COVID-19
ANALYTICS
PUC-RIO

Lockdowns, Mobility and the Dynamics of Covid-19

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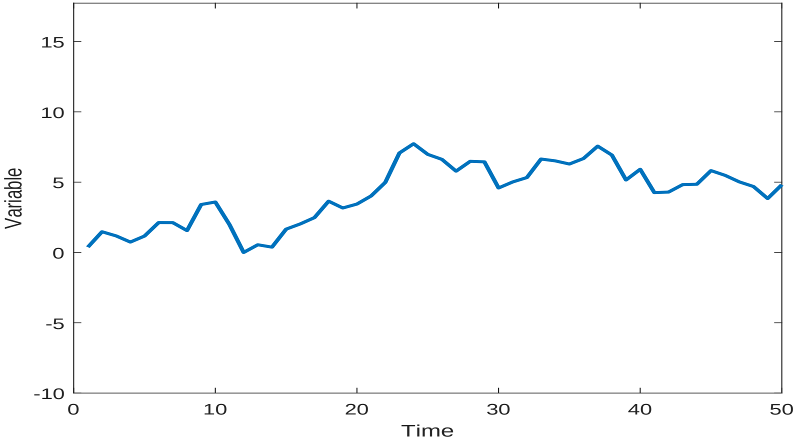
Based on
Lockdown effects in US states: an artificial counterfactual approach, joint with Carlos B. Carneiro, Iúri H. Ferreira, Henrique F. Pires, and Eduardo Zilberman
and
Mobility restriction and Covid-19 Dynamics: Evidence from Brazil, joint with Henrique F. Pires and Leonardo Ladalardo

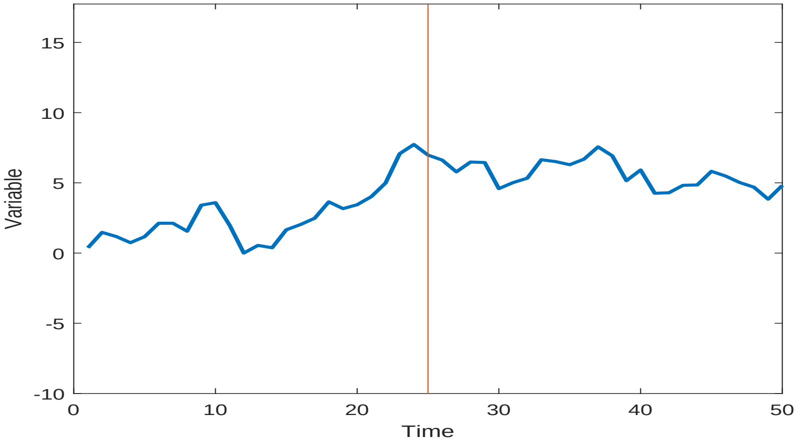
- Question: the causal impact of lockdowns on the short-run evolution of the number of cases and deaths in US states.
- Early dynamics of the Covid-19 pandemic.
- Method: Artificial Counterfactual (ArCo)

  Carvalho, Masini and Medeiros (JoE, 2018); Masini and Medeiros (JASA, 2021+)
- Identification strategy:
  1. Different timing in which US states adopted lockdown policies.
  2. For each treated state, we construct an artificial counterfactual.
- Result: On average, and in the very short-run, the counterfactual accumulated number of cases would be two times larger if lockdown policies were not implemented.

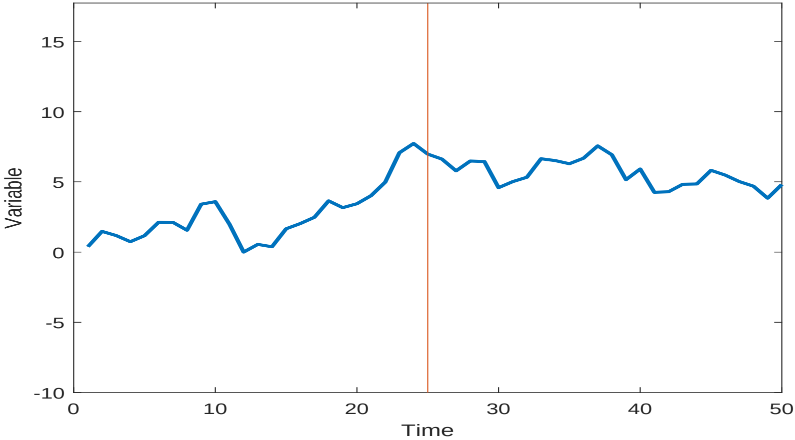
Observe **aggregated time-series data**, say Y, from $t = 1$ to T.



