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PERISCOPE

PAN-EUROPEAN RESPONSE TO THE IMPACTS OF COVID-19 AND FUTURE PANDEMICS AND EPIDEMICS

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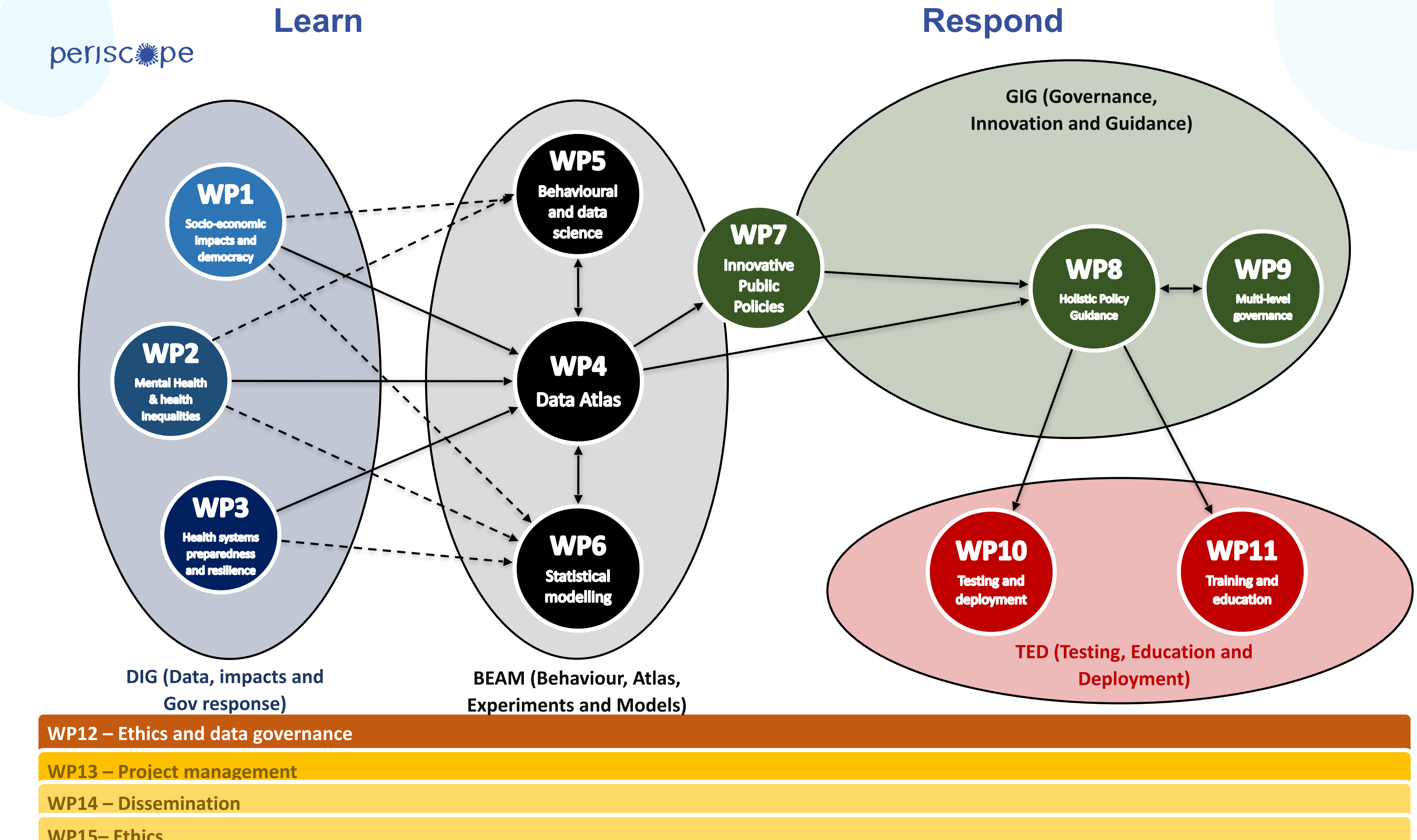
The PERISCOPE Project

The PERISCOPE project (Pan-European Response to the ImpactS of COvid-19 and future Pandemics and Epidemics) is funded under the EC Coronavirus Global Response initiative (SSC1-PHE-CORONAVIRUS-2020-2-RTD)

Started on 1 November 2020, it aims to learn the direct and indirect impacts of COVID-19 and to respond with sustainable policies and technologies

To achieve these aims, it involves multidisciplinary research in Engineering and Statistics, Economics and social sciences, Health sciences.


