

Does the stay-at-home order help with preventing the COVID-19 transmission?

Zhen Miao

February 25, 2021

1 Non-Technical Executive Summary

During the outbreak of COVID-19, almost all of countries around the world implemented different kinds of interventions, such as closure of educational institutions, social circle/bubble to limit social contacts, etc. One of the most commonly used method is stay-at-home orders for the general population which are also referred as ‘lockdown’. We are interested in the effect of stay-at-home orders and want to find a way to quantify this effect.

In one word, we want to understand and quantify effects of the stay-at-home order during the pandemic.

- Proposed Question: Does the stay-at-home order help with preventing the COVID-19 transmission?
- Key findings: The stay-at-home order is significantly associated with reducing the transmission rate (p-value=0.002).

2 Technical Exposition

2.1 Exploratory Data Analysis

2.1.1 Wrangling & Cleaning Process

Since only *2_ecdc/country_response_measures* contains interventions conducted by governments in details including the exact start dates and end dates, we decided to focus on analyzing the spread of COVID-19 in Europe. However, *2_ecdc* only contains weekly new confirmed cases which are considerably loose. Therefore, we choose to use data on daily new confirmed cases of COVID-19. More specifically, we are using the *New confirmed cases of COVID-19 (7-day smoothed)* in *1_owid/owid-covid-data* to reduce the consequence of disorder on reporting confirmed cases, as most relative reports are using smoothed data for their analysis. Since the data during the first outbreak in Spring 2020 is more complete and 4 months are a circle of an outbreak, we decide to use the data

starting from the first confirmed case and its following 120 days. Among all European countries, only 15 countries have recorded stay-at-home orders and France (FRA) is kicked out since its recorded new cases have negative values without further explanation. We conduct our analysis on the remaining 14 countries and Romania (ROU) is an example and discussed in details.

2.1.2 An example of Romania

Figure 1 includes observed daily confirmed cases, the start date of stay-at-home order and the end date of stay-at-home order in Romania (ROU). It is clear that after the stay-at-home order, observed daily confirmed cases were still increasing and its peak is obtained even one month after the stay-at-home order. Although intuitively we believe that the slow down of outbreak of COVID-19 is due to the stay-at-home order, it is really hard to quantify the effect of the stay-at-home order simply from observed daily confirmed cases and this long delay may decrease people’s confidence on the effect of stay-at-home order. This delay may due to tons of infected patients who are in the incubation period (which is as long as 21 days for COVID-19) without being tested and continuously infect people around them. Therefore we could apply a related epidemiology model which may capture the intervention effect and help us to better understand the spreading pattern of COVID-19. By exploring the CDC COVID-19 website (<https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/forecasts-cases.html>), which records and compares the performance of many competing COVID-19 forecast models, we decide on using the survival-convolution model for predicting COVID-19 cases and assessing effects of mitigation strategies by Wang et al. (2020). This model accounts for transmission during a pre-symptomatic incubation period and use a time-varying effective reproduction number to reflect the temporal trend of transmission and change in the transmission rate to a public health intervention.

2.2 Model Fitting

As one of the best CDC forecasting models, we found that with only a very small number of parameters (transmission rates at intervention dates, e.g. 4 parameters in our analysis), it can capture the spreading pattern of infectious disease as well as having a strong interpretability. Thus, we can trust their prediction for transmission rate, which characters the number of people infected by a patient per day on average and we will use this value to evaluate the effect of stay-at-home order. The fitting result of all 14 countries are included in Appendix and here we will Romania (ROU) as an example to illustrate the intervention effect in Figure 2.