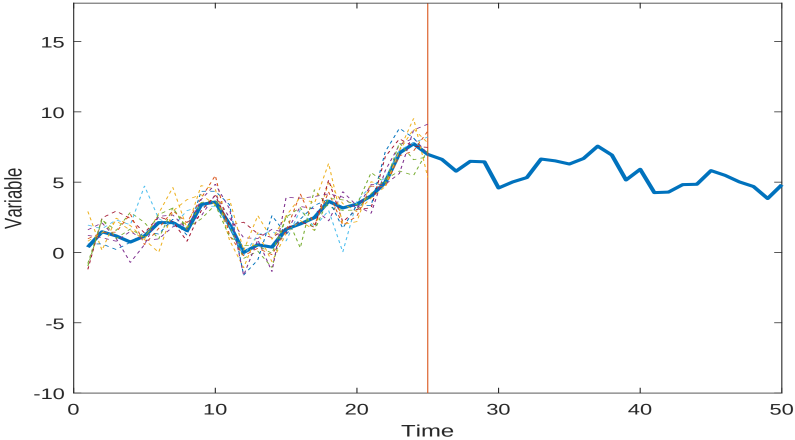
Intervention (treatment, event, ...) occurs at $t = T_0$.



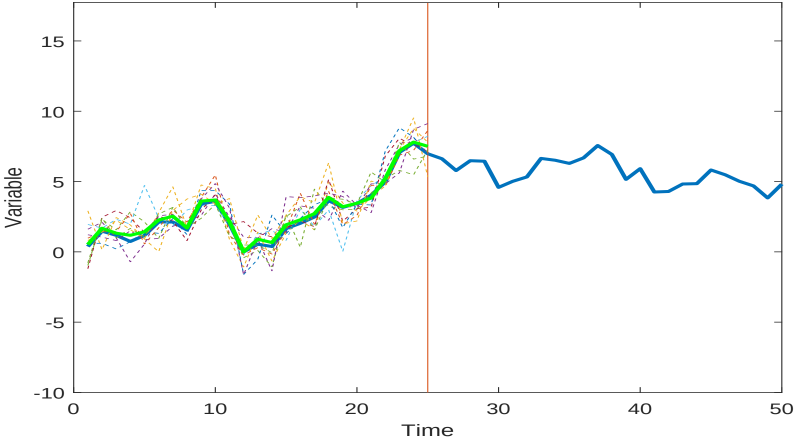
What are the **causal effects** of the intervention on Y?



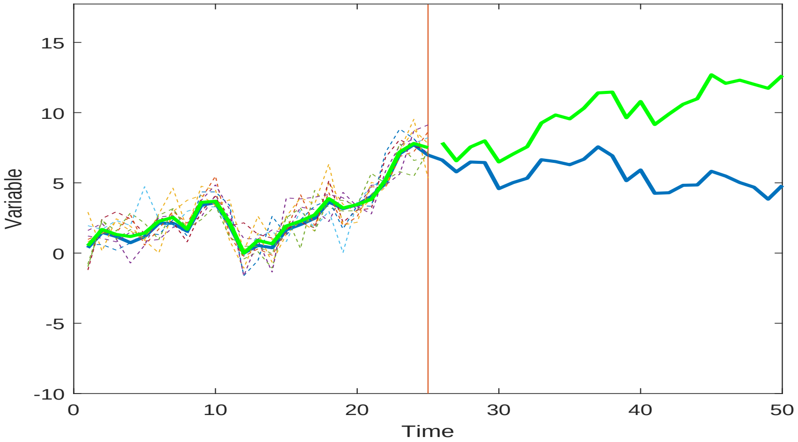
Large set of observed variables from **untreated "peers"**, X.



