How Robust are the Estimated Effects of Nonpharmaceutical Interventions against COVID-19?

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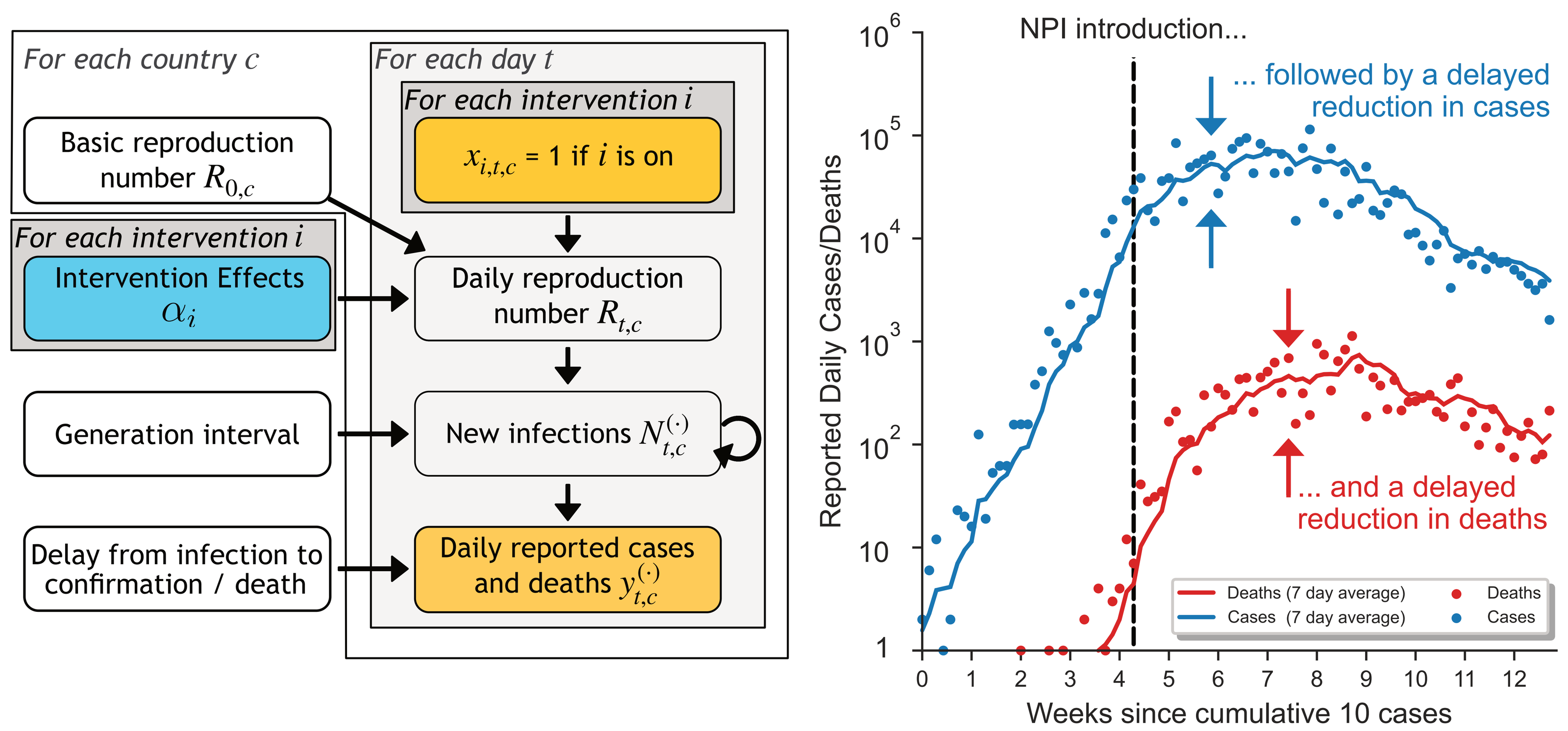
Summary

To what extent are effectiveness estimates of nonpharmaceutical interventions (NPIs) against COVID-19 affected by the assumptions that our models make?
Approach. We perform a large scale empirical investigation, evaluating 2 SotA NPI effectiveness models and 6 variants that make **different assumptions**.
Results. Considering only models that include transmission noise, we find that policy relevant conclusions are remarkably robust.

Paper Code

Data Driven NPI Effectiveness Models

Our models links the reported number of cases and deaths in country c on day t, $C_{t,c}$ and $D_{t,c}$ to the active NPIs.



