Policy Interventions and Voluntary Actions for Battling COVID-19

Multilevel Vector Autoregression Modeling Using the CMU and UMD Survey Data

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Photo by David Ramos/Getty Images

Problem Statement

A growing body of literature evaluates the effectiveness of non-pharmaceutical interventions (NPIs) to combat COVID-19 [1,2]. However, the previous modeling rarely accounted for changes in people's behavior stemming from awareness-driven voluntary actions. Additionally, the analysis, benefiting from granular survey data in the assessment of NPIs, is limited.

One attempt to tackle the issue [3] highlighted the importance of both (1) governmental regulations and (2) voluntary behavior in keeping people at home. Disentangling between the two mechanisms is critical in grasping a complex picture of policy implementation and its effect on the pandemic outbreak.

By employing CMU and UMD survey data, structured by time, age, and geography, we estimate the impact of interventions' rigidity on COVID-19 transmission, accounting for the simultaneity between the rigidity of official guidelines, people's behavior, and measures for the COVID-19 transmission. We also demonstrate that the approach can help cast light on predicting official COVID-related indicators such as death rate and hospital admissions.

Generally, the methodology developed in this work is instrumental for exploratory and hypotheses-generating purposes, which can be further validated by causality establishing techniques and enrich subsequent policy practices.

Overall purpose: to demonstrate the possibilities of leveraging the CMU and UMD data in the analysis of the relationships between policy interventions and voluntary actions for mitigating COVID-19 pandemic.

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1. Brodeur, A., Gray, D. M., Islam, A., & Bhuiyan, S. (2020). A Literature Review of the Economics of COVID-19.
2. Abouk, R., & Heydari, B. (2020). The immediate effect of covid-19 policies on social distancing behavior in the united states. Available at SSRN.
3. Gatto, M., Bertuzzo, E., Mari, L., Miccoli, S., Carraro, L., Casagrandi, R., & Rinaldo, A. (2020). Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures. Proceedings of the National Academy of Sciences, 117(19), 10484-10491.

Data for the United States

Sample: 34 states which had more than 20,000 total COVID-19 cases and experienced growth in the number of cases from May 1, 2020 till September 1, 2020.

We use the following set of indicators from CMU dataset:

Community CLI (A4): % of resp. who know people with COVID symptoms in a community.

CLI Symptoms (anosmia/ageusia, fever, cough, shortness of breath, difficulty breathing): % of people reporting that they have experienced these symptoms in the past 24 hours.

Avoiding Contact (C7): % of resp. for all the time and most of the time. This is a key behavior-related variable that reflects the extent of compliance with social distancing.

Worked Outside (C3): % of resp. who worked outside their home. This indicator mostly stems from governmental directions, which is relevant to control for.

Testing Shortage (B5): % of respondents who tried to get tested but failed. Differences in testing experience are one of the factors that may determine the number of infected cases, therefore, is also critical to account for.

Additional variables:

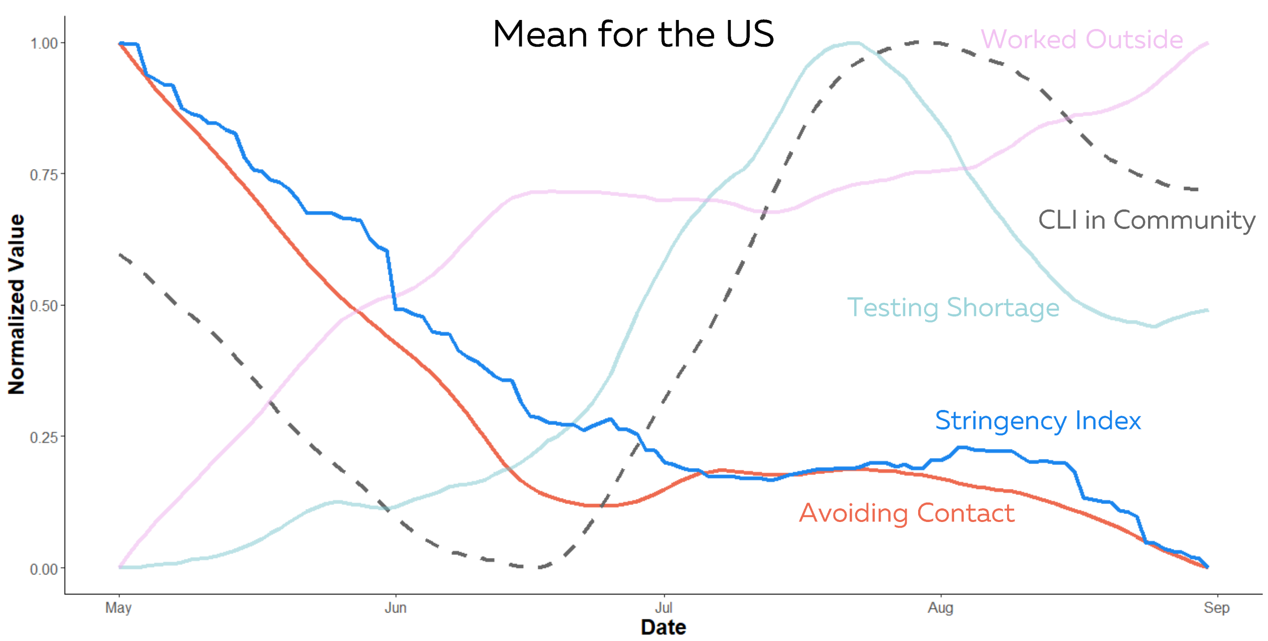
Stringency Index: the rigidity of "lockdown style" measures that restrict people's behavior (created by Oxford CGRT).

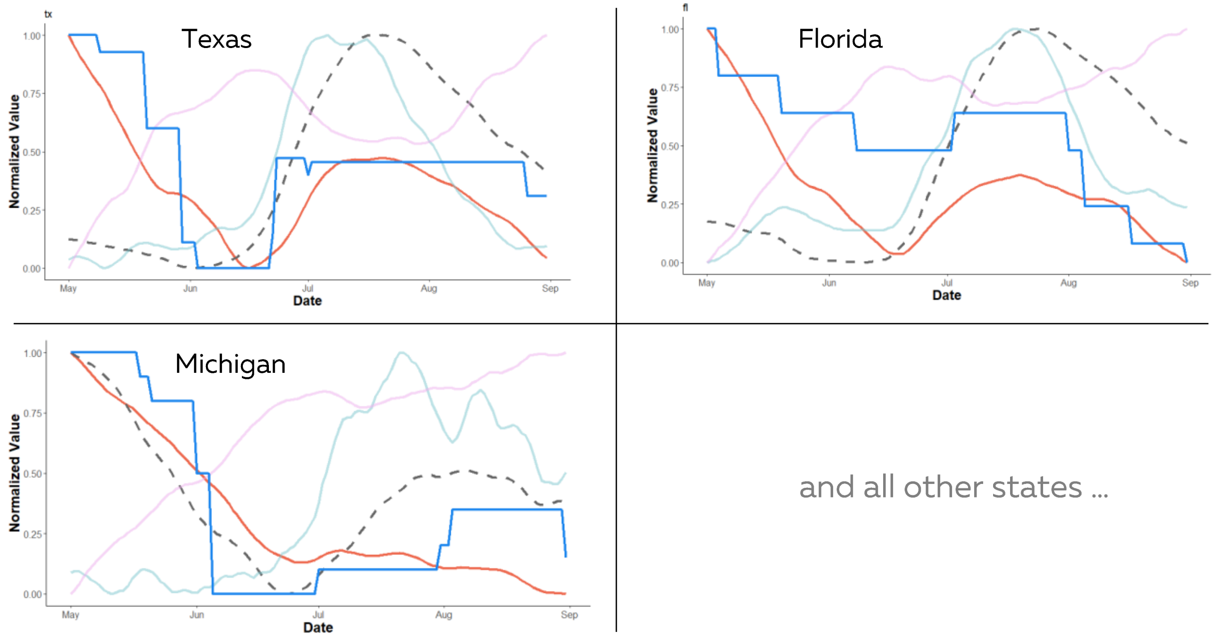
New Cases and New Deaths: the number of new confirmed COVID-19 cases and deaths respectively per 100,000 population (COVIDcast).