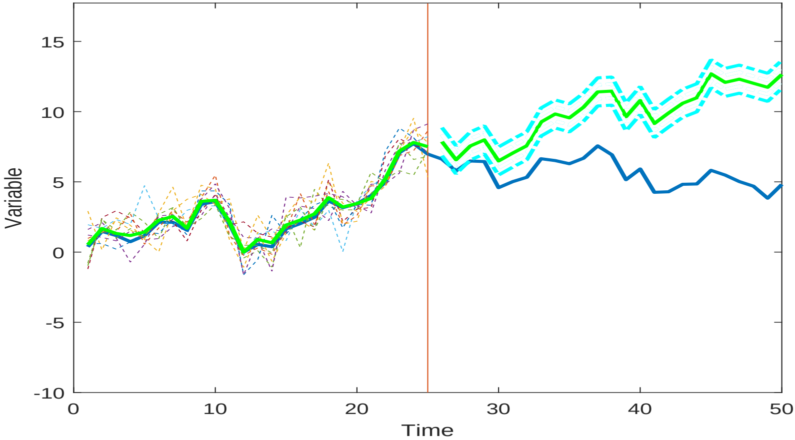
Counterfactual estimation “in-sample” (before intervention).



Counterfactual extrapolation (after the intervention).



Confidence intervals.



- The dimension of $\boldsymbol{x}$ is large comparable to T_0.
- The variables of interest display trends.
- Inference on counterfactual dynamics.

Solution: Masini and Medeiros (JASA, 2021+)

Counterfactual model: $\widehat{Y}_t = \boldsymbol{X}_t'\widehat{\boldsymbol{\omega}}$, where

$$\widehat{\boldsymbol{\omega}} = \arg\min_{\boldsymbol{\omega}} \left[\frac{1}{L-10} \sum_{t=10}^{L} \left(Y_t - \boldsymbol{X}_t'\boldsymbol{\omega} \right)^2 + \lambda \sum_{j=1}^{p} \kappa_j |\beta_j| \right],$$

$\kappa_j = |x_{j,L}|$, $j = 1, \ldots, p-1$, and $\kappa_p = 1$. L is, for each state, the number of days from the first reported case until the lockdown plus ten extra days

- Data source: Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE).
- We consider the cumulative cases for a subset of the 50 US states and the District of Columbia.
- Data in epidemiological time, which means that the day one in a given state is the day that the first Covid-19 case was confirmed there.
- All variables are log transformed and we also include a logarithmic trend in $\boldsymbol{X}$.

Empirical Strategy

Treatment and Control Groups

- Identification: some states adopted a lockdown strategy (the treatment), whereas others did not (control group).
- Lockdown strategies include a mix of state-wide non-pharmaceutical measures aiming to limit social interactions.
- Assumption: whenever an individual becomes infected, it takes an average of ten days to show up as a confirmed case in the statistics.
- We choose to start the in-sample from the tenth day as a way to smooth the initial volatility of the data.
- We restrict the analysis up to the 58th epidemiological day.

US states divided into groups:

1. Treatment: a state-wide lockdown policy must be established at least 20 days after the first case.
   This criteria excludes states that adopted a state-wide lockdown strategy too early, such as Connecticut, New Jersey, Ohio, among others.
2. The group of potential controls should consist of states that adopted a lockdown policy too late (or never adopted).

Empirical Strategy

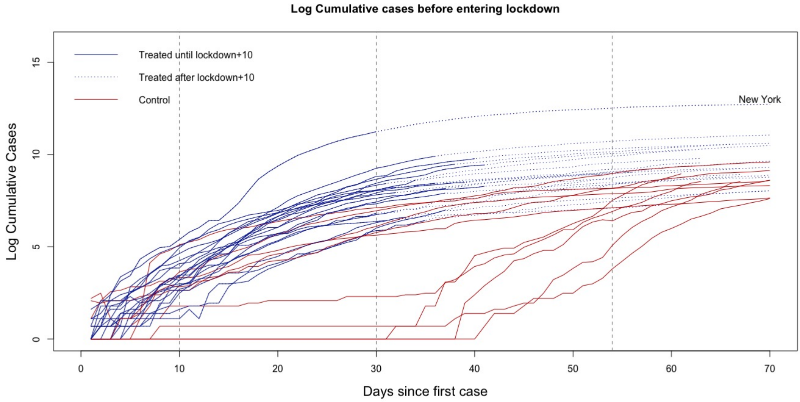
Number of Days from First Case until Lockdown

