado	14	2.498	3.116	3.297	3.983	0.670	0.410	0.310	0.160	0.720	0.350	0.110	0.020	0.030
Connecticut	14	7.701	3.112	3.334	3.959	1.000	1.000	0.960	0.580	0.150	0.020	0.020	0.000	0.000
Delaware	4	5.084	2.787	3.017	3.529	0.990	0.950	0.540	0.190	0.050	0.000	0.000	0.000	0.000
Florida	17	3.674	2.991	3.246	3.748	0.580	0.540	0.140	0.060	0.020	0.020	0.000	0.010	0.000
Georgia	6	4.938	2.997	3.301	3.789	1.000	0.970	0.960	0.710	0.290	0.090	0.010	0.000	0.000
Hawaii	15	4.031	2.956	3.278	3.827	1.000	0.980	0.830	0.520	0.210	0.090	0.040	0.010	0.010
Idaho	16	4.665	2.884	3.143	3.449	1.000	1.000	0.990	0.590	0.110	0.010	0.000	0.070	0.000
Illinois	18	5.077	3.030	3.218	3.683	0.880	0.780	0.790	0.520	0.070	0.010	0.000	0.010	0.000
Indiana	4	4.955	3.029	3.221	3.663	1.000	1.000	0.830	0.500	0.090	0.000	0.000	0.000	0.000
Iowa	19	4.338	3.066	3.364	4.006	0.600	0.750	0.580	0.210	0.120	0.020	0.000	0.000	0.000
Kansas	16	3.960	3.139	3.365	3.858	0.900	0.910	0.960	0.670	0.820	0.520	0.370	0.010	0.000
Kentucky	18	4.274	2.994	3.209	3.614	0.550	0.640	0.130	0.000	0.000	0.000	0.000	0.000	0.000
Louisiana	10	3.847	2.674	2.881	3.329	0.410	0.750	0.800	0.510	0.440	0.150	0.010	0.010	0.000
Maine	7	3.272	3.077	3.281	3.912	1.000	0.860	0.490	0.210	0.070	0.020	0.140	0.020	0.000
Maryland	19	1.640	3.068	3.301	3.735	0.550	0.500	0.650	0.560	0.370	0.270	0.380	0.260	0.250
Massachusetts	4	7.128	3.077	3.295	3.808	0.770	0.880	0.940	0.800	0.760	0.430	0.040	0.000	0.000
Michigan	15	5.172	2.875	3.107	3.622	0.980	0.980	0.460	0.050	0.040	0.000	0.010	0.000	0.000
Minnesota	14	4.333	3.053	3.312	3.677	0.940	0.910	0.410	0.390	0.010	0.020	0.000	0.000	0.020
Mississippi	4	3.269	2.959	3.196	3.683	0.000	0.010	0.090	0.210	0.110	0.040	0.000	0.010	0.010
Missouri	15	4.582	2.961	3.214	3.579	0.760	0.900	0.490	0.280	0.020	0.000	0.000	0.000	0.000
Montana	19	2.058	3.010	3.219	3.630	0.700	0.730	0.850	0.690	0.470	0.280	0.140	0.220	0.120
Nebraska	18	2.341	3.060	3.302	3.852	0.830	0.960	0.430	0.140	0.010	0.240	0.490	0.160	0.050
Nevada	19	5.991	3.075	3.240	3.788	0.990	1.000	0.860	0.520	0.490	0.150	0.030	0.000	0.000