Hospital Admissions: the estimated percentage of new hospital admissions with COVID-associated diagnoses (COVIDcast).

CMU data

Motivation for the Method and Its Description





Simultaneity

Heterogeneity

We can notice two main trends in the selected indicators: simultaneity (co-evolving variables can be causes and effects at the same time) and heterogeneity by states. Multilevel VAR (mlVAR package in R) allows us to model such data structure and computes networks of contemporaneous, between-subject, and **temporal** (with a 14-days lag in the current study) effects as a result.

The estimation procedure is given by:

Level 1: $y_{[t,p,i]} = \mu_{[p,i]} + \beta_{[p,i]}\left(y_{[t-1,p]} - \overline{y}_p\right) + \varepsilon_{[t,p,i]}, \quad \varepsilon_{[t,p,i]} \sim N(0,\, \theta_{[p,i]})$, Level 2: $\begin{bmatrix}\mu_{[P,i]}\\ \beta_{[P,i]}\end{bmatrix} \sim N\left(\begin{bmatrix}0\\ \beta_{*i}\end{bmatrix}, \begin{bmatrix}\omega_{\mu_i} & \omega^{(\beta_i\mu_i)\top}\\ \omega^{(\beta_i\mu_i)} & \Omega^{(\beta_i)}\end{bmatrix}\right)$

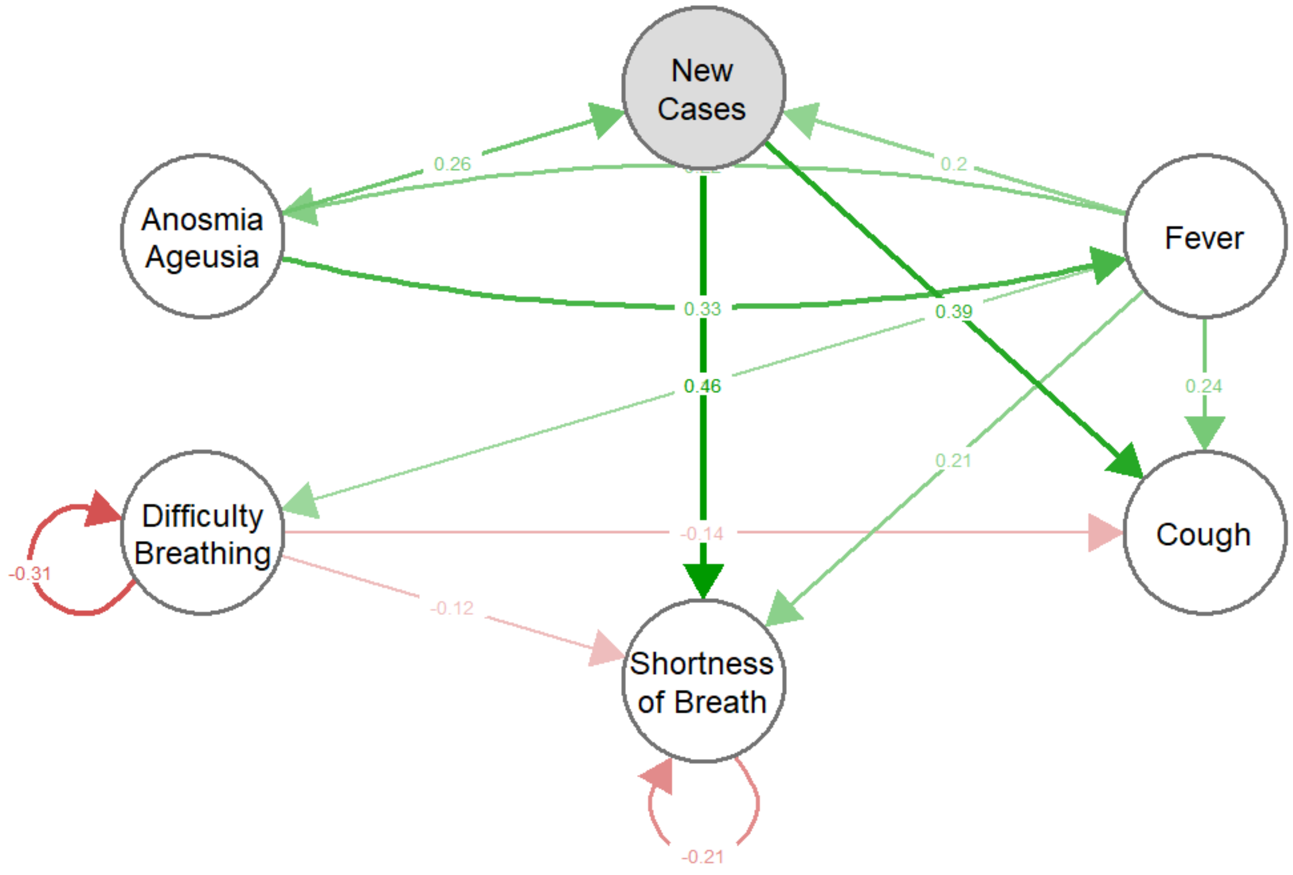
Indices: t – time, p – subjects, i – responses; $y_{[i]}$ – response variables, $\mu_{[p,i]}$ – means of responses, $\beta_{[p,i]}$ – temporal effects

See Epskamp et al. (pp. 24-26, 2018) for more details.

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018). The Gaussian graphical model in cross-sectional and time-series data. Multivariate Behavioral Research, 53(4), 453-480.