State	First Case	Lockdown (T_0+10)	Days Diff.	State	First Case	Lockdown (T_0+10)	Days Diff.
Alabama	03/13/2020	04/14/2020	32	Mississippi	03/12/2020	04/13/2020	32
Alaska	03/13/2020	04/07/2020	25	Missouri	03/08/2020	04/16/2020	39
Arizona	01/26/2020	04/10/2020	75	Montana	03/13/2020	04/07/2020	25
Arkansas	03/13/2020	-	-	Nebraska	03/06/2020	-	-
California	01/26/2020	03/29/2020	63	Nevada	03/05/2020	04/11/2020	37
Colorado	03/06/2020	04/05/2020	30	New Hampshire	03/02/2020	04/06/2020	35
Connecticut	03/10/2020	04/02/2020	23	New Jersey	03/05/2020	03/31/2020	26
Delaware	03/11/2020	04/03/2020	23	New Mexico	03/11/2020	04/03/2020	23
DC	03/16/2020	04/03/2020	18	New York	03/02/2020	04/01/2020	30
Florida	03/02/2020	04/11/2020	40	North Carolina	03/03/2020	04/09/2020	37
Georgia	03/03/2020	04/13/2020	41	North Dakota	03/12/2020	-	-
Hawaii	03/07/2020	04/01/2020	25	Ohio	03/10/2020	04/02/2020	23
Idaho	03/13/2020	04/04/2020	22	Oregon	02/29/2020	04/02/2020	33
Illinois	01/24/2020	03/31/2020	67	Pennsylvania	03/06/2020	04/11/2020	36
Indiana	03/06/2020	04/02/2020	27	Rhode Island	03/01/2020	04/07/2020	37
Iowa	03/09/2020	-	-	South Carolina	03/07/2020	04/17/2020	41
Kansas	03/08/2020	04/09/2020	32	South Dakota	03/11/2020	-	-
Kentucky	03/06/2020	04/05/2020	30	Tennessee	03/05/2020	04/10/2020	36
Louisiana	03/11/2020	04/02/2020	22	Texas	03/05/2020	04/12/2020	38
Maine	03/12/2020	04/12/2020	31	Vermont	03/08/2020	04/04/2020	27
Maryland	03/06/2020	04/09/2020	34	Virginia	03/08/2020	04/04/2020	27
Massachusetts	02/01/2020	04/02/2020	61	Washington	01/22/2020	04/02/2020	71
Michigan	03/11/2020	04/03/2020	23	West Virginia	03/18/2020	04/03/2020	16
Minnesota	03/06/2020	04/04/2020	29	Wisconsin	03/10/2020	04/04/2020	25

Control   Treated

Empirical Strategy

(Log) Cumulative cases for each State in treated and control groups.



- In-sample: tenth day and the following twenty days.
- Out-of-sample: 31th-58th epidemiological day.

Empirical Strategy
Possible Confounders

1. Endogenous behavior of individuals
   - ☺ Similar across control and treated states.
   - ☺ Impact of lockdown policies above and beyond individual responses.

2. Lockdown is not the only policy in the menu.
   - ☹ Negative bias in our estimates, suggesting even more sizable effects of lockdowns.
   - ☹ Lockdown policies in treated states may be designed altogether with other containment measures $\longrightarrow$ results should be interpreted as the average effect of a "combo" of policies.

A causal model to guide the interpretation of the results.

- $Y_{s,t+l}$: cases of or deaths by Covid-19 in state s and period $t+l$;
- L_{st}: indicator variable that a state s adopted a lockdown policy in period t;
- P_{st}: indicator variable of alternative policies implemented;
- I_{st}: available information to individuals that maybe be useful to affect behavior and/or contain the pandemic;
- B_{st}: summarizes the relevant behavior of individuals, such as adherence to social distancing, use of masks, etc; and
- U_{st}: confounders that might affect the determination of policies, individuals' behavior, and the pandemic evolution.

A Causal Model

Direct Acyclic Graph and Timing of Events

$$
\begin{tikzcd}
 & L_{st} \arrow[r] \arrow[dr] & I_{st} \arrow[d] \arrow[dr] & \\
U_{st} \arrow[ur] \arrow[dr] \arrow[rrr, bend right=60] & & B_{st} \arrow[r] & Y_{s,t+l} \\
 & P_{st} \arrow[uu] \arrow[urr] & &
\end{tikzcd}
$$

- Every period, potential confounders are determined.
- Second, public policies (L_{st} and P_{st}) are set.

