Why Economists Disagree: An Illustration of Irreconcilability Using the US State Level Unemployment Rate Data

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Abstract

In the literature, the unemployment rate has been explained by two hypotheses: the natural rate hypothesis vs. the hysteresis hypothesis. The former hypothesis refers to the rate of unemployment towards which the economy naturally gravitates in the long run. The latter hypothesis refers to the long-lasting effects of shocks on the unemployment rate. We test these two competing hypotheses using conventional unit root tests on the US unemployment rate at the state level and provide empirical evidence for both the hysteresis and the natural rate hypotheses. We then explain why reconciliation of opposite views regarding the unemployment rate is unlikely.

Key Words: unit root, panel unit root, unemployment, natural rate hypothesis, hysteresis

JEL Classification: C22, C23, E24, J64

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Introduction

The literature suggests two theories regarding the unemployment rate: the natural rate hypothesis[1] (Friedman, 1968, 1977) vs. the hysteresis hypothesis (Blanchard & Summers, 1987). The natural rate hypothesis refers to the rate of unemployment towards which the economy naturally gravitates in the long run. It is also described as the equilibrium unemployment rate defined as the unemployment rate that would occur when the economy is at its full employment level of output. According to the natural rate hypothesis, the equilibrium unemployment rate is determined by the structure of the labor market, i.e., labor demand and labor supply, and is unaffected by actual unemployment.[2] The hysteresis hypothesis, on the other hand, posits that the equilibrium unemployment rate depends on the history of the actual unemployment rate; and accordingly, a random shock, like a recession, will have a permanent effect on the unemployment rate.

Due to their opposing implications for policy, the fundamental differences between the natural rate hypothesis and the hysteresis hypothesis continue to exist to this day. The natural rate hypothesis supports the position that 'market economy is self-correcting.' Consider the example of labor market that Milton Friedman used in his presidential address to the American Economic Association in 1968. According to Friedman (1968, p. 8), "A lower level of unemployment is an indication that there is an excess demand for labor that will produce upward pressure on real wage rates. A higher level of unemployment is an indication that there is an excess supply of labor that will produce downward pressure on real wage rates." An important implication

1 According to Arrow et al. (2011), the 1968 paper by Milton Friedman was one of the 20 most influential papers published in the *American Economic Review* during its first hundred years. In appreciation of Friedman's 1968 paper, Arrow et al. (2011, pp. 3-4) wrote:

> This presidential address is the origin of the "vertical long-run Phillips curve," along with a contemporary paper by Edmund S. Phelps. It introduced the idea of a "natural" rate of unemployment as the only rate compatible with the sustained coincidence of actual and expected rates of inflation. This is the basis of the conclusion that the Phillips curve is vertical in the long run, allowing only a temporary trade-off between unemployment and inflation. From this followed possible implications for the conduct of macro-policy, especially monetary policy. An enormous amount of research and discussion followed.

2 In a recent study, Blanchard (2018) argues that the original natural rate hypothesis articulated by Milton Friedman is composed of two sub-hypotheses: first, the natural rate of unemployment is independent of monetary policy; and, second, there is no long-run trade-off between the deviation of unemployment from the natural rate and inflation. He refers to the joint hypothesis as the "natural rate hypothesis," and the two separate sub-hypotheses as the "independence hypothesis" and the "accelerationist hypothesis." For our research purpose in this article, we do not make such a distinction.

of Friedman's argument is that a favorable shock that leads the economy into economic expansion and results in a lower level of unemployment and/or an adverse shock that leads the economy into recession and results in a higher level of unemployment are indicators of market corrections. Thus, the natural rate hypothesis sees no need for government intervention to actively manage the rate of unemployment. In contrast, the hysteresis hypothesis suggests that a high unemployment rate that results from an adverse shock, if left unchecked, may continue and become a serious social problem even in the long run. This possibility provides a rationale for governments to play an active role in managing the economy and to fight against the high level of unemployment.

The underlying reason for the differences between the natural rate hypothesis and the hysteresis hypothesis can be traced to the concept of the Phillips curve. Historically, Phillips (1958) showed an inverse relationship between the percentage change in the nominal wage rate and the unemployment rate in the United Kingdom during 1861-1957. Later, when analyzing the US data, Samuelson and Solow (1960) confirmed Phillips's results. Since then, the Phillips curve has evolved through several stages, and the original interpretation of the Phillips curve as a stable trade-off between inflation and unemployment has given way to the view that no such trade-off exists for policymakers to exploit[3] (Humphrey, 1978; Farmer, 2013; Blanchard, 2018).

Consider the following mathematical model representing the Phillips curve:[4]

$$\pi_t = E\pi_t - \beta(U_t - U_t^*)\, \nu_t \quad \ldots\ldots\ldots\ldots (1)$$

where π_t is the current rate of inflation, $E\pi_t$ is the expected rate of inflation, U_t is the actual rate of unemployment, U_t^* is the natural rate of unemployment, and ν_t is random (supply) shock. The term $(U_t - U_t^*)$ is cyclical unemployment (the deviation of unemployment from its natural rate), and β is a parameter that measures the responsiveness of inflation to cyclical unemployment. Equation (1) states that the inflation rate depends on expected inflation,

3 Debates about the relationship between inflation and unemployment are nothing new. Since the 1950s, economists have been investigating to determine the exact relationship between these two concepts. See, for example, Morton (1950), Phelps (1967), Tobin (1967, 1972), Schwarzer (2012, 2014, 2018), Crump, Eusepi, Giannoni, and Sahin (2022), among others.

4 The formulation of the Phillips curve here is based on the contemporary prominent macroeconomics textbook by N. Gregory Mankiw (2010). Although the original Phillips curve shows a negative relationship between the unemployment rate and the rate of wage in inflation, Mankiw (2010, p. 390) argues that the modern Phillips curve that economists use today differs from the original Phillips curve in three different ways: First, the modern Phillips curve substitutes price inflation for wage inflation. Second, the modern Phillips curve includes expected inflation due to the work of Milton Friedman and Edmund Phelps. Third, the modern Phillips curve includes supply shocks.

cyclical unemployment, and supply shock. A negative sign before the cyclical unemployment implies that *ceteris paribus*, higher unemployment is associated with lower inflation.

In the derivation of the Phillips curve, adaptive expectations play an important role.[5] Adaptive expectations suggest that people form expectations of inflation based on recently observed inflation. For example, *ceteris paribus* people expect prices to rise this year at the same rate as they did last year. That is, the expected inflation $(E\pi_t)$ this year would, on average, equal the actual inflation (π_{t-1}) last year.[6] We use this information to modify equation (1) as:

$$\pi_t = \pi_{t-1} - \beta(U_t - U_t^*) + \nu_t \text{ .... } (2)$$

If the hysteresis hypothesis holds, the natural rate of unemployment would be a function of the past actual unemployment rate. This relationship can be expressed as:

$$U_t^* = \alpha + \rho U_{t-1} + \xi_t \text{............ } (3)$$

where α and ρ are parameters and ξ_t is an error term. Substituting equation (3) into equation (2), we get:

$$U_t = \alpha + \rho U_{t-1} + \varepsilon_t \text{ .... } (4)$$

where,

$$\varepsilon_t = 1/\beta(\pi_{t-1} - \pi_t + \nu_t) + \xi_t$$

Equation (4) is now in the form of standard first-order autoregressive process, where the unemployment rate represents a reduced form function of the factors that affect labor market institutions. Based on equation (4), we can predict three outcomes regarding the unemployment rate. First, if the parameter ρ in the equation is equal to 1, then the hysteresis hypothesis may be true. Second, if the parameter ρ is zero, then the unemployment rate stays at a constant level α and in this case, the natural rate hypothesis may be true. Third, an intermediate case is also possible whereby the parameter ρ takes a

5 According to Farmer (2013, p. 248), when the natural rate hypothesis was first proposed, Milton Friedman assumed that expectations are adaptive.

