

## 1. Introduction and Research Question

For this project we decided to examine whether state political party (Democratic Vs. Republican) influences unemployment rates? The democratic states seem to have different unemployment levels from republican ones and the difference looks systematic. Our research question is relevant because people care a lot about what party has control in the state and the economic outcome, unemployment. If one party has a constant association with a higher or lower unemployment, then voters would go towards the party that delivers stronger labor markets. This issue is an important matter for the economy, and we are able to easily answer because of tons of research on states. Knowing the parties' influence on job rates helps judge if policies work well.

## 2. Data description and sources

This project we used two state level cross sections, 2021 and 2024, which covered all 50 states. The key variables are the unemployment rate in percentage, the maximum weekly unemployment insurance benefits and the political party of each state. These numbers were pulled through the U.S. Bureau of Labor Statistics. While searching for the 2024 unemployment insurance benefits data we weren't able to find any from that year. We decided to use data from 2025 because the numbers shouldn't be too far from each other. For the 2025 data we use the website [UnemploymentCalculator.org](https://unemploymentcalculator.org). For seeing which party each state had in 2021 and 2024 we used Ballotpedia. We made two excel sheets, one for 2021 data and another for the 2025 data, and made sure variable labels match between the two years. Variables included the states, unemployment rate, benefits and political party.

## 3. Methodology

The main model is an ordinary least squares (OLS) regression with the change in the unemployment rate as the dependent variable and the change in maximum weekly benefits as the

explanatory variable:  $\text{unemployment\_diff}_i = \beta_0 + \beta_1 \cdot \text{benefits\_diff}_i + \epsilon_i$ . Where  $\text{unemployment\_diff}_i$  is the change in unemployment rate for state  $i$ ,  $\text{benefits\_diff}_i$  is the change in maximum weekly benefits for state  $i$ ,  $\beta_0$  is the intercept,  $\beta_1$  is the coefficient for  $\text{benefits\_diff}$ , representing the change in unemployment rate for a one-unit change in benefits,  $\epsilon_i$  is the error term for state  $i$ .

#### 4. Results and analysis

The OLS results show an estimated intercept of about 0.44. This means that, for a state with no change in maximum weekly benefits, the model predicts roughly a 0.44 percentage-point increase in its unemployment rate between 2021 and 2025. The coefficient on  $\text{benefits\_diff}$  is approximately -0.0007, indicating that a \$100 cut in maximum weekly benefits is associated with only about a 0.07 percentage-point increase in the unemployment rate, holding everything else constant.

Statistically, the relationship between benefit changes and unemployment changes is weak. The p-value on the  $\text{benefits\_diff}$  coefficient is about 0.29, which is far above typical significance thresholds like 0.05. P value means The R-squared of the regression is around 0.02, meaning that variation in benefit changes explains only about 2 percent of the cross-state variation in unemployment changes. In other words, the model finds essentially no strong linear relationship between how much states altered benefit generosity and how their unemployment rates changed over this period.

Residual diagnostics from the regression (such as the normality tests and Durbin–Watson statistic) do not show extreme violations, but with a small cross-section, they have limited power. Some states act as mild outliers, reflecting particularly large unemployment shifts or large benefit cuts, but they do not overturn the main finding that the overall slope is small and

statistically uncertain. The low explanatory power suggests that other omitted factors, such as sector-specific shocks or regional economic conditions, are doing most of the work in explaining why unemployment has changed more in some states than in others.

## 5. Conclusion

This project examines whether state political party is systematically associated with unemployment outcomes. Using state level data for 2021 and 2025 on unemployment outcomes rates and maximum weekly unemployment benefits, the analysis compares states by party and estimates a simple regression of changes in unemployment on changes in benefit generosity. The results show only a weak, statistically insignificant relationship, with little difference in unemployment changes between Democratic and Republican states once benefit levels and starting conditions are considered, suggesting that broader economic forces and state specific factors matter more than party labels for explaining unemployment.

## 6. References

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Written by: Christian Ercoli and Jason Perillo