The first confirmed case was occurred on 03-03-2020 in ROU. Daily new cases were still increasing after the stay-at-home order, however the transmission rate turned to go down. This means the effect of stay-at-home order reflects quickly and timely on the transmission rate rather than daily new cases. Moreover, we can see the effect of stay-at-home order becomes weaker after 14 days, which

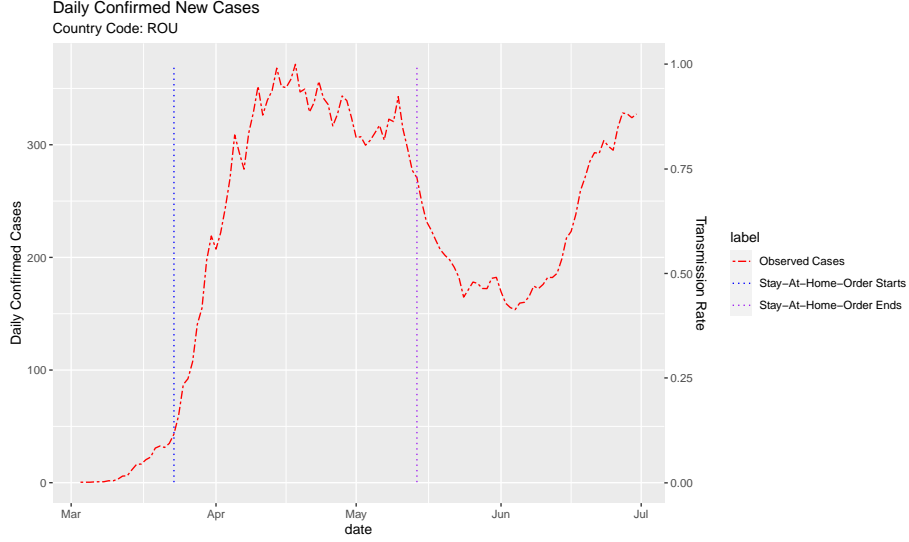


Figure 1: Analyze the effect of stay-at-home order via observed daily confirmed cases.

can be due to tiredness of staying at home. Hence, additional interventions may be needed to further decrease the transmission rate. When the stay-at-home order ends, daily new cases are still decreasing. However, the transmission rate bounced up which would bring the second wave.

For Romania, we assume that the transmission rate is piece-wise linear and its estimate is in Figure 2. It shows that the model captures the peak date of new cases, the trend of the epidemic and the second wave of pandemic after stay-at-home order ends. We model the transmission rate as a four-piece linear function to account for the change in the start and the end of stay-at-home order, and one additional knot at 2-weeks after the stay-at-home order to account for a post intervention effect. During the beginning of the pandemic, since no intervention is implemented, the transmission rate continuously increases from 0.423 to 0.503 in 20 days with a slope 0.004 and increasingly more people were infected. After the stay-at-home order, during the immediate 2 weeks the transmission rate turns to decrease from 0.503 to 0.253 with a slope -0.018 . The change of slopes equals to -0.022 which quantifies the effect of the stay-at-home order. Afterwards the transmission rate continuously decreases from 0.253 to 0.196 with a slope -0.002 . The change of the slopes from -0.022 to -0.002 means that the effect of stay-at-home order becomes weaker on reducing the transmission rate which is possible since people are tired of staying at home and want to enjoy the fresh air. When the stay-at-home order ends, the transmission rate bounces up. From the end of stay-at-home order to the end of our analysis period, it increases from 0.196 to 0.299 with a slope 0.002 which means another outbreak is coming. The change of slopes from -0.002 to 0.002 equaling 0.004 again

demonstrates the ability of the stay-at-home order on reducing the transmission rate.

Table 1 includes the change of slopes of transmission rates at the beginning of the stay-at-home order and at the end of the stay-at-home order for 14 countries in Europe.

