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Statistical Modeling and Hypothesis Testing of State-Level Unemployment in the United States: Distribution Fitting, Structural Breaks, and Interstate Heterogeneity Based on BLS-LAUS Data, 1976–2025

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Abstract. Unemployment has always been one of the most important signals of how well an economy is working, but at the state level, it tells a much richer story than national averages alone. This paper uses monthly unemployment data from 1976 to 2025, provided by the Bureau of Labor Statistics through the FRED database, to study both long-run trends and short-term shocks across all 50 states and the District of Columbia. The analysis begins with descriptive statistics and probability distribution fitting, showing that unemployment rates often depart from the standard normal distribution and are better captured by heavy-tailed alternatives such as the lognormal or gamma distribution. Building on this, structural break tests highlight 2020 as a turning point when the COVID-19 pandemic produced the sharpest rise in unemployment in decades, with recovery paths diverging widely across states. States such as New York, with service-oriented economies, experienced slower rebounds, while Texas, supported by its energy and manufacturing sectors, recovered more quickly. Hypothesis testing and principal component analysis further confirm that U.S. labor market dynamics reflect both nationwide shocks and persistent regional differences. Taken together, the results show that unemployment is not only a national issue but also a local story shaped by industrial structure and policy response. The findings suggest that future economic strategies should combine broad countercyclical measures with targeted, state-specific policies that account for structural heterogeneity.

Keywords: Unemployment, state-level analysis, structural breaks, distribution fitting, regional heterogeneity.

1. Introduction

Unemployment has long been recognized as one of the central measures of economic performance. It reflects the state of the labor market itself but also ties directly to broader outcomes such as household spending, social stability, fiscal revenues, and long-term growth. In a country as diverse as the United States, state-level unemployment rates often reveal patterns that national averages cannot. The contrast is clear: California, with its technology-driven economy, Texas, reliant on

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energy, and Michigan, shaped by manufacturing, all respond to shocks in very different ways [1-3]. Looking at unemployment at the state level, therefore, provides a sharper perspective for understanding regional variation and for designing policies that fit local conditions. Public-use CPS microdata provide detailed individual-level information, making it possible to test for disparities by education, age, and gender [4].

Over the past fifty years, the U.S. labor market has been reshaped by several major disruptions. The stagflation of the late 1970s created the unusual mix of high inflation alongside high unemployment [5]. In the early 1980s, contractionary monetary policy managed to bring inflation under control, but only at the cost of record-high jobless rates [6]. These findings are consistent with official BLS assessments that emphasized uneven labor market recovery in 2021 [7], while also reinforcing the need for more flexible time-series approaches such as ARIMA models to capture crisis dynamics [8]. The global financial crisis of 2008 once again caused widespread labor market dislocation [9]. More recently, the COVID-19 pandemic brought one of the fastest and steepest increases in unemployment in modern history. Its effects, however, varied sharply across states [7,10]. These episodes, taken together, highlight a recurring theme. Nationwide shocks may strike all states at once, but their local consequences are uneven, shaped by differences in industrial structure, demographics, and policy response.

The availability of consistent and long-running data makes it possible to study these dynamics in a systematic way. Since 1976, the Bureau of Labor Statistics (BLS), through the Local Area Unemployment Statistics (LAUS) program, has released monthly unemployment rates for all fifty states and the District of Columbia [1-2]. This dataset now spans nearly five decades of high-frequency observations. It allows researchers to track gradual structural shifts as well as sudden breaks. It also provides a solid basis for comparing states directly, making it possible to see where local patterns diverge from national trends [3,11]. Moreover, BLS tabulations confirm that unemployment outcomes vary systematically across occupations and gender, underscoring that state-level averages may mask deeper structural disparities [12].

