Measuring the effect of different political actions to contrast the contagion of COVID19

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1 Introduction

Since the beginning of the COVID-19 epidemic, policy makers in different countries have introduced different political action to contrast the contagion. The containment restrictions span from worldwide curfews, stay-at-home orders, shelter-in-place orders, shutdowns/lockdowns to softer measures and stay-at-home recommendations and including in addition the development of contact tracing strategies and specific testing policies. The pandemic has resulted in the largest amount of shutdowns/lockdowns worldwide at the same time in history.

The timing of the different interventions with respect to the spread of the contagion both at a global and intra-national level has been very different from country to country. This, in combination with demographical, economic, health-care related and area-specific factors, have resulted in different contagion patterns across the world.

Therefore, our goal is two-fold. The aim is to measure the effect of the different political actions by analysing and comparing types of actions from a global perspective and, at the same time, to benchmark the effect of the same action in an heterogeneous framework such as the Italian regional context.

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In doing so, some issue arises concerning the identification and codification of the different measures undertaken by governments, the analysis related to whether a strategies resemblance can be detected across countries and the measurement of the effects of containment policies on contagion. Thus, after an introductory section explaining data and variables, a second section regards some explanatory analysis facing the codification of containment policies and the strategies resembling patterns. The third section deals with the measurement of policies effect from a global perspective, lastly the forth section analyze Italian lockdown and regional outcomes. Conclusion are drawn in the last section.

#Data and Variables

The data repositories used for this project are *COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University*[1] for contagion data (Dong, Du, and Gardner (2020)), and *Oxford COVID-19 Government Response Tracker (OxCGRT)*[2] for policies tracking (Thomas et al. (2020)), together with *World*

Bank Open Data Repository for demographic data.

Contagion data..

The *Oxford COVID-19 Government Response Tracker (OxCGRT)* collects all the containment policies adopted by government worldwide by making available information on 11 indicators of government containment responses of ordinal type. These indicators measure policies on a simple scale of severity / intensity and are reported for each day a policy is in place, specifying if they are “targeted”, applying only to a sub-region of a jurisdiction, or a specific sector; or “general”, applying throughout that jurisdiction or across the economy.

The containment ordinal variables considered are:

- **School closing** records closings of schools and universities with levels: 0 - No measures 1 - recommend closing 2 - Require closing (only some levels or categories, eg just high school, or just public schools) 3 - Require closing all levels.
- **Workplace closing** records closings of workplaces with levels:0 - No measures 1 - recommend closing (or work from home) 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) all-but-essential workplaces (e.g. grocery stores, doctors).
- **Cancel public events** records cancelling public events with levels: 0- No measures 1 - Recommend cancelling 2 - Require cancelling.
- **Restrictions on gatherings** records the cut-off size for bans on private gatherings with levels: 0 - No restrictions 1 - Restrictions on very large gatherings (the limit is above 1000 people) 2 - Restrictions on gatherings between 101-1000 people 3 - Restrictions on gatherings between 11-100 people 4 - Restrictions on gatherings of 10 people or less.
- **Close public transport** records closing of public transport with levels: 0 - No measures 1 - Recommend closing (or significantly reduce volume/route/means of transport available) 2 - Require closing (or prohibit most citizens from using it).
- **Stay at home requirements** records orders to “shelter-in- place” and otherwise confine to home with levels: 0 - No measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and ‘essential’ trips 3 - Require not leaving house with minimal exceptions (e.g. allowed to leave only once a week, or only one person can leave at a time, etc.).
- **Restrictions on internal movement** records restrictions on internal movement with levels: 0 - No measures 1 - Recommend not to travel between regions/cities 2 - internal movement restrictions in place.
- **International travel controls** records restrictions on international travel with levels: 0 - No measures 1 - Screening 2 - Quarantine arrivals from high-risk regions 3 - Ban on arrivals from some regions 4 - Ban on all regions or total border closure.
- **Public info campaigns** records presence of public info campaigns with levels: 0 -No COVID-19 public information campaign 1 - public officials urging caution about COVID-19 2 - coordinated public information campaign (e.g. across traditional and social media).
- **Testing policy** describing who can get tested by public health system with levels: 0 - No testing policy 1 - Only those who both (a) have symptoms AND (b) meet specific criteria (e.g. key workers, admitted to hospital, came into contact with a known case, returned from overseas) 2 - testing of anyone showing COVID-19 symptoms 3 - open public testing (e.g. “drive through” testing available to asymptomatic people).