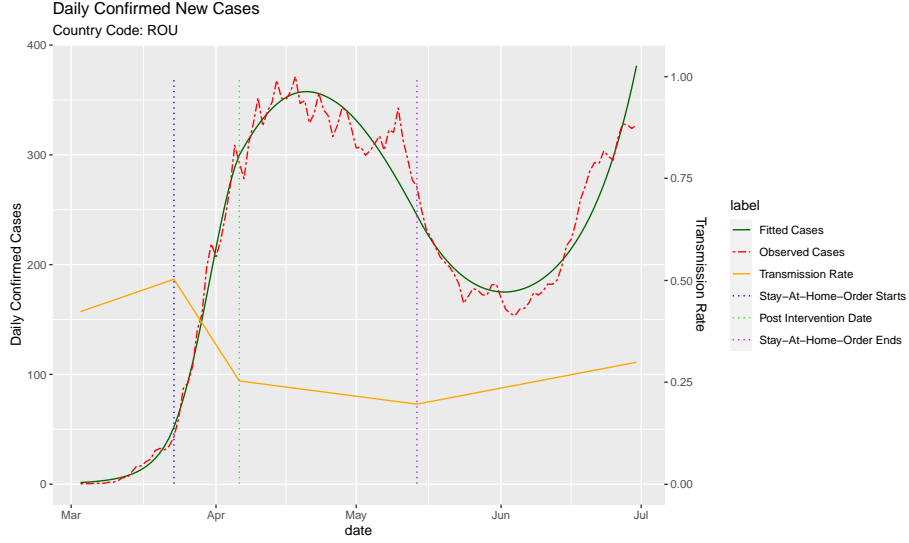


Figure 2: Analyze the effect of stay-at-home order via a survival-convolution model in ROU. Plots for other countries are delayed in Appendix.

Country Code	AUT	BEL	CYP	CZE	GRC	HUN	IRL
start of lockdown	-0.049	-0.031	-0.016	-0.037	-0.004	-0.008	-0.005
end of lockdown	-0.001	0.005	0.001	0.003	0.001	0.002	0.006
Country Code	ITA	LUX	POL	ROU	SVN	ESP	GBR
start of lockdown	-0.022	-0.049	-0.010	-0.022	0.027	-0.044	-0.015
end of lockdown	0.001	0.002	-0.002	0.004	0.008	0.007	-0.001

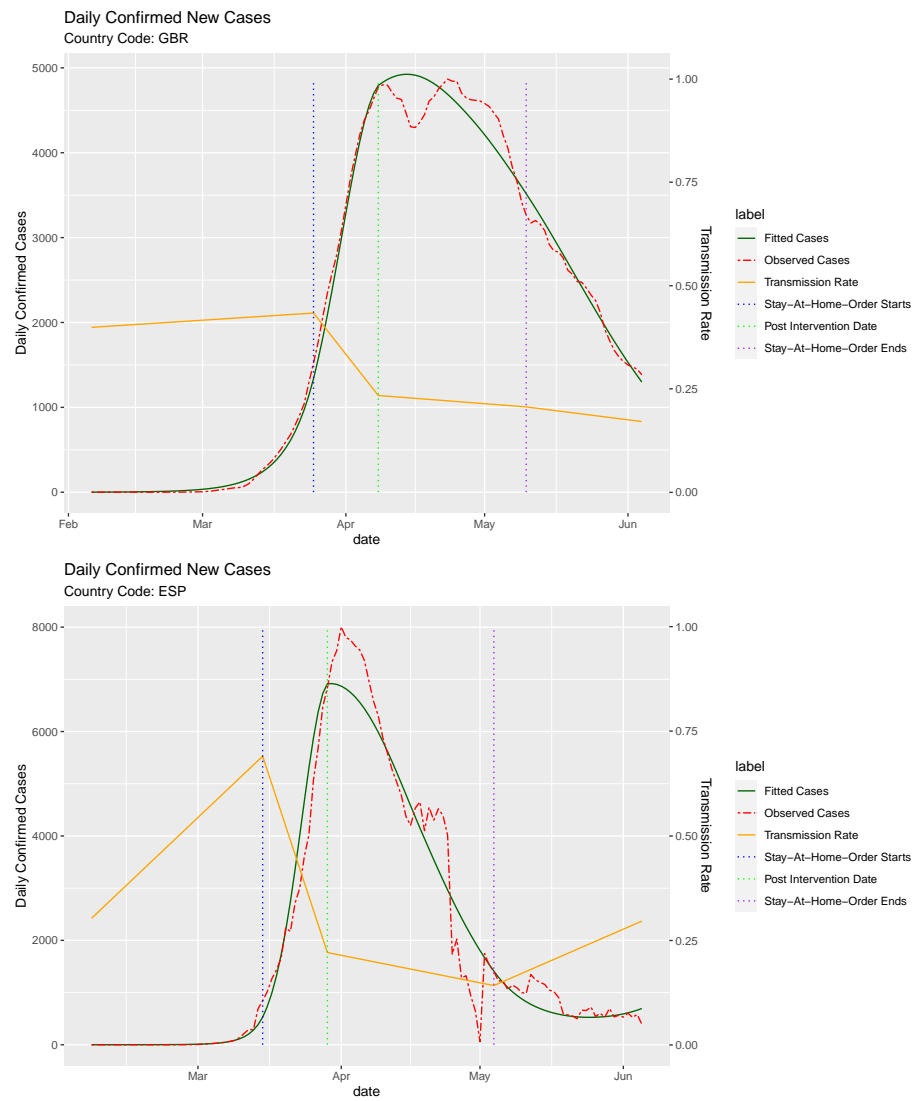
Table 1: Table including changes of slopes at the start of the stay-at-home order and at the end of the stay-at-home order.