CMU data

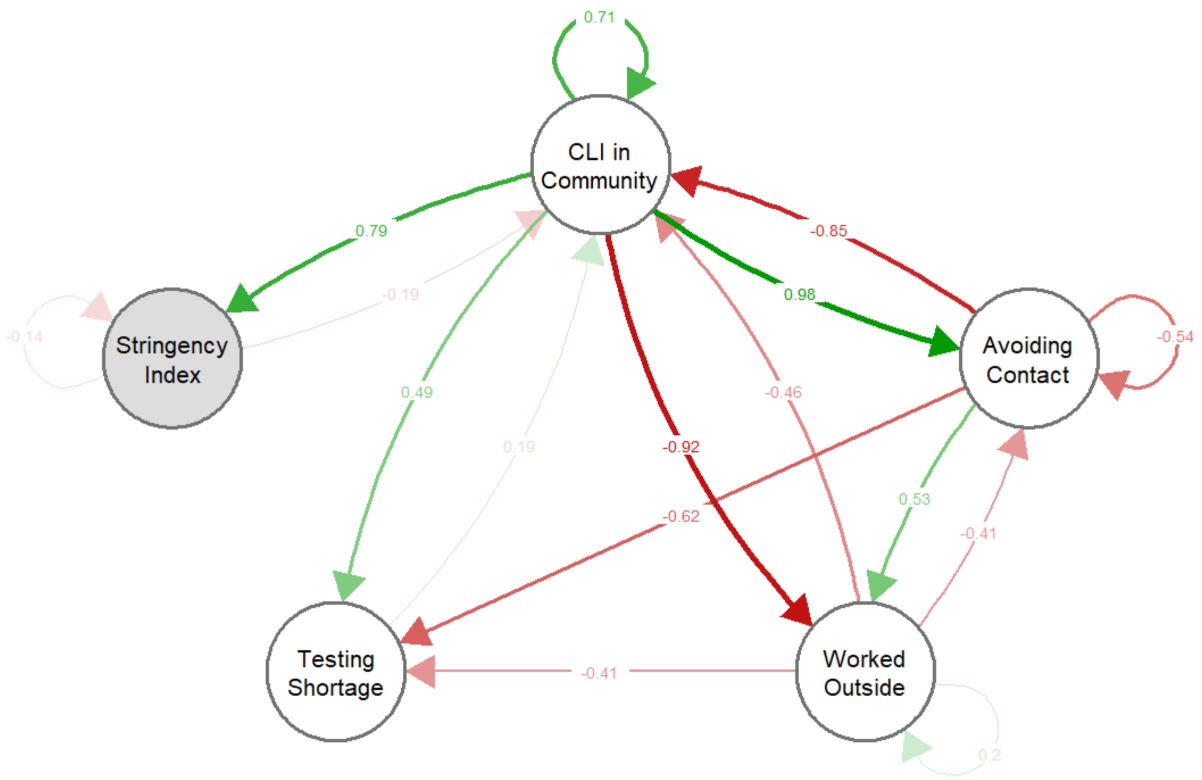
CLI Symptoms and New Cases: Temporal Effects



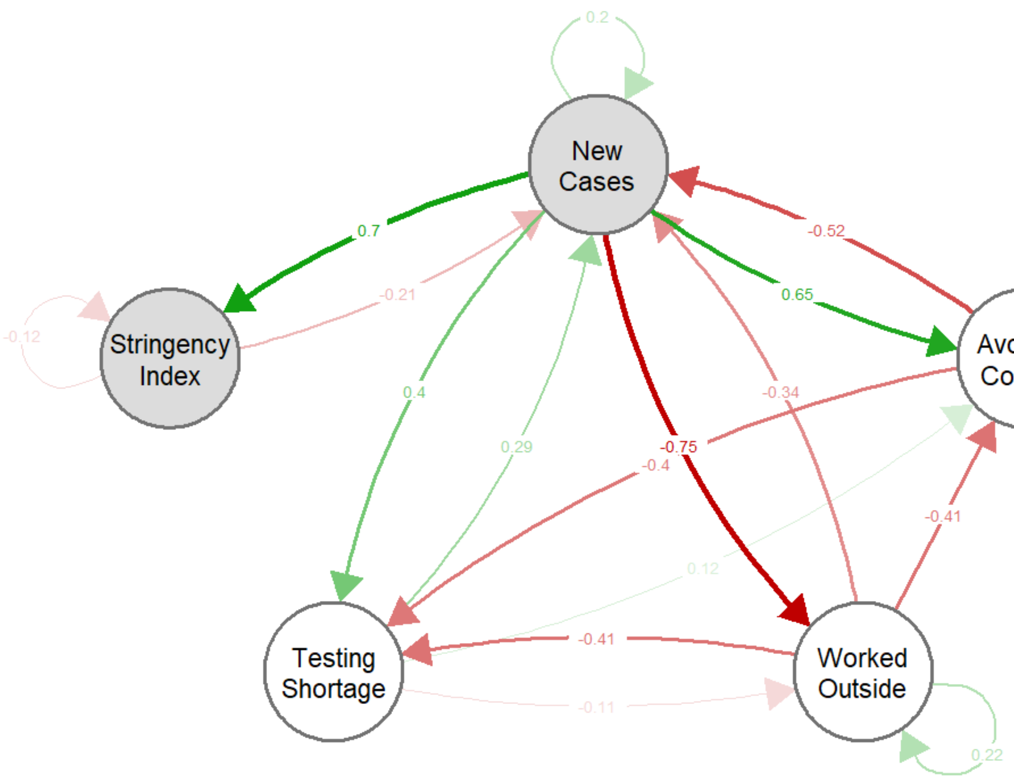
- Anosmia/ageusia and fever directly increase the new cases confirmed -> these symptoms distinguish COVID-19 from flu above all.
- Sequence of symptoms over time: anosmia/ageusia and fever provoke each other, then fever leads to difficulty breathing, shortness of breath, and cough.

CMU data

Temporal Effects for the US



CLI in Community



New Cases

- 2 variables for measuring the spread of COVID-19: New Cases and Community CLI.
- The estimated effects are almost identical, which adds more validity to the CLI variable.
- Over time both Stringency Index and Avoiding Contact decrease CLI, which, in turn, enlarges both variables. This means that on average within 14 days policy rigidity, as well as people's behavior, reduce the infection transmission, whereas high levels of transmission lead to the amplification of preventive actions from the side of both government and population.