2 Containment strategies and resembling patterns

Identification and codification of different measures undertaken by governments performed by University of Oxford results in 11 ordinal variables selected as lockdown policies. This sets up the necessity to analyze and to aggregate them in a synthetic way in order to find out whether specific combinations of those policies making up political strategies come out to have a resemblance pattern across countries.

Therefore, we performed a Principal Component Analysis based on the polychoric correlation. It allows to estimate the correlation between two theorised normally distributed continuous latent variables, from two observed ordinal variables. It has no closed form but it is estimated via MLE assuming the two latent variables follows a bivariate normal density.

The interpretation of the first three principal components (accounting for the 80% of total variance) appears to be clear (see Figure): the first one is closely related with freedom of movements and gathering restrictions together with information campaigns strategy, crucial in cases of draconian measures, the second one is related with the strategy of informing and testing the population, lastly the third one is related to informing and contact tracing the population. Summarizing, on one hand a first containment strategy aims at social distancing the entire population, on the other hand a second one aims at act locally and rapidly detect and isolate the positive cases, with two (alternative or complementary) tools: tracing contacts of infected and/or blanket population testing.

3 Containment strategies and resembling patterns

4 Effect of policies from a global perspective

Some countries have underestimated the dangerousness of the Coronavirus disease 2019 (COVID-19) and the importance of applying the containment measures. The little concern of some countries regarding the COVID-19 infectious disease is due to many and different reasons. Some countries decided to save the economy instead of people's lives as a method of responding to war; in this case, a pandemic war.

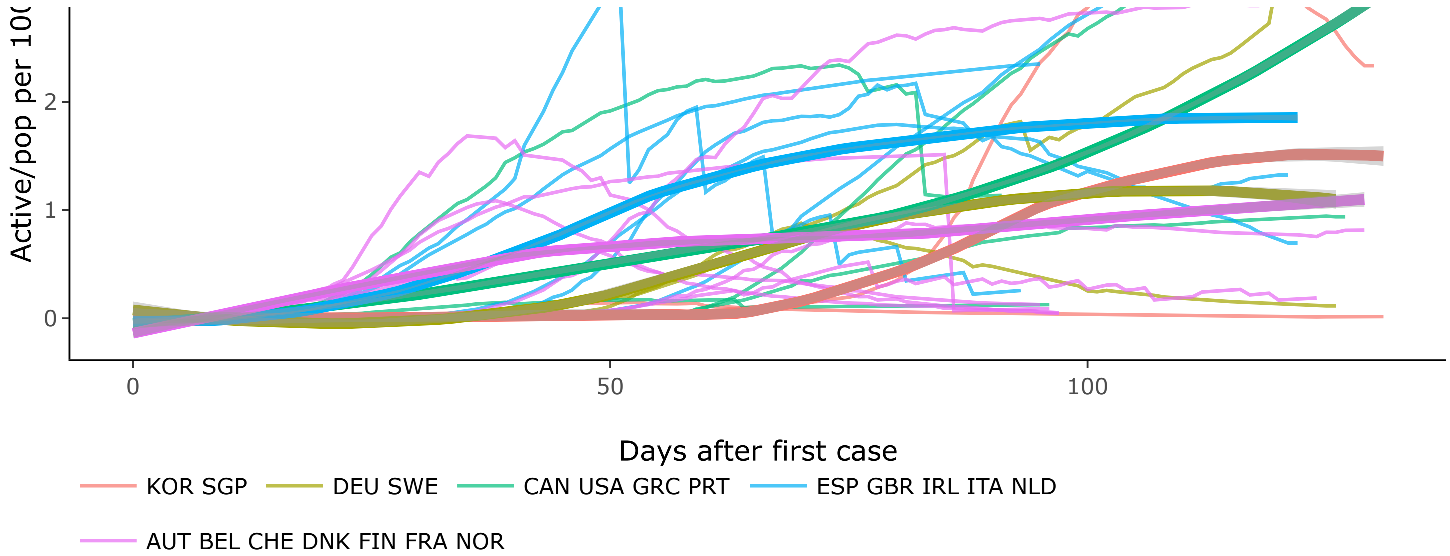
For that, we want to analyze which countries adopt the "optimal" policy measures to contain the contagion of COVID-19. Thanks to the Thomas et al. (2020) data sets, we know which actions each government took and when. The indicators of government response considered are 17 in total, which can be resumed in indicators of a lockdown/social distancing measures, contact tracing measures, movement restrictions, testing policy, public health measures, and governance and socio-economic measures.