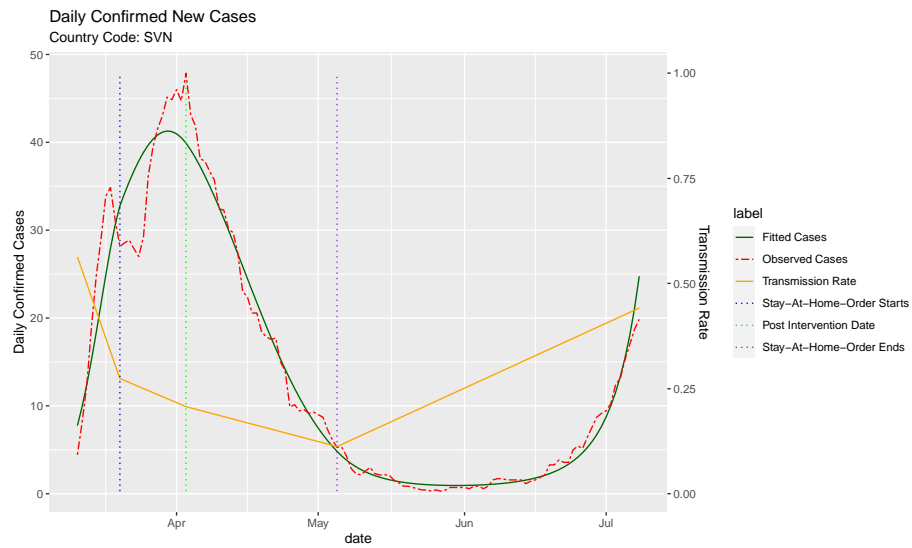
Since the sample size is small, it is hard to justify the normality assumption of Student T-test. Here we use data in Table 1 and a one-sample Wilcoxon test to evaluate whether the stay-at-home order effect on the change of slopes is statistically significant. At the beginning of the stay-at-home order, the stay-at-home order is significantly associated with a decrease in the transmission rate (p-value=0.002). In the end of the stay-at-home order, the stay-at-home order is significantly associated with an increase in the transmission rate (p-value=0.003).

