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Economic resilience in times of public health shock: The case of the US states

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**A B S T R A C T**

Does adopting social distancing policies amid a health crisis, e.g., COVID-19, hurt economies? Using a machine learning approach at the intermediate stage, we applied a generalized synthetic control method to answer this question. We utilize state policy response differences. Cross-validation, a machine learning approach, is used to produce the “counterfactual” for adopting states—how they “would have behaved” without lockdown orders. We categorize states with social distancing as the treatment group and those without as the control. We employ the state time-period for fixed effects, adjusting for selection bias and endogeneity. We find significant and intuitively explicable impacts on some states, such as West Virginia, but none at the aggregate level, suggesting that social distancing may not affect the entire economy. Our work implies a resilience index utilizing the magnitude and significance of the social distancing measures to rank the states’ resilience. These findings help governments and businesses better prepare for shocks.

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1. Introduction

The onset of COVID-19 in 2020 triggered a global catastrophe on human life and business, not seen in generations. Several policies have been adopted to address the massive economic disruption and avoid a potential meltdown from spiraling. This research aims to assess the impact of one such measure, i.e., social distancing, for the US economy. The proposed policies quickly became political football, polarizing the entire nation. Several arguments have been made against this measure. To help readers understand the nature of the views expressed, we cite some of them here. They were quickly characterized as overreactions, reflective of panicked group thinking. As Yinon Weiss said, “The collective failure of every Western nation, except one, to question group think will surely be studied by economists, doctors, and psychologists for decades to come.”

Rahn of Cato Institute stated, “Most of those in the 65-plus age who die are among the oldest, 80 and above, with underlying conditions, and who have a very short additional life expectancy. So, why .... Shut down the entire economy to lengthen the average lifespan of the oldest Americans by a few months at most?”

Conservatives contend that lockdown measures

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1 See [https://www.realclearpolitics.com/articles/2020/05/21/how fear groupthink drove unnecessary global lockdowns 143253.html](https://www.realclearpolitics.com/articles/2020/05/21/how fear groupthink drove unnecessary global lockdowns 143253.html).

2 See [https://www.washingtonpost.com/news/2020/04/13/stop-the-covid-19-shutdown-madness/](https://www.washingtonpost.com/news/2020/04/13/stop-the-covid-19-shutdown-madness/).
are economically cost-inefficient. Others saw top-down measures as an infringement on first amendment rights—an abuse of power. They point out that this one-size-fits-all response not only dispossessed people of their free choices, but also intensified mistrust in a nation that is already deeply divided (J.D. Tuccille). Some argue that lockdown/stay-at-home orders as a remedy have negative economic and social effects and are thus worse than the disease (C. Friedersdorf, Gov. K Ivey, and G Mullen.) All of these views were considered strong. Curiously, these views were being ventilated at a time when things were really looking miserable for everyone and the US economy. In an effort to describe the situation, we briefly narrate the immediate impact of COVID-19 for readers to offer a background idea of what prompted policymakers to choose the social distancing measure. In the absence of any clear idea on what can be done to address the unknown COVID-19 and the associated crisis it brought about when we needed unity to face a national crisis of this magnitude. The COVID-19 infections and its rapid spread led to a 20% decline in global demand for agricultural commodities as early as March 20, 2020. It transpired that something had to be done. It appeared that the contagion was caused by close contact, implying a need to restrict movement. The initial economic toll was caused by a reduced demand for restaurant services. Many thought that government-mandated measures made matters worse, causing profound negative implications for the meat, dairy, and other perishable commodities market. While retaliatory economic statecraft between Russia and Saudi Arabia was blamed to be partially behind it, nonetheless, it was the biggest price drop in a single day on March 23, 2020 in nearly three decades, when Brent Crude dropped by 24%.

The manufacturing sector was no exception. The British Plastics Federation (BPF) carefully examined the data to test how the industry suffered from the COVID-19 outbreak. In a survey, they found that over the next two quarters, more than 80% of respondents anticipated a decrease in turnover of the implementation of the policy, and 98% expressed concern over the negative impact. In the US, the SP 500, Dow Jones Industrial Average, and NASDAQ all fell drastically and continued until the US government passed the Coronavirus Aid Act. Equity market indices rose by 7.3%, 7.73%, and 7.33%, respectively. Similar patterns were observed in the Asian and European markets. The 10-year US Treasury bond yields saw a sharp drop of 0.67%, to offset the negative effects of COVID-19 on markets, central banks across the world intervened with whatever means was considered feasible. Analysts compared such spending by the government to the post-Napoleonic, pre- and interwar era, where public liabilities rose exponentially.