6 Consider the pool player example. We would expect a pool player to miss fairly often; better pool players, however, will miss less often. But not even the worst player would predictably miss the pocket always to the left or always to the right. Systematic mistakes are easily eliminated. When it comes to forming expectations, the model may be quite complex and expectations may be off substantially, although on average less for agents that are better informed. Yet none of the agents would be expected to always underestimate or overestimate inflation. The implication is that expectations will not be systematically biased. As a result, systematic policies that work by fooling the public are anticipated and will not work. In a similar vein, we would expect underestimates as often as overestimates so that expectations of inflation are unbiased and thus are not wrong on the average (Balvers, 2000).

value between zero and one. In this case, the unemployment rate may evolve towards its steady state level $\alpha/1\text{-}\rho$. Song and Wu (1997, p. 236) refer to second and third cases as strong and weak versions of the natural rate hypothesis.

An extensive review of the literature shows that the stationarity and nonstationarity time series properties of the unemployment rate have been widely used to distinguish between the natural rate hypothesis vs. the hysteresis hypothesis. Therefore, our goal in this paper is to determine whether the unemployment rate is stationary or nonstationary. Analysis of the US unemployment rate is important because empirical evidence on the US unemployment rate is controversial. For example, studies by Mitchell (1993, p. 1497), Breitung (1994, p. 366), and Hatanaka (1996, p. 98) found that the US unemployment rate was nonstationary, supporting the hysteresis hypothesis. In contrast, studies by Nelson and Plosser (1982, p. 152), Perron (1988), Xiao and Phillips (1998, p. 38), and Song and Wu (1997, p. 241) found that the US unemployment rate was stationary, supporting the natural rate hypothesis. None of these studies, however, examined the time period after 2000.

Since 2000, the United States experienced two major recessions: one in 2001 and another in 2007-2009.[7] It is plausible that the policies adopted by states to deal with the recessions in the 1980s and 1990s could be different from those to deal with the recessions in the 2000s. If policymakers showed blindfold confidence in the extant literature, it would likely lead to policy failures. Arguably, in an integrated global economy, the real cost consequences of economic fluctuations that arise due to policy failures have the potential to spill over national boundaries. Examples include the Asian economic crisis in 1997, the global financial crises in 2007-2009, and most recently the COVID-19 pandemic.[8] This provides another motivation for a comprehensive analysis of the unemployment rate to determine its time series property focusing on the US states that have not been examined before.[9]

7 According to the National Bureau of Economic Research (NBER), the 2001 recession lasted eight months from March 2001 to November 2001, while the recession that began in December 2007 lasted 18 months until June 2009.

8 The COVID-19 pandemic, also known as the coronavirus pandemic, is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This new strain of virus was first identified from an outbreak in Wuhan, China, in December 2019. The Johns Hopkins Coronavirus Resource Center (CRC) offers a continuously updated domestic and international data on COVID-19 accessible through their website at https://coronavirus.jhu.edu/.

9 Several studies have analyzed the unemployment rate for other individual countries or specific regions. For Australia, see Liu, Sun, and Lin (2012) and Smyth (2003). For Britain, see Layard and Nicksell (1986). For Canada, see Johnson and Kneebone (1991), Jones (1995). For Japan, see Brunello (1990). For the EU, see Blanchard and Summers (1986), Layard and Calmfors (1987), Leon-Ledesma

We analyzed the unemployment rate using a panel of annual data from all 50 states for the period 1976 – 2016. Consistent with the literature, we found that, depending on the model chosen, the unemployment rate can be stationary or nonstationary, thereby supporting both the natural rate hypothesis and the hysteresis hypothesis. Our work is closely related to the work of Cheng, Durmaz, Kim and Stern (2012), who also investigated the nature of the US unemployment rates, including data of the two major recessions after 2000. Using panel methods and controlling for cross-sectional dependence, they found evidence that the unemployment rate was stationary when the data during the great recession was not included in the analysis; while adding data from the great recession, they also found much stronger evidence for the hysteresis. Our work diverges from theirs in two important ways. Firstly, they use monthly data from the FRED and convert to quarterly data by taking the beginning of the period values (page 432); we use seasonally adjusted annual data as reported by the Bureau of Labor Statistics (BLS). Secondly, their data period ends in the second quarter of 2010; we use a longer time series until 2016 and assess whether the unemployment rate is stationary or nonstationary. Unlike all previous studies that conform contradictory economic theories, our contribution to the literature is to report, using the unemployment rate as an example, more anomalies about the unit root tests that are used commonly. In conclusion, we explain why reconciliation among economists holding opposite views concerning the unemployment rate may not be possible.

Review of State Level Unemployment Rate Differentials

During or shortly after the financial crisis of 2007 – 2009, 26 million Americans lost their job, or could not find full-time work, or had given up looking for work[10] (Financial Crisis Inquiry Report, 2011). According to Barnanke (2018), job losses averaged 120,000 per month from the beginning of the recession in December 2007 through August 2008, and accelerated to 670,000 per month from September 2008 through March 2009, the period of

(2002). For OECD, see Alogoskoufis et al. (1988), Mitchell (1993), Roed (1996), Song and Wu (1998). Our focus in this paper will be the unemployment rate in the United States at the state level.

10 The financial crisis of 2007 – 2009 should not be brushed off as a topic only of historical interest; it warrants a systematic analysis to understand both causes and consequences of severe societal disruptions.

most intense economic panic.[11] Since then, there has been a revived interest to improve our understanding of the rise in the unemployment rate during the recession and the accompanying severity of joblessness among the unemployed. Following the crisis, although unemployment rates rose in all states, the magnitude of increase in unemployment rate varied across states. We note this fact for the purpose of this paper. We believe large differentials in unemployment rates across states are an important public policy issue because prolonged high unemployment levels may give rise to unintended social consequences.

In our sample period from 1976 to 2016, unemployment rates vary sharply across 50 states. Table 1 presents a summary statistics of unemployment rate by state. As can be seen in the table, the mean of the annual averages of the unemployment rate was the highest in West Virginia (8.2 percent), while the mean of the annual averages of the unemployment rate was the lowest in Nebraska (3.5 percent). Although not reported here, we compared the unemployment rate of each of the 50 states to that of the national average. Except for a few periods, the unemployment rate was systematically higher than the national average in Alaska, California, Michigan, Mississippi, and West Virginia, while it was systematically lower than the national average in Nebraska, North Dakota, South Dakota, and Virginia.

Numerous studies offer several explanations of persistent differences in unemployment rates among the states. Walden (2012, p. 252) classifies representative work in this area into three broad categories: (i) explaining differences in the levels of state unemployment rates (Patridge & Rickman, 1995, 1997; Blackely, 1989; McHugh & Widdows, 1984; and McGee, 1985); (ii) identifying convergence or divergence of state unemployment rates (Nissan & Carter, 2001; Murphy & Payne, 2003); and, (iii) explaining changes in unemployment rates among states, particularly during recessions (Connaughton & Madsen, 1980, 2010). Most importantly, these studies underscore the need for a clear understanding of the reasons for states to formulate an appropriate policy to combat unemployment effectively.

11 The distinguished American Economist, Ben S. Bernanke, who served as the Chair of the Federal Reserve from 2006 to 2014, was one of the three recipients of the Nobel Prize in Economics in 2022, the other two being Douglas W. Diamond and Philip H. Dybvig. The Royal Swedish Academy of Sciences awarded the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel to these scholars for their contribution to improve the understanding of the role of banks in the economy, particularly during financial crises (Press Release: The Prize in Economic Sciences 2022).

In an early study, Campbell and Campbell (1969) document why the unemployment rate might differ from one state to another. Examining the effects of minimum wage laws on unemployment, using data from 1950 to 1965, they found a wide variation in the relationship between minimum wage and the unemployment rate at the state level. On average, states with the minimum wage laws had higher rates of unemployment than states without the laws. In addition, when states increased their minimum wages, unemployment in those states would tend to increase relative to the rate of unemployment in other states. In a follow-up study, Neumark and Wascher (1992) confirm Campbell and Campbell's (1969) findings.

The industrial structure was another frequently cited reason why unemployment rates differed across states in the 1980s. Analyzing data for the period from 1980 to 1983, McGee (1985) found that states with a greater share of their employment in industries with low unemployment were likely to have lower unemployment rates than the national average. In a subsequent study, Partridge and Rickman (1995) evaluated the industrial restructuring of the 1980s and found that most of the changes in employment were state idiosyncratic, not the result of national restructuring, and that the state-idiosyncratic employment growth was primarily cyclical and not persistent in the long run. Despite the limited industry mobility implied by the large effects on unemployment, differences in change of the industry mix, Partridge and Rickman (1995) concluded that national restructuring played a little role in unemployment differences in the 1980s.