Learn
Respond
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GIG (Governance, Innovation and Guidance)
WP1
Socio-economic impacts and democracy
WP2
Mental Health & health inequalities
WP3
Health systems preparedness and resilience
WP5
Behavioural and data science
WP4
Data Atlas
WP6
Statistical modelling
WP7
Innovative Public Policies
WP8
Holistic Policy Guidance
WP9
Multi-level governance
WP10
Testing and deployment
WP11
Training and education
TED (Testing, Education and Deployment)
DIG (Data, impacts and Gov response)
BEAM (Behaviour, Atlas, Experiments and Models)
WP12 – Ethics and data governance
WP13 – Project management
WP14 – Dissemination
WP15– Ethics

WP4 - Data Atlas (maps)

Policy measures (CoronaNet)

- Daily categorization of all policies undertaken at the NUTS-2 level

Economic data (OECD)

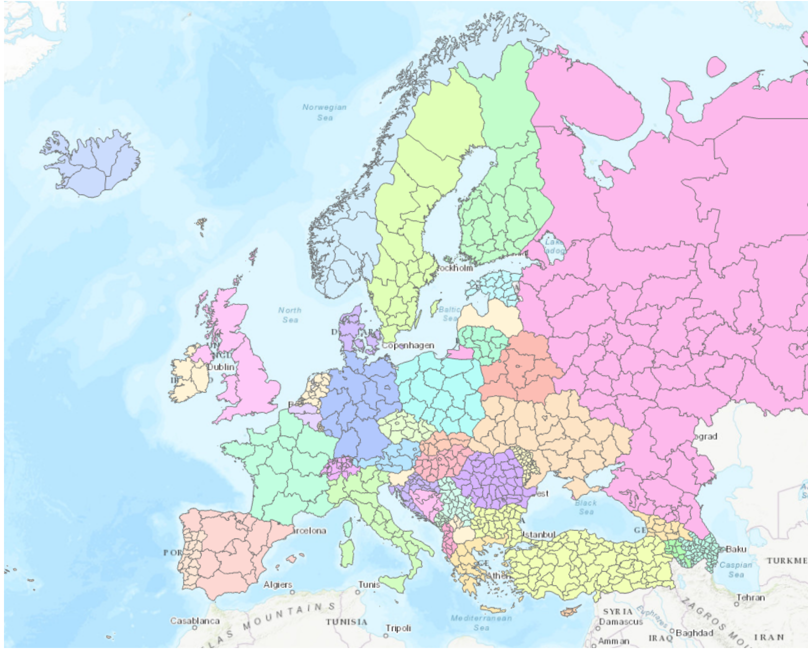
- Monthly economic data, at the country level. It includes Employment rate, Unit labour costs (quarterly), Interest rate, GDP (quarterly), Industrial production, Export/Import of goods, Retail trade volume, Share prices, Consumer prices, Exchange rates.

Health data (ECDC)

- Weekly Covid-19 counts from the ECDC, at the country level. It includes Positive Cases, ICU admission rates, current occupancy for COVID-19, number of tests, positivity rate.

