

The Impact of Lifting Stay-at-Home Orders on Local Unemployment Rates in the United States During COVID-19 Using Arizona and California as comparison

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Abstract. Facing the pandemic, the local governments of the United States have implemented different measures against the spread of COVID-19. These measures severely hit the labour market. The paper focuses on the effect of lifting the stay-at-home Order on the region-level unemployment rate. Two neighbouring states, Arizona and California are chosen as the treatment group and the control group. The paper used the DID method to study the policy's impact on the unemployment rate given that Arizona and California had different opening timelines. Three models with different specifications are developed. The result shows that lifting of the stay-at-home Order has significantly reduced the unemployment rate in the regions in Arizona by 1.962 percent. The result also shows the heterogeneity of the treatment effects across time. The policy's influence gradually increased in the first 3 months and faded away after the first 16 months. The paper then provided possible explanations for such observations.

1 Introduction

The COVID-19 pandemic triggered an unprecedented global crisis, leading to widespread lockdowns, economic instability, and significant disruptions in the labour market. The U.S., for example, has over one hundred million confirmed cases of COVID-19 and over one million deaths, ranking it as the 17th highest per capita worldwide [1].

In response to this unexpected disaster, U.S. state and local governments-imposed lockdowns, public gathering spots and school closures, emergency declarations, and other measures to slow the virus's spread [2]. While these measures were crucial for public health, they also caused severe economic consequences, including increased unemployment rates and heavy losses in retail, hospitality, and personal services sectors. One of the policies implemented across most states was the stay-at-home Orders, which reduced the risk of disease transmission by limiting interpersonal contact.

Although the stay-at-home Orders made obvious progress by decreasing factors associated with movement by 6%- 7%, states faced the challenge of deciding when and how

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to lift these restrictions [3]. Furthermore, reopening strategies and timelines varied significantly across states [4], raising a key question: How effective was lifting the stay-at-home policy in reducing the unemployment rate?

This paper will focus on the question mentioned above by comparing two neighbouring states – Arizona and California – which adopted very different reopening timelines. Arizona lifted its stay-at-home order earlier than California, on May 15, 2020, while California maintained restrictions alongside phased opening until June 15, 2021 [2]. This stark contrast in policy timelines creates a natural experiment for analysing the economic effects of reopening.

Using a Difference-in-Difference (DID) approach, this study examines unemployment data from 26 regions in California and 7 regions in Arizona from 2019 to 2022. By analysing unemployment rates and labour force participation data, the study aims to offer evidence-based insights into the economic impacts of reopening policies.

The findings will contribute to the growing body of research on the economic impacts of COVID-19 policies. They aim to guide governments and policymakers in navigating future crises and balancing economic recovery with public health priorities. This study underscores the importance of data-driven decisions and highlights how regional policy differences can lead to distinct economic outcomes.

2 Literature Review

Relevant research have been done to investigate the economic consequences of COVID-19 policies through methods such as event study, heterogeneity analysis, DID approach, etc. For example, a study from IRLE (Institute for Research and Labor Employment) used the above methods and came to the conclusion that stay-at-home orders drove early COVID-19 unemployment spikes, increasing unemployment insurance (UI) claims by 1.9% of employment levels each week, totalling 4 million claims (23.5% of total UI claims) between March and April 2020 [5]. Another study of Béland et al. shows that in-person industries like recreation and retail were worst hit, while remote-capable sectors were less affected [6].

A state-level study has also been done by the UC Berkeley Labor Centre, named COVID-19 Series: Resources, Data, and Analysis for California. The series shows that for every 100,000 people losing jobs, up to 67,000 might lose job-based health care, underlining California workers' vulnerability during the epidemic. Front-line critical workers were more exposed to COVID-19. They were mostly in low-wage jobs, and about 80% of these jobs did not offer remote work [7].

However, current research mostly focuses on the impact of the initial implementation stage of stay-at-home orders, and there is relatively little exploration of the impact on local unemployment rates in the United States after the cancellation of stay-at-home orders. This study focuses on the specific impact of lifting home stay orders on unemployment rates, and conducts in-depth exploration by analysing regional data of Arizona and California lifting stay-at-home orders at different time points.