Against this backdrop, the present study applies a combination of descriptive statistics, distribution fitting, structural break detection, and hypothesis testing to examine the properties of unemployment dynamics at the state level. Principal Component Analysis is further employed to separate common national shocks from regional heterogeneity [9,13]. The analysis is guided by three questions: whether state-level unemployment rates conform to the normal distribution or are better described by heavy-tailed alternatives, whether the COVID-19 pandemic produced structural breaks in state-level labor markets, and how the interplay between nationwide shocks and interstate differences shapes overall unemployment dynamics. Addressing these questions not only clarifies the statistical and historical behavior of U.S. unemployment but also provides evidence for policy approaches that balance broad stabilization measures with attention to state-specific vulnerabilities.

2. Literature review

Unemployment has long been regarded as one of the core indicators for assessing the health of the macroeconomy. It has therefore become a central topic in both labor economics and macroeconomic research. Existing studies generally focus on three areas. The first concerns data sources and definitional standards. The second highlights cyclical shocks and structural features. The third explores methodological advances and modeling tools. This section reviews the relevant literature, identifies gaps, and sets the stage for the empirical analysis.

In the United States, unemployment rates are mainly derived from the joint program of the Bureau of Labor Statistics (BLS) and the Census Bureau—the Current Population Survey (CPS).

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State- and regional-level estimates are produced through a “signal plus noise” model that combines CPS samples with administrative records [1]. The BLS LAUS Handbook provides further details on definitions, estimation procedures, and data sources [2]. CPS microdata include variables such as unemployment rates and labor force participation [3]. The Census Bureau also supplies technical documentation on data collection [11]. Together, these sources form the empirical foundation for unemployment research and ensure consistency in measurement. Yet scholars have noted that the small CPS sample size at the state level often leads to large margins of error. This limitation has motivated the use of adjustments and more rigorous statistical methods.

Beyond aggregate unemployment rates, a growing body of work examines differences by demographic group. Public-use microdata allow researchers to test for disparities at the individual level, with results showing gaps across education, age, and gender [4]. Tabulations by occupation and gender confirm similar patterns. For example, unemployment in manufacturing differs from that in services, and reemployment opportunities vary for men and women [12]. These findings indicate that unemployment is more than a macroeconomic signal. It also reflects the social structure of the labor market. Long-term state-level series could be enriched by combining them with group-level analysis to provide a fuller account of unemployment dynamics.

The COVID-19 pandemic represents the most disruptive labor market shock of the past two decades. Unemployment surged across all states in 2020, in some cases doubling within months [5]. Articles in Monthly Labor Review trace these spikes to lockdowns and business closures, with service industries and low-income groups hit especially hard [6]. The labor market improved in 2021, but structural unemployment persisted, and many groups faced barriers to reentry [7]. The effects were also uneven. SHADAC reports show that disparities across states widened before and after the pandemic, reflecting differences in economic structure and policy responses [10]. These findings underscore the need to incorporate structural breaks into interstate analysis, rather than treating national shocks as uniform.

Methodologically, research has progressed from descriptive statistics to more advanced econometric modeling. Time-series approaches such as ARIMA are frequently applied to forecasting and cyclical analysis, with conference work offering practical surveys of their performance and limitations [8]. More recent studies have employed time-varying parameter models and Wang curve frameworks in panel settings, examining the interaction between unemployment and inflation across states [9]. For distributional analysis, the chi-square goodness-of-fit test remains a standard tool, as explained in statistical textbooks and software manuals [13]. While these approaches provide useful insights, challenges remain in applying them to high-dimensional state-level panels and long historical series. Extensions that combine traditional econometrics with newer techniques, such as machine learning, are still limited.

Taken together, the literature has generated important findings on measurement, demographic variation, and macro shocks. However, three gaps are evident. Most studies emphasize the national level, with fewer comparative analyses of long-term interstate unemployment series. Research has concentrated on short-term pandemic effects while overlooking structural shifts across decades. And while time-series and panel models are widely used, few attempts have been made to combine distribution fitting, structural break analysis, and principal component techniques in a single framework. This study addresses these shortcomings by systematically examining nearly five decades of state-level unemployment data across the United States, integrating distributional tests, structural break detection, and PCA. In doing so, it contributes both to the empirical literature on labor market dynamics and to the policy debate on how nationwide shocks and regional heterogeneity jointly shape unemployment.