In the literature regarding the review of differentials in the state unemployment rate, the study by Nissan and Carter (2001) is of particular interest. Unlike other studies that attempt to explain the unemployment rate differentials across states, Nissan and Carter (2001) examined whether state unemployment rates had been converging or diverging over time. Analyzing data from 1978 to 1999, they found that unemployment rates were still dispersed, although the dispersion was narrowing down. About one-third of the states consistently experienced unemployment either above or below their expected levels. Approximately 90 percent of average state unemployment changes in rates were tied to changes in the national rate, and the remaining 10 percent of the changes in rates were due to unique characteristics of the particular state.

In summary, the extant literature on unemployment rate differentials at the state level indicates that the labor market structure across states is likely to differ due to their unique laws, regulations, unionizations or simply due to their geographic locations. Also, the labor market structure is likely to change over time due to changes in demography -- for example, increases in female labor-force participation or in-migration or out-migration, etc. -- due to sectoral shifts in the economy. However, none of the studies that use unit root methods to analyze the US unemployment rate properly take into account the state level unemployment rate differentials. To bridge the gap between the state level unemployment rate differentials and the unit root literature, we analyzed a panel of the unemployment rate for all 50 states over the period 1976 – 2016. We offer new evidence of more anomalies about the unit root tests that are commonly in use today.

Empirical Analysis and Results

We collected annual data on the unemployment rate for all fifty US states over the period 1976-2016.[12] We used officially reported seasonally adjusted annual data as opposed to quarterly or monthly data.[13] The data set includes recessions of 1980, 1981-1982, 1990-1991, 2001 and 2007-2009. This provides us with a unique opportunity to examine the natural rate hypothesis versus the hysteresis hypothesis for a contemporary period.

The literature suggests that data in logarithmic form achieve stationarity better than unlogged data. Besides, the use of logarithms is useful in computations involving numbers that are either very large or very small in absolute value (Weber, 1976, p. 115). In our sample, the unemployment rate never exceeds 0.178, a number for West Virginia in 1983, and for all other states and years, it was always less than 0.178. Because we believe these numbers to

12 The data were obtained from the official website of the US Bureau of Labor Statistics (BLS). Data files are available from the authors upon request.

13 Time series properties of annual data can have very different characteristics from monthly or quarterly data. Roassana and Seater (1995) show how temporal aggregation of economic time series, such as converting monthly data to quarterly or annual data, creates substantial loses in information and can cause misleading results in the empirical analysis. Likewise, Aruoba (2008) documents the empirical properties of revisions to major macroeconomic variables in the United States and finds that the revisions are quite substantial compared to the initial releases of the macroeconomic variables. As users of secondary data, we can do nothing about the data revisions. However, we do take note of possible implications of the use of secondary data for policy and economic research.

Table 1 **– Summary Information of Annual Unemployment Rate by State (1976 to 2016) (Original Series)**

(No of observation: 50 states × 41 years = 2050)

State	Mean	Standard Deviation	Minimum	Maximum
Alabama	.072	.024	.039	.141
Alaska	.079	.013	.063	.109
Arizona	.063	.017	.038	.103
Arkansas	.065	.015	.039	.099
California	.073	.019	.048	.122
Colorado	.054	.014	.027	.087
Connecticut	.055	.017	.023	.092
Delaware	.054	.017	.030	.087
Florida	.062	.018	.032	.110
Georgia	.061	.017	.035	.105
Hawaii	.049	.016	.025	.093
Idaho	.060	.016	.030	.099
Illinois	.070	.019	.043	.117
Indiana	.062	022	.030	.119
Iowa	.046	.014	.025	.085
Kansas	.047	.009	.031	.070
Kentucky	.068	.019	.041	.114
Louisiana	.073	.020	.042	.127
Maine	.059	.015	.033	.086
Maryland	.053	.012	.034	.082
Massachusetts	.055	.017	.027	.096
Michigan	.080	.029	.036	.153
Minnesota	.049	.013	.026	.080
Mississippi	.076	.018	.051	.120
Missouri	.060	.015	.032	.098
Montana	.058	.012	.034	.086
Nebraska	.035	.008	.023	.056
Nevada	.066	.024	.039	.135
New Hampshire	.043	.013	.023	.073
New Jersey	.063	.018	.036	.104
New Mexico	.067	.013	.037	.096
New York	.066	.015	.042	.102
North Carolina	.058	.019	.032	.108
North Dakota	.039	.009	.026	.058
Ohio	.067	.021	.039	.126
Oklahoma	.052	.013	.030	.083
Oregon	.072	.018	.048	.115
Pennsylvania	.065	.017	.041	.115
Rhode Island	.065	.021	.031	.112
South Carolina	.066	.019	.037	.112
South Dakota	.037	.007	.024	.054
Tennessee	.065	.019	.038	.117
Texas	.060	.012	.042	.087
Utah	.049	.015	.025	.087
Vermont	.047	.013	.027	.083
Virginia	.047	.012	.023	.074
Washington	.070	.017	.046	.119
West Virginia	.082	.029	.043	.178
Wisconsin	.056	.018	.031	.105
Wyoming	.049	.014	.027	.088
50 States	0.060	0.020	0.023	0.178

Table 2 **– Summary Information of Annual Unemployment Rate by State (1976 to 2016) (Natural Logarithm)**

(No of observation: 50 states × 41 years = 2050)

State	Mean	Standard Deviation	Minimum	Maximum
Alabama	-2.670015	.3156042	-3.225094	-1.958255
Alaska	-2.544161	.1666584	-2.759811	-2.213043
Arizona	-2.787494	.2647965	-3.256332	-2.266726
Arkansas	-2.745089	.2331998	-3.219074	-2.311004
California	-2.63698	.2506273	-3.016356	-2.100476
Colorado	-2.943768	.2834873	-3.590179	-2.437685
Connecticut	-2.941083	.3260349	-3.732682	-2.376292
Delaware	-2.957632	.3256923	-3.477134	-2.43578
Florida	-2.809283	.2944932	-3.432773	-2.202275
Georgia	-2.830993	.2610245	-3.33286	-2.250813
Hawaii	-3.052769	.3360415	-3.678713	-2.365048
Idaho	-2.837725	.2670219	-3.481692	-2.309443
Illinois	-2.694973	.2694935	-3.136425	-2.139111
Indiana	-2.827701	.350102	-3.493086	-2.122086
Iowa	-3.107493	.2919853	-3.654072	-2.464952
Kansas	-3.074381	.1921256	-3.467354	-2.652122
Kentucky	-2.720776	.2699927	-3.177196	-2.170536
Louisiana	-2.641769	.2610104	-3.157063	-2.059601
Maine	-2.863208	.275178	-3.391971	-2.444286
Maryland	-2.956783	.239757	-3.364089	-2.490623
Massachusetts	-2.931632	.3178096	-3.611727	-2.341599
Michigan	-2.579344	.3631432	-3.321055	-1.871811
Minnesota	-3.045264	.2627886	-3.61404	-2.525335
Mississippi	-2.598806	.2359658	-2.973062	-2.114862
Missouri	-2.837262	.2498686	-3.413525	-2.316252
Montana	-2.863805	.2233718	-3.354696	-2.450097
Nebraska	-3.36277	.2330204	-3.754479	-2.877161
Nevada	-2.772564	.3353704	-3.222755	-2.000324
New Hampshire	-3.177266	.3112308	-3.762858	-2.616958
New Jersey	-2.792438	.2904515	-3.297371	-2.262643
New Mexico	-2.710773	.2148934	-3.283329	-2.336589
New York	-2.740634	.2327617	-3.15241	-2.279537
North Carolina	-2.88625	.3167326	-3.441998	-2.220704
North Dakota	-3.269373	.2292452	-3.617512	-2.837991
Ohio	-2.732891	.2901271	-3.222805	-2.063697
Oklahoma	-2.987241	.2524037	-3.494324	-2.480942
Oregon	-2.658798	.2495386	-3.019991	-2.158963
Pennsylvania	-2.761519	.255274	-3.186392	-2.162178
Rhode Island	-2.772234	.3305859	-3.470993	-2.188986
South Carolina	-2.752536	.2775017	-3.28047	-2.185251
South Dakota	-3.314888	.2079079	-3.706301	-2.906688
Tennessee	-2.770927	.2766778	-3.254088	-2.143186
Texas	-2.820944	.2045891	-3.14974	-2.435179
Utah	-3.053912	.297215	-3.657282	-2.439726
Vermont	-3.085822	.2699654	-3.576015	-2.485554
Virginia	-3.073342	.275558	-3.772112	-2.59712
Washington	-2.675796	.2423565	-3.058193	-2.124556
West Virginia	-2.551967	.3340338	-3.135457	-1.725218
Wisconsin	-2.924971	.300858	-3.466458	-2.252352
Wyoming	-3.046717	.2898577	-3.600633	-2.419981
50 States	-2.863935	.3340999	-3.772112	-1.725218