CMU data

Lag Selection for Temporal Effects

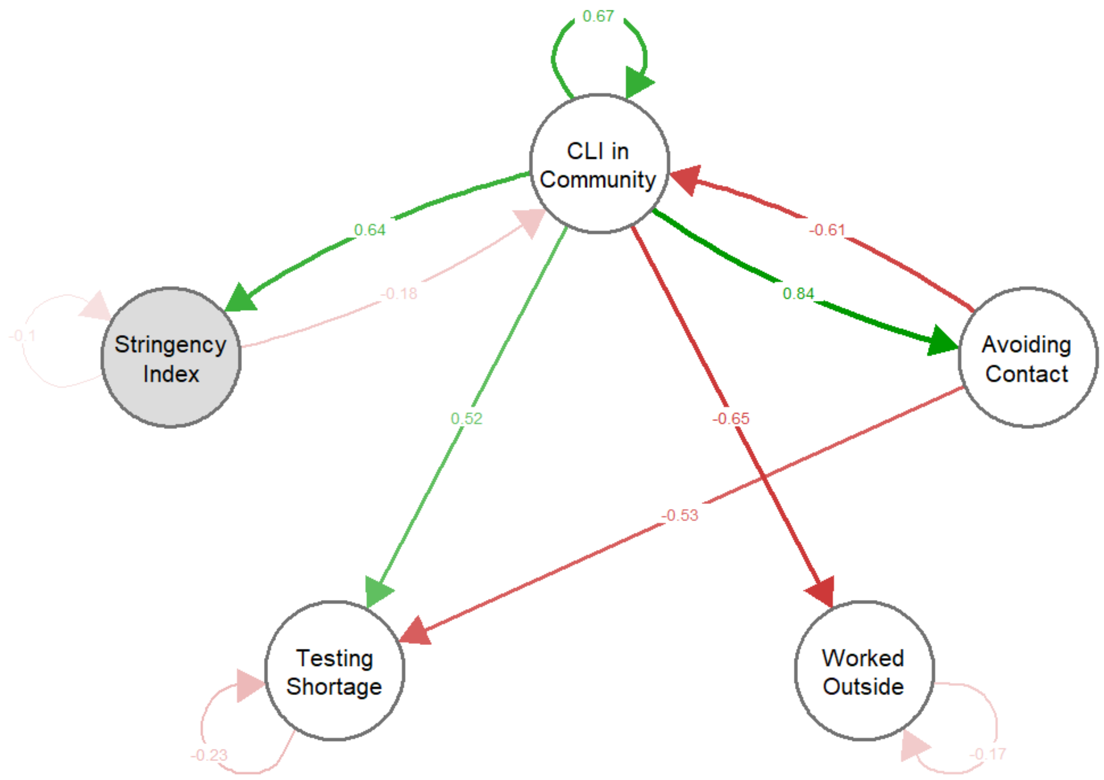
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
CLI in Community ⟶ CLI in Community	1.02	1.02	1.01	0.99	0.97	0.93	0.90	0.87	0.84	0.81	0.79	0.77	0.74	0.71	0.68	0.65	0.62	0.59	0.55	0.50	0.46
Avoiding Contact ⟶ CLI in Community	-0.06	-0.13	-0.20	-0.26	-0.33	-0.39	-0.45	-0.51	-0.57	-0.63	-0.69	-0.74	-0.80	-0.85	-0.88	-0.92	-0.96	-0.98	-1.00	-1.02	-1.03
Worked Outside ⟶ CLI in Community	-0.02	-0.06	-0.10	-0.14	-0.18	-0.23	-0.27	-0.30	-0.33	-0.36	-0.39	-0.42	-0.44	-0.46	-0.47	-0.48	-0.49	-0.50	-0.51	-0.51	-0.52
Testing Shortage ⟶ CLI in Community	0.01	0.03	0.05	0.06	0.08	0.10	0.11	0.13	0.14	0.15	0.16	0.17	0.18	0.19	0.20	0.21	0.21	0.21	0.21	0.20	0.20
Stringency Index ⟶ CLI in Community	-0.01	-0.03	-0.04	-0.05	-0.06	-0.07	-0.09	-0.10	-0.12	-0.13	-0.15	-0.16	-0.18	-0.19	-0.21	-0.21	-0.22	-0.23	-0.23	-0.24	-0.24

Time lags, days

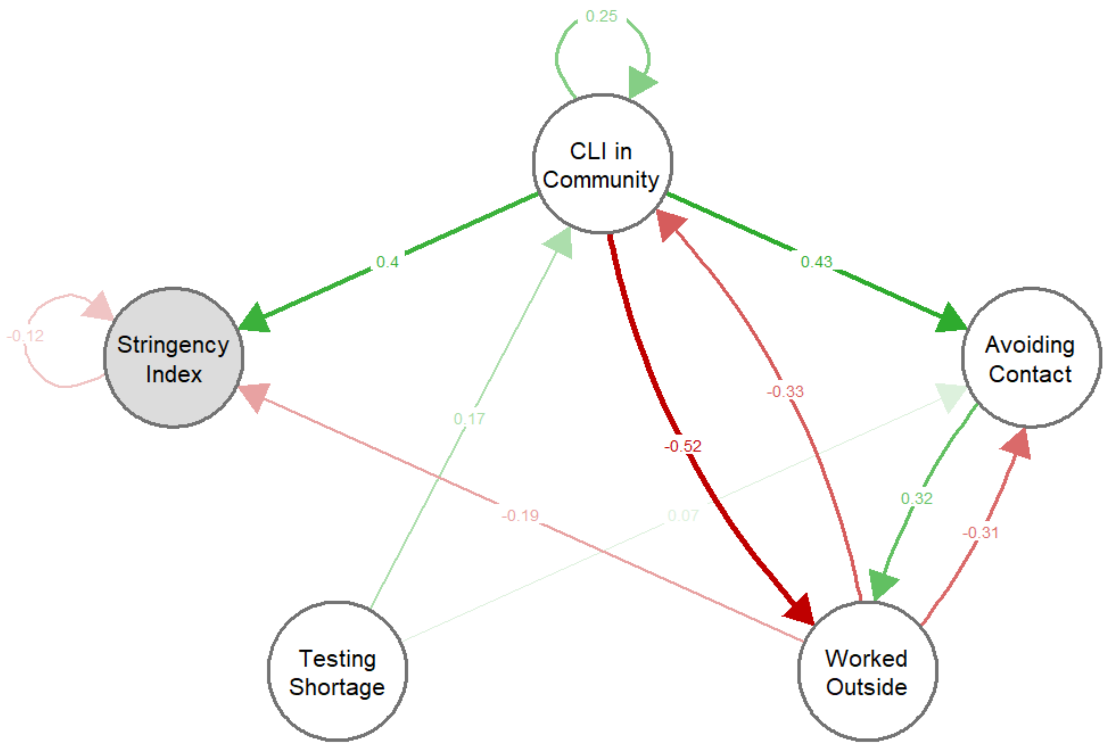
- We ran an array of models with different lags to justify the usage of a 14-days lag.
- The heatmap informs us that community CLI has been affected mostly by itself throughout the first 1-5 days. Over time this effect begins to decay, while the influence of other variables on CLI becomes more pronounced.
- Starting from roughly the 14th day, the magnitude of all associations looks relatively stable, therefore, the lag of 14 days is retained in further analysis.