Boundary maps

- Map of the NUTS-2 level regions of Europe, 40 in total, with related ISO codes



WP4- Data Atlas (pilots)

Economic data (WP1)

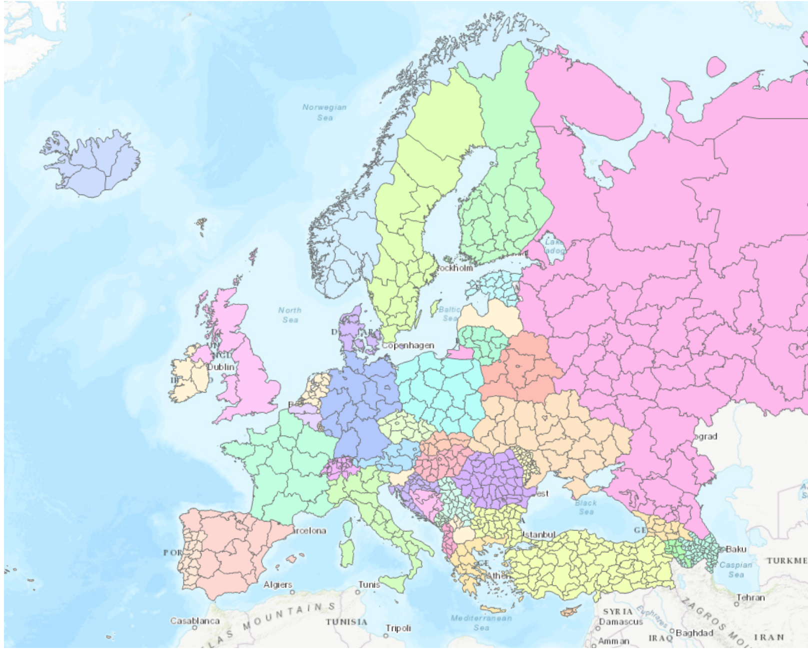
- Mobility data

Health data (WP2, WP3)

- Mental health care utilization
- Inequalities and impact on vulnerable populations
- indirect health impacts (project 4CE)
- Impact on health systems

Behavioural data (WP5)

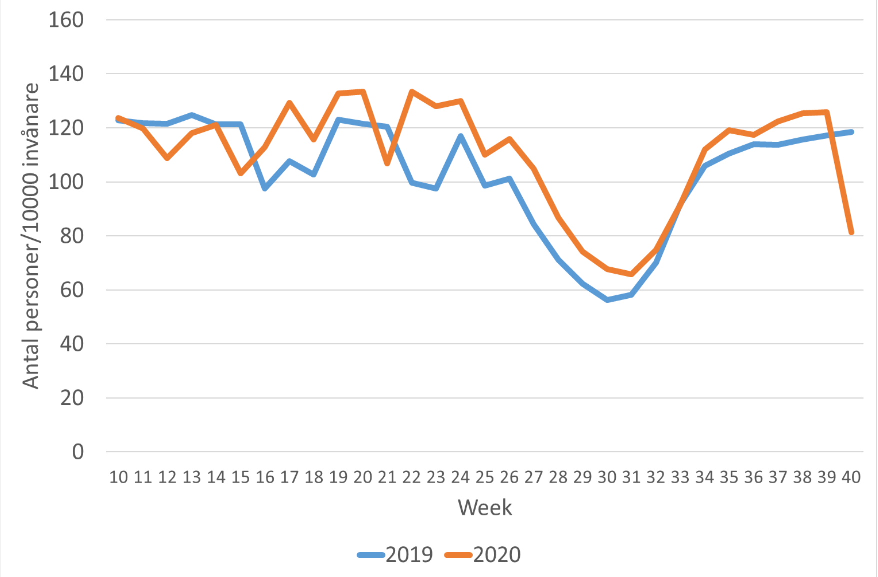
- Vaccine hesitancy



WP 2- Mental health pilots

Health care data, Stockholm Region

Nb of adults per 10 000 inhabitants in Stockholm, with person visits or telemedicine in psychiatric outpatient care, per week (during March-September) 2019 and 2020.
Total population 2.4 million indiv, more data available on age group, sex, specialized vs primary care, new visits vs re-visits, distance vs physical



Repeated cross-sectional survey: COVID-CZEMS

Repeated cross-sectional survey with M.I.N.I interview

3000 Czech adults in November 2017 and May 2020

Higher rates of major depressive episodes, suicidality and anxiety disorders in 2020