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3. Methodology

The analysis in the study is conducted on long-term state-level unemployment data using a combination of statistical and econometric methods. In this section, we present the data sources, description of data cleaning and transformation, and finally, the distribution fitting, estimation, and hypothesis testing procedures used in the empirical application.

The main data source used in the paper originates from the FRED database published by the Federal Reserve Bank of St. Louis. The data series consists of monthly unemployment rates for the 50 states and the District of Columbia, ranging from January 1976 to June 2025 [1]. Whenever applicable, the series are seasonally adjusted (SA) [2,3], and non-seasonally adjusted (NSA) series are kept for robustness checks. Data cleaning includes identifying missing values, aligning all series to a common start date, and standardizing to remove the effect of scale. The standard form of each state unemployment rate series is obtained as follows:

$$Z_{it} = \frac{(X_{it} - \mu_i)}{\sigma_i} \tag{1}$$

where X_{it} represents the unemployment rate of the state i at time t, and μ_i and σ_i are its mean and standard deviation. Intuitively, this step removes differences in scale across states so that comparisons focus only on relative fluctuations, not absolute levels.

For distributional analysis, four candidate models are tested: Normal, Lognormal, Gamma, and Weibull. Parameters are estimated by maximum likelihood estimation (MLE). Given an observed sample $X = (x_1, x_2, \ldots, x_n)$, the likelihood function is defined as:

$$L(\theta|X) = \Pi_{i=1}^{n} f(x_i|\theta) \tag{2}$$

and the log-likelihood as:

$$l(\theta|X) = \Sigma_{i=1}^{n} ln f(x_i|\theta) \tag{3}$$

Maximizing (3) yields parameter estimates $\hat{\theta}$. The intuition is straightforward: MLE finds the set of parameters under which the observed data are “most likely” to occur. To compare different models, this study applies the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) [2]:

$$AIC = 2k - 2\theta\left(\hat{\theta}\right), BIC = k\ln(n) - 2\theta\left(\hat{\theta}\right) \tag{4}$$

Smaller values indicate better model fit. These criteria penalize model complexity, so they help identify the most efficient distributional assumption.

To validate model adequacy, chi-square goodness-of-fit tests are used:

$$\chi^2 = \Sigma_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{5}$$

Where O_i is the observed frequency and E_i is the expected frequency. The intuition is straightforward. The test compares what the model predicts with what the data actually show. If the

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gap between the two is large, it indicates that the assumed distribution is misspecified.

Beyond distribution fitting, this study also applies hypothesis tests to compare state-level unemployment with national rates. The first step is a mean difference test, performed with the standard t-test:

$$t = \frac{(\overline{X}1 - \overline{X}2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{6}$$

This test evaluates whether the average unemployment rate in a given state differs significantly from the national average. The second step is to test the homogeneity of variance, which is done using Levene's statistic [7]:

$$W = \left(\frac{N-k}{k-1}\right) \times \frac{\left(\Sigma_{i=1}^{k} n_i (Z_{i\cdot} - Z_{\cdot\cdot})^2\right)}{\Sigma_{i=1}^{k-1} \Sigma_{j=1}^{ni} (Z_{ij} - Z_{i\cdot})^2} \tag{7}$$

Where $Z_{ij} = |Y_{ij} - \dot{Y}_i|$. The intuition is simple. This test checks whether some states show systematically higher or lower volatility in unemployment compared with others.