CMU data

Temporal Effects for the US by Ages



18–34 age group

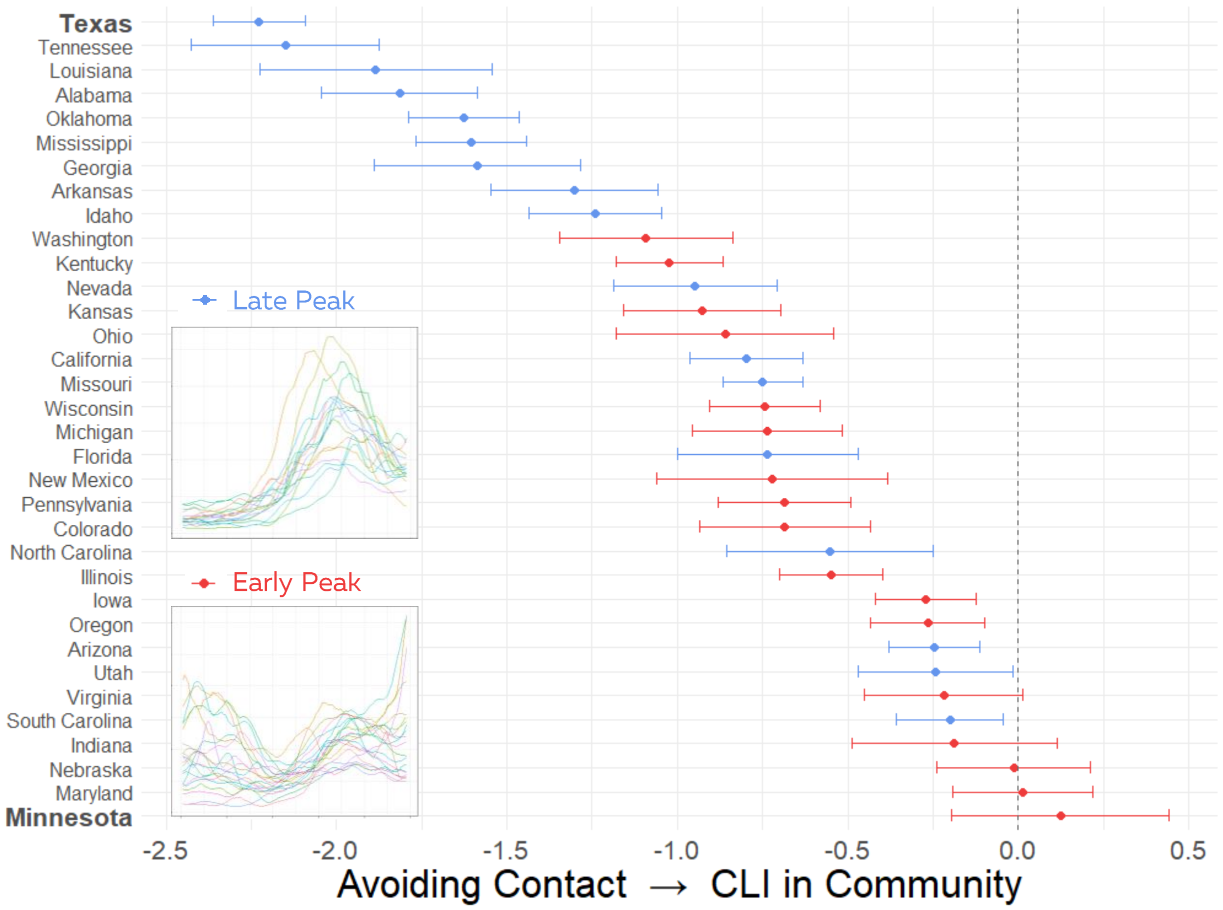


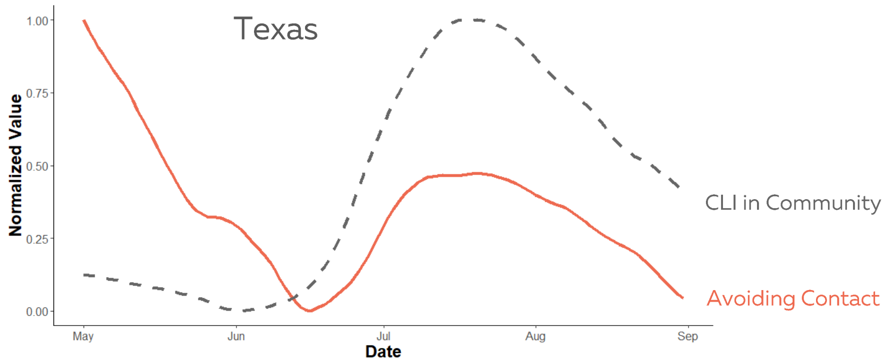
55+ age group

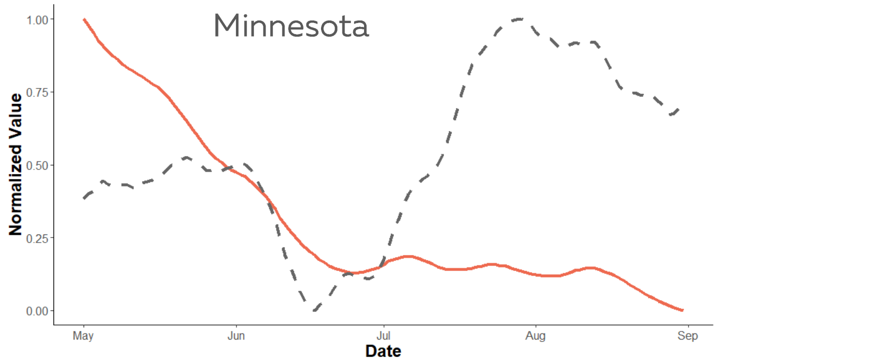
- The pattern of temporal links between the variables of interest for younger ages is close to the one observed for the whole sample.
- However, the older ages demonstrate a dissimilar structure of relationships: Stringency Index and Avoiding Contact variables do not work as mechanisms mitigating the spread of COVID-19 (CLI) for them, the paths are insignificant.
- These findings may have crucial substantive implications: policy interventions and self-protective behavior for older people may not be as effective for them as for the younger cohort. This can be explained by younger people infecting older people through social interactions within a family. The last model for the US in this section brings about evidence of the plausibility of such a statement (see slide 10).