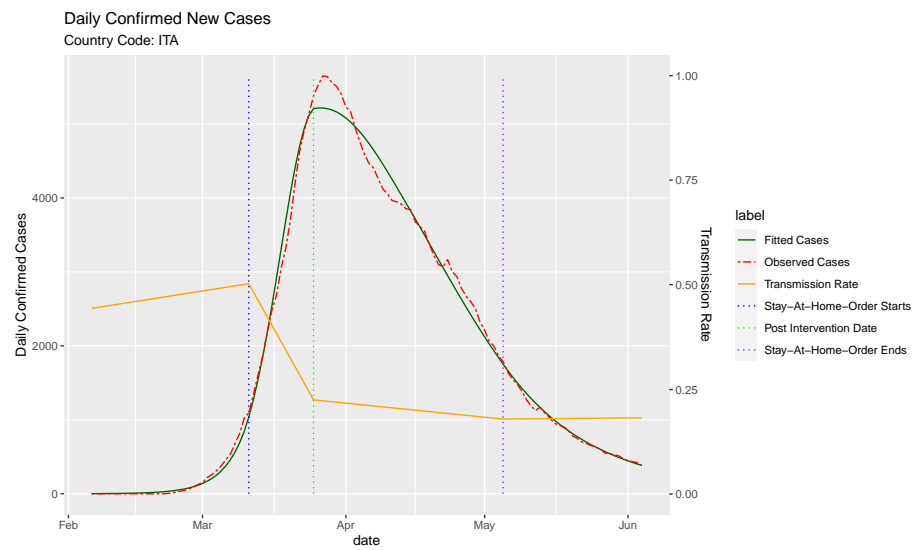
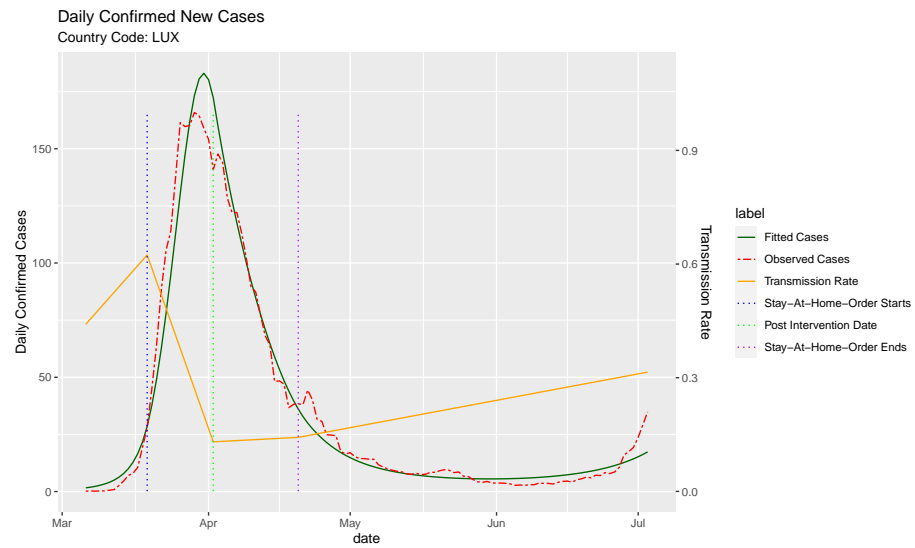
2.2.1 Discussion