In addition, some variables as the size of the population are considered from the World Bank Open Data (https://data.worldbank.org/) to have some additional covariates that can influence the variation in government responses to COVID-19.

We restrict the full range of responses to COVID-19 from governments around the countries analyzed in Section 3, i.e., Korea, Singapore, Germany, Canada, Sweden, Greece, Portugal, Spain, United States of America, Irland, United Kingdom, Italy, Netherlands, Austria, Switzerland, Finland, Norway, Denmark, and France.

The daily number of active persons is analyzed as a measure of the COVID-19 situation, i.e., the number of confirmed minus the number of deaths minus the number of recovered. Being a count variable, we decide to use a Negative Binomial Regression, also correcting for the possible overdispersion. Therefore, the hierarchical structure is induced by the nested structure of countries inside the clusters and by the longitudinal structure. For that, we decide to use a generalized mixed model with family negative binomial. The countriea, clusters, and date's information are supposed to be used as random effects in the model. The indicators from Thomas et al. (2020) and the demographic/economic/health variables from the World Bank Open Data (https://data.worldbank.org/) enter as fixed effect in the model.

So, the aim is to understand how the lockdown policies influence the number of active people. The observations are aligned concerning the first active case across the countries to have observations directly comparable from a longitudinal point of view. The following plot represents the number of active people during 131 days for each countries, and the corresponding mean value of the clusters.



The temporal variability between countries and clusters is clear, as confirmation about the decision to use the generalized mixed model.

4.1 Exploratory Analysis

The set of confounders considered in this analysis can be divided into three main areas:

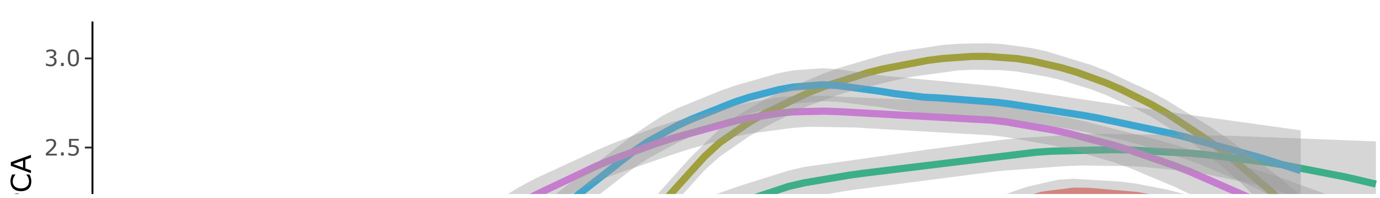
1. **Longitudinal economic** variables from Thomas et al. (2020);
2. **Longitudinal health system** variables from Thomas et al. (2020);
3. **Fixed demographic/economic/health variables** from the World Bank Open Data (https://data.worldbank.org/).

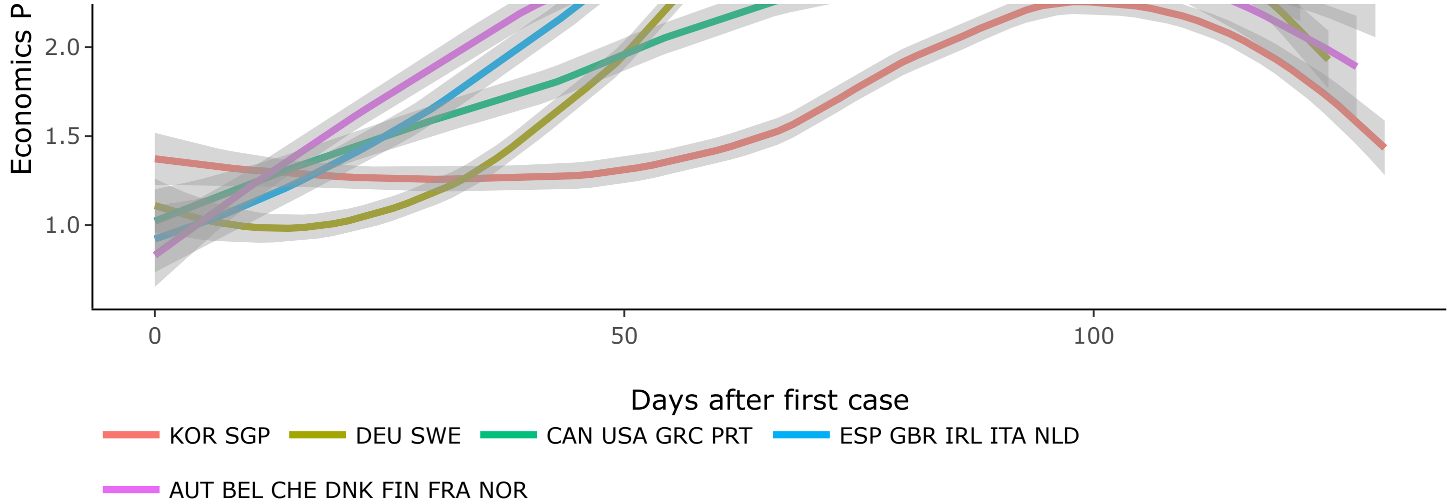
4.1.1 Longitudinal economic Variables | 4.1.2 Demographic/economic/health system fixed variables | 4.1.3 Longitudinal health system variables