CMU data

Effects and Confidence Intervals by States





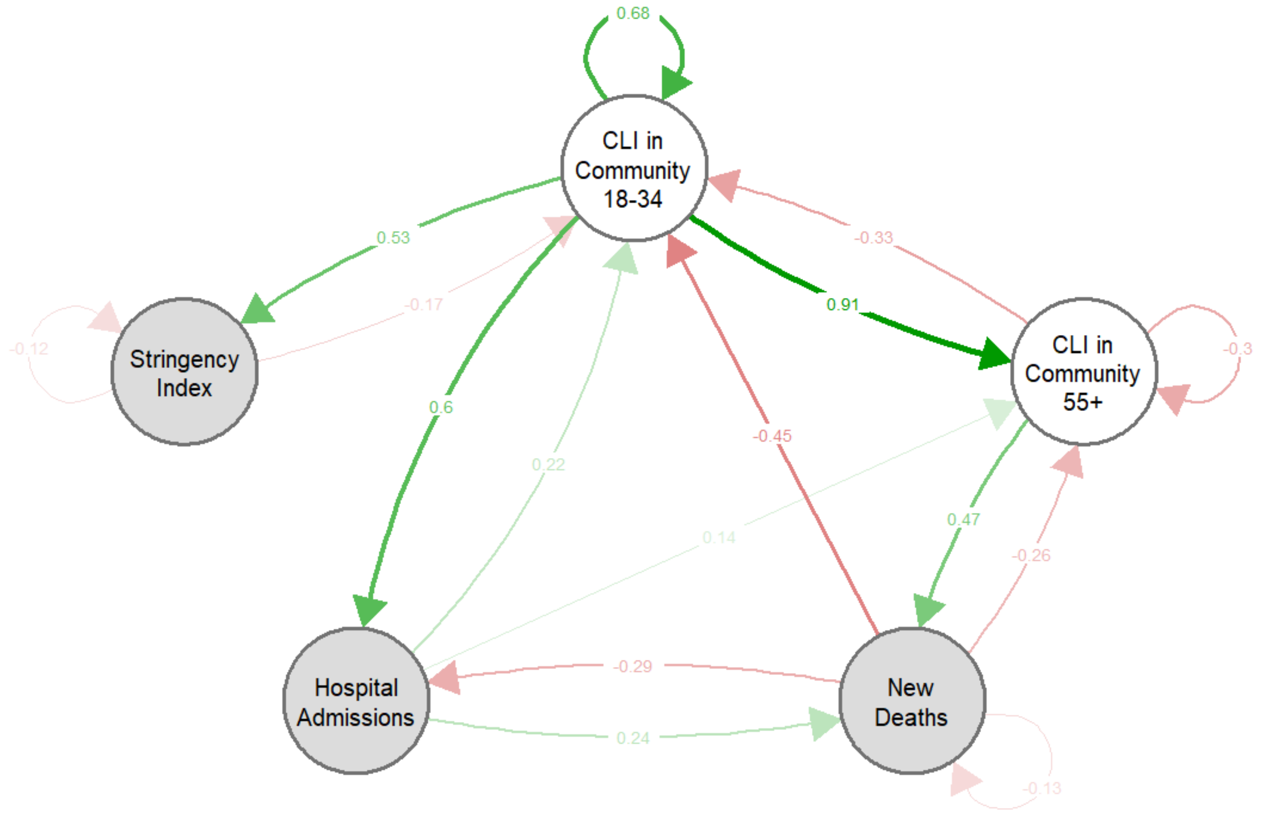


- Time series cluster analysis on the New Cases variable by states -> different patterns of temporal distribution -> 2 clusters.
- The magnitude of the Avoiding Contact effect on CLI is larger for the 'Later Peak' cluster -> those states are more effective as, perhaps, they had more time to accumulate richer knowledge for combating COVID spread.
- Right panel portrays the actual variables' distribution to clarify the possibility of dissimilar effects. In Texas, the infection transmission was declining if people had intensified their attempts to avoid contact roughly 2 weeks earlier, while in Minnesota people did not increase social distancing when the spread of COVID started to grow, hence, the decline in cases infected does not seem to be attributable to people's behavior (= the effect is insignificant).

Clusters of states obtained by the Hierarchical Clustering with DTW distance based on the number of new cases

CMU data

Deaths, Hospitalizations and CLI in Community



- Additionally, we estimated a model that includes CLI for both ages, Stringency Index, and official statistics data – Hospital Admissions and New Deaths from COVID.
- The graph demonstrates that CLI for younger people over time leads to the growth of New Deaths through increasing older people's CLI, which supports our initial speculations about younger people being the chief transmitter of COVID for the elderly.
- Interestingly, CLI in the younger group positively impacts itself over time, while CLI in the older group affects itself negatively. One explanation is that the younger generation is more socially active; through social interactions, they pass the disease on to their peers as well, especially in cases when they are asymptomatic careers. In contrast, older people once infected normally do not transfer the disease within their age group.
- High deaths in 2 weeks are followed by low hospitalization rate and low CLI in both cohorts. Inversely, hospital admissions over time are followed by a greater number of deaths and high CLI in both cohorts. This may reflect the temporal sequence of the observed effects and can inspire future hypotheses generation and examination.

Data for Countries

Sample: 43 countries with more than 100,000 total COVID-19 cases.

We use the following set of indicators (May 5, 2020 – October 31, 2020).

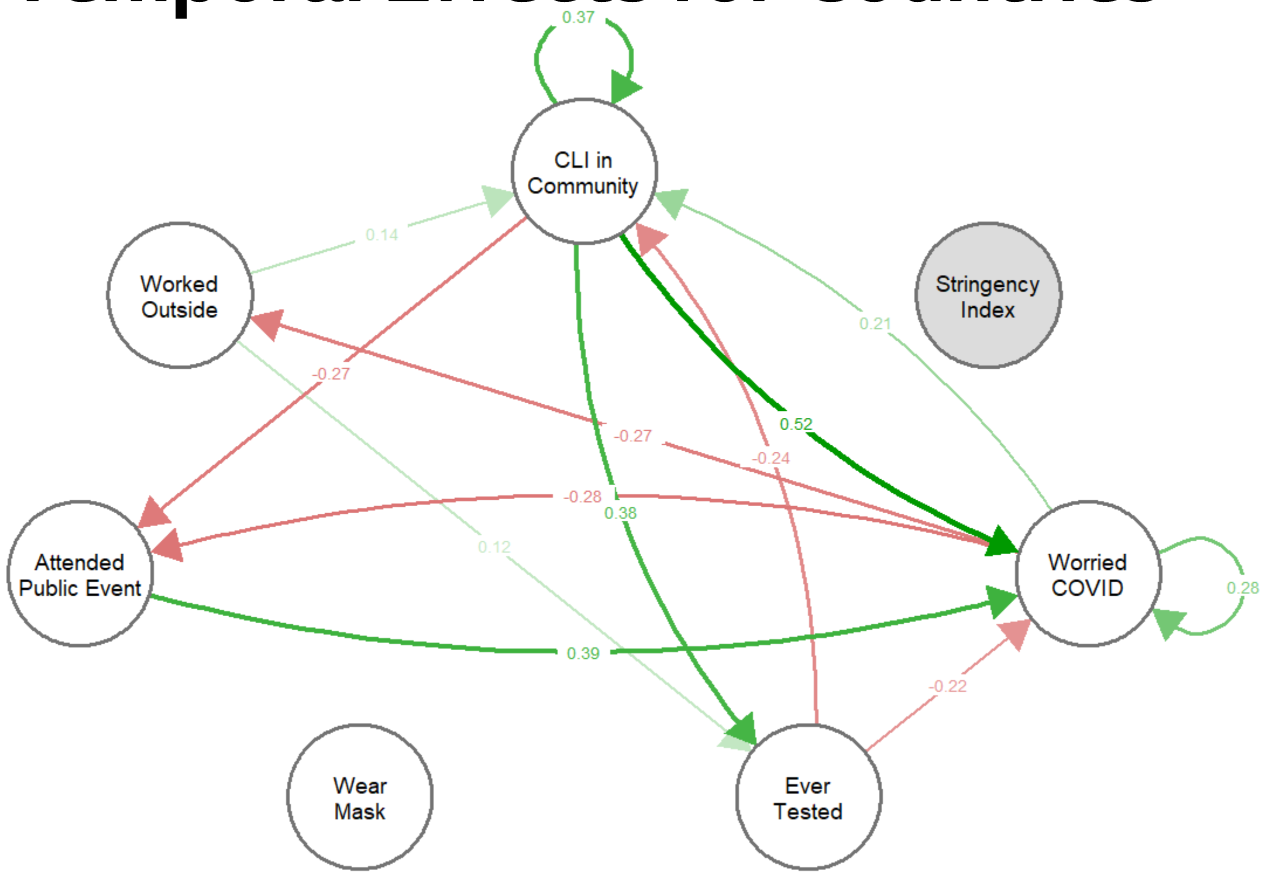
> **Community CLI:** % of resp. who know people with COVID symptoms in a community.
>
> **Worried COVID:** % of resp. who are very worried or somewhat worried that they or someone in their family might become seriously ill from COVID-19.
>
> **Ever Tested:** % of resp. who have gotten a test for COVID-19.
>
> **Wear Mask:** % of resp. who wear a mask all the time or most of the time when in public.
>
> **Attended Public Event:** % of resp. who attended a public event with more than 10 people in the last 24 hours.
>
> **Worked Outside:** % of resp. who went to work outside of the place they were staying in the last 24 hours.

Additional variables:

> **GDP per capita** from Google COVID-19 Open Data repository.
>
> **Stringency Index**. the rigidity of “lockdown style” measures that restrict people’s behavior.
>
> **New Deaths:** the number of new deaths from COVID-19 per 100,000 population, averaged by a 7-day window.