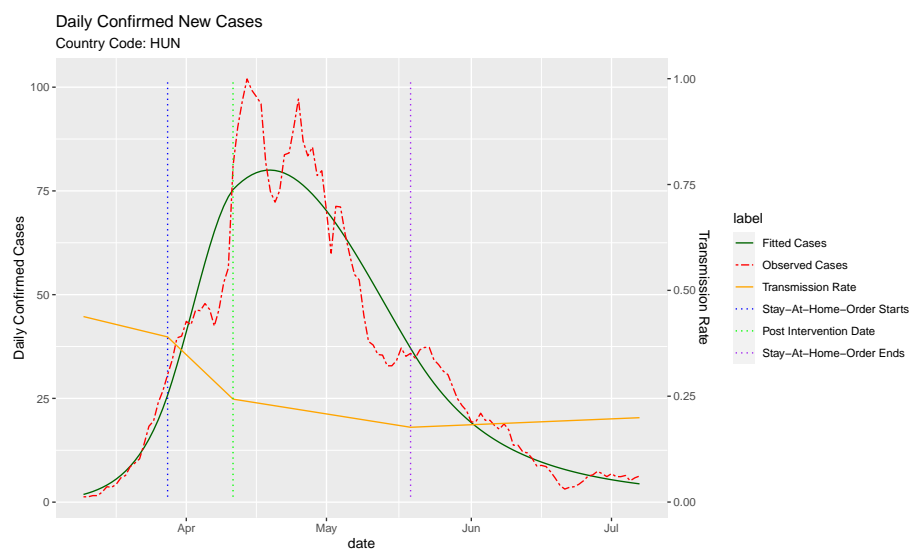
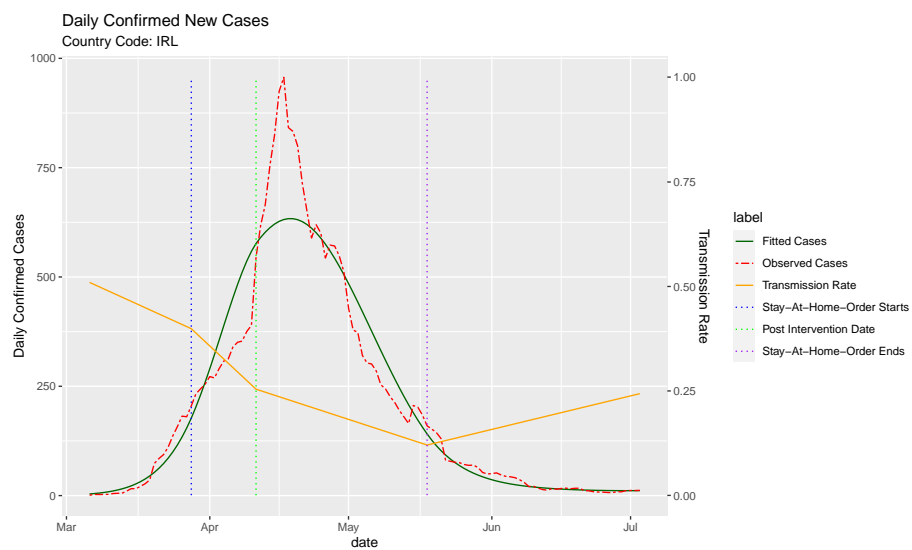
Assumption: the transmission rate is a piecewise linear function with changes of slopes on a set of given date which are usually chosen as dates of intervention. Note that the simplicity of the transmission rate doesn't decrease this model's ability of fitting data and on the other side the limited number of parameters guarantee that this model won't overfit the data. Superspreader event commonly plays an important role during a pandemic, however this survival-convolutional model cannot capture that.