  P_{st} already encodes the transmission mechanisms (e.g., behavioral responses) through which policies other than lockdowns.
- Third, conditional on confounders and policies, individuals' information is updated.
- Fourth, individuals behavior are determined by confounders, policies and information.
- Finally, the variable of interest ($Y_{s,t+l}$) is determined.

- Lockdown policies, L_{st}, do not directly affect the number cases or deaths, $Y_{s,t+l}$.

  Effects via some mediating variables: individuals' behavior (above and beyond endogenous responses to the pandemic in the absence of lockdowns) or available information.

- Two threats to the identification of the causal effect:
  1. Non-observed variables (U_{st}) affect the probability of lockdown adoption and the evolution of the pandemic simultaneously.
  2. Simultaneous implementation of alternative policies.

     Local authorities could adopt other containment policies P_{st} as a substitute to the lockdown policy L_{st} in control states, or as a complement in the treated ones.

A Causal Model: Alternative Policies

Implementation Dates for Mandatory Mask Wearing

State	Date	State	Date
Arizona	No	Massachusetts	11/06/2020
Arkansas	07/20/2020	Nebraska	No
California	06/29/2020	North Dakota	11/14/2020
Illinois	06/26/2020	South Dakota	No
Iowa	11/17/2020	Washington	06/26/2020

- In the early stages of the pandemic, mandatory mask-wearing was not encouraged by the World Health Organization (WHO), which only changed its recommendation in the beginning of July.
- We restrict the sample to the first 56 days after the first Covid-19 case in each state. The last calendar day in the sample is May 11 (Arkansas).

A Causal Model

Causal Direct Acyclic Graph (DAG) with timing of restrictions

$$
\begin{tikzcd}
 & L_{st} \arrow[r] \arrow[dr] & I_{st} \arrow[d] \arrow[dr] & \\
 & & B_{st} \arrow[r] & Y_{st+l} \\
U_{st} \arrow[uur] \arrow[urrr, bend right] & & &
\end{tikzcd}
$$

- The most important alternative policy was not implemented until the end of the period considered.
- Mandatory mask wearing among control states does not seem to attenuate the effect of interest.

Empirical Strategy: Confounding Effects

The Nature of the Treatment

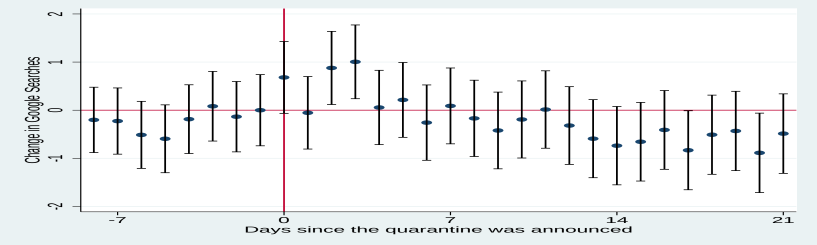
- What a lockdown policy does?
- Why would it affect the variables of interest?

Two mechanisms:

1. A lockdown affects individuals' behavior by reducing mobility.
2. The policy might affect the available information.
   - ⋆ For instance, its implementation can increase the awareness of individuals about the pandemic and provide incentives to further changes in behavior.
   - ⋆ Despite considering the theoretical possibility of an informational transmission channel, some auxiliary empirical evidence suggests that its relevance is quite limited.

Empirical Strategy: Confounding Effects

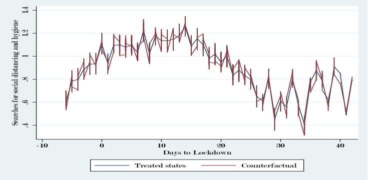
The Nature of the Treatment

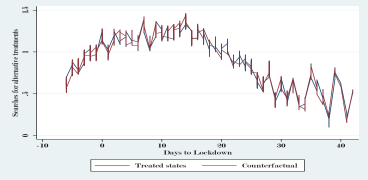


- The number of (changes in) pandemic-related Google searches in the days immediately before and after the policy is implemented.
- small increase in searches a few days after the lockdown announcement, but its magnitude is very limited and it vanishes almost immediately.

Empirical Strategy: Confounding Effects

The Nature of the Treatment





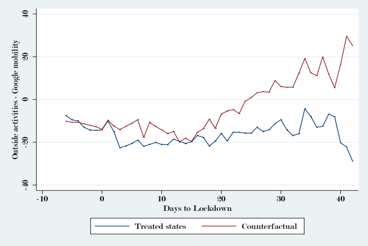
- Do Lockdown measures impact Google searchers related to traditional and alternative methods to fight the pandemic?
  - ⋆ The search terms for traditional methods include "social distancing", "mask use" and "washing hands".
  - ⋆ The search terms for alternative treatment include "zinc", "hydroxychloroquine", and "Covid alternative treatments"
- Little evidence that the search patterns are systematically different between treatment and control groups.