UMD data

Temporal Effects for Countries

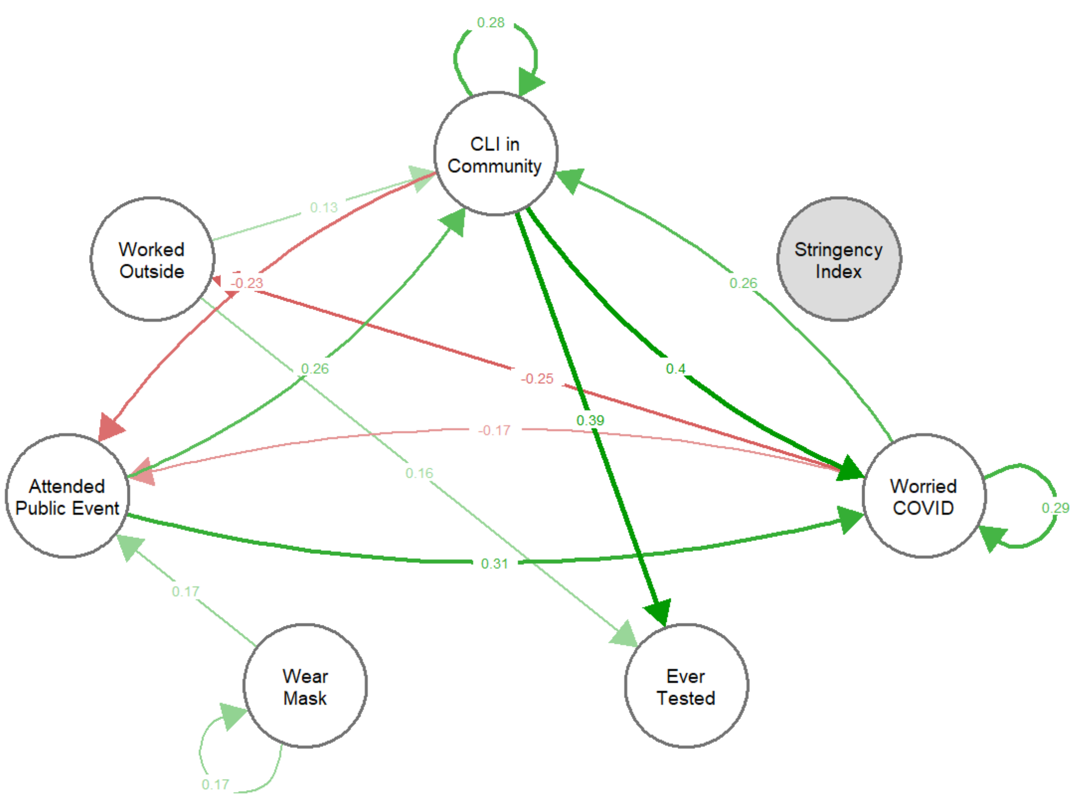


- It is noticeable that Wearing a Mask (social behavior proxy) and Stringency Index do not affect CLI in the analyzed countries.
- CLI increases worries about COVID, while worries about COVID, in turn, lead to higher CLI. Worries about COVID decrease attendance of public events, which in turn enlarges worries. Also, people are less pone to attend public events when CLI is growing.
- People who cannot afford distant work and thus work outside of their place are tested on coronavirus more, which seems logical.
- Note that the plot depicts an aggregated – hence highly averaged – picture. Further, we detail our findings by ages and concrete countries.

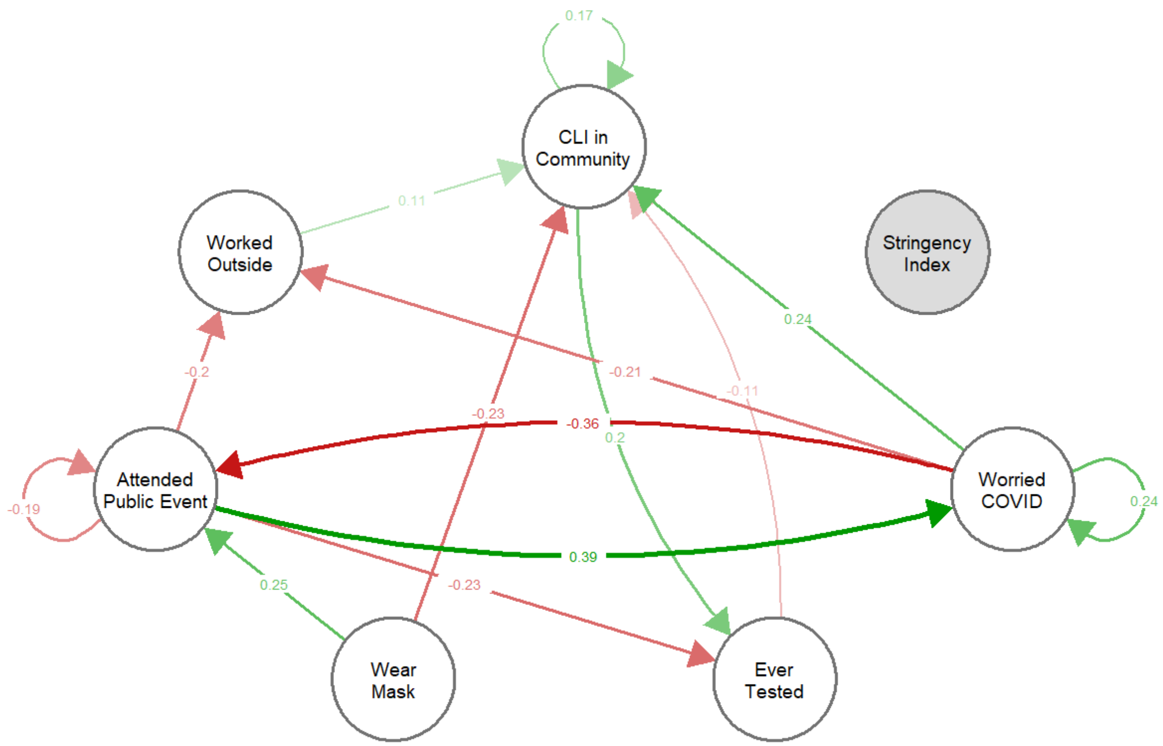
Only highly significant (p<0.01) edges shown