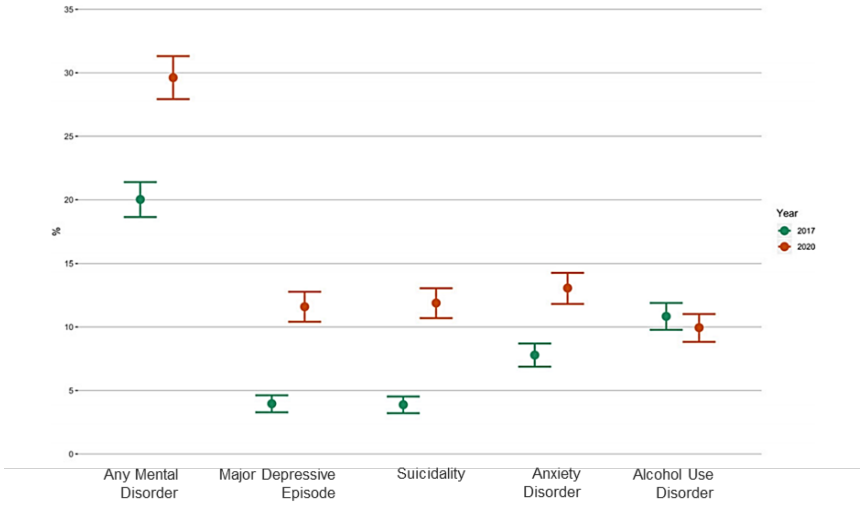
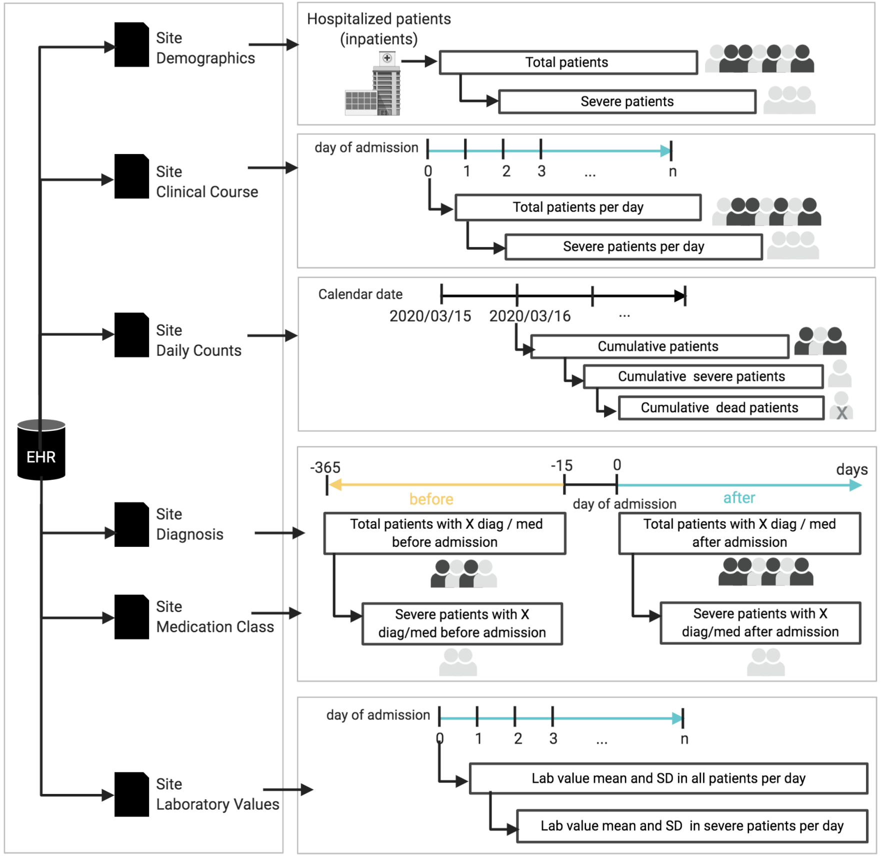


Fig. 1. Prevalence of mental disorders among non-institutionalized adults in the Czech Republic: November 2017 and May 2020.