Table 3 **– Summary Information of Annual Unemployment Rate by State (1976 to 2016) (First Differences of Original Series)**

(No of observation: 50 states × 40 years = 2000)

State	Mean	Standard Deviation	Minimum	Maximum
Alabama	-.0002052	.0140902	-.0277741	.0536304
Alaska	-.0002409	.0077207	-.0178249	.022948
Arizona	-.0011083	.0140524	-.0361418	.0387379
Arkansas	-.0007446	.0073527	-.0125016	.0236706
California	-.0009277	.0120912	-.0203304	.0387717
Colorado	-.000628	.0097222	-.0183666	.0245501
Connecticut	-.0010501	.0098915	-.0229138	.0226257
Delaware	-.0010932	.0090069	-.0143775	.0332188
Florida	-.0010713	.011498	-.0212499	.0413331
Georgia	-.0007063	.0099805	-.0163999	.0370441
Hawaii	-.001594	.0083936	-.0151863	.0284029
Idaho	-.0004357	.0103604	-.016226	.0367283
Illinois	-.0001891	.0122864	-.0274308	.0391678
Indiana	-.0004098	.0124327	-.0263911	.0441387
Iowa	-.000084	.0073643	-.0126914	.0220597
Kansas	-.000012	.0067487	-.0096534	.0226799
Kentucky	-.0000982	.0111704	-.0214496	.0393642
Louisiana	-.0001543	.0109244	-.0285539	.0190899
Maine	-.0012063	.009203	-.0207548	.0259612
Maryland	-.0005845	.008079	-.0164799	.0277603
Massachusetts	-.0014793	.0108565	-.0199458	.025738
Michigan	-.00112	.0166168	-.0314718	.056896
Minnesota	-.0004856	.0082581	-.0172067	.0234154
Mississippi	-.0001855	.010534	-.0154203	.0291306
Missouri	-.0004283	.0101673	-.0269992	.0313384
Montana	-.0004521	.0070329	-.010418	.0177603
Nebraska	-1.53e-06	.0051061	-.0109151	.0138839
Nevada	-.000774	.0137615	-.0224318	.0460318
New Hampshire	-.0009252	.0096575	-.0161954	.0237725
New Jersey	-.0013623	.0108844	-.0210531	.0371686
New Mexico	-.0005309	.0091012	-.018452	.0307451
New York	-.0013503	.0093388	-.0150616	.0288413
North Carolina	-.000302	.0123985	-.0224732	.0447807
North Dakota	-.0001328	.0043538	-.0083126	.0097443
Ohio	-.0007105	.0127523	-.0290696	.0387876
Oklahoma	-.0002098	.0094852	-.0131837	.0262699
Oregon	-.0011227	.0126862	-.0193682	.0474446
Pennsylvania	-.000631	.0099286	-.0242686	.0277022
Rhode Island	-.0007249	.012176	-.0278942	.0320463
South Carolina	-.0005961	.013221	-.0295648	.0443789
South Dakota	-.000109	.0049606	-.0083984	.0187051
Tennessee	-.0003194	.0119265	-.0298618	.0388723
Texas	-.0002881	.0090139	-.0180447	.0276879
Utah	-.000544	.010406	-.0225076	.0372813
Vermont	-.0012664	.0077344	-.0137693	.0191051
Virginia	-.0004625	.0080351	-.0135863	.0274982
Washington	-.0008644	.0111204	-.0180781	.037688
West Virginia	-.0003315	.0142873	-.0302178	.0385184
Wisconsin	-.000352	.0111575	-.0288107	.0368463
Wyoming	.0003275	.009757	-.0189921	.0326262
50 States	-.0006056	.0103658	-.0361418	.056896

Table 4 – Summary Information of Annual Unemployment Rate by State (1976 to 2016) (First Differences of Natural Logarithm)

(No of observation: 50 states × 40 years = 2000)

State	Mean	Standard Deviation	Minimum	Maximum
Alabama	-.0032122	.1724851	-.2381673	.6672645
Alaska	-.0034048	.0923978	-.2264216	.2648215
Arizona	-.0151967	.2079034	-.5293496	.4831698
Arkansas	-.0139157	.113871	-.2349217	.3595316
California	-.013016	.1554109	-.2327216	.4268794
Colorado	-.0141046	.1809626	-.3129714	.4105392
Connecticut	-.015045	.1857702	-.3752725	.335535
Delaware	-.0173088	.1688969	-.3382914	.5135026
Florida	-.0157516	.1734995	-.2877388	.5059717
Georgia	-.0105688	.1505912	-.2383764	.4663024
Hawaii	-.0283842	.1779437	-.2388954	.506211
Idaho	-.009392	.1686218	-.236846	.5425584
Illinois	-.0030276	.1637868	-.2651885	.4842045
Indiana	-.0078849	.1740957	-.2689946	.5594916
Iowa	-.0021905	.1415014	-.2079909	.4218149
Kansas	-.0002868	.1378764	-.2261426	.4005144
Kentucky	-.0018884	.1504972	-.223191	.4791183
Louisiana	-.0024153	.14821	-.4740968	.3281949
Maine	-.0202968	.1544967	-.2876966	.387491
Maryland	-.0108831	.1474659	-.2678096	.5046208
Massachusetts	-.0238801	.1919435	-.3500206	.4168777
Michigan	-.0161976	.1810998	-.2944174	.5388261
Minnesota	-.0101045	.1547219	-.308609	.3586929
Mississippi	-.0029952	.1315038	-.1973178	.3672578
Missouri	-.0080252	.155675	-.3198028	.4122996
Montana	-.009047	.1234821	-.2198739	.3532271
Nebraska	-.0000475	.1316938	-.2253056	.3289371
Nevada	-.0108722	.1874744	-.4074295	.5228541
New Hampshire	-.0209334	.2136412	-.3531678	.4919307
New Jersey	-.0185365	.1696403	-.2590735	.5284152
New Mexico	-.0068527	.1379447	-.2507031	.5242462
New York	-.018759	.1437169	-.2412603	.4254265
North Carolina	-.0053581	.1932033	-.2882235	.5502167
North Dakota	-.0038833	.1099448	-.1531405	.2694292
Ohio	-.0113583	.1641564	-.2680786	.4712725
Oklahoma	-.0039739	.1851173	-.3113389	.5316167
Oregon	-.0163109	.1661321	-.2575727	.5458052
Pennsylvania	-.009531	.1397359	-.2368565	.4174862
Rhode Island	-.0108679	.1802167	-.4097373	.4320269
South Carolina	-.0100246	.1842347	-.3564687	.5019586
South Dakota	-.0035956	.1291051	-.202801	.4762924
Tennessee	-.0058874	.160229	-.2995837	.4641519
Texas	-.0055749	.1453211	-.2583017	.4551666
Utah	-.0122978	.2032791	-.3167622	.7133856
Vermont	-.0234283	.1538125	-.236829	.3464942
Virginia	-.0094798	.1697432	-.2753003	.5290096
Washington	-.0123117	.1504239	-.2106564	.5306695
West Virginia	-.004989	.1567586	-.1858896	.5744054
Wisconsin	-.0073178	.1750745	-.3300979	.5611351
Wyoming	.0071321	.1881053	-.2652032	.7260265
50 States	-.0100696	.1609511	-.5293496	.7260265

be small, we analyzed the data in the natural logarithmic form. For comparison purposes, however, our study reports result both for the original series and for their natural logarithmic transformation. (We note here that we have postponed further discussion of the importance of the use of variables in original series and for their natural logarithmic transformation to **Summary, Discussion, and Conclusion Section** at page 127 below. Table 1 and Table 2 provide the summary statistics of data for the original series and their natural logarithmic transformation. Similarly, Table 3 and Table 4 provide the summary statistics of data in the first differences of the original series and in the first differences of the natural logarithmic transformation of the original series.