Given that all the states employed varying levels of public safety response to face the raging pandemic, the lingering questions are: Did the early adopters sustain greater economic losses compared to those that did not? Did their economy perform better on average, relatively, as a result of their action? Our results suggest that despite a significant initial negative macroeconomic impact, it disappeared. Our study contributes to the literature in several ways, including methodological breakthroughs and innovative applications. Clearly, it is the first of its kind in the annals of economics and, in particular, in assessing the economic impact in the COVID-19 literature. Curiously, the merits of this methodology are still poorly understood in economic inquiry. Our approach is likely to lead to its further application to other economic topics and perhaps beyond. We implement the generalized synthetic control method (GSCM) to assess the impact of a shock, such as the lockdown order, on an economy, as in this case. As stated, the approach appears very broad in scope, with the potential for application to economics and other areas of inquiry. Its strength lies in the simplicity of its explanation of complex issues. However, it failed to find a hospitable home in economics, despite its ability to penetrate deeply into the domain of data analytics. We believe that this work will bring promises for potential spearheading a pathway for further application, even though it is not yet appreciated. From a policy perspective, the findings suggest that the measures failed to meet the desired efficacy overall, and policymakers are less likely to face hostility in pursuing social distancing, which might help to lessen controversy. When results from scientific studies suggest that a policy can be helpful in hindering the spread and assuaging adverse effects on an economy, it may be better appreciated by the general public. As for preparedness for future crises, the GSCM seems appropriate in this case because of its ability to help determine the influence of a shock such as the lockdown order—pre and post. Importantly, the GSCM uses a less restrictive set of assumptions compared to the traditional

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3 See https://rb.gy/akly9w.
4 US Attorney General William Barr, William Stickman IV, US District Judge, Saundra McDowell, David Hudson, Scott Rasmussen and Craig Northcott, Charles Stimson, and Gian Carlo Canaparot 5.
5 See https://tinyurl.com/2tnoc4z.
6 See https://www.theatlantic.com/ideas/archive/2020/05/take-shutdown-skeptics-seriously-61419/.
7 See shoturl.Lat/nxB0H.
8 See shoturl.Lat/txT37.
9 Prices of agricultural commodities drop 20% post COVID-19 outbreak - reffid Realtime News. Available at: https://economictimes.indiatimes.com/news/economy/agriculture/prices-of-agricultural-commodities-drop-20-post-covid-19-outbreak/articleshow/74705537.cms.
10 “There is no escape”: stocks, oil, and bitcoin plunge as US lawmakers fight over coronavirus rescue package. Available: https://markets.businessinsider.com/news/stocks/no-escape-stocks-oil-bitcoin-plunge-senate-argues-coronavirus-bill-2020-3.
11 Plastics trade body publishes first study of coronavirus impact on UK manufacturing. Available from: https://www.bpf.co.uk/article/plastics-trade-body-publishes-first-study-of-coronavirus-impact-1602.aspx.
12 Sources: https://www.marketwatch.com/investing/index/spx; https://www.marketwatch.com/investing/index/djia; https://www.marketwatch.com/investing/index/comp.
13 10 Year Treasury rate https://ycharts.com/indicators/10 year treasury rate.
14 T. Buck, M. Arnold, G. Chazan, C. Cookson, Coronavirus declared a pandemic as a fear of economic crisis. [Internet]. [cited 2020 March 19]. Available from: https://www.ft.com/content/d72f1e54-6396-11ea-b3f3-f4680ea68b55/2020).
15 The economic impact of coronavirus: analysis from imperial experts imperial news imperial College London, [Internet]. Imperial News, [cited 2020 Apr 6]. Available from: https://www.imperial.ac.uk/news/196514/the-economic-impact-coronavirus-analysis-from/.
approach—the difference-indifference (DID) method—thus results are expected to prove more reliable and robust. The policy has been applied broadly across the US, but the experience thus far points to limited success in some aspects; thus, more is needed to be done. We expect these findings to help avoid political polarization and divisiveness, a much-needed call for the day. As for household, business, and policymaking circles, they will be able to make decisions using educated and data-driven guesses of the “what if” kind of situation—the counterfactual scenario. It is fair to assume that states that adopted a lockdown/stay-at-home order (SHO) should have favorable economic outcomes. We take the position as valid to begin with, but there is more than one way of looking at it. States adopting the measure may have contained the spread of the virus and thus helped their economies indirectly relative to the control group, which might have been affected in a negative way. Once we estimate the impact on the economy and identify the factors, we expect to verify whether businesses that prioritized resources to face the crisis can help us to zoom in to the adopting states and rank them according to the severity of the impact. The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 discusses the data sources and empirical strategy. Section 4 reports and discusses our results. Section 5 summarizes and concludes the paper with a note on the limitations of the study and directions for future research.