WP2 -4CE Pilot



WP5 - Behavioural pilot

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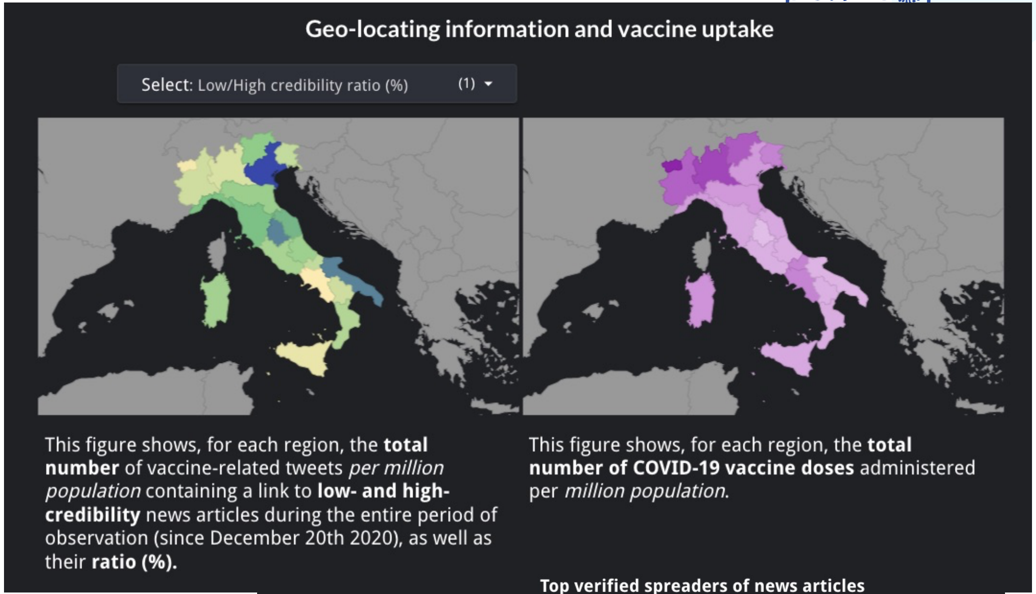
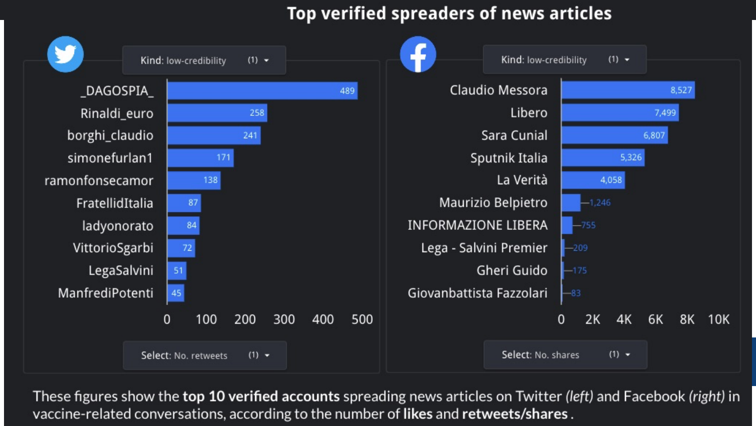
VaccinItaly:

- Method and tool for analysis of disinformation and information diffusion with respect to COVID-19 Vaccines in Italy
- Next step: broaden analysis and tool coverage to more EU countries





http://genomic.elet.polimi.it/vaccinitaly/

WP6 - Dynamic SIR models – Standard framework

- ***Time dependence (PAR)***

The time dependence of COVID-19 transmission represents a critical factor to understand the epidemic dynamics. The evolution of the epidemics is characterized by time heterogeneity, which leads to a non-linear growth. Therefore, the exponential growth assumption of conventional SIR models needs to be relaxed in favor of a time dependent modelling framework*:

$$Y_t \mid \mathscr{F}_{t-1} \sim Poisson(\lambda_t)$$

$$log(\lambda_t) = \mu + \sum_{i=1}^{p} a_i log(1 + Y_{t-i}) + \sum_{j=1}^{q} b_j log(\lambda_{t-j})$$