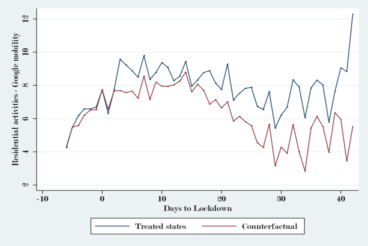
$$\begin{tikzcd}
& L_{st} \arrow[dr] & I_t \arrow[d] \arrow[dr] & \\
& & B_{st} \arrow[r] & Y_{st+l} \\
U_{st} \arrow[uur] \arrow[urr] \arrow[urrr, bend right] & & &
\end{tikzcd}$$

- By eliminating the casual link between L_{st} and I_t, this simplification allows a straightforward interpretation of the treatment.
- The lockdown policy affects pandemic evolution mainly through its effects on behavior.
- To confirm this, we evaluate the impact of lockdown policies in mobility.

A Causal Model

Impact on Mobility: Outside and Residential





- Lockdown policies affected the pandemic evolution mainly through its effects on behavior.
- This is captured by substantial decrease (increase) in outside (residential) mobility in treated states relative to the counterfactuals.

- Linear model from the DAG:

$$Y_{s,t+l} = \pi B_{st} + \mu I_{st} + \delta U_{st} + \epsilon_{st}^{Y},$$

where π, μ, and δ are parameters and ϵ_{st}^{Y} is an error.

- The behavior of individuals:

$$B_{st} = \alpha L_{st} + \eta I_{st} + \epsilon_{st}^{B},$$

where α and η are parameters and ϵ_{st}^{B} is an error.

- Reduced-form:

$$Y_{s,t+l} = \beta L_{st} + \gamma I_{st} + \delta U_{st} + \epsilon_{st},$$

where $\beta = \alpha\pi$, $\gamma = \pi\eta + \mu$, and $\epsilon_{st} = \pi\epsilon_{st}^{B} + \epsilon_{st}^{Y}$.

- Since we do not observe U_{st}, OLS estimation of the reduced-form equation does not identify β.

- Solution: The ArCo methodology.

  For each state, we find a (non-necessarily convex) combination $\boldsymbol{\omega}$ of states in the control pool that most closely matches the number of cases in the treated state.

- Thus, we propose the following estimator,

$$\widehat{\boldsymbol{\beta}}_{s,t+l} = Y_{s,t+l} - \omega_0 - \boldsymbol{\omega}'\boldsymbol{Y}^C_{t+l},$$

  where $\boldsymbol{Y}^C_t$ is the vector of cases for the control states.

- Also, note that

$$\widehat{\beta}_{s,t+l} = \beta + \delta(U_{st} - \omega_0 - \boldsymbol{\omega}'\boldsymbol{U}^C_t),$$

  where $\boldsymbol{U}^C_t$ is the vector of non-observed confounders for the control group.

- It is clear that if

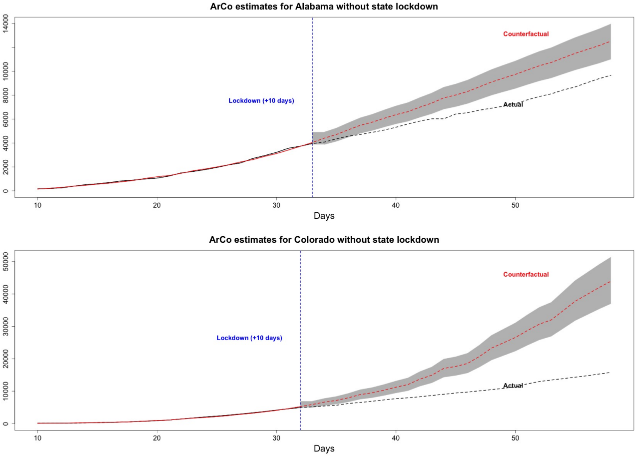
$$U_{st} = \omega_0 + \boldsymbol{\omega}'\boldsymbol{U}_t^C,$$

then the proposed estimator recovers the effect of the lockdown policy on the number of registered cases.