New	8	4.658	2.976	3.181	3.690	0.960	1.000	0.880	0.430	0.270	0.010	0.000	0.000	0.000
New Jersey	14	4.632	3.024	3.320	3.803	0.990	0.390	0.340	0.310	0.250	0.080	0.030	0.000	0.000
New Mexico	19	4.749	3.043	3.268	3.771	0.830	0.660	0.150	0.050	0.020	0.000	0.000	0.030	0.080
New York	5	4.645	3.136	3.312	3.747	0.990	0.850	0.580	0.560	0.070	0.050	0.050	0.040	0.000
North	2	7.160	2.889	3.077	3.408	1.000	0.970	0.700	0.190	0.120	0.000	0.000	0.000	0.000
North Dakota	19	3.610	3.049	3.286	4.009	1.000	1.000	0.800	0.060	0.030	0.000	0.030	0.060	0.010
Ohio	9	2.962	3.024	3.268	3.667	1.000	0.940	0.900	0.720	0.070	0.010	0.020	0.100	0.070
Oklahoma	5	3.947	2.969	3.186	3.627	0.990	0.820	0.620	0.760	0.530	0.000	0.000	0.000	0.000
Oregon	19	2.735	3.154	3.386	3.823	0.910	0.810	0.610	0.600	0.530	0.500	0.200	0.430	0.050
Pennsylvania	17	3.380	3.086	3.245	3.671	0.690	0.460	0.240	0.190	0.340	0.120	0.080	0.000	0.000
Rhode Island	15	5.207	3.069	3.296	3.611	1.000	1.000	0.860	0.630	0.610	0.070	0.000	0.000	0.000
South	16	3.480	3.097	3.334	3.983	0.980	0.960	0.900	0.750	0.720	0.140	0.060	0.000	0.000
South Dakota	18	3.778	2.962	3.276	3.739	0.090	0.030	0.010	0.000	0.020	0.000	0.010	0.100	0.240
Tennessee	17	4.009	3.087	3.315	3.840	0.940	0.920	0.870	0.530	0.070	0.000	0.000	0.000	0.000
Texas	5	2.649	3.078	3.249	3.810	0.960	0.670	0.250	0.110	0.160	0.740	0.380	0.060	0.040
Utah	3	4.190	3.049	3.349	3.860	1.000	0.960	0.670	0.450	0.030	0.000	0.000	0.000	0.000
Vermont	15	4.674	3.140	3.405	3.972	0.850	0.780	0.550	0.170	0.080	0.010	0.000	0.000	0.000
Virginia	11	3.626	3.058	3.318	3.830	1.000	0.800	0.420	0.050	0.070	0.020	0.000	0.020	0.010
Washington	5	4.672	3.038	3.256	3.809	0.680	0.300	0.190	0.130	0.110	0.010	0.000	0.000	0.040
West Virginia	16	4.742	3.101	3.455	4.287	1.000	0.990	0.800	0.620	0.160	0.000	0.000	0.000	0.000
Wisconsin	3	5.161	2.946	3.160	3.693	0.990	0.910	0.290	0.140	0.040	0.000	0.000	0.000	0.000
Wyoming	19	4.868	2.978	3.197	3.563	1.000	0.980	0.950	0.630	0.260	0.000	0.000	0.000	0.000