However, to do this, we need to make assumptions! For example, many models assume *constant, mulitplicative* NPI effects:

$$R_{t,c} = R_{0,c} \prod_i \exp(-\alpha_i x_{i,t,c}).$$

However, for example, we could let the NPIs interact *additively*:

$$R_{t,c} = R_{0,c} \left(\hat{\alpha} + \sum_{i \in \mathcal{I}} \alpha_i \left(1 - x_{i,t,c}\right) \right), \quad \text{with } \hat{\alpha} + \sum_{i \in \mathcal{I}} \alpha_i = 1,$$

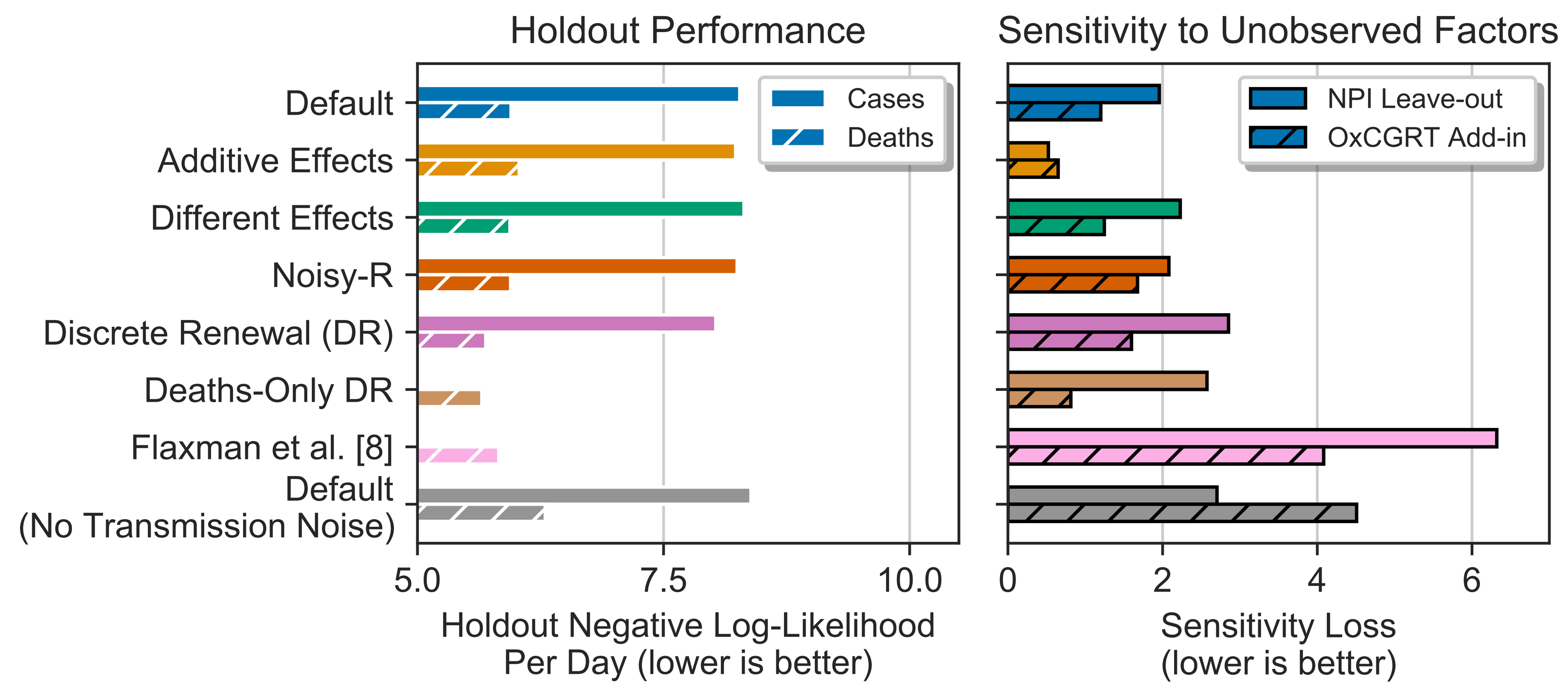
$\alpha_i > 0 \; \forall i$ and $\hat{\alpha} > 0$.

Plausible Models

We want to answer: **to what extent do the assumptions that we make affect our NPI effectiveness results?**
Therefore, we extend 2 SoTA models and propose 6 variants that make different assumptions: • *Additive Effects*; • *Different Effects*; • *Noisy-R*; • *Discrete Renewal*; • *Deaths-Only Discrete Renewal*; • *Default (No Transmission Noise)*. We also evaluate the *Default* model (from our previous work), and the model of *Flaxman et al.*.

Model Comparison

How do we know which models to trust? We use **holdout validation** and **sensitivity to unobserved factors**.



Models that include noise on the measure of transmission have effectiveness estimates that both generalise to unseen countries better and are more robust to unobserved factors.