Dicky-Fuller (DF) and Phillips-Perron (PP) Unit Root Test Results

Researchers working on econometric time series analysis acknowledge that the literature on the unit root is vast and often confusing (Maddala, 1992; Greene, 2000; Bierens, 2001; Patterson, 2011, 2012). From a practitioner's viewpoint, it remains unclear which tests, if any, are superior to others, and much empirical work continues to use the simple testing procedure (Phillips & Xiao, 1998). The most commonly used tests for a unit root are the Dickey-Fuller (DF) test, proposed by Fuller (1976) and Dickey and Fuller (1979, 1981), and the Phillips-Perron (PP) test, proposed by Phillips (1987) and Phillips and Perron (1988). The Dickey-Fuller test is based on the regression of the observed variable on its one period lagged value sometimes including an intercept. It assumes that error terms (e_t) are uncorrelated and independently and identically distributed (iid). If e_t are correlated, the DF tests do not have the correct asymptotic size. Phillips (1987), and Phillips and Perron (1988) argue that the Phillips-Perron test, which uses a semiparametric approach to detecting the presence of a unit root in a time series, overcomes the problems associated with the DF tests.[14] The Phillips-Perron test arguably allows for a wide class of time series with heterogeneously and serially correlated errors. In this section, we report results from these popular tests.

Since our goal is to determine whether the unemployment rate is stationary or nonstationary, we test the null hypothesis that the unemployment rate has a unit root, against the alternative that it does not have a unit root. The

14 Luitel and Mahar (2021) further demonstrate the limits of DF and ADF tests.

Table 5 – Unit Root Test Results in Level (Original Series)

	Dickey-Fuller Test		Phillips-Perron Test	
	Model 1§	**Model 2§§**	**Model 3†**	**Model 4††**
Alabama	-1.800**	-2.056	-9.179	-10.762
Alaska	-1.659*	-3.592**	-5.827	-19.810**
Arizona	-3.084***	-3.024	-16.140**	-15.932
Arkansas	-1.041	-1.509	-6.633	-8.748
California	-1.998**	-1.975	-13.722**	-13.795
Colorado	-1.861**	-1.895	-10.996*	-11.215
Connecticut	-2.585***	-2.770	-13.687**	-13.831
Delaware	-2.123**	-1.977	-8.789	-8.824
Florida	-2.244**	-2.194	-13.133**	-13.058
Georgia	-2.072***	-2.136	-10.713*	-11.003
Hawaii	-2.819***	-2.640	-12.833*	-13.203
Idaho	-1.841**	-2.199	-10.992*	-12.528
Illinois	-1.985**	-2.008	-10.855*	-10.970
Indiana	-1.631*	-1.727	-8.916	-9.357
Iowa	-1.563*	-1.844	-7.820	-8.916
Kansas	-2.386**	-2.343	-13.188**	-14.239
Kentucky	-1.795**	-1.889	-9.186	-9.173
Louisiana	-1.626*	-2.171	-7.026	-9.867
Maine	-2.096**	-2.099	-11.318*	-12.167
Maryland	-2.058**	-2.047	-11.375	-11.672
Massachusetts	-2.714***	-2.639	-14.757**	-14.562
Michigan	-1.687**	-1.832	-8.696	-9.623
Minnesota	-2.013**	-2.025	-11.306*	-11.601
Mississippi	-1.701**	-1.895	-8.105	-8.739
Missouri	-1.992**	-2.000	-11.116*	-11.171
Montana	-1.484*	-2.164	-7.519	-11.302
Nebraska	-1.877**	-1.927	-9.268	-9.487
Nevada	-1.869**	-1.943	-11.670*	-12.273
New Hampshire	-2.517***	-2.477	-16.366**	-16.440*
New Jersey	-2.554***	-2.464	-12.860*	-12.567
New Mexico	-2.450***	-2.421	-11.040	-13.037
New York	-2.670***	-2.581	-13.552**	-14.234
North Carolina	-1.975**	-1.997	-11.159*	-11.856
North Dakota	-1.384*	-2.781	-4.709	-12.434
Ohio	-1.853**	-1.948	-10.118	-10.830
Oklahoma	-2.340**	-2.364	-11.912*	-12.355
Oregon	-2.181**	-2.183	-13.103**	-13.353
Pennsylvania	-1.852**	-1.959	-10.021	-11.718
Rhode Island	-1.805**	-1.825	-11.156*	-11.442
South Carolina	-2.117**	-2.073	-12.107*	-12.204
South Dakota	-1.891**	-2.126	-9.699	-10.398
Tennessee	-1.866**	-1.941	-9.681	-10.017
Texas	-2.222**	-2.278	-12.206*	-12.141
Utah	-2.160**	-2.302	-12.239*	-13.255
Vermont	-2.986***	-2.890	-13.012**	-14.751
Virginia	-2.122**	-2.116	-11.109*	-11.507
Washington	-2.043**	-2.152	-11.593*	-13.080
West Virginia	-1.423*	-2.127	-6.603	-9.912
Wisconsin	-1.891**	-1.941	-9.957	-10.203
Wyoming	-2.209**	-2.260	-9.922	-10.066
50 States Average	-1.950**	-2.007	-11.052*	-11.683

Note: ***indicates 1 percent significance level, **indicates 5 percent significance level and *indicates 10 percent significance level. §Model 1: $\Delta y_t = \alpha + \delta y_{t-1} + u_t$. §§Model 2: $\Delta y_t = \alpha + \beta t + \delta y_{t-1} + u_t$. †Model 3: $y_t = \alpha + \rho y_{t-1} + u_t$. ††Model 4: $y_t = \alpha + \beta t + \rho y_{t-1} + u_t$.

Table 6 – Unit Root Test Results in Level (Natural Logarithm)

	Dickey-Fuller Test		Phillips-Perron Test	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Alabama	-1.698**	-1.927	-8.674	-10.302
Alaska	-1.613*	-3.495*	-5.714	-19.150**
Arizona	-2.966***	-2.899	-15.354**	-15.221
Arkansas	-0.887	-1.388	-6.452	-8.749
California	-1.978**	-1.951	-13.763	-13.771
Colorado	-1.749**	-1.834	-10.473	-10.980
Connecticut	-2.299**	-2.400	-12.435*	-12.446
Delaware	-2.042**	-1.927	-9.002	-9.060
Florida	-2.130**	-2.073	-12.401*	-12.478
Georgia	-2.070**	-2.088	-10.016	-10.039
Hawaii	-2.141**	-2.086	-11.750*	-12.332
Idaho	-1.722**	-2.162	-11.056*	-13.115
Illinois	-1.906**	-1.929	-10.404	-10.570
Indiana	-1.454*	-1.544	-7.932	-8.383
Iowa	-1.471*	-1.698	-7.451	-8.324
Kansas	-2.337**	-2.303	-13.103**	-14.205
Kentucky	-1.710**	-1.801	-8.750	-8.684
Louisiana	-1.760**	-2.296	-7.573	-10.708
Maine	-1.877**	-1.918	-10.768*	-11.671
Maryland	-2.040**	-2.030	-11.096*	-11.449
Massachusetts	-2.302**	-2.256	-13.323**	-13.230
Michigan	-1.405*	-1.541	-7.430	-8.249
Minnesota	-1.894**	-1.900	-10.504*	-10.806
Mississippi	-1.662*	-1.846	-7.821	-8.443
Missouri	-1.873**	-1.891	-10.373	-10.497
Montana	-1.471*	-2.172	-7.636	-11.719
Nebraska	-1.793**	-1.814	-8.847	-8.969
Nevada	-1.926**	-1.973	-11.804*	-12.085
New Hampshire	-2.346**	-2.314	-15.857**	-15.899
New Jersey	-2.325**	-2.249	-12.191*	-12.015
New Mexico	-2.325**	-2.275	-10.501*	-12.212
New York	-2.395**	-2.366	-13.011**	-13.850
North Carolina	-1.955**	-1.991	-10.943*	-11.506
North Dakota	-1.400*	-2.775	-4.828	-12.866
Ohio	-1.734**	-1.817	-9.416	-10.086
Oklahoma	-2.425**	-2.412	-12.621*	-12.877
Oregon	-2.105**	-2.123	-12.881*	-13.201
Pennsylvania	-1.817**	-1.887	-9.799	-11.345
Rhode Island	-1.803**	-1.825	-11.158*	-11.330
South Carolina	-2.055**	-2.014	-11.929*	-11.988
South Dakota	-1.845**	-2.082	-9.552	-10.273
Tennessee	-1.722**	-1.804	-8.829	-9.229
Texas	-2.150**	-2.211	-12.306*	-12.264
Utah	-2.132**	-2.292	-12.345*	-13.582
Vermont	-2.423**	-2.411	-11.428*	-13.067
Virginia	-2.047**	-2.037	-10.581*	-11.042
Washington	-2.036**	-2.151	-11.743*	-13.337
West Virginia	-1.374*	-2.063	-5.911	-9.226
Wisconsin	-1.754**	-1.791	-9.196	-9.411
Wyoming	-2.126**	-2.135	-9.897	-9.904
50 States Average	-1.850**	-1.920	-10.517*	-11.281

