Stochastic SIR-based Examination of the Policy Effects on the COVID-19 Spread in the U.S. States

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Abstract
Since the global outbreak of the novel COVID-19, many research groups have studied the epidemiology of the virus for short-term forecasts and to formulate the effective disease containment and mitigation strategies. The major challenge lies in the proper assessment of epidemiological parameters over time and of how they are modulated by the effect of any publicly announced interventions. Here we attempt to examine and quantify the effects of various (legal) policies/orders in place to mandate social distancing and to flatten the curve in each of the U.S. states. Through Bayesian inference on the stochastic SIR models of the virus spread, the effectiveness of each policy on reducing the magnitude of the growth rate of new infections is investigated statistically. This will inform the public and policymakers, and help them understand the most effective actions to fight against the current and future pandemics. It will aid the policy-makers to respond more rapidly (select, tighten, and/or loosen appropriate measures) to stop/mitigate the pandemic early on.

Key Words: Bayesian inference, COVID-19 pandemics, viral epidemiology, intervention analyses, mitigation strategies, SIR compartmental models

1. SIR Model in Epidemiology

The popular Susceptible-Infected-Recovered (SIR) model in epidemiology is a well-established *compartmental* model to understand the disease dynamics; see Figure 1 below. It is based on a series of the ordinary differential equations (ODE) as follows.

$$\begin{aligned} \frac{d}{dt}S(t) &= -\lambda(t)S(t)\frac{I(t)}{N} \\ \frac{d}{dt}I(t) &= \lambda(t)S(t)\frac{I(t)}{N} - \mu I(t) \\ \frac{d}{dt}R(t) &= \mu I(t) \end{aligned}$$

where N is the static population size, μ is the stationary recovery rate, and $\lambda(t)$ is the additive spreading rate defined by

$$\lambda(t) = \lambda_0 + \textstyle\sum_{i=1}^{m} \lambda_i \cdot J(t_i^{beg} \leq t \leq t_i^{end})$$

with λ_i being the intervention-specific spreading rate in the given time range [t^{beg}, t^{end}]. Other variations of this model are also available, for example, by including the incubation period, re-infection, etc.

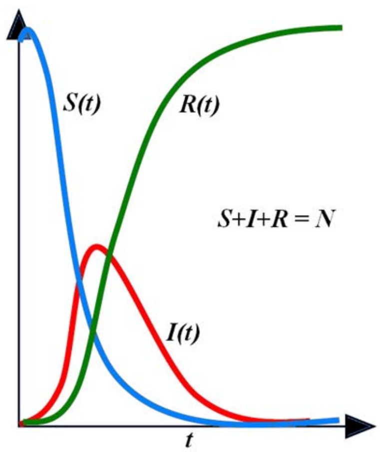

Figure 1: Graphical illustration of the temporal evolution of the SIR model

2. Bayesian Inference

The popular but computationally intensive Bayesian inference incorporates the *prior* knowledge and the posterior distribution here is approximated via ***MCMC sampling***. For this research, the Markov chains were initialized through the automatic differentiation variational inference (ADVI). We have set 1000 *burn-in* (tuning) for each chain to sample from an equilibrium distribution. Also, 4000 steps were used for each chain to approximate the posterior (ergodicity), and convergence was checked. We estimated the parameters *evolving* over time, enabling a short-term forecast with the *uncertainty quantification* (UQ). The following table lists various policies and interventions we considered in this study.

Table 1: List of COVID-19 policies and interventions under examination

- state of emergency declared
- stay at home/shelter
- closed K-12 schools, day cares
- closed businesses, restaurants, movie theaters, gyms
- mandated face mask in public spaces
- religious gatherings exempt without social distance mandate
- banned visitors to nursing homes
- stopped personal visitation in state prisons
- stopped initiation/enforcement of evictions
- waived waiting period for unemployment insurance
- ordered freezing utility shutoffs
- SNAP waiver
- allowed/expanded Medicaid coverage including telehealth
- suspended elective medical procedures
- reopened ACA enrollment