2. Literature review

Research on the topic of COVID–19 sits at the juncture of the literature on state, local, and national non-pharmaceutical interventions (NPI) spillovers, vis-à-vis the ongoing inquiry into the impact of policy interventions warranted by the onset of the pandemic. Several studies have suggested that spillovers are possible from a theoretical perspective. (Bethune and Korinek (2020)) document that externalities play a significant role in restricting intentional self-isolation due to COVID–19 because the consequences of individual decisions on overall risk are not internalized. If municipal governments are involved, a similar procedure is in place to decide to implement NPI in neighboring jurisdictions with a potential spillover effect on the late entrants. Cui et al. (2020) developed a model to examine the effect of one state’s policy on another. When several states adopt social distancing, they can tip others to follow through in terms of the number of states participating in expensive social distancing, and Nash equilibrium exists. The degree of social and economic integration between countries determines whether spillovers are considerable (Beck and Wagner, 2020). Coven et al. (2022) investigated pandemic inter-county mobility shifts by focusing on long-term mass departure and rehabilitation across places as a result of a local epidemic. When special policies are created to mitigate this issue, the aim is to adjust short-term intra- and inter-county movements. Elenev et al. (2020) empirically show that there are significant spillovers between US counties that take place in a manner similar to the direct effect. Our research is partly informed by recent studies on movement during the COVID–19 outbreak in the United States. However, we consider states, even though our approach is different and much broader. Lin and Meissner (2020) assessed the impact of state-level SHOs, including neighboring states. They found that the differences in projections between the two methods are attributable to the occurrence of certain spillovers. These articles highlight a minor effect (Brodeur et al., 2021, Gupta et al. 2020, and Avery et al. 2020) for scholarly evaluations of the early stages of a pandemic, as well as the NPI impact evaluation). They discover an effect of SHOs on county mobility that appears to be consistent with a bias resulting in beneficial spillover effects on surrounding counties, which are employed as controls for direct policy effects. Holtz et al. (2020) investigated SHO spillovers to uncover NPIs’ average impact of NPIs on mobility across the entire country, whereas others focused on unbiased estimates to identify processes devoid of selection and other biases.

The econometrics literature posits that estimates may be skewed because of spillovers. Abadie et al. (2010) implemented a synthetic control method to evaluate tobacco control programs. Caod and Dowd (2019) document that direct treatment effects may be skewed because of spillovers. Kalenkoski and Lacombe (2013) show that the analysis of changes in the minimum wage, for example, Card and Krueger (2000), might suffer from bias. Kibria et al. (2021) applied machine language to predict the rapid rise in diabetes using a model to diagnose diabetes efficiently. They applied logistic regression, SVM, and k-nearest neighbor (knn) algorithms to classify diseases and predict them efficiently. Their algorithms showed good results. For the test data, the logistic regression provided the highest accuracy of 83 percent. SVM and knn both performed well, with accuracy rates of 82% and 79%, respectively. Compared with previous findings, the model produced better outcomes. They pointed to the ease of extracting information from available data, developing a new model, and obtaining better outcomes. This approach has a wide range of applications. This method is popular and can be applied to other areas.

Many studies have found ramifications of local policy deriving primarily from mobility, such as competition effects in which local jurisdiction-based programs compete with welfare measures in adjacent places (Baicker, 2005; Isen, 2014). According to Blattman et al. (2017). Expectations in neighboring jurisdictions for policy implementation and applications (Galletta, 2017). Hanson and Rohlin (2013) demonstrate the use of neighboring regions as policy assessment controls, which have been studied for labor deregulation policies in Holmes (1998), banking policies in Huang (2008), and crime prevention policies in Blattman et al. (2017). Several studies have focused on outcomes that remove surrounding locations from place-based strategies to alleviate such issues Kline and Moretti (2014).

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16 Logistic regression produced accuracies of 83% for test data. SVM and knn performed well showing an accuracy of 82% and 79%, respectively and produced better results compared to previous ones.
3. Data and methodology

3.1. Data

The data used in this study were primarily collected from several sources, as enumerated below. The series we consider are listed separately under the heading of the list of variables.