Note: The P - values for $t_n(\tau_i)$ and critical values for F-QKS statistics computed using the bootstrapping procedure and 5000 replications

Source: Research finding.

Results of QKS statistics indicate that the null hypothesis of unit root over the quantiles [0.1, 0.9] is rejected for 41 out of 50 US states, i.e. Connecticut, North Carolina, Massachusetts, Nevada, Rhode Island, Michigan, Wisconsin, Delaware, Illinois, Indiana, Georgia, Wyoming, New Mexico, West Virginia, Vermont, Washington, Idaho, New Hampshire, New York (States), New Jersey, Alaska, Missouri, Arizona, Iowa, Minnesota, Kentucky, Utah, Hawaii, Tennessee, Kansas, Oklahoma, Alabama, Louisiana, and South Dakota at 1% level of significance, and Florida, Virginia, North Dakota, South Carolina, Pennsylvania, Maine, and Mississippi at 5% level of significance.

The null hypothesis of the unit root has been rejected for other states, i.e. Ohio, Arkansas, Oregon, Texas, Colorado, California, Nebraska, Montana, and Maryland. For the above-mentioned states, the stochastic convergence toward cross-average has been rejected at a 10% significant level.

To analyze the stochastic behavior of relative unemployment series in each quantile, there were used the results of the value of $\widehat{\pi_1}(\tau)$ and p-value of $\mathrm{t_n}(\tau_\mathrm{i})$ statistics for which the null hypothesis of the unit root has been rejected by QKS test statistics. The values of $\widehat{\pi_1}(\tau)$ and p-value of $\mathrm{t_n}(\tau_\mathrm{i})$ statistics indicate that relative unemployment rate series show three types of response to shocks over the quantiles. (1) The values of $\hat{\rho}_1(\tau)$ and the p-value of $\mathrm{t_n}(\tau_\mathrm{i})$ statistics for the relative unemployment rate series of Alaska and South Dakota indicate an upward straight-line pattern. In these states, the positive shocks to the relative unemployment rate are more persistent than the negative shocks. (2) The values of $\hat{\rho}_1(\tau)$ for the relative unemployment rate series of Mississippi form an inverse U-shape pattern. Shocks to low and high quantiles of relative unemployment rate series have a transitory effect, while only shocks to middle quantiles [0.4, 0.6] have persistence effects. (3) For other states, i.e. Connecticut, North Carolina, Massachusetts, Nevada, Rhode Island, Michigan, Wisconsin, Delaware, Illinois, Indiana, Georgia, Wyoming, New Mexico, West Virginia, Vermont, Washington, Idaho, New Hampshire, New York (States), New Jersey, Missouri, Arizona, Iowa, Minnesota, Kentucky, Utah, Hawaii, Tennessee, Kansas, Oklahoma, Alabama, Louisiana, Florida, Virginia, North Dakota, South Carolina, Pennsylvania, and Maine, the values of $\hat{\rho}_1(\tau)$ form a downward straight-line pattern and the p-value of $\mathrm{t_n}(\tau_\mathrm{i})$ statistics is less than 0.1 over high quantiles [0.5, 0.9]. In the above-mentioned states, negative shocks to relative unemployment rate series have more persistence effects than positive shocks.

Conclusion

In this paper, we examined the stochastic convergence hypothesis in the US states unemployment toward cross-average over the period from 1976:1 to 2018:6. To the end, various conventional unit root tests were applied as well as a novel quantile unit root test. While the conventional unit root tests did not reject the null hypothesis of unit root for most of the relative unemployment rate series, using the quantile unit root test, the null hypothesis of the unit root was rejected for 41 out of 50 states. Most of the relative unemployment rates indicate the unit root properties at low quantiles except Alaska and South Dakota, which behave as a unit root process at high quantiles. Results indicate that in Alaska, which has had average unemployment rates greater than cross-average overall decades, when it locates at boom period and the unemployment rate is at a low level, the negative shocks to unemployment have transitory effects. But when the state experiences a recessionary period and its unemployment rate is high, the positive shocks to its unemployment rate will have a long-lasting effect.

In Alabama, Arizona, Florida, Georgia, Illinois, Indiana, Kentucky, Louisiana, Michigan, Mississippi, Missouri, Nevada, New Jersey, New Mexico, New York, Pennsylvania, Rhode Island, South Carolina, Tennessee, Washington, and West Virginia, which have unemployment rates greater than the cross-average over most decades, the negative shocks to the unemployment rate over boom period have long-lasting effects and result in convergence toward cross-average. In contrast, positive shocks to their unemployment rate over a recessionary period lead to a divergence while having transitory effects disappearing in the short run.

In Connecticut, Delaware, Hawaii, Idaho, Iowa, Kansas, Maine, Massachusetts, Minnesota, New Hampshire, North Carolina, North Dakota, Oklahoma, Utah, Vermont, Virginia, Wisconsin, and Wyoming, which have had unemployment rates less than cross-average over most decades, the economy has experienced a boom period, and negative shocks to unemployment rate have had long-lasting effects, and result in divergence toward cross-average. Yet, when their economy locates in a recessionary period, positive shocks to their unemployment rate result in convergence toward cross-average, but have transitory effects and disappear in the short run.

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