- The additional identification hypothesis is that the combination of estimated weights does not only reproduce the trends in the in-sample period but also the non-observed relevant variables.
- β recovers precisely the effect of lockdowns through the behavioral channel.

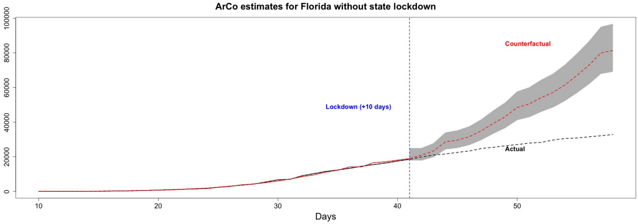
Results: Cases

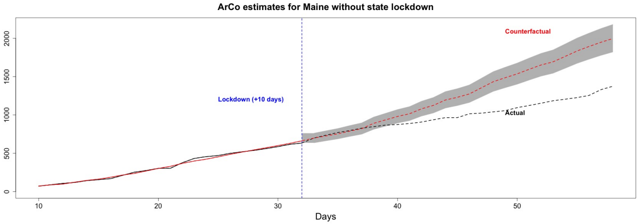
Alabama and Colorado



Results: Cases

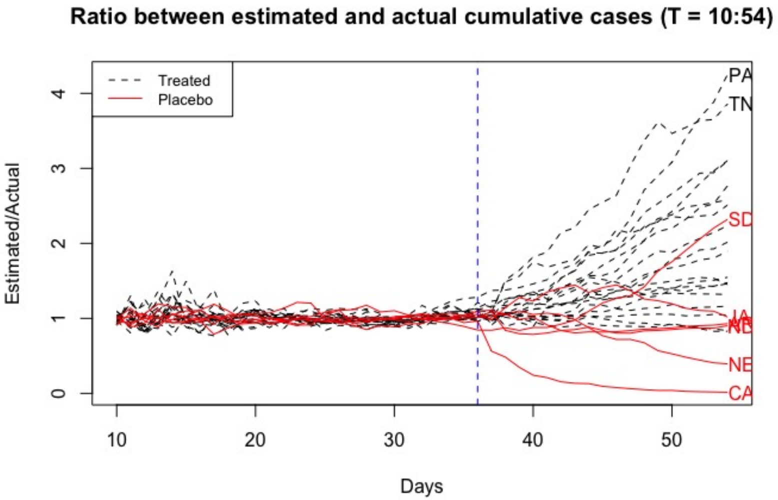
Florida and Maine





Results: Cases

Placebo: Ratio Estimated and Actual Cumulative Cases



Results: Cases

ArCo estimates (58th day)

	Mean ArCo	Med ArCo	Mean lb	Med lb	Mean ub	Med ub
Control	1.04	0.92	0.91	0.80	1.18	1.03
Treated	3.08	2.28	2.46	1.91	3.67	2.63
Treated (-NY)	2.37	2.08	1.99	1.72	2.75	2.32

Results: Cases

ArCo estimates (58th day)

State	ArCo forecast	ArCo lb	ArCo ub	Treated
Alabama	1.30	1.14	1.44	Yes
Colorado	2.78	2.34	3.25	Yes
Florida	2.48	2.11	2.94	Yes
Georgia	1.68	1.43	2.10	Yes
Kansas	1.49	1.34	1.69	Yes
Kentucky	2.68	2.31	2.99	Yes
Maine	1.45	1.33	1.59	Yes
Maryland	2.08	1.72	2.32	Yes
Mississippi	1.03	0.98	1.08	Yes
Missouri	0.74	0.61	0.86	Yes
Nevada	0.82	0.63	1.05	Yes
New Hampshire	2.90	2.15	3.55	Yes
New York	16.48	11.44	21.18	Yes
North Carolina	3.69	2.95	4.28	Yes
Oregon	3.96	3.21	4.33	Yes
Pennsylvania	5.63	4.99	6.41	Yes
Rhode Island	1.72	1.47	2.06	Yes
South Carolina	1.18	1.03	1.31	Yes
Tennessee	4.25	3.56	4.95	Yes
Texas	3.19	2.56	4.00	Yes