Additional Tests

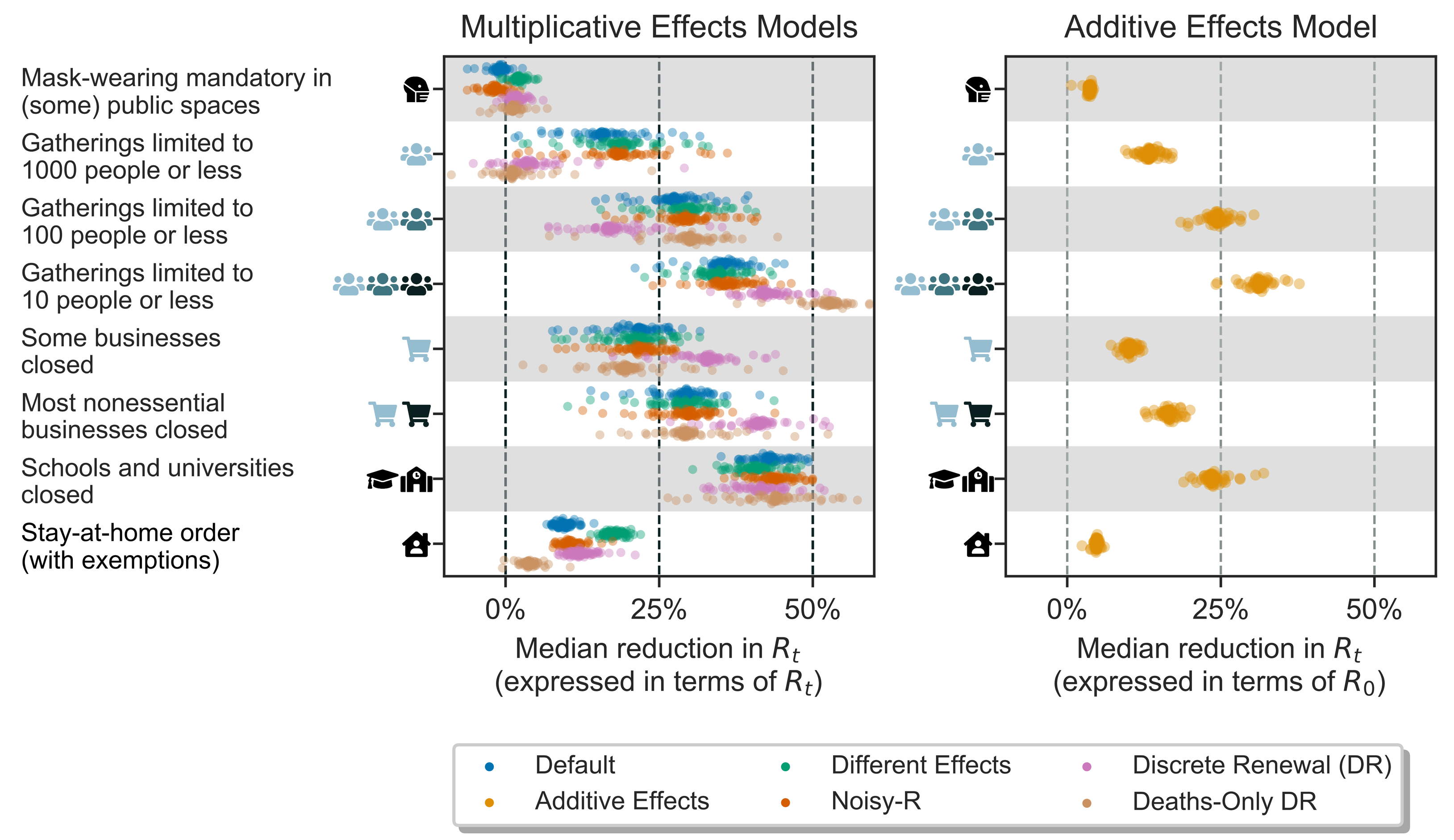
All of our models require additional assumptions. We additionally test sensitivity across 6 tests, categorised as follows.

Epidemiological Parameters. Our models require external knowledge of COVID-19, such as the delays between infection and case/death reporting. We vary these parameter values, as well as priors placed over NPI effectiveness and R_0.

Data. We leave regions out one-at-a-time, and vary data preprocessing parameters. Collecting NPI data is challenging, but if results vary significantly to these tests, additional data should be collected.

Result Robustness

We find clear trends in NPI effectiveness estimates across variations in **model structure, data, and epidemiological parameters**.



Effectiveness in Context

Most of our models assume that:

- There are no NPI interactions.
- NPI effectiveness doesn't change across time.
- NPI effectiveness is fixed across countries.

How does this affect our results?
We consider a simplified versions of the *Noisy-R* model that observes 'ground truth' values of $R_{t,c}$. We show that the maximum likelihood solution computes NPI effectiveness as a marginal average effectiveness, where the average is taken **over our data distribution**.

Implications. For example, in our data, *Stay-at-Home Orders* were only issued when many other NPIs were active. Therefore, it's effectiveness estimate should be interpreted as 'the average additional benefit when a country implemented a *Stay-at-home order*, provided other NPIs were active'.