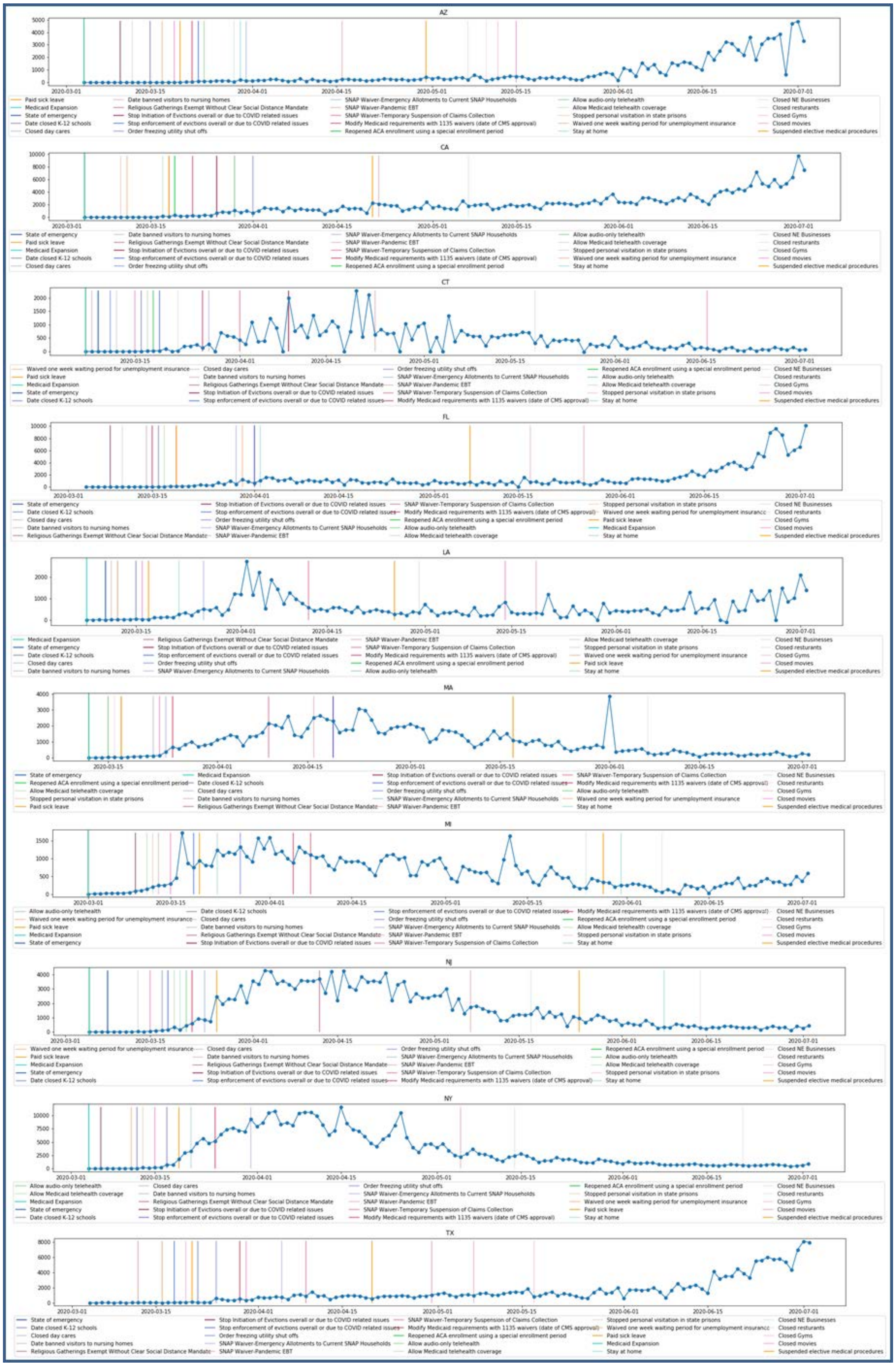

Figure 2: Temporal evolutions of the new COVID-19 cases in some selected U.S. states along with the dates of policy implementations

3. Results and Observations

It was observed that different states do **not** exhibit the same effects of reducing the spread rate $\lambda(t)$ by each intervention and policy. The trends were observed to be *divergent* in quite a few cases; see Figure 2 above. It is concluded that the case number alone is deficient to understand the true disease dynamics, and more covariates/information are needed to understand the reasons behind. Furthermore, the inference and forecasts got complicated by the potential delay (2 to 4 weeks) of the policy effect since the onset of each intervention. This is creating major uncertainties to deal with and thus, it is recommended that *lifting* certain policies should be implemented with *extreme precautions*.

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