3 Modelling

3.1 Data

The dataset for this investigation is from the Local Area Unemployment Statistics by the U.S. Bureau of Labor Statistics [8]. The dataset contains the unemployment rate and size of the labour force, in 26 regions in California and 7 regions in Arizona for each month from 1976 to 2024.

3.2 Method

The Difference in Difference method is used to study the effect of lifting the stay-at-home order on the unemployment rate. Areas in Arizona that experienced an earlier lifting of the stay-at-home order in May 2020 will be in the treatment group. In contrast, areas in California, where the policy ended later with a phased reopening in June 2021, will be in the control group. Given that the two states are neighbours, the parallel trend assumption is likely to hold.

The paper uses an event study model, which is model (3), to test the parallel trend assumption. In Figure 1, the dependent variable is the unemployment rate for regions in California and Arizona from 2019 to 2022. The estimates are based on a model that accounts for the periods before, during, and after the stay-at-home order was lifted. The horizontal axis shows the time relative to the treatment, where -2 represents two months before the treatment. The vertical bands represent ± 1.96 times the standard error of each point estimate, indicating the uncertainty around the estimates.

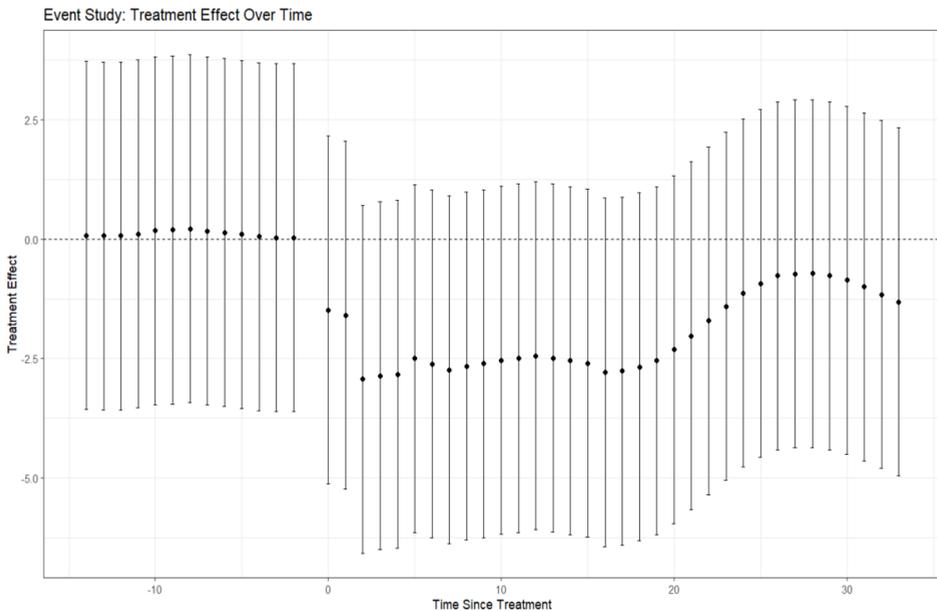


Fig. 1. Result of Model (3): Treatment Effect over time.

The difference in the timing of lifting stay-at-home orders creates a quasi-experiment. Using the DID method allows for the estimation of the causal effect of lifting the stay-at-home order on unemployment rates.

The DID approach will be used in three different models. The first one is without covariate, portrayed below:

$$Y = \beta_0 + \beta_1 D_{post} + \beta_2 D_{Tr} + \beta_3 D_{post} D_{Tr} + e \quad (1)$$

Y represents the unemployment rate of a region in a given month. The variable D_{post} is a dummy variable indicating whether the observation occurred after May 2020, with $D_{post} = 1$ for months after the intervention, and $D_{post} = 0$ otherwise. The variable D_{Tr} is a dummy variable for the treatment group, where $D_{Tr} = 1$ for Arizona, which lifted the stay-at-home order earlier, and $D_{Tr} = 0$ for California, which lifted the order later. The interaction term $D_{post} D_{Tr}$ is the key DID estimator, capturing the causal effect of the lifting of the stay-at-home order on unemployment rates. Finally, e is the error term.