We analyze four economic variables from Thomas et al. (2020):

Name	Measurement	Description
Income Support	Ordinal	Government income support to people that lose their jobs
Debt/contract relief for households	Ordinal	Government policies imposed to freeze financial obligations
Fiscal measures	USD	Economic fiscal stimuli
International support	USD	monetary value spending to other countries

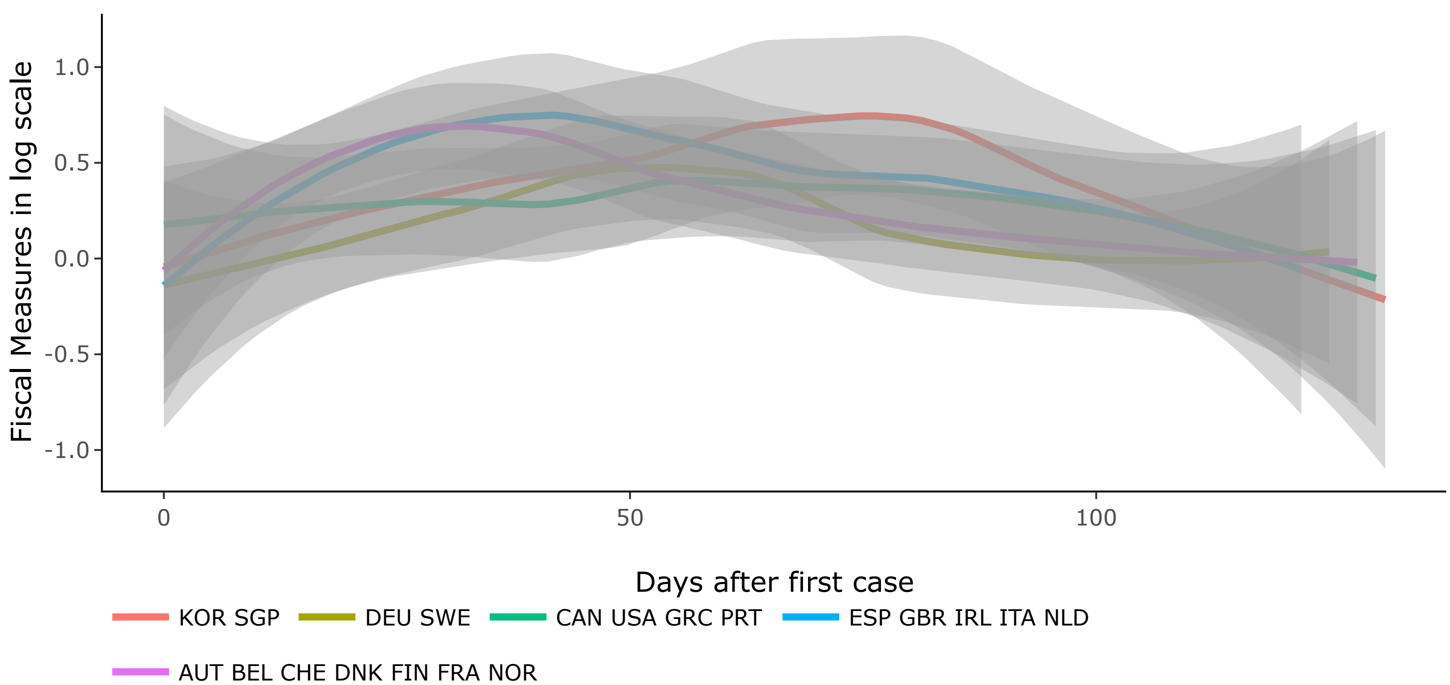
However, having 9 ordinal policies lockdown covariates, the two first economic variables are combined into one continuous variable using the Polychoric Principal Component Analysis, to diminish the number of covariates inside the model.