- ***Effects of NPI covariates (PARX)***

We aim to provide an alternative quantitative approach of NPIs' effectiveness using a time dependence model that can take lagged effects into account. To this aim we extend the Poisson autoregressive model adding NPIs covariates**:

$$Y_t \mid \mathscr{F}_{t-1} \sim Poisson(\lambda_t)$$

$$log(\lambda_t) = \mu + \sum_{i=1}^{p} a_i log(1 + Y_{t-i}) + \sum_{j=1}^{q} b_j log(\lambda_{t-j}) + \eta^T X_t$$

As NPIs have been implemented in a policy mix approach, policy covariates have been grouped to compare their effects. Different time lags between government intervention and epidemiological effect have been considered to address reverse causality issues.

- *Monitoring COVID-19 contagion growth. A. Agosto, A. Campmas, P. Giudici, A. Renda, Revised for Statistics in Medicine.
- **Which policy response is more useful to reduce COVID counts?, Working paper, P. Giudici and B. Tarantino

WP6 - Dynamic SIR models – Bayesian framework

- ***Bayesian models and MCMC methods***

The Bayesian framework* is more flexible in model specification and more suited to measure uncertainty of model outputs. The prior distribution is combined with the likelihood functions to obtain the posterior distribution of model parameters. MCMC methods based on Hamiltonian Monte Carlo algorithms have been implemented to approximate the posterior distribution.

- ***Time-varying parameters***

Standard PARX model assumes that model parameters do not change over time. However, the spread of the disease can change over time, especially as a result of policy measures. To address this extension we introduce spline functions. Every continuous function on the interval $[a, b]$ can be well approximated by a polynomial spline of degree p. Let $S_{p,k}$ be a finite dimensional space; $p+k+1$a set of basis functions $\{B_1(x), \ldots, B_{p+k+1}(x)\}$. Then f can be approximated with the linear combination: $f(x) = \sum_{j=1}^{p+k+1} \beta_j B_j(x)$. We then assume:

$$\boldsymbol{Y_t \mid \mathscr{F}_{t-1}, G_{t-1} \sim Poisson(\lambda_t) where log(\lambda_t) = \mu\left(\frac{t}{T}\right) + \sum_{i=1}^{p} a_i\left(\frac{t}{T}\right) log(1 + Y_{t-i}) + \sum_{j=1}^{q} b_j\left(\frac{t}{T}\right) log(\lambda_{t-j})}$$

➢ * Hindsight is 2020 vision: a characterisation of the global response to the COVID-19 pandemic. D. Warne, A. Ebert, C. Drovandi, W. Hu, A. Mira and K. Mengersen, BMC Public Health, 2020.

WP6 - Dynamic SIR models – Rt

- ***Poisson autoregressive methodology***

The Susceptible Infected Recovered (SIR) methodology allows the determination of the reproduction rate of the virus based on the incubation period of the disease and the instantaneous reproduction rate. However, the assumption that the number of cases is assumed to grow at a constant rate does not hold. As a result, the reproduction rate is obtained as the ratio between the fitted number of infections at time t ($\hat{I}_t$) and the total of the previous 7 days (in line with the incubation period):

$$R_t = E(T)\frac{\hat{I}_t}{\sum_{t=1}^{t-1}\hat{I}_t}$$

- ***Cori et al. (2013) Bayesian methodology***

The method of Cori et al. (2013) estimates the instantaneous reproduction within a Bayesian framework, in which the incidence at time t is modelled as a Poisson process and the prior parameters are Gamma distributed, obtaining a posterior Gamma distribution for R_t. In formulas:

$$R_t = \frac{I_t}{\sum_{s=1}^{t} I_{t-s} w_s}$$

where I_t is the number of infections on day t and w_s is the generation interval.