The second model with covariate is portrayed below:

$$Y = \beta_0 + \beta_1 D_{post} + \beta_2 D_{Tr} + \beta_3 D_{post} D_{Tr} + \beta_4 X + e \quad (2)$$

X represents a control variable, which is the size of the labour force.

The third model is portrayed below:

$$Y_{ist} = \gamma_s + \lambda_t + \sum_{\tau=0}^m \delta_{-\tau} D_{s,t-\tau} + \sum_{\tau=1}^q \delta_{+\tau} D_{s,t+\tau} + X'_{ist} \beta + \epsilon_{ist} \quad (3)$$

The unit of observation, i , is region. For example, San Francisco-Oakland-Hayward. The level of aggregation, s , at which treatments are assigned is state. For example, California. The time period, t , can be 202205 (Year 2022, May). λ_t represents time-fixed effects and γ_s represents group-fixed effects. The term $D_{s,t+\tau}$ denotes dummy variables indicating whether the treatment occurred τ periods ago. For example, if the treatment was active two periods ago, $D_{s,t+2} = 1$, and all other $D_{s,t+\tau}$ values will be 0. The coefficient before $D_{s,t+\tau}$ represents the treatment effect for the τ th period after the intervention. There are m pre-treatment periods and q post-treatment periods in total. If $D_{s,t-\tau}$ is 1, then the treatment is active τ periods later. X'_{ist} represents a control variable. The model uses $\beta_{-\tau}$ to test for the presence of pre-treatment trends, while $\beta_{+\tau}$ is used to analyze the dynamics of the treatment effect after the policy intervention. This model allows for different treatment effects at different time periods. The model is inspired by previous works of Angrist and Pischke [9] and Granger [10].

4 Findings and evaluation

Table 1. Results of Model 1 and Model 2

	Dependent variable Unemployment rate	
	(1)	(2)
Post	2.224***	2.596***
	(0.263)	(0.256)
treatment	1.008**	0.163
	(0.494)	(0.461)
Labor force		-0.00000**
		(-0.00000)
Personal income		-0.002***
		(0.0001)
Post: treatment	-1.986***	-1.962***
	(0.570)	(0.529)
Constant	5.724***	11.135***
	(0.227)	(0.367)

Observations	1584	1440
R2	0.046	0.230
Adjusted R2	0.044	0.228
Residual Std. Error	4.016 (df=1580)	3.676 (df=1434)
F Statistic	25.270*** (df=3; 1580)	85.773*** (df=5; 1434)
Note:	*p<0.1 **p<0.05 ***p<0.001	

In Table 1, column (1) represents the results generated from the first model, and column (2) represents the second model. Comparing columns (1) and (2), the estimates are similar, indicating that the results are robust to the inclusion of the additional covariate.

From column (2), it is evident that lifting the stay-at-home order in Arizona led to a significant reduction in the unemployment rate by 1.962 percentage points. The estimated treatment effect is significantly different from zero and negative, suggesting that lifting the stay-at-home order helped reduce the unemployment rate in Arizona.

These results suggest that earlier reopening policies may reduce unemployment by allowing businesses to resume operations sooner, which may be particularly relevant for future policy decisions in similar circumstances.

However, there are also certain limitations. The DID estimator shows the treatment effect only for Arizona. It is not clear if these results can be applied to other states. To check if similar effects happen in other states, repeating the DID analysis with data from those states can be helpful. There is also concern about the spillover effect since it is unclear if Arizona's decision to lift the stay-at-home order influenced the unemployment rate in California. Additionally, the general equilibrium effect should also be aware of. When more states lift their stay-at-home orders at the same time, the impact of lifting the order on unemployment rates may change.

Furthermore, both models (1) and (2) assume that the treatment effect is constant over time. This overlooks how the impact of the treatment may change over time. Hence, the third model is used for further investigation, to see if the treatment has different effects at different periods. Fig.1 shows the estimated impact of lifting the stay-at-home order on the unemployment rate by using the third model.