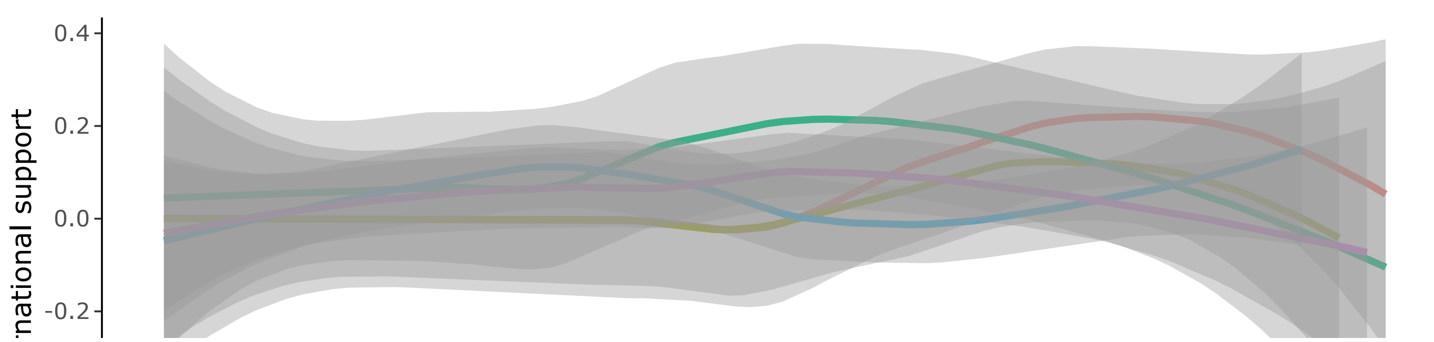


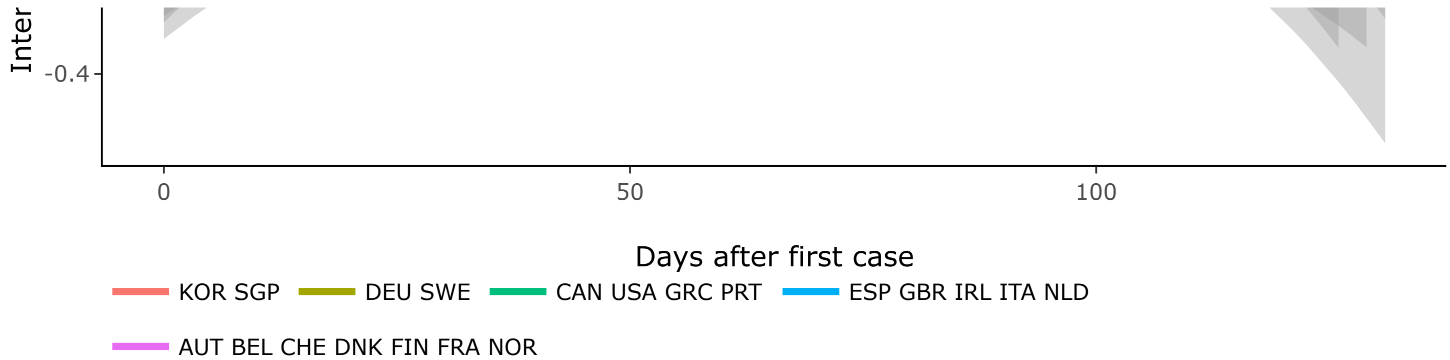


The Economic PCA has a temporal pattern, with more considerable variability near the last days of observations. Korea and Singapore's population received less money from the government than the other countries. The European ones are the best as financial support to society.

Therefore, the USD's two economic variables are examined and transformed into a logarithmic scale to de-emphasize large values.







The fiscal measure and international support variables have a large within-clusters variability. As we will see, these two variables will not enter into the final model.