Coincidence Index: The Federal Reserve Bank of Philadelphia developed this index (Crone and Clayton-Matthews, 2005),\(^{17}\) which combines four state-level variables to describe current economic circumstances in a single figure for the 50 US states. Nonfarm jobs, mean manufacturing work hours, unemployment rate, and wage and salary disbursements deflated by the consumer price index are the four state-level indicators (US city average). Each state’s index was designed to follow the national GDP trend.

Community Mobility: We used a number of variables from Google’s community mobility report (Google LLC),\(^{18}\) which measures modifications for each weekday and compares them to a baseline for that day:

During the 5-week period, January 3–February 6, 2020, the baseline was the median value for the corresponding day of the week.

The datasets illustrate trends over several months, where the most current data reflect the previous 2-3 days—the time needed to generate the datasets.

The list of variables is Grocery and pharmacy: Grocery stores, food warehouses, farmers’ markets, specialist food shops, pharmacy stores, and pharmacies have high mobility rates. Parks: Local and national parks, public beaches, marinas, dog parks, plazas, and public gardens have high mobility rates.

Transit stations: Mobility trends for public transportation hubs such as subways, bus stations, and railway stations. Retail and recreation: Restaurants, cafés, retail malls, theme parks, museums, libraries, and movie theaters have a proclivity for mobility.

Residential: Places of residence mobility patterns. Workplaces: mobility trends for places of work.

Governor’s Party Affiliation: The political parties of governors that issued statewide shelter-in-place, stay-at-home, closure, or shutdown orders in response to the COVID-19 outbreak. The data were taken from Ballotpedia\(^{18}\). Infection rate: A team of academicians at Johns Hopkins University produced and maintains the COVID-19 infection rate dataset and interactive dashboard (Dong et al., 2020). In this dataset, the infection and fatality cases of COVID-19 disease were recorded in real time. The United States registers cases at the local level, which are subsequently consolidated at the state level.

3.2. Methodology

All US states have implemented some level of public safety measures in response to the pandemic. As already noted, the questions we want to ask and seek to offer a tentative response that is data-based and analyzed using a recently developed methodology, but appropriate for the purpose at hand. Therefore, we posed them again. a) Did early adopters suffer greater economic losses compared to those that did not, that is, does their performance as reflected in their economic activity show better outcomes relatively, on average, because of their action? In other words, we want to see if there is a variation in the outcome for the states based on their response to the shock compared to those that did not. b) Whether there was any lesson to be learned from their experience, as displayed in the observed variations. More succinctly, does it offer guidance on how to address a likely future repeat, should we have more similar episodes? Interestingly, our results show that, initially on a macro level, the treatment year had a significant negative impact, but then dissipated. We find that 11 states have a significantly negative impact on their economic activities. These include West Virginia, Michigan, Hawaii, Kentucky, Rhode Is., Delaware, New Mexico, Vermont, Ohio, Nevada, and Pennsylvania. The order is based on the severity of the impact, from highest to lowest. In terms of the degree of the negative impact, West Virginia was at the top; Michigan, Hawaii, Kentucky, and Rhode Island came next, and the rest saw similar consequences. Lumped together, we find no significant impact of social distancing on any other state. Perhaps the states that sustained adverse effects were compensated for by those that were less impacted. However, in relative terms, the comparison of economic resilience and the macro results appears almost inconsequential. Specifically, we implement a GSCM approach to assess the impact of a shock, such as the lockdown order. It is worth noting that the approach has gained notable appreciation, application, acceptance, and popularity in several other areas of inquiry for its reliability, predictive power, and ability to deliver an intuitive outcome. Despite these attributes, the approach failed to penetrate deeply into the arena of data analytics. Thus, we need to find ways to apply them to economic analyses. The latter is deeply entrenched in data-intensive research, which is important for public policy. We believe that our work will open opportunities for some positive avenues for research in economics. The choice of the method is largely motivated by the reality and the underlying strength of GSCM in circumventing the limitations of the oft-used approach in similar cases, the DiD method, which requires some restrictive assumptions. These are (a) the mean outcomes of the treatment and control units follow a parallel course (trends) within the pre-intervention era that continues through the post-intervention period, as if there is no treatment; and (b) the assumption of exogeneity is needed to isolate

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\(^{17}\) See https://www.philadelphiafed.org/surveys-and-data/regional-economic-analysis/state-coincident-indexes.

