Monitoring COVID-19 contagion growth in Europe

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Motivation

- The spread of the COVID-19 virus caught many governments by surprise
- Although data is (still) incomplete, good statistical analysis can provide evidence for policy making
- We focus on comparative analysis of the disease spread in different countries, to understand which policy mix is more effective

Contribution

- Our work extends the Susceptible Infected Recovered (SIR) model (see, e.g., Kermack and McKendrick, 1927 and Gu et al., 2020)
- We focus on the Infection part of the model, and extend it taking time dependence into account
- This allows the model to adapt to "time shocks" such as a change in prevention measures, a change in testing procedures, or a local outburst of cases
- Our findings show that we can better monitor contagion and assess the impact of containment policies

As in the exponential growth models used within the SIR approach, contagion is assumed to follow a Poisson distribution, with intensity:

$$\lambda_t = \lambda_0 \exp(\gamma t),$$

where γ is usually estimated by regressing the logarithm of the cumulative number of cases up to time t, N_t, on the number of days since the start of the epidemic:

$$\log(N_t) = \kappa + \gamma t,$$

We model $Y_t = N_t - N_{t-1}$, the count of new cases at time (day) t as Poisson distributed, with a log-linear autoregressive intensity:

$$Y_t|\mathcal{F}_{t-1} \sim Poisson(\lambda_t)$$

$$\log(\lambda_t) = \omega + \alpha \log(1 + y_{t-1}) + \beta \log(\lambda_{t-1}),$$

where the series $y \in \mathbb{N}$ is observed, and $\omega \in \mathbb{R}$, $\alpha \in \mathbb{R}$, $\beta \in \mathbb{R}$ are to be estimated from the data up to t.

The model

Interpretation

- $\alpha + \beta$ expresses the "persistence" of the contagion series, similarly to the exponential growth parameter γ
- α represents the short-term dependence on daily variations, and β the long-term dependence on all the process history, including past "shocks"
- It can be shown that:

$$\log(\lambda_t) = \omega \frac{1-\beta^t}{1-\beta} + \beta^t \log(\lambda_0) + \alpha \sum_{i=0}^{t-1} \beta^i \log(1 + y_{t-i-1}).$$

when $\alpha = 0$, the model approaches an exponential growth one.

The model

Reproduction rate

To estimate the disease reproduction rate R_0, we calculate the b ratio between the new fitted cases in t and the total number of fitted cases in the previous $(t-1,\ldots,t-8)$ days:

$$b = \frac{\hat{\lambda}_t}{\sum_{i=1}^{l} \hat{\lambda}_{t-i}} \text{ with } l = 8.$$

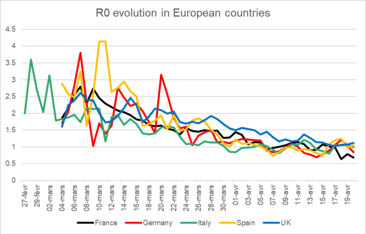
We then calculate a baseline level of R_0 as follows:

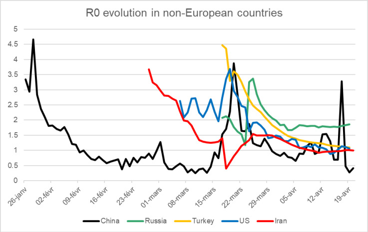
$$R_0 = E(T) \times b$$

which, assuming an average infection time of $E(T) = 7.5$, gives $R_0 = 7.5 \times b$

Results

Reproduction rates

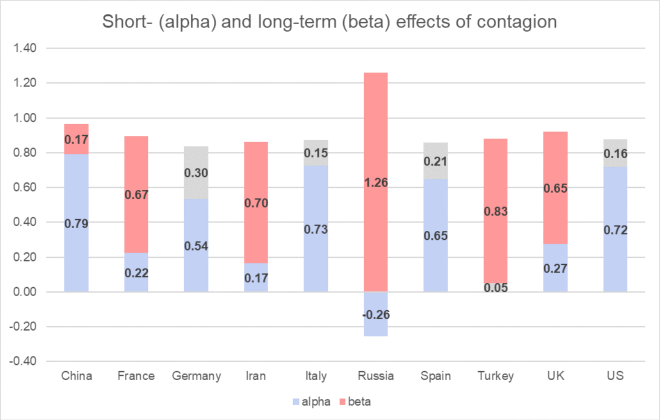




(taken from CEPS on-line infographics as of 22 April 2020, based on WHO data)

Results

Estimated coefficients



(taken from CEPS on-line infographics as of 22 April 2020, based on WHO data)

Results

Goodness of fit

(taken from CEPS on-line infographics as of 22 April 2020, based on WHO data))

Research developments

- Extending the results to more countries and regions
- Develop a summary metric to "rank" countries
- Extend the model to include spatial contagion and causal covariates
- Measure the impact of the COVID-crisis on global financial markets and economies