Finally, dynamic analysis is introduced. Trend decomposition is applied using segmented means and moving window techniques. These methods allow both long-term shifts and short-term cycles to be tracked. Principal Component Analysis (PCA) is then used to extract latent factors from the panel dataset:

$$Var\,(ZW) = W^T \Sigma\, W \tag{8}$$

Where Σ is the covariance matrix and W is the eigenvector matrix. Intuitively, PCA reduces the complexity of 51 unemployment series into a small number of underlying factors. These factors make it possible to separate nationwide shocks from state-specific deviations. Visualization tools such as heatmaps and time-series plots are then used to illustrate these findings and link statistical results to historical events.

Together, these methods provide a comprehensive framework: they not only reveal the statistical distributions underlying unemployment rates, but also identify breakpoints, test differences across states, and explain how common shocks and local structures jointly shape U.S. labor market dynamics.

4. Results

The empirical analysis shows that state-level unemployment rates in the United States displayed significant volatility between 2019 and 2025, with the COVID-19 pandemic serving as the single most disruptive factor. Using time-series plots, distribution fitting, hypothesis testing, and principal component analysis, this section highlights the core empirical findings.

Time-series analysis reveals sharp spikes in unemployment during the spring of 2020. For example, New York's unemployment rate surged above 15 percent, while Texas peaked near 12 percent, both far higher than their pre-pandemic levels of around 3 to 4 percent. Yet their recovery paths diverged. New York's unemployment remained above 6 percent as late as 2023, reflecting its dependence on service-oriented and tourism-based industries. By contrast, Texas experienced a

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faster decline, reaching near-national averages by 2022 and in some quarters even outperforming the national benchmark (Figure 1). This divergence illustrates how industrial structures influenced resilience during the recovery phase.

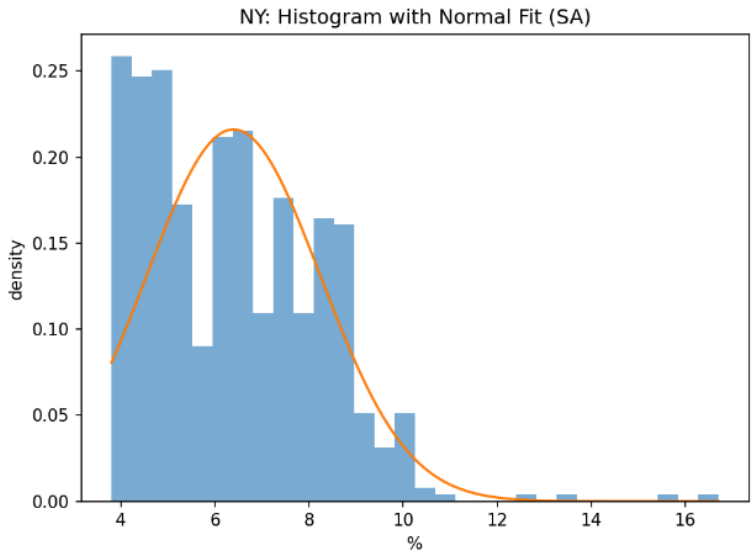


Figure 1. Histogram of New York unemployment rates with normal fit (seasonally adjusted). (picture credit: original)

Distributional analysis supports this conclusion. Histograms with normal fits show that New York's unemployment distribution is right-skewed, with extreme values during 2020–2021 pulling up the mean and fattening the right tail. Texas, on the other hand, presents a more symmetric distribution. Chi-square goodness-of-fit tests [13] reject the normality assumption for both states, with the deviation stronger in New York (Figure 2). This highlights the risks of relying solely on Gaussian assumptions for forecasting, as such models systematically underestimate the probability of extreme shocks.