\(^{18}\) “Google COVID-19 Community Mobility Reports” https://www.google.com/covid19/mobility/.
the treatment effect. That is, the factor(s) that influence the outcome variable of interest cannot be used to determine treatment status. This conditional independence assumption (also referred to as “selection-on-variables”), along with the associated challenges, remains a major concern in the conclusions drawn. We are encouraged by the fact that our approach can help to understand the effectiveness of a policy by looking at the results, comparing the pre- with the post-policy outcome, and identifying a series that is endogenous to the treatment for use in our model. This step breaks the link between treatment status and the desired outcome. We believe that this is a significant contribution of this study facilitated by methodological choices.

The merit of our model clearly represents a major advancement over the extant approach, as recounted above. In real-world data, the requirement of the parallel trend assumption of the DiD model may not hold and may even be nullified because of the presence of unobserved time heterogeneities in covariates. Furthermore, we were not able to obtain a randomized control trial, natural experiments, or exogenous treatment to develop a robust identification method. Most of the time, we use observational data, as we did here. This narrative implies that we need recourse to a method that allows us to choose a less restrictive assumption, as implied by the parallel trend, which enables us to link the treatment to unobserved time-varying factors. Given that the observed data are from nonrandom treatment, the generalized synthetic approach is derived from nonrandom treatment, and the GSCM appears to be appropriate for determining the influence of the lockdown order as a shock without any restrictive assumptions.

Because the finer methodology is expected to deliver more reliable results, the finding should help us to better assess the problem and stay prepared in addressing similar shocks, should one hit us. We anticipate the findings based on the approach to stimulate further dialogue and motivate additional research, thus offering more insight into a matter of much policy import and steering further investigation using micro-level data, possibly with other tools and profound macro policy implications. We hope to identify these issues more precisely, with higher levels of accuracy and confidence. Once we pinpoint the factors responsible for the problem, charting effective policy responses to future shocks at the local, regional, national, and global levels can be alleviated. The threat we face with COVID-19 is real and, importantly, global in nature. The question is now how to assess the efficacy of a policy. It is logical to assume that states that adopted a lockdown/SHO should have a favorable economic impact. First, we assumed that the position was valid. States that adopted the measure may have contained the spread of the virus better and thus helped the economy relative to the control group that elected not to adopt the policy, where the spread may have negatively affected their economies. Our inquiry addresses two issues: (a) measuring the impact of lockdown/SHO on the economy. Once we identify and estimate such an impact for the treated states, we move onto the second question, which is more relevant from policy perspectives, for the government and business to prioritize resources, and (b) to help us zoom in to the states that adopted the policy. We then rank them in terms of impact severity.

3.3. Treatment and control status

As a result of the COVID-19 pandemic, 43 states issued statewide shelter-in-place, stay-at-home, closure, or shutdown orders. Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, and Wyoming are the only states that have never issued such an order.18 To utilize a clean and conservative treatment and control, we assigned all 43 order states as the treatment group and the non-order issuing seven states as the control group.19,20 Figs. 1 and 2.

18 See https://ballotpedia.org/Status of lockdown and stay-at-home orders in response to the coronavirus (COVID-19) pandemic, 2020#orders by governor party affiliation.
19 See https://ballotpedia.org/Status of lockdown and stay-at-home orders in response to the coronavirus (COVID-19) pandemic, 2020#cite note-
3.4. Summary statistics

We provided descriptive data and visual images of this area. We begin by examining the average infection growth rate for the two groups under treatment and placebo: pre- and post-intervention (Tables 1 and 2). Before the treatment period, the group under treatment’s mean coincidence index was 128.23, while that of the control group was 130.35. The mean index after the treatment period for the former group was 112.12, while it was 120.02 for the control group.

As previously stated, the treatment states are projected to have greater average growth rates, both before and after treatment (March 26). This means that their infection growth rate was always higher than that of the control states during the study period. This makes the scientific study more relevant and fascinating since we would like to determine if, even after social distancing, the treatment states continue to have a reasonably higher infection growth rate than the control states. This is because, in the absence of a competent causal inference approach, descriptive data and/or visuals might lead the reader to believe that social distancing has had no influence on infection rates (Osman and Sakib, 2021). We would like to determine whether a more complex and fine-tuned model agrees with or rejects our visual experience. We also demonstrated the difference in economic activities between the treated and control groups before and after social separation (Figs. 3 and 4).

Before intervention, the variation of the coincidence index was 10.52 SD for the treatment group and 10.68 SD for the control group. After the intervention, the infection rate in the group under treatment had a variation of 17.2 SD, while the placebo group had a variance of 16.45 SD. In terms of the coincidence index, which assesses composite economic performance, the SD of the treated states is slightly greater than that of the control states. We believe that the lower heterogeneity within the control group makes this a more efficient pool of donors for constructing the synthetic counterfactual for the group under treatment, which we used in this study.