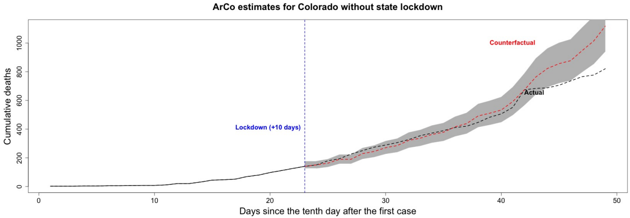
Results: Cases

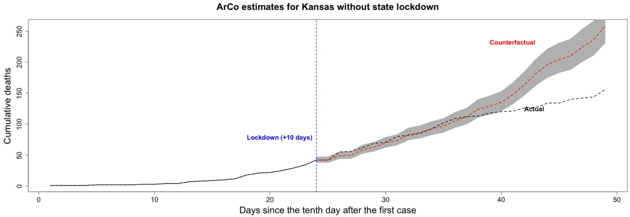
ArCo estimates (58th day)

State	ArCo forecast	ArCo lb	ArCo ub	Treated
Arkansas	0.97	0.93	1.03	No
California	0.01	0.01	0.01	No
Iowa	0.93	0.81	1.02	No
Nebraska	0.28	0.23	0.32	No
North Dakota	0.92	0.78	1.09	No
South Dakota	3.13	2.72	3.59	No

Results: Deaths

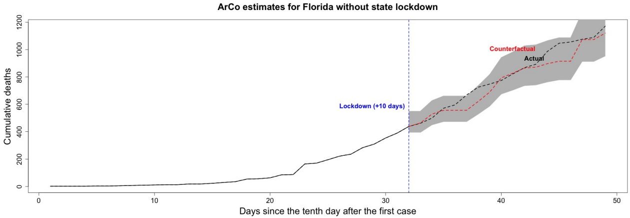
Colorado and Kansas

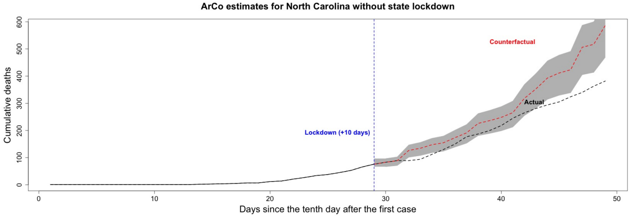




Results: Deaths

Florida and North Carolina





Conclusions

- Purely data-driven approach to assess the impact of lockdowns on the short-run evolution of the number of cases and deaths in some US states.

- Also, as opposed to some recent papers that use a difference-in-difference approach, we adopt a variant of the synthetic control approach.

- On average, according to the artificial controls, the counterfactual accumulated number of cases would be two times larger were lockdown policies not implemented in treated states.

- State- and Municipal-level panel (IV) regression (weakly data):

$$S_{it} = \alpha_i + \lambda_t + \beta GM_{i,t-h} + \boldsymbol{\psi}'\boldsymbol{N}_{it} + \boldsymbol{\gamma}'\boldsymbol{GT}_{it} + U_{it},$$

  where:

  - ⋆ $S_{it} = \{Y_t, \Delta Y_t\}$; Y_t: cases
  - ⋆ GM_{it}: Google mobility
  - ⋆ $\boldsymbol{N}_{it}$: news-based variables
  - ⋆ $\boldsymbol{GT}_{it}$: Google Trends
  - ⋆ α_i and λ_t: fixed and time effects

- Very preliminary results

- Newspaper used for news collection: G1 (about 109.355 news found based on the search word “Covid”)
- News have been filtered and counted based on a given set of keywords found on their title:
  1. Cons: words that are arguably “against” Covid proliferation (mask, hygiene, quarantine, lockdown, ...
  2. Pros: words that are arguably “favorable” for Covid proliferation, as fake-news, agglomeration, ...
  3. Dead: words regarding “death”
  4. Vac: words regarding “vaccine”
  5. Cas: words regarding number of “cases”
  6. Agreg: total number of news regarding “Covid”
- The counts have been normalized.

	Y_t	ΔY_t
$h = 0$ (no lag on mobility)		
Internal	26.58***	−4.80*
External	−14.56***	1.87**
$h = 1$ (one week lag)		
Internal	18.56**	−7.44***
External	−12.19***	2.40***

- Model in levels suffers from strong endogeneity problems: mobility restrictions are usually adopted when the disease dynamics is accelarating
- Model in first-differences mitigate part of the problem
- Challenge: find valid instruments for mobility