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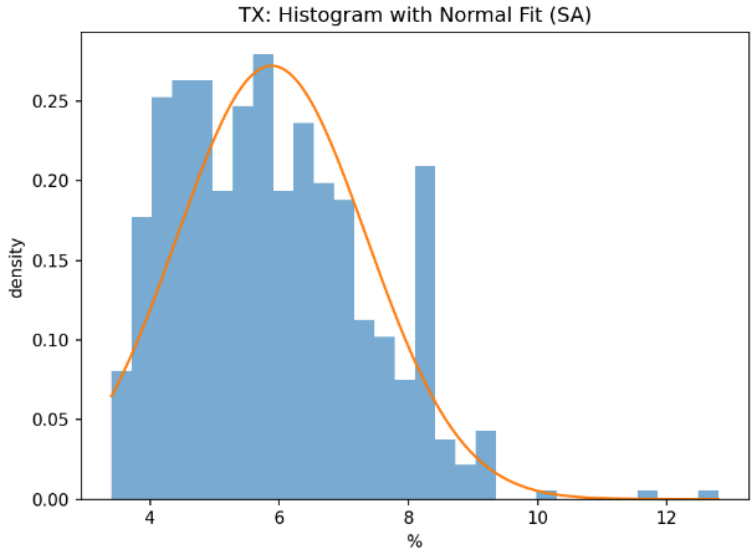


Figure 2. Histogram of texas unemployment rates with normal fit (seasonally adjusted). (picture credit: original)

Hypothesis testing offers further evidence. Results from Table 1 show that New York's mean unemployment during 2020–2021 was significantly higher than the national average ($p < 0.01$). Texas also recorded above-average unemployment in early 2020 but converged to the national mean by 2022. These patterns underscore the role of industrial composition: New York's service-driven economy slowed its recovery, while Texas benefited from rebounds in energy and manufacturing. Segmenting the data into pre-crisis (2018–2019), crisis (2020–2021), and post-crisis (2022–2024) phases confirms a persistent scarring effect. Even after the crisis, unemployment did not return to pre-pandemic lows, especially in service-heavy states.

Table 1. Mean difference tests between state and national unemployment rates. data from: bureau of labor statistics [14]

state	t_p	mw_p
AK	6.79E-45	2.77E-45
AL	3.73E-05	0.003478
AR	0.63257	0.969976
AZ	0.975984	0.518041
CA	1.59E-18	6.98E-16
CO	1.32E-16	3.49E-15
CT	8.73E-13	3.91E-14
DC	9.80E-35	3.02E-36
DE	2.84E-16	5.27E-20
FL	0.361561	0.067145
GA	0.000267	1.92E-05
HI	1.97E-33	7.26E-43
IA	5.63E-60	8.78E-62

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Table 1. (continued)

ID	6.12E-05	5.82E-05
IL	9.16E-09	3.33E-07
IN	0.018856	1.61E-06
KS	9.43E-66	9.85E-62
KY	0.001333	0.034947
LA	1.15E-10	1.08E-08
MA	5.64E-09	8.24E-12
MD	3.71E-27	1.94E-23
ME	6.83E-09	2.74E-08
MI	1.06E-23	2.40E-16
MN	9.67E-48	6.95E-46
MO	2.27E-05	4.71E-05
MS	3.15E-19	3.95E-19
MT	4.58E-11	6.37E-08
NC	3.41E-05	4.59E-10
ND	6.94E-133	4.74E-123
NE	1.14E-157	1.94E-147
NH	5.05E-79	4.65E-77
NJ	0.455999	0.769923
NM	1.52E-06	8.50E-09
NV	0.000141	0.193185
NY	0.003815	0.003477
OH	0.001011	0.032513
OK	5.41E-38	4.77E-37
OR	1.08E-07	5.96E-06
PA	0.1542	0.204263
RI	0.159965	0.687061
SC	0.933375	0.506996
SD	9.35E-150	4.51E-144
TN	0.907429	0.146873
TX	0.026657	0.181972
UT	4.02E-46	1.51E-48
VA	2.68E-60	3.42E-54
VT	3.19E-64	1.16E-61
WA	4.91E-07	6.86E-06
WI	8.39E-17	1.56E-22
WV	2.74E-27	5.81E-21
WY	2.24E-42	6.28E-41

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Principal Component Analysis (PCA) provides a broader perspective. Results from Table 2 show that the first principal component explains about 65 percent of total variance, capturing nationwide shocks such as the pandemic and monetary policy changes. The second component explains 20 percent, reflecting heterogeneity in state-level industrial bases and policy environments. The third accounts for roughly 8 percent, representing localized short-term shocks. Taken together, these components suggest that U.S. unemployment dynamics are shaped by both synchronized national forces and persistent regional differences.