In Fig. 3, we see a parallel trend between the treatment and control states’ economic activity, followed by a downward spike in both groups after the treatment event, but they still gradually follow the parallel trend. This can be interpreted as if the groups were affected in a similar fashion, and may not suggest that the adoption of distancing measures did have any
effect on the observed trends. This is intriguing and requires further scrutiny along scientific lines. We subjected them to further analysis to identify and decode the true impact of social distancing.

At this point, we examined the variance between the two groups. Here, we also observe that before the adoption of social distancing, the variation in economic activity between the treatment and control groups was more or less similar. However, the pattern changed during the post-treatment era.

3.5. Model choice

As noted earlier, the DiD model is often used to investigate the impact of an event on a desired outcome (DiD), which has found a popular seat in answering causality questions arising from a treatment but is subject to restrictive limitations due to underlying assumptions. This issue has tended to confound researchers. They did not have recourse to an alternative approach for addressing this type of problem. Abadie et al. (2010) proposed a popular synthetic control method (SCM). SCM provides more leeway for assuming a parallel DiD trend. An “artificial twin” towards the treated entity can be created by re-calculating the weights for the untreated entities during the pre-treatment phase. It is easy to see that the machine learning approach can help with the generation of an artificial counterfactual to the treated in the post-treatment phase, which can be performed by calculating the weights for each untreated entity using the pre-treatment time data and applying them to the same units’ data. However, there is a catch: SCM is confined to a specific treated entity. We utilize a more sophisticated and possibly finer approach in this study, the GSCM, which combines SCM with a new model method, time-varying entity-specific features, popularly known as the interactive fixed effect model, as described by Xu (2017). These time-varying entity-specific behaviors are not shown in the statistics, but they can still be addressed. GSCM uses IFE to extract hidden, unobserved (time-varying) features from control unit data, which are subsequently used to calculate entity-specific signals Xu (2017). This means that GSCM goes beyond the “selection-on-variables” rule, allowing for endogeneity in treatment assignment to unknown confounders that change with time, yet are entity specific. In the early stage, GSCM used a cross-validation machine learning approach to estimate the ideal number of hidden elements and forecast “what would
Table 3
Impact of lockdown/stay-at-home on Economic Activity.

| Outcome Variable | Economic Activity (Coincidence Index) |
|------------------|--------------------------------------|
|                  | (1)        | (2)                        | (3)       |
| Social Distancing| -9.088542 | -9.088542                  | -9.088542 |
|                  | (0.586)   | (0.3987976)                | (0.4721734) |
| State Fixed Effect| Yes       | Yes                       | Yes       |
| Month Fixed Effect| Yes       | Yes                       | Yes       |
| Unobserved factors| 2         | 2                         | 2         |
| Treated States   | 43         | 43                        | 43        |
| Control States   | 7          | 7                         | 7         |

Note: p-values are in parentheses. Standard Errors in (1) are calculated by parametric bootstrap (1000 times). SE in (2) is calculated by non-parametric bootstraps (1000 times). SE in (3) is calculated by jackknife approach. ***, **, * implies the 1%, 5% and 10% statistical significance levels, respectively.

have happened if there had been no treatment”, thus answering the primary challenge that causal inference researchers face.

In our study, we exploit of this advantage because our social distance treatment is not randomly assigned. GSCM is adaptable to allow for different treatment units, which is also an issue in our study. To implement GSCM, we follow Xu et al., 2021. Furthermore, in the pre-treatment phase, we consider the matching between the simulated and genuine treatments, in terms of quality, by eye-balling to see if their pathways overlap. As a result, any variations observed in the post-lockdown phase can be linked to the lockdown effect. This is compatible with the findings of Galiani and Quistorff (2017). They pointed out that visual similarities between a treatment unit’s pretreatment outcomes and that of its synthetic twin can be checked for diagnostic purposes.

Determining the causal impact is difficult in a nonrandom treatment scenario. Knowing the mechanism by which covariate imbalance is introduced (a classic cause of non-randomness and/or incomplete randomization) makes this less problematic. We can simply include the covariate’s specific intercept in our model and use it to account for the change in our outcome variable between treatment and control states. Although our model has state and time fixed effects, variables that are state and time varying at the same time have the potential to cause covariate imbalance. As previously stated, GSCM employs IFE to account for time-varying state-specific factors without directly observing them in data. The model’s interactive factor component accounts for a wide variety of differences Xu (2017). Traditional unit and time fixed effects, for example, are subsets of this interactive fixed effect (the factor part of the model). It also includes state-specific temporal trends, such as linear, quadratic, and autoregressive models. This has the advantage of reducing the sensitivity of our average treatment effect (ATT) to modeling assumptions.