Note: ***indicates 1 percent significance level, **indicates 5 percent significance level and *indicates 10 percent significance level. §Model 1: $\Delta y_t = \alpha + \delta y_{t-1} + u_t$. §§Model 2: $\Delta y_t = \alpha + \beta t + \delta y_{t-1} + u_t$. †Model 3: $y_t = \alpha + \rho y_{t-1} + u_t$. ††Model 4: $y_t = \alpha + \beta t + \rho y_{t-1} + u_t$.

decision rule is to reject the null hypothesis if the calculated test statistic is statistically significant; thus, the significant values indicate that the unemployment rate is stationary. Table 5 reports results of unit root tests in levels of the original series, and Table 6 reports results of unit root tests in levels of the natural logarithmic transformation.

Consider the results reported in Tables 5 and 6. It can be observed from the results displayed in the tables that the unit root finding in the unemployment rate depends on the choice of a regression model. These results are not surprising. It is well recognized in the literature that these results are due to the low power of these tests. In a peer review process, a reviewer made the comment, "the original Dickey-Fuller test, which allows for no lags in the autoregression, would be an awful test to use for almost all macroeconomic data that displays serial correlation in first differences. Also, the Phillips-Perron testing framework has been shown in multiple Monte Carlo studies to have poor size and power properties." Interestingly, however, despite the recommendation made by Maddala and Kim back in 1998 to completely discard these tests, they still appear in applied work.[15]

From the policy-making point of view, it would be useful to determine if the unemployment rate is stationary in level or in differences. We, therefore, took the first difference of the unemployment rate and tested for the existence of unit root. Table 7 reports the results of unit root tests in the first differences of the original series, and Table 8 reports the results of unit root tests in the first differences of the natural logarithmic transformation. As can be seen in the tables, the results unambiguously indicate that we reject the null hypothesis of a unit root using the first-differenced data. Since the unemployment rate appeared to show stationarity in its first differences, we did not take further differences of the series and test for unit root.

If one relies on these popular tests, the results reported in Tables 5, 6, 7, and 8 tend to support the hypothesis that the unemployment rate is nonstationary. This can be interpreted to suggest that the unemployment rate shows hysteresis. Although our results are consistent with the results reported by Song and Wu (1997, p. 240), we continue to explore the validity of

15 The unit root tests have made inroads into other disciplines beyond economics. For example, research work into environmental science, such as the analysis of climate change or paleoclimate data, see Kaufmann et al. (2006, 2013), Davidson et al. (2016), Storelvmo et al. (2016).

Table 7 **– Unit Root Test Results in First Differences (Original Series)**

	Dickey-Fuller Test		Phillips-Perron Test	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Alabama	-4.308***	-4.253***	-24.091***	-24.121***
Alaska	-5.858***	-5.706***	-25.995***	-25.502***
Arizona	-5.354***	-5.267***	-28.523***	-28.579***
Arkansas	-3.570***	-3.621**	-20.772***	-20.906**
California	-3.132***	-3.088*	-17.351**	-17.141*
Colorado	-4.091***	-4.045**	-22.240***	-22.234**
Connecticut	-3.592***	-3.426*	-18.284***	-17.797*
Delaware	-4.055***	-4.019**	-22.760***	-23.034**
Florida	-3.318***	-3.254*	-17.760**	-17.646*
Georgia	-4.417***	-4.329***	-24.553***	-24.400***
Hawaii	-3.816***	-3.703**	-20.733***	-20.605**
Idaho	-4.130***	-4.114**	-22.434***	-22.617**
Illinois	-4.634***	-4.592***	-27.463***	-27.512***
Indiana	-4.162***	-4.133**	-24.254***	-24.438***
Iowa	-4.409***	-4.395***	-26.707***	-27.006***
Kansas	-4.974***	-4.943***	-28.959***	-28.795***
Kentucky	-4.682***	-4.722***	-28.078***	-28.568***
Louisiana	-4.693***	-4.645***	-26.531***	-26.565***
Maine	-4.148***	-4.085**	-24.208***	-24.205**
Maryland	-3.595***	-3.532*	-18.598***	-18.499*
Massachusetts	-3.468***	-3.345*	-17.241**	-16.742*
Michigan	-4.710***	-4.672***	-28.069***	-28.077***
Minnesota	-4.485***	-4.429***	-26.083***	-25.985***
Mississippi	-4.603***	-4.571***	-25.871***	-26.005***
Missouri	-4.454***	-4.411***	-25.167***	-25.116***
Montana	-3.946***	-3.898**	-20.362***	-20.365**
Nebraska	-4.860***	-4.794***	-28.973***	-29.010***
Nevada	-3.245***	-3.163	-18.236***	-17.733*
New Hampshire	-3.805***	-3.738**	-20.768***	-20.507**
New Jersey	-3.815***	-3.737**	-20.885***	-20.973**
New Mexico	-5.068***	-4.995***	-25.374***	-25.486***
New York	-3.813***	-3.738**	-20.593***	-20.555**
North Carolina	-4.065***	-4.010**	-22.815***	-22.733**
North Dakota	-6.106***	-5.966***	-36.193***	-36.192***
Ohio	-4.304***	-4.266***	-24.057***	-23.962**
Oklahoma	-5.514***	-5.442***	-31.030***	-30.896***
Oregon	-4.168***	-4.119**	-22.684***	-22.374**
Pennsylvania	-3.889***	-3.836**	-22.023***	-22.027**
Rhode Island	-3.205***	-3.156	-17.604**	-17.556*
South Carolina	-4.490***	-4.436***	-25.673***	-25.544***
South Dakota	-4.988***	-4.988***	-29.735***	-30.014***
Tennessee	-4.311***	-4.274***	-23.198***	-23.267**
Texas	-4.631***	-4.617***	-24.286***	-24.134**
Utah	-4.258***	-4.212**	-22.626***	-22.539**
Vermont	-4.357***	-4.262***	-22.693***	-22.703**
Virginia	-4.153***	-4.090**	-21.855***	-21.810**
Washington	-3.751***	-3.699**	-20.155***	-20.109**
West Virginia	-4.190***	-4.184**	-24.188***	-24.286**
Wisconsin	-4.908***	-4.870***	-29.668***	-29.727***
Wyoming	-5.375***	-5.317***	-30.630***	-30.482***
50 States Average	-4.026***	-3.976**	-21.906***	-21.797**

Note: ***indicates 1 percent significance level, **indicates 5 percent significance level and *indicates 10 percent significance level. §Model 1: $\Delta y_t = \alpha + \delta y_{t-1} + u_t$. §§Model 2: $\Delta y_t = \alpha + \beta t + \delta y_{t-1} + u_t$. †Model 3: $y_t = \alpha + \rho y_{t-1} + u_t$. ††Model 4: $y_t = \alpha + \beta t + \rho y_{t-1} + u_t$.