For further details about the definition of the economic variables, please see the BSG Working Paper Series (https://www.bsg.ox.ac.uk/sites/default/files/2020-05/BSG-WP-2020-032-v5.0_0.pdf).

4.2 Model

The aim is to model the number of active people, i.e., confirmed - deaths - recovered, after 14 days, when the lockdown policies were applied. Therefore, the number of **active people lagged** to $t+14$ days, and an **offset term** representing the number of active people at time t are considered to analyze the influences of the restrictions imposed at time t on the number of active at time $t+14$.

The data has a **three-level structure**. The variability of the data comes from nested sources: countries are nested within clusters, and the observations are repeated across time, i.e., longitudinal data.

For that, the mixed model approach is considered to exploit the different types of variability coming from the hierarchical data structure. At first, the Intraclass Correlation Coefficient (ICC) is computed:

$$ICC_{date;active} = 0.0936 \quad ICC_{Countries;Active} = 0.4015 \quad ICC_{Clusters;Active} = 0.0951$$

Therefore, the 40.15% of the data's variance is given by the random effect of the countries, while the 9.36% by the temporal effect and 9.51% by the clusters effect. Therefore, the mixed model requires a random effect for the countries; the other two effects is selected using the conditional AIC.

The dependent variable is the number of active persons; therefore, a count data model is considered. To control the overdispersion of our data, the negative binomial regression with Gaussian-distributed random effects is performed using the glmmTMB R package developed by Brooks et al. (n.d.). Let n countries, and country i is measured at n_i time points t_{ij}. The active person y_{ij} count at time $t+14$, where $i=1,\dots,n$ and $j=1,\dots,n_i$, follows the negative binomial distribution:

$$y_{ij} \sim NB(y_{ij}|\mu_{ij},\theta) = \frac{\Gamma(y_{ij}+\theta)}{\Gamma(\theta)y_{ij}!} \cdot \left(\frac{\theta}{\mu_{ij}+\theta}\right)^{\theta} \cdot \left(\frac{\mu_{ij}}{\mu_{ij}+\theta}\right)^{y_{ij}}$$

where θ is the dispersion parameter that controls the amount of overdispersion, and μ_{ij} are the means. The means μ_{ij} are related to the other variables via the logarithm link function:

$$\log(\mu_{ij}) = \log(T_{ij}) + X_{ij}\beta + Z_{ij}b_i \quad b_i \sim \mathcal{N}(0,\psi)$$

where $\log(T_{ij})$ is the offset that corrects for the variation of the count of the active person at time t, and $\mathrm{E}(y_{ij}) = \mu_{ij}$, $\mathrm{Var}(y_{ij}) = \mu_{ij}(1+\mu_{ij}\theta)$ from Hardin and Hilbe (2018). The X_{ij} is the design matrix for the fixed effects, i.e., economic, demographic and health variables, and β the corresponding set of fixed parameters. In the same way, Z_{ij} is the design matrix describing the random effect regarding the countries and the date, and b_i the corresponding parameter.

After some covariates selection steps and random effects selection, the final model returns these estimations for the fixed effects:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.012	0.326	-0.035	0.972
pca_EC	-0.547	0.070	-7.791	0.000
pop_density_log	0.103	0.031	3.354	0.001
pca_hs	0.053	0.020	2.607	0.009
workplace_closingF1	-0.290	0.138	-2.108	0.035
workplace_closingF2	-1.191	0.134	-8.902	0.000
workplace_closingF3	-0.513	0.170	-3.021	0.003
gatherings_restrictionsF1	-0.506	0.162	-3.120	0.002
gatherings_restrictionsF2	-1.259	0.141	-8.945	0.000
gatherings_restrictionsF3	-1.519	0.173	-8.804	0.000
gatherings_restrictionsF4	-1.702	0.179	-9.513	0.000
transport_closingF1	-0.056	0.106	-0.527	0.598
transport_closingF2	-0.501	0.198	-2.529	0.011
stay_home_restrictionsF1	-0.057	0.109	-0.528	0.598
stay_home_restrictionsF2	-0.111	0.148	-0.751	0.453
stay_home_restrictionsF3	-0.824	0.292	-2.826	0.005
testing_policyF1	0.216	0.091	2.376	0.017
testing_policyF2	0.558	0.113	4.945	0.000
testing_policyF3	1.349	0.158	8.544	0.000
contact_tracingF1	0.196	0.083	2.369	0.018
contact_tracingF2	0.360	0.095	3.784	0.000
ClustersCl2	1.461	0.173	8.454	0.000
ClustersCl3	1.955	0.158	12.377	0.000
ClustersCl4	2.365	0.148	16.029	0.000
ClustersCl5	2.403	0.159	15.122	0.000

while the variance for the random effects are equals:

	Variance
Country	0.283
Date	4.320

We drop off the random effect associated with the Clusters having low variability, and the conditional AIC equals the one computed without the variable Clusters as a random intercept.