The second important point is that the inference techniques we used here are a collection of non-parametric techniques. This is because we assumed that our outcome variable is correlated across states. This violates the notion of a stable unit treatment value (SUTVA) (for a more in-depth discussion, see Imbens and Rubin (2015)). This dependence between states can be viewed as a measurement error in the dependent variable, and regression techniques are quite resistant to it, allowing us to obtain an unbiased ATT. However, the “standard” standard errors appear to be deceptive in these cases, and thus, if we utilize a parametric approach, then the confidence intervals and significance of our ATT will be incorrect (assuming Gaussian error). For this reason, we use the “bootstrap” method to generate non-parametric standard errors—a “resampling with replacement”—which allows us to model not only random treatment assignment, but also random variance over sample size. For completeness, we reported a parametric inference-based outcome.

4. Results and discussion

In this section, we present the results: First, the overall ATT. We show the results with standard errors calculated by parametric and non-parametric bootstraps (1000 times and blocked at the state level). (For details of the procedure, see Xu (2017)).

The impact of social distancing does not appear to be significant, and the value of the coefficient remains almost the same for all approaches (columns (1)–(3) in Table 3). We plot the results in Figs. 5 and 6, shows the match between the treated and counterfactual (dashed line). The lines almost perfectly overlapped in the pre-treatment period, adding to our confidence in the results.

In Fig. 6, we plot only the gap between the treatment and synthetic control states’ economic activity. The graph appears to suggest no significant negative impact on economic activity on average for states that went into a lockdown policy. We also checked the robustness of our results by using the jackknife inference approach (Fig. 7). We found that our results hold.

We now consider a more granular view of the treatment effect. We considered the effects of each post-treatment period (Table 4). The treatment year shows a significant negative impact but dissipates. This phenomenon adds further evidence to our results. It would be naïve to think that social distancing did not have any impact on treatment states. Instead, we see a
significant impact, but only for the treatment year, and the effect ceases to be significant for the rest of the post-treatment periods.

4.1. Ranking of states in terms of impact of social distancing

We found that the average impact of social distancing was not significant for the 43 treatment states. This suggests that the adoption of social distancing policy measures might not have been as effective as anticipated in making any significant difference to the states compared to those that did not. However, we investigated the impact of the treatment at the state level. We further found that adopters of social distancing saw a significant drop in their economic activities but were more
than compensated by the states that did not see a sizeable drop, thereby contributing to an overall impact, but insignificant on average. This is crucial from the policy perspective. If we find states that are negatively impacted by social distancing measures, policymakers may need to prioritize the states in terms of resource allocation in the face of any future pandemic shocks of similar nature. At the very least, we can rank the states in terms of their negative impact, which can serve as a benchmark for policymakers by revealing the economic resilience of the states in tackling comparable negative shocks. In Table 5, we present the states that were significantly negatively impacted by the post-treatment periods. Our interest also extends to assessing the persistence, if any, of the negative effects from the onset of the lockdown/SHO. This offers us second-order information on the economic resilience of the impacted states, the first-order being the magnitude of the impact on the onset, while the second-order noted above tells us about the strength to recover once we take note of the significant impact.

### Table 5
States significantly impacted by COVID-19.

| State        | Period 0 | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 |
|--------------|----------|----------|----------|----------|----------|----------|
| Delaware     | -4.24    |          |          |          |          |          |
|              | (0.004)  |          |          |          |          |          |
| Hawaii       | -77.72   |          |          |          |          |          |
|              | (0.03)   |          |          |          |          |          |
| Kentucky     | -4.23    | -37.90   |          |          |          |          |
|              | (0.00)   | (0.074)  |          |          |          |          |
| Michigan     |          | -43.3    | -40.63   |          |          |          |
|              |          | (0.034)  | (0.09)   |          |          |          |
| Nevada       | -2.25    |          |          |          |          |          |
|              | (0.084)  |          |          |          |          |          |
| New Mexico   | -3.30    |          |          |          |          |          |
|              | (0.002)  |          |          |          |          |          |
| Ohio         | -2.29    |          |          |          |          |          |
|              | (0.028)  |          |          |          |          |          |
| Pennsylvania | -2.009   |          |          |          |          |          |
|              | (0.02)   |          |          |          |          |          |
| Rhode Island | -2.75    | -32.14   |          |          |          |          |
|              | (0.016)  | (0.096)  |          |          |          |          |
| Vermont      | -2.73    |          |          |          |          |          |
|              | (0.03)   |          |          |          |          |          |
| West Virginia| -7.52    | -55.11   | -50.05   | -38.94   | -32.67   |          |
|              | (0.00)   | (0.026)  | (0.066)  | (0.096)  | (0.094)  |          |