Table 8 – Unit Root Test Results in First Differences (Natural Logarithm)

	Dickey-Fuller Test		Phillips-Perron Test	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Alabama	-4.044***	-3.988**	-22.636***	-22.646**
Alaska	-5.669***	-5.518***	-25.521***	-25.053***
Arizona	-5.354***	-5.272***	-29.183***	-29.266***
Arkansas	-3.356***	-3.427*	-20.138***	-20.272**
California	-2.957***	-2.912	-16.638**	-16.398*
Colorado	-4.089***	-4.050**	-22.659***	-22.661**
Connecticut	-3.417***	-3.306*	-18.017**	-17.842*
Delaware	-4.066***	-4.024**	-23.136***	-23.318**
Florida	-3.081***	-3.020	-16.990**	-16.893*
Georgia	-4.599***	-4.510***	-25.747***	-25.693***
Hawaii	-3.470***	-3.389**	-19.681***	-19.502**
Idaho	-3.793***	-3.785**	-20.402***	-20.594**
Illinois	-4.370***	-4.327***	-25.371***	-25.392***
Indiana	-3.727***	-3.699**	-20.850***	-20.991**
Iowa	-3.934***	-3.921**	-22.557***	-22.821**
Kansas	-4.911***	-4.880***	-28.914***	-28.681***
Kentucky	-4.608***	-4.679***	-27.886***	-28.526***
Louisiana	-4.976***	-4.919***	-28.136***	-28.149***
Maine	-3.787***	-3.728**	-21.403***	-21.329**
Maryland	-3.524***	-3.457*	-18.153***	-18.048*
Massachusetts	-3.199***	-3.096	-16.982**	-16.546*
Michigan	-4.132***	-4.103**	-24.109***	-24.112**
Minnesota	-4.189***	-4.135**	-24.046***	-23.973**
Mississippi	-4.753***	-4.719***	-27.465***	-27.611***
Missouri	-4.336***	-4.294***	-24.620***	-24.544***
Montana	-3.891***	-3.844**	-19.953***	-19.957**
Nebraska	-4.621***	-4.551***	-27.164***	-27.175***
Nevada	-3.252***	-3.153	-18.355***	-17.846*
New Hampshire	-3.495***	-3.434*	-19.504***	-19.231**
New Jersey	-3.697***	-3.624**	-20.580***	-20.626**
New Mexico	-4.706***	-4.643***	-23.533***	-23.662**
New York	-3.681***	-3.615**	-20.266***	-20.202**
North Carolina	-3.836***	-3.778**	-20.988**	-20.904**
North Dakota	-5.833***	-5.685***	-34.076***	-34.002***
Ohio	-4.072***	-4.036**	-22.510***	-22.399**
Oklahoma	-5.594***	-5.519***	-31.703***	-31.632***
Oregon	-3.889***	-3.846**	-20.878***	-20.551**
Pennsylvania	-3.607***	-3.559**	-20.127***	-20.146**
Rhode Island	-3.032***	-2.982	-16.718**	-16.684*
South Carolina	-4.555***	-4.495***	-27.479***	-27.316***
South Dakota	-4.906***	-4.910***	-29.069***	-29.358***
Tennessee	-4.084***	-4.050**	-21.773***	-21.835**
Texas	-4.502***	-4.490***	-23.972***	-23.813**
Utah	-4.028***	-3.982**	-21.202***	-21.113**
Vermont	-3.860***	-3.782**	-20.348***	-20.270**
Virginia	-4.017***	-3.954**	-21.413***	-21.381**
Washington	-3.701***	-3.650**	-20.223***	-20.184**
West Virginia	-4.381***	-4.372***	-25.380***	-25.399***
Wisconsin	-4.772***	-4.733***	-29.266***	-29.309***
Wyoming	-5.083***	-5.028***	-29.104***	-28.931***
50 States Average	-3.749***	-3.701**	-20.239***	-20.117**

Note: ***indicates 1 percent significance level, **indicates 5 percent significance level and *indicates 10 percent significance level. §Model 1: $\Delta y_t = \alpha + \delta y_{t-1} + u_t$. §§Model 2: $\Delta y_t = \alpha + \beta t + \delta y_{t-1} + u_t$. †Model 3: $y_t = \alpha + \rho y_{t-1} + u_t$. ††Model 4: $y_t = \alpha + \beta t + \rho y_{t-1} + u_t$.

subsequently developed panel unit root tests mainly due to the criticism that the above tests have low power.

Panel Unit Root Tests Results

Proponents argue that the panel unit root tests overcome the low power of the DF and PP unit root tests due to the increased sample size.[16] In this section, we report results from the following panel unit root tests: Levin-Lin-Chu (2002), Breitung (2000; Breitung & Das 2005), Im-Pesaran-Shin (2003), Fisher-type test of Madala and Wu (1999) and Choi (2001) using ADF and Phillips-Perron-type individual unit root tests, and Hadri (2000) Lagrange multiplier tests. Since our objective in this paper is to shed light on the limits of panel unit root tests as opposed to developing any new method, we do not describe these tests here. Interested readers may refer to their original papers for details.

With regard to the regression specifications of the panel unit root tests that we use in our analysis, we take note of the following issues. First, we included panel means in Levin-Lin-Chu, Breitung, Im-Pesaran-Shin, and Fisher-type test using ADF, and Phillips-Perron-type individual unit root tests. Second, while the AR parameter was common in Levin-Lin-Chu and Breitung, it was panel specific in the Im-Pesaran-Shin and Fisher-type test using ADF, and Phillips-Perron-type individual unit root tests. Third, we did not include panel means and AR parameter in the Hadri (2000) Lagrange multiplier test. Fourth, we ran regression models for all panel unit root tests, including and not including a time trend. The results are presented in Table 9 for the original series and in Table 10 for their natural logarithmic transformation. In each of these tables, the top half reports results of panel unit root tests when the time trend was not included in the regression model and the bottom half reports results when the time trend was included in the regression model.

Consider the results in Tables 9 and 10. The test statistics from Levin-Lin-Chu, Breitung, Im-Pesaran-Shin, and Fisher-type test using ADF unit root tests reject the null hypothesis of a common unit root in the panel. In contrast, Hadri residual based LM test that reverses the null hypothesis rejects the

16 There are two different ways one can increase the sample size. For instance, one may use a longer time period of the same unit of observation (longer time series data), or, one may keep track of several units of observation over time (panel data). However, longer time series data may suffer from the problem of structural changes, while the panel data may suffer from the problem of cross-sectional heterogeneity. For applied economic research, which of the two is a bigger problem is not always clear (Maddala & Kim, 1998, p. 133).

Table 9: Panel Unit Root Test Results of Unemployment Rate at the State Level (Original Series)

Method	AR Parameter	Panel Means	Statistic	Probability	Number of panels	Number of Periods	Findings
No Trend							
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu Adjusted t^*	common	included	-12.2673	0.0000	50	41	Stationary
Breitung lambda	common	included	-6.7043	0.0000	50	41	Stationary
Null: Unit root (assumes individual unit root process)							
Im, Pesaran and Shin Z-t-tilde-bar	panel-specific	included	-4.3210	0.0000	50	41	Stationary
ADF-Fisher modified inverse chi-squared	Panel-specific	Included	20.0182	0.0000	50	41	Stationary
PP-Fisher modified inverse chi-squared	Panel-specific	included	6.3052	0.0000	50	41	Stationary
Null: No unit root (assumes common unit root process)							
Hadri Z-stat	-	-	24.9105	0.0000	50	41	Nonstationary
With Trend							
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu Adjusted t^*	common	included	-9.9285	0.0000	50	41	Stationary
Breitung lambda	common	included	-2.8505	0.0022	50	41	Stationary
Null: Unit root (assumes individual unit root process)							
Im, Pesaran and Shin Z-t-tilde-bar	panel-specific	included	-5.6443	0.0000	50	41	Stationary
ADF-Fisher modified inverse chi-squared	Panel-specific	Included	13.0614	0.0000	50	41	Stationary
PP-Fisher modified inverse chi-squared	Panel-specific	included	1.0607	0.1444	50	41	Nonstationary
Null: No unit root (assumes common unit root process)							
Hadri Z-stat	-	-	41.5069	0.0000	50	41	Nonstationary

Table 10: Panel Unit Root Test Results of Unemployment Rate at the State Level (Natual Logarithm)