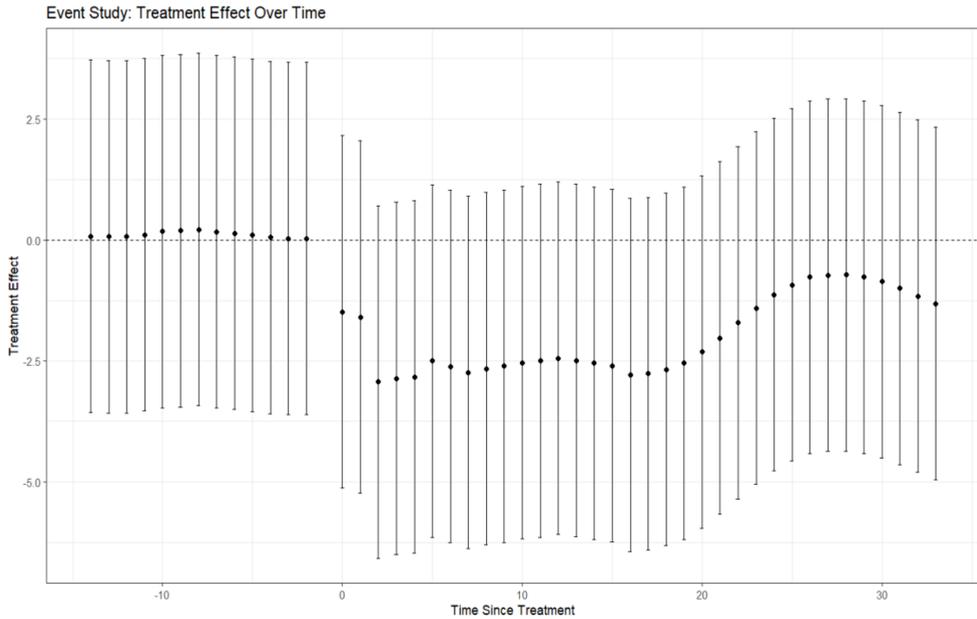


Fig. 2. Result of Model (3): Treatment Effect over time.

In Figure 2, the confidence intervals for treatment effects before time zero (the period when the treatment happened) all include zero, meaning there was no significant effect of the treatment before it was applied. This supports the parallel trend assumption. After the policy was implemented (on the right side of the graph), the point estimates of treatment effects are mostly below the zero line, showing a potential negative impact on the outcome. The effect gets stronger in the first 3 months after the treatment but eventually starts to decrease over time. It should also be noted that the confidence interval for the treatment effects after the policy includes zero, so the results are not statistically significant. If the research obtains a larger amount of data, the result may be improved.

Several factors may explain why the treatment effects become stronger in the first three months after the stay-at-home order was lifted. Firstly, finding a job takes time. Although reopening creates many new jobs, people need time to search for information. Thus, the vacant positions will be filled gradually and the treatment effect will increase gradually. Secondly, as businesses in Arizona reopen and the economy gradually recovers, more job opportunities become available. Over time, the availability of jobs increases, which contributes to the growing treatment effect. Lastly, some individuals who returned to the labour market initially may drop out of the labour market over time, which further increases the treatment effect.

However, the treatment effects faded after the first 16 months, as seen in the convergence of the treatment effects to 0. California, the control group, adopted a partial reopening strategy and adjusted its stay-at-home order in November 2020 [2]. This means the control group can be considered as receiving the treatment partially at later time periods. As more businesses reopened over time, the control group experienced increasing exposure to the treatment, which led to the estimated treatment effects converging to 0.

5 Conclusion

This research uses three DID models to study the treatment effect of lifting stay-at-home order on the unemployment rate, using data from regions in Arizona and California. The first

two models both show significant results. This means that lifting the policy does reduce the unemployment rate. The result of the event study method (3rd method) supports the parallel trend assumption. However, the treatment effects after the treatment occurred are not statistically significant. The research also lists possible limitations in general equilibrium effect, spillover effect and external validity. Further research is needed for a more comprehensive evaluation. For instance, using data from other states could offer a broader perspective on whether these results hold in different states.

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