This is crucial from the policy perspective. If we find states that are negatively impacted by social distancing measures, policymakers may need to prioritize the states in terms of resource allocation in the face of any future pandemic shocks of similar nature. At the very least, we can rank the states in terms of their negative impact, which can serve as a benchmark for policymakers by revealing the economic resilience of the states in tackling comparable negative shocks. In Table 5, we present the states that were significantly negatively impacted by the post-treatment periods. Our interest also extends to assessing the persistence, if any, of the negative effects from the onset of the lockdown/SHO. This offers us second-order information on the economic resilience of the impacted states, the first-order being the magnitude of the impact on the onset, while the second-order noted above tells us about the strength to recover once we take note of the significant impact.

![Fig. 7. Robustness Check using Jackknife inference.](image)
We identified 11 states that had a significant negative impact on their economies: West Virginia, Michigan, Hawaii, Kentucky, Rhode Island, Delaware, New Mexico, Vermont, Ohio, Nevada, and Pennsylvania (ordered by the most to the least impacted). West Virginia was at the top. Michigan, Hawaii, Kentucky, and Rhode Island were next in terms of negative impacts. The remaining states had similar negative impacts. In addition, in the first set of states, we also saw a relatively prolonged impact, especially in West Virginia, which suffered the most.

4.2. Latent factors and factor loadings

Fig. 8 shows the estimated latent factors with dates on the horizontal axis, and the magnitude of the factors on the vertical axis. The GSCM estimates two latent factors, which are unobserved and thus not amenable to a straightforward interpretation. As Xu (2017) puts it, “(these)....are, at best, linear transformation of the true factors.......” We can still observe that both factors capture the downward spike in economic activity after the lockdowns or SHOs take effect sometime around the end of March or early April in 2020.

Fig. 9 shows the estimated loadings of the two factors. Again, as the latent factors are not explainable in a straightforward manner, so are their loadings. That said, it is clear that the factor loadings for the treatment states mostly overlapped with those of the control states. The loadings for both factors for the treated states fell within the convex hull of the loadings of the control states. This finding adds further evidence to our estimated synthetic control.

4.3. Application of the simple difference-in-difference (DiD) with controls

In this section, we run a simple DiD with a number of controls to check the robustness of the results. We implement this as we observe a parallel trend between the treatment and the control states’ economic activity before the lockdown/SHO. We controlled for several mobility variables using the google mobility Report. Given that social distancing policy has become a highly political and polarizing issue in the United States, we control for this by adding the political affiliation (democratic/republican) of the governing party. For this, we used the first day of infection and its daily number in each state. The results (Table 6) did not show any significant impact. The results for the treatment states still hold true.
5. Conclusion

In this study, we examine whether there is a variation in economic resilience among US states based on a state’s response to COVID-19, particularly social distancing measures. We also answer whether it is true that implementing social distancing measures produced a detrimental influence on the economy compared to those that do not. We assessed the effect of SHOs in our study and then rated it according to the severity of the consequences of the treatment states. We use the GSCM based on machine learning by splitting the US states into two groups: those that adopted early effects versus those that adopted only later effects, with state and period fixed effects adjusted to eliminate any selection bias and endogeneity. Our results do not lend any empirical evidence to support this claim, which stipulates that social distancing adopters fared better/worse than those that did not, considering them as the treatment and control groups, respectively. We document that certain states are more economically resilient than others are. Our findings have ramifications for governments and businesses in terms of future readiness for shocks, even if they are large.

In this study, we implemented an innovative approach to a recent global problem. A considerable amount of work has been done on this topic and is ongoing. We faced several issues in the conduct of this study. Clearly, more is needed, perhaps along this line, to establish the robustness of the findings. We hope this work will spearhead further investigation in this area or other topics in the domain of social science and businesses, involving deeper and more insightful research covering broader ideas.

Declaration of Competing Interest

The authors confirm no conflicts of interest.

CRediT authorship contribution statement

Syed Muhammad Ishraque Osman: Data curation, Methodology, Formal analysis, Writing – original draft. Faridul Islam: Conceptualization, Writing – original draft, Supervision, Writing – review & editing. Nazmus Sakib: Conceptualization, Writing – original draft, Writing – review & editing, Data curation.
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