Method	AR Parameter	Panel Means	Statistic	Probability	Number of panels	Number of Periods	Findings
No Trend							
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu Adjusted *t**	common	included	-12.7571	0.0000	50	41	Stationary
Breitung lambda	common	included	-7.1354	0.0000	50	41	Stationary
Null: Unit root (assumes individual unit root process)							
Im, Pesaran and Shin *Z-t*-tilde-bar	panel-specific	included	-3.4765	0.0003	50	41	Stationary
ADF-Fisher modified inverse chi-squared	Panel-specific	Included	20.8245	0.0000	50	41	Stationary
PP-Fisher modified inverse chi-squared	Panel-specific	included	5.0312	0.0000	50	41	Stationary
Null: No unit root (assumes common unit root process)							
Hadri *Z*-stat	-	-	23.6232	0.0000	50	41	Nonstationary
With Trend							
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu Adjusted *t**	common	included	-10.3808	0.0000	50	41	Stationary
Breitung lambda	common	included	-2.0998	0.0179	50	41	Stationary
Null: Unit root (assumes individual unit root process)							
Im, Pesaran and Shin *Z-t*-tilde-bar	panel-specific	included	-4.8214	0.0000	50	41	Stationary
ADF-Fisher modified inverse chi-squared	Panel-specific	Included	14.0380	0.0000	50	41	Stationary
PP-Fisher modified inverse chi-squared	Panel-specific	included	0.1532	0.4391	50	41	Nonstationary
Null: No unit root (assumes common unit root process)							
Hadri *Z*-stat	-	-	43.1699	0.0000	50	41	Nonstationary

null hypothesis of no unit root in any of the series in the panel in favor of a common unit root in the panel. However, results from Fisher-type using Phillips-Perron-type individual unit root tests are sensitive whether we include or do not include the time trend in the regression. When the time trend is not included, the results indicate that we reject the null hypothesis of unit root, but when the time trend is included, we do not reject the null hypothesis of a unit root.

Our findings are consistent with both groups of studies in the unit root literature: one that provides support for the US unemployment rate to be nonstationary such as Mitchell (1993), Breitung (1994), and Hatanaka (1996), and another that provides support for the US unemployment rate to be stationary such as Nelson and Plosser (1982), Perron (1988), Xiao and Phillips (1998), and Song and Wu (1997). These studies, including ours, imply that all unit root tests combined together allow researchers to make an argument for the unemployment rate, depending on the model chosen, to be either stationary or nonstationary. Thus, one cannot definitely answer whether the unemployment rate is stationary or nonstationary. This also explains why the empirical evidence on the unemployment rate remains inconclusive.[17]

Summary, Discussion, and Conclusion

The stationarity and nonstationarity time series properties of the unemployment rate have been extensively used in the literature to distinguish between the natural rate hypothesis vs. the hysteresis. In this paper, we reexamine these time series properties using a larger panel of the unemployment rate data from the United States at the state level that includes recessions of 2001 and 2007-2009, which have not been examined before. We begin our analysis using the most popular Dicky-Fuller and Phillips-Perron unit root tests. Because these tests are known to have low power, we extend our analysis to the use of subsequently developed more powerful panel unit root tests. These tests include Levin-Lin-Chu, Breitung, Fisher-type test using ADF and Phillips-Perron-type individual unit root tests, and Hadri Lagrange multiplier tests. Overall, the results indicate that depending on the regression model chosen, the unemployment rate can be proved stationary or nonstationary, supporting both the natural rate hypothesis and the hysteresis hypothesis.

17 Our findings reinforce the point made by Mark Blaugh some 40 years ago, "In many areas of economics, different econometric studies reach conflicting conclusions and, given the available data, there are frequently no effective methods for deciding which conclusion is correct. In consequence, contradictory hypotheses continue to coexist sometimes for decades or more" (1980, p. 245).

In our assessment, the unemployment rate brings to the fore a number of anomalies that have existed in the unit root literature. Below we will explain why reconciliation among economists holding opposite views with regard to the unemployment rate is unlikely.

Economists distinguish between two types of quantity variables: stocks and flows. Understanding the difference between them is crucial in avoiding confusion when analyzing the data. Stock is a quantity measured at a point in time, whereas flow is a quantity measured per unit of time. Stock and flow are related in that a stock is an accumulation of flows over time. It is only in this context that the argument put forward by Granger (1986) -- a time series that requires differencing d times to become $I(0)$ is said to be integrated of order d and is denoted $I(d)$, where the number d equals the number of unit roots in the characteristic equation for the time series (Said & Dickey, 1984, p. 599) -- makes sense. As such, these arguments justify continued use of testing for unit root to determine the order of integration of a series to the present day.

With regard to the unemployment rate, the term "rate" does not make the unemployment rate a flow variable. At any point in time, the number of people unemployed is a stock variable, whereas the number of people losing their jobs per unit of time is a flow variable. Dividing a stock variable by another stock variable does not convert the stock variable into a flow variable. The unemployment rate, defined as the number of people unemployed and looking for work divided by the labor force (the sum of unemployed plus employed) ($Unemployment\ Rate = \frac{Unemployed}{labor\ Force}$), is a level (stock) variable. Its rate of change (flow) is captured by the first differences. It would have been useful to determine whether the unemployment rate is stationary in level or in changes. However, all unit root tests that are currently in use in applied economic research are far removed from the real reason what they were initially designed to test.

Dickey-Fuller, Augmented Dickey-Fuller and Phillips-Perron tests, developed in the 1970s and 1980s, were supposed to determine whether a time series belongs to the difference stationary (DS) process or to the trend stationary (TS) process (Nelson & Kang, 1984; Hatanaka, 1996). Harvey (1997) questions the arbitrary distinction of a variable between the DS process and the TS process. As we noted in **Emperical Analysis and Results Section** at page 117 above, to scholars, researchers, and policymakers who debate whether to use a variable in a change specification or a log specification, the hypothesis of the unit root (ρ = 1) would be of some interest. If a variable strictly follows a pure random walk model, both specifications would be equivalent. To see why, define the percentage change of a variable from the previous period:

$$\Delta\% x_t = \frac{X_t - X_{t-1}}{X_{t-1}}$$

Now, define the first difference operator in the natural logarithmic form:

$$\begin{aligned}\Delta x_t &= (1-L) lnX_t \\ &= lnX_t - lnX_{t-1} \\ &= ln\left(\frac{X_t}{X_{t-1}}\right) \\ &= ln\left(1+\left[\frac{X_t - X_{t-1}}{X_{t-1}}\right]\right) \\ &= \frac{X_t - X_{t-1}}{X_{t-1}}\end{aligned}$$

where we use the fact that for x close to zero$(1+x) \cong x$ (Hamilton, 1994, p. 438). Thus, a variable in change specification achieves the same objective as using the variable in log specification. To date, this important distinction has largely been ignored by the proponents of unit root tests. Consequently, much of the discussion has been centered on the technical details over what should or should not be done to carry out unit root tests that have resulted in type III errors.[18] If the research design used in the data analysis is found to be flawed, the final outcome by all accounts remains questionable.

Above all, from the statistical hypothesis testing point of view, stationarity and nonstationarity time series properties of a variable are two mutually exclusive and collectively exhaustive events. This implies that if a variable, in our case the unemployment rate, is nonstationary, it cannot be stationary at the same time or vice versa. This fact, thus far, has not been even identified in the unit root literature. Interestingly, the methods developed to test for unit root allow researchers to have it both ways: if one wants a variable to be stationary, it can be proved stationary; and if one wants it to be nonstationary, it can be proved nonstationary. Thus, we cast doubt on the scientific validity of the methods used to achieve such results.

18 For a discussion of avoiding Type III, Type IV, and Type V errors through collaborative research, see Yamatani and Mann (2013)

We conclude this paper putting its contribution to the literature in the historical context. When studies compared the forecasting qualities in the 1970s and found out that the forecasts from the structural models predicted no better than the reduced form time series models, the structural models based on the Keynesian framework that were developed in the 1960s began losing confidence and the development of reduced form models based on the assumption of market-clearing approach gained prominence (Epistein, 1987; Greene, 2000, p. 748). Thus, the time period between the 1970s and the 1980s was partially responsible for the diminished enthusiasm in the Keynesian economic thinking, giving rise to the market-clearing approach to study the behavior of individual households and businesses including both short term business cycles and long term economic growth (Barro, 1997, preface). From the point of view of the history of economic thought, this period is an interesting time for a paradigm shift in economic thinking and merits further investigation, which we leave for the future research endeavor.

Declarations

Availability of data and materials

Data are publicly available from the official website of the US Bureau of Labor Statistics (BLS). The programming language and data files used in the analysis for this manuscript are available from the authors upon request.

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