WP6 - Dynamic SIR models – Data

- ***Epidemiological data:*** WHO (new COVID-19 cases)
- ***NPI covariates:*** Oxford COVID-19 Government Response Tracker (OxCGRT)

Our main NPI of interest where those that introduce physical distancing measures, defined as *C - containment and closure policies. To code them, a three-step data preprocessing has been applied:*

1. *From ordinal to binary scale*

0 → *No intervention – Recommendation*

1 → *Required intervention*

2. *From individual measures to combinations of NPIs*

X1 Closure policies

X2 Restrictions on gatherings and events

X3 Internal mobility restrictions

X4 **External mobility restrictions**

3. *Time-lag between* intervention initiation and effect on disease counts

1-day | *7-days* | *14-days*

Country → 4 EU pilot countries (FR, DE, IT, SP)

Timeframe → March 2020– March 2021

WP6 - Dynamic SIR models - Empirical findings

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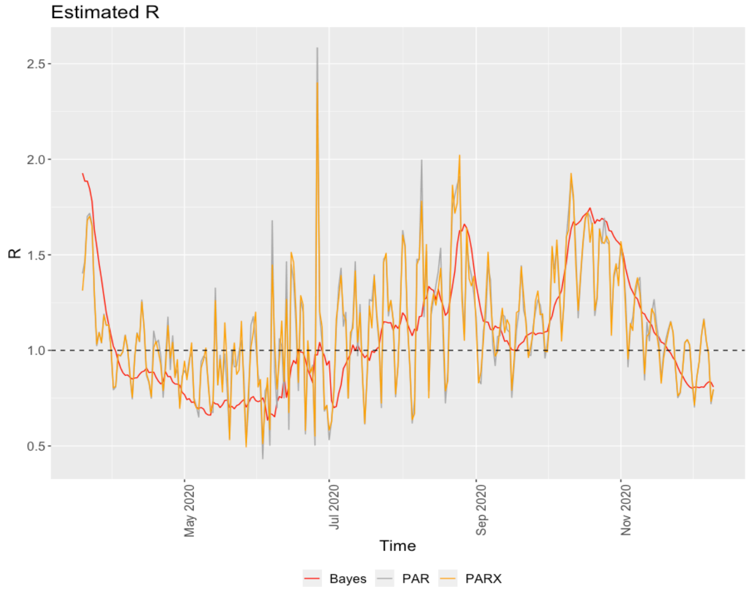
Standard framework

- The application of PAR/PARX models to four European countries reveals that the inclusion of time-lagged policy intervention slightly improves model predictions over a pure autoregressive model.
- Time-lag selection of policy variables confirms the large number of days occurring between the activation of a policy and the realization of its epidemiological effects (about 2 weeks).
- Although significant, the magnitude of policy effects seems to be limited if compared to the autoregressive component.

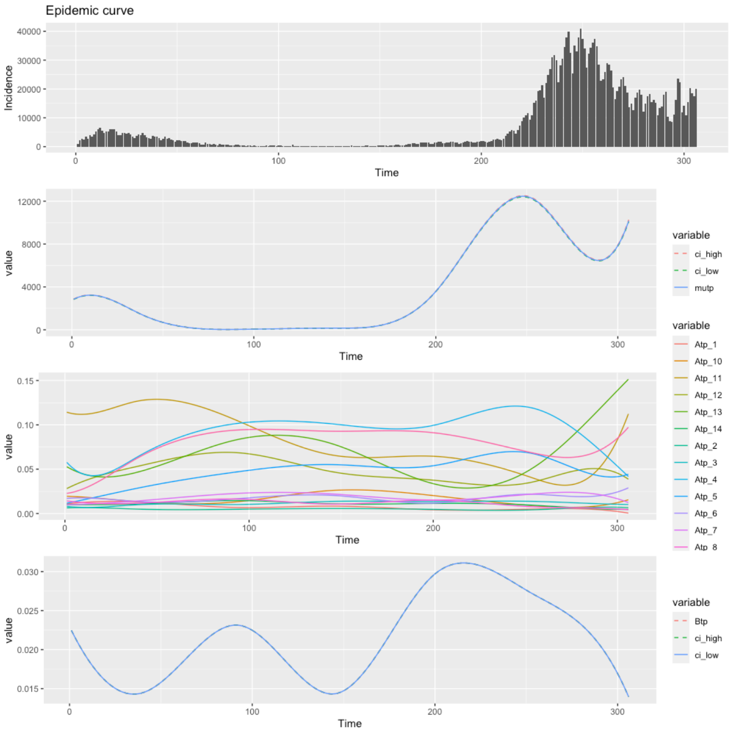
Response variable: COVID-19 case counts;
Covariates: NPIs (binary coding)