UMD data

Temporal Effects for Countries By Age



18–34 age group



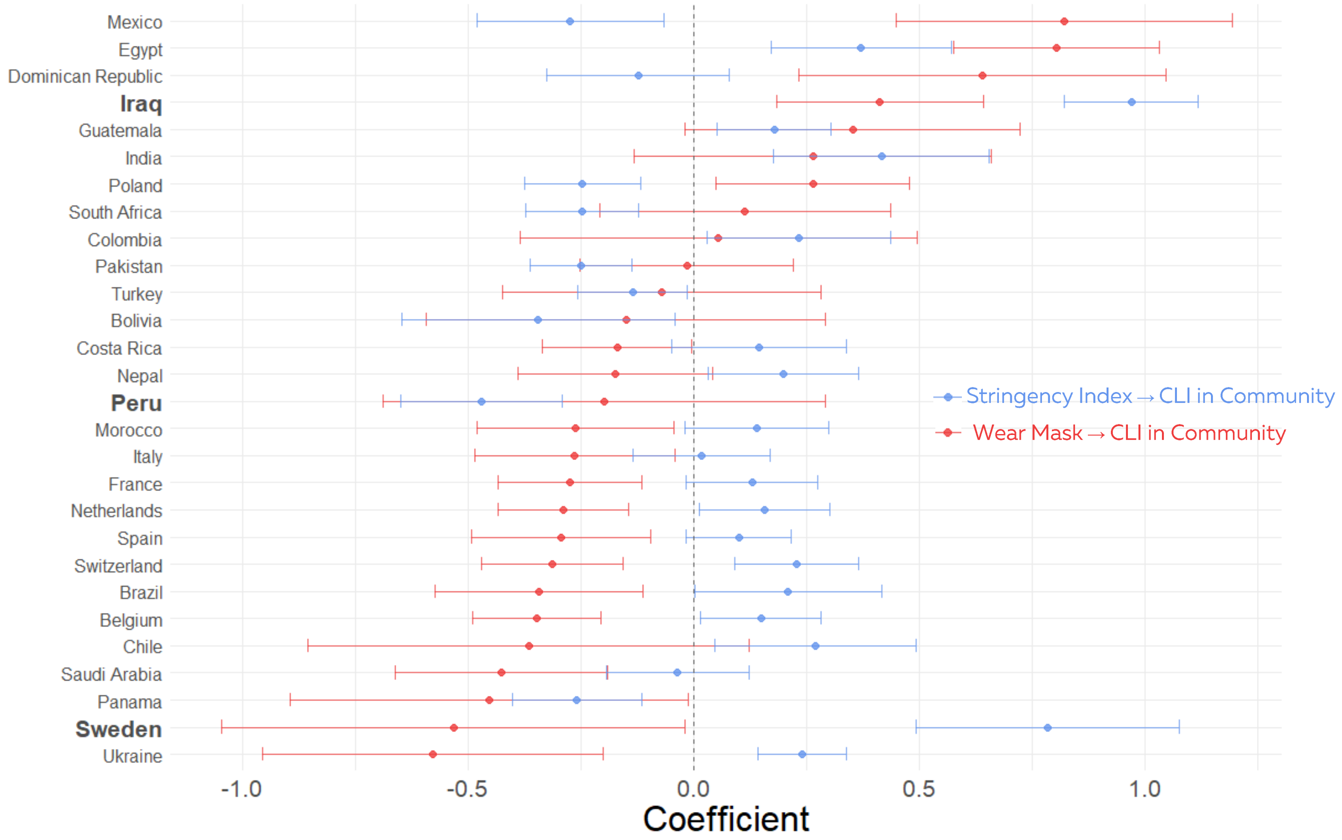
55+ age group

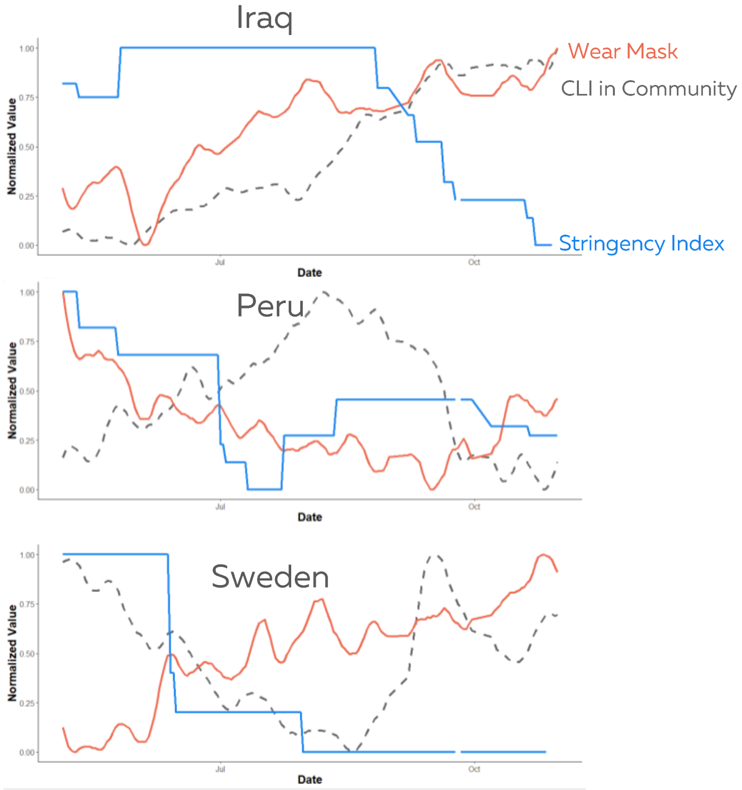
- Stringency Index still does not affect CLI in both age groups. However, wearing a mask for older people reduces CLI, whereas for younger people wearing a mask increases through the attendance of public events -> younger people may acquire a false sense of security when they wear a mask in public.
- Attending public events (analogous to avoiding contacts): the same structure of effects by ages as in the US.
- For both ages worries about COVID decrease attendance of public events, which, in turn, enlarges worries.

Only highly significant (p<0.01) edges shown

UMD data

The Effect of Stringency Index and Wearing a Mask on CLI





- In 35% of countries, both effects are zero (not shown in the graph). The remained observations are characterized by at least one significant coefficient.
- Surprisingly, in some developing countries (e.g., Mexico, Egypt, Dominican Republic) wearing a mask may deteriorate the spread of COVID (positive effect) -> people do not wear a mask properly or masks do not help due to, for example, high population density. The picture for Iraq visually depicts such a relationship: fluctuations of wearing masks and CLI variables are changing in the same direction with some noticeable lag for the former. In the rest of the plotted countries, the mentioned effect is negative (if significant).
- Also, unexpectedly, Stringency, being insignificant in most countries, is estimated to mitigate the spread of COVID in some regions when it declines (positive coefficient) (e.g., Sweden, Switzerland, Belgium). This may signify that when policy regulations are on a lower level, people start to wear masks voluntarily, compensating for the absence of harsh government measures, which over time relieves the infection transmission. It is visible in the graph for Sweden: CLI and Stringency are changing together with similar lagged downward pattern, whereas the involvement of people in wearing masks practices expands.
- There are some countries, such as Peru, in which Stringency looks vital in terms of alleviating the COVID spread. The distribution for Peru visually allows us to detect that the reduction of policy measures was followed by the escalation of the disease's spread but after the introduction of some policy measures (~August), the wave went down.

Conclusions

1. Policy interventions and self-protective behavior for older people may not be as fruitful for them as for the younger cohort; this can relate to the fact that younger groups infect the elderly within families. Country leaders should account for that when designing NPIs.

2. The obtained empirical evidence may indicate that the US states which experienced a later peak in CLI happened to be more effective in reducing COVID spread through following social distancing norms. These states need a more laborious investigation to reveal the underlying reasons for their better performance, which can advise future decision-making processes.

3. The case of countries with less stringent actions (like Sweden) may imply that people can be committed to mitigating the pandemic and will voluntarily attempt to prevent the infection proliferation. Future studies will aid improved policy decisions by figuring out the optimal stringency level that can boost responsible behavior of the population regarding the prevention of coronavirus spread

4. The granularity of the data by time, age, and space, as well as their behavior-oriented content, is informative for the evaluation of the COVID policy issues.

Thank you for your attention!

Photo by David Ramos/Getty Images