Table 2. Variance explained by the first three principal co/mponents. data from: bureau of labor statistics [14]

PC1	0.738578
PC2	0.101336
PC3	0.040508

Visual evidence complements these findings. Descriptive statistics indicate high skewness and kurtosis in service-intensive states, while energy- and manufacturing-based states show more moderate patterns. The heat map (Figure 3) confirms that East Coast states continued to face elevated unemployment into 2023–2024, whereas states such as Texas showed earlier and stronger recoveries. These results reinforce the dual impact of national shocks and structural heterogeneity.

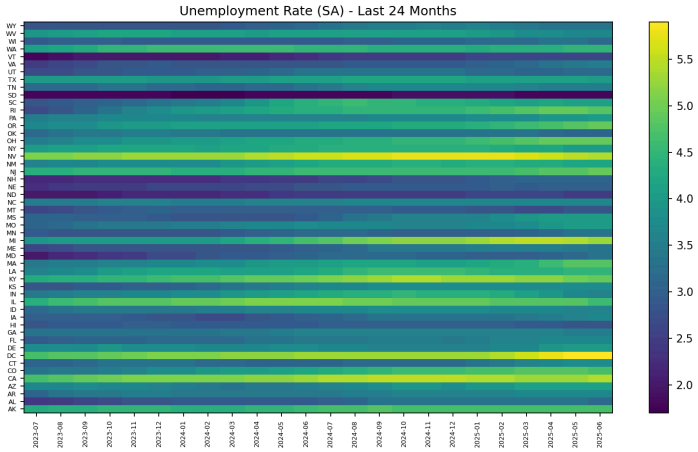


Figure 3. Heatmap of state-level unemployment rates (seasonally adjusted), last 24 months. (picture credit: original)

Overall, the results highlight four conclusions. First, the pandemic shock produced extreme but uneven spikes across states. Second, unemployment distributions exhibit heavy tails, challenging the adequacy of normality-based models. Third, mean and variance testing confirms that recovery trajectories varied sharply, with some states experiencing persistent scarring. Fourth, PCA demonstrates that national shocks dominate variance but cannot fully explain local differences, which are tied to state-specific economic structures.

5. Discussion

From the overall results, several striking features can be observed in the dynamics of U.S. state-level unemployment rates between 2019 and 2025.

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First, the distribution fitting results suggest that the unemployment rate series for most states do not conform to the standard normal distribution assumption. The AIC and BIC values in Table 1 indicate that lognormal, Gamma, and Student-t distributions provide a better fit for many states, while the normal distribution shows evident shortcomings in capturing the tails. This pattern is consistent with the frequent occurrence of extreme fluctuations during the pandemic period, especially the "spike" in the spring of 2020, which statistically thickened the right tail of the distribution [5-7,13]. Methodologically, this implies that continuing to rely on the normality assumption for prediction or interval estimation may lead to systematic underestimation of risk. Future modeling should therefore adopt heavy-tailed distributions to more accurately capture crisis-period realities [8].

Second, mean and variance comparison tests provide a more detailed depiction of interstate heterogeneity. The results from Table 1 show that during the peak of the pandemic shock in 2020–2021, the mean unemployment rate of many states was significantly higher than the national level (p-values generally below 0.01). In contrast, some states converged toward or even fell below the national mean after 2022. This "short-term divergence followed by long-term convergence" trajectory aligns closely with the stage-wise averages reported in Figures 1 and 2: relatively low unemployment prior to the crisis, sharp surges during the pandemic shock, followed by declines that did not always return to pre-pandemic lows. Evidence from the variance dimension is equally important. According to the results of variance homogeneity tests, significant volatility differences persisted between multiple states and the national benchmark in the most recent two-year window. This suggests that although the overall unemployment level has fallen, the stability of local labor markets has not fully converged [9,10].