3 Appendix

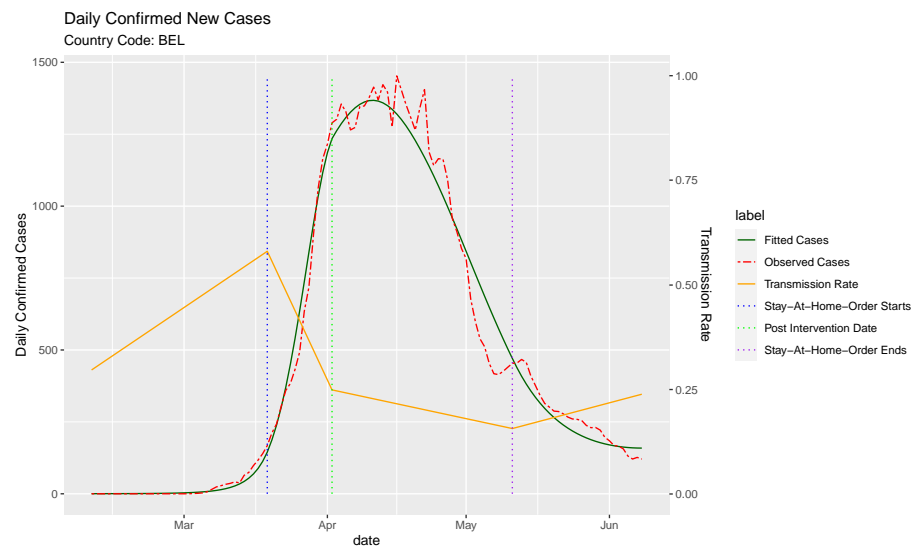
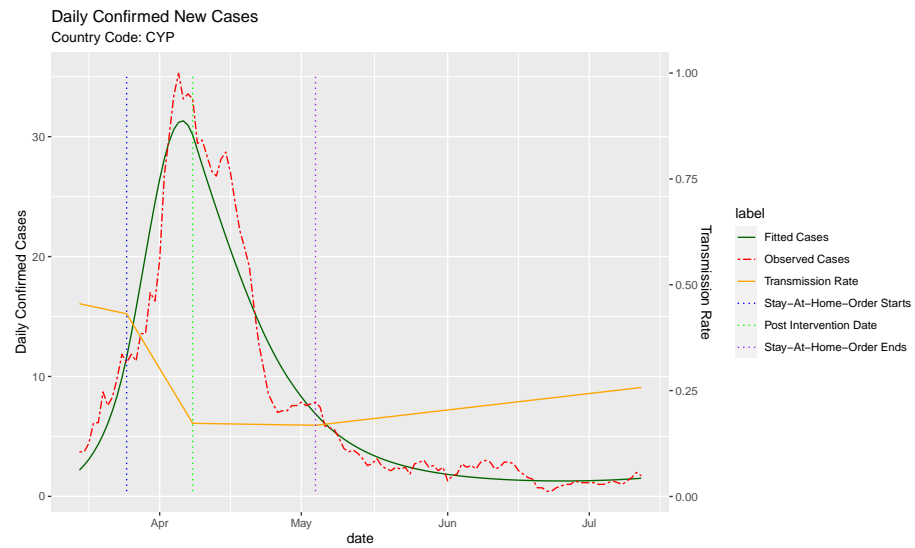


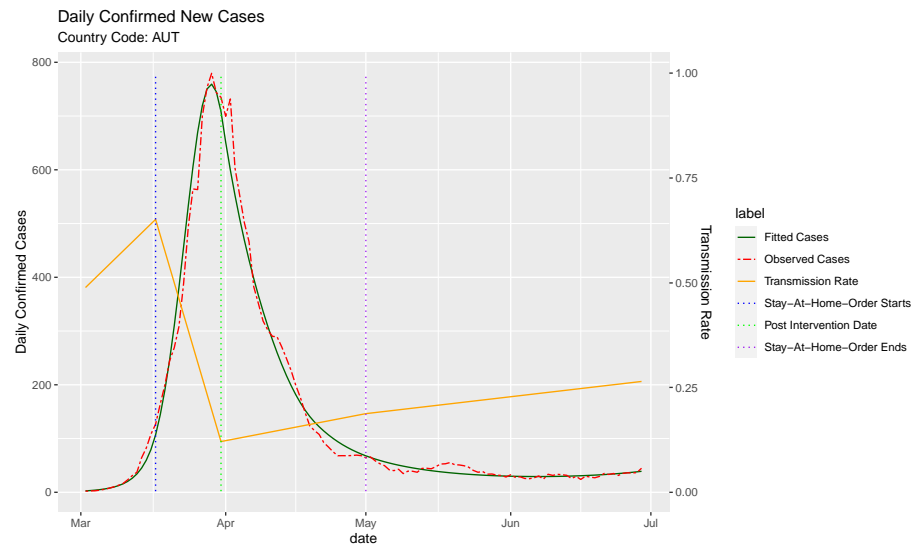












References

Wang, Q., Xie, S., Wang, Y., and Zeng, D. (2020). Survival-convolution models for predicting covid-19 cases and assessing effects of mitigation strategies. *Frontiers in Public Health*, 8:325.