Country	*Lag*	*NPIs*	*Coefficient estimates*
France	14	x3	-0.202***
		x4	-0.237***
Germany	14	x1	-0.211***
Italy	14	x1	-0.079***
		x2	-0.075***
		x3	-0.074***
Spain	14	x2	-0.302***



WP6 - Dynamic SIR models - Empirical findings

Bayesian framework (Italy)



- Rolling window one-step ahead forecasts have been computed over 7-days to gauge model performance, resulting in **0.34 MAPE** (on average).
- $\mu(\bullet)$: Increasing trend in correspondence of epidemic peak, still growing in the last period of analysis.
- $AR(14)$: lags of order 7 (i.e. incubation period) dominates in order of magnitude.
- $MA(1)$: incorporates high “local” variability also for small counts with respect to mean trend.
- The inclusion of policy covariates does not sensibly improve predictions.

WP6 - Dynamic SIR models (European Forecast Hub)

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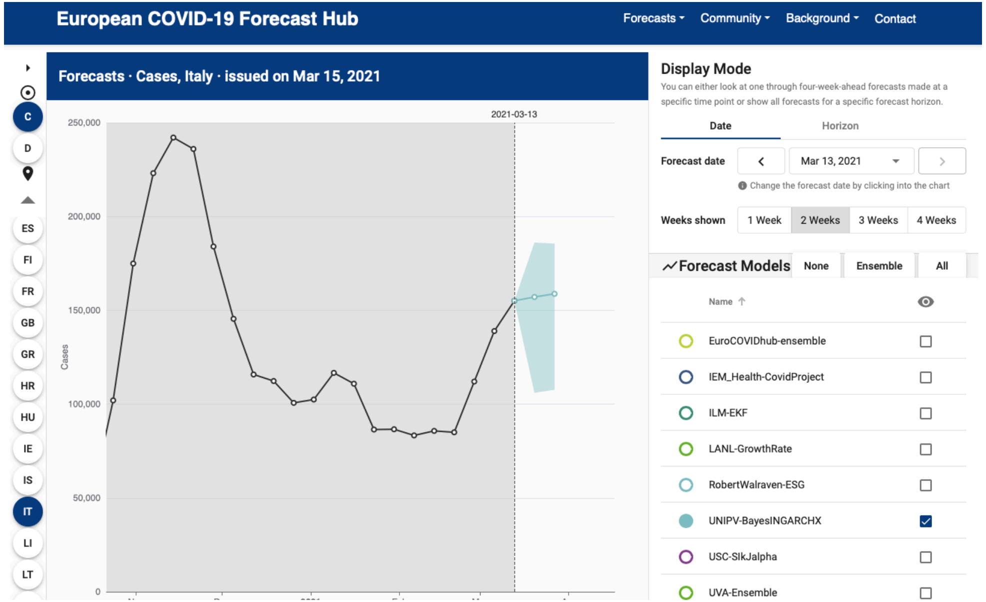
Comparison of models have been carried out through 3 different dimension to assess the best predictive performance:

- Classical vs Bayesian modelling framework
- Identity (linear) and log link function
- Static and Time-Varying (b-splines) coefficients

Model	MAPE over last 7-days
Classic INGARCH(p,q) – identity link	24%
Classic INGARCH(p,q) – log link	7%
Bayesian TV – identity link	16%
Bayesian TV- log link	19%



Forecasts of Bayesian INGARCH model are submitted to EU Forecast Hub.

Target: new COVID—19 cases

Countries: FR, DE, IT and SP

Horizon: 4 weeks ahead

THANKS!

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