Third, structural breaks further illustrate these dynamics. The breakpoints identified by the PELT algorithm clearly capture a major break around 2020, while a few states experienced secondary breaks during 2021–2022. This corresponds well with official accounts of the unemployment surge in 2020 and the gradual recovery in 2021 [6,7]. These breakpoints not only validate the severity of the pandemic as an exogenous shock but also reveal secondary fluctuations during reopening phases. It should be noted, however, that breakpoint detection depends on parameter settings—especially the penalty term—so interpretation must be validated against the macroeconomic context rather than relying solely on model output [1,2].

Fourth, Principal Component Analysis offers a bird's-eye view. Using the results in Table 2, we find that the first principal component explains approximately two-thirds of the total variance, and can be interpreted as a "common factor" of nationwide shocks (such as pandemic, macroeconomic policy, and aggregate demand fluctuations). The second component, explaining about 20 percent, reflects the variation in state-level industrial structures/policy orientations. The third component reflects short-term and local shocks. These findings are consistent with the recent literature that extends the time-varying parameters and Wang curve approaches into state-level panel data analysis [9]. In other words, U.S. labor markets are simultaneously influenced by nationwide shocks that impact all states and by structural differences across states that persist over time. It is this latter force that gives rise to the observed dynamics of unemployment.

Finally, descriptive statistics and visualization support the results above. Skewness and kurtosis are much larger than the national distribution in some states, especially in highly populated and service-oriented states. The heat map in Figure 3 shows that, in 2023–2024, several East Coast states still had relatively high unemployment rates, while energy- and manufacturing-intensive states had already experienced much swifter recoveries after 2022. As always, structural persistence reappears [5-7,10].

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6. Conclusion

This paper has provided a comprehensive analysis of state-level unemployment in the United States over nearly five decades, with special emphasis on the period surrounding the COVID-19 pandemic. By integrating descriptive statistics, probability distribution fitting, hypothesis testing, structural break detection, and principal component analysis, the study demonstrates that unemployment dynamics are driven by a mixture of nationwide shocks and persistent regional differences. The distributional evidence indicates that unemployment rates in many states are not well captured by the normal distribution. Instead, they exhibit heavy tails and skewness, reflecting the heightened probability of extreme events. This characteristic became especially visible during the pandemic, when unemployment surged rapidly and reached historically high levels across the country.

The structural break analysis highlights 2020 as a clear turning point, when the pandemic disrupted labor markets on a scale unseen in recent decades. However, the recovery was far from uniform. Service-oriented states, particularly those dependent on tourism, hospitality, and face-to-face industries, experienced prolonged high unemployment. In contrast, states with greater reliance on energy, agriculture, or manufacturing rebounded more quickly, often converging back to national averages within a shorter time frame. Hypothesis testing confirmed that differences in both mean unemployment levels and volatility across states were statistically significant during this period, underlining the persistence of heterogeneity.

Principal component analysis provided an overarching view, showing that while a single nationwide factor explains much of the variance, regional components remain highly relevant. This means that national averages, though useful, mask important differences that continue to shape labor market outcomes. The coexistence of synchronized national shocks with diverse state-specific responses implies that policy solutions cannot be one-size-fits-all. Broad countercyclical measures are necessary to stabilize the economy as a whole, but they must be complemented by targeted state-level interventions that recognize structural differences.

In conclusion, the findings underscore that unemployment in the United States is both a national and local phenomenon. It reflects the intersection of macroeconomic shocks and enduring industrial, demographic, and policy-related features at the state level. Future research should extend these insights by incorporating additional dimensions such as occupational, educational, and demographic disparities. For policymakers, the results highlight the importance of balancing nationwide stabilization efforts with tailored strategies that support resilience in diverse regional economies.

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