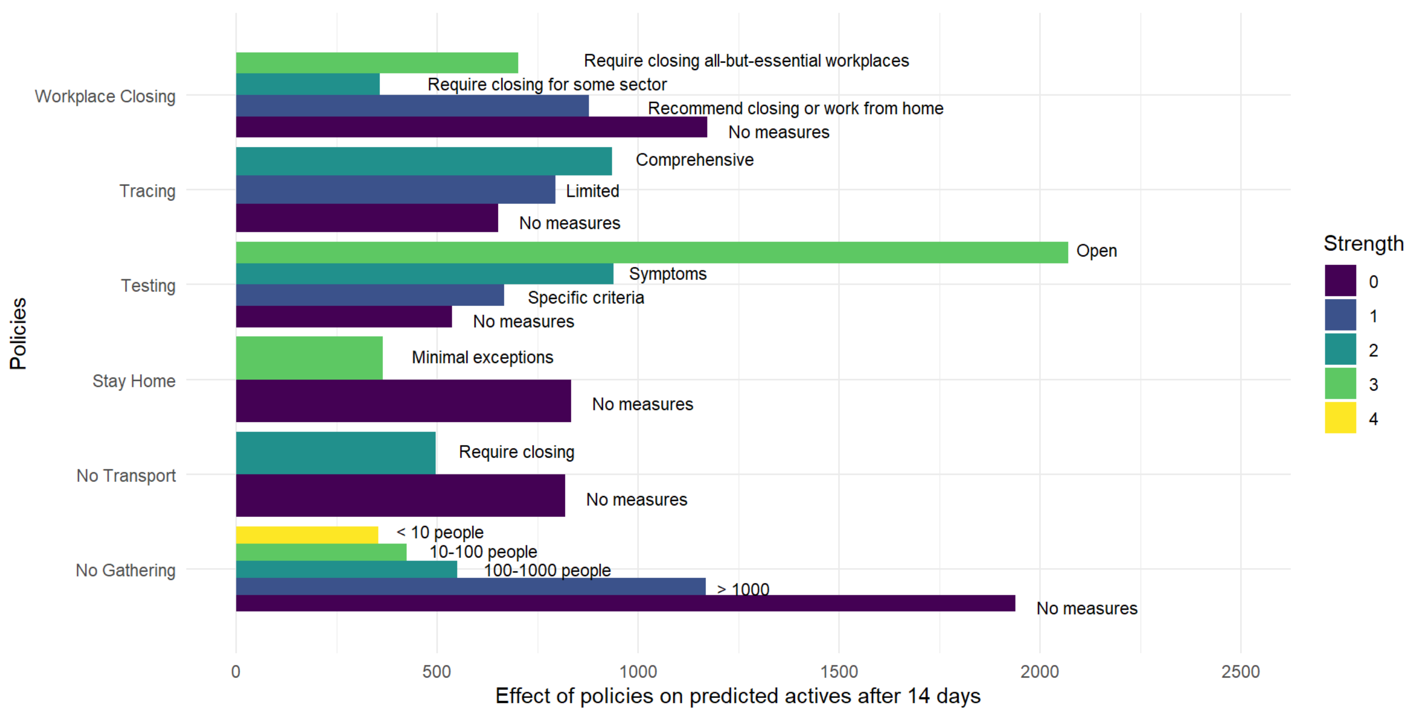
The marginal R^2, i.e., the variance explained by the fixed effects, equals 0.28, while the conditional one, i.e., the variance explained by the entire model, including both fixed and random effects, equals 0.89 considering the lognormal approximation Nakagawa and Schielzeth (2013).

Therefore, the model seems correctly formulated. We will analyze the effects related to the following variables:

1. The fixed effect of the lockdown policies;
2. The fixed effect of the clusters;
3. The fixed effect of the combination of lockdown policies and clusters;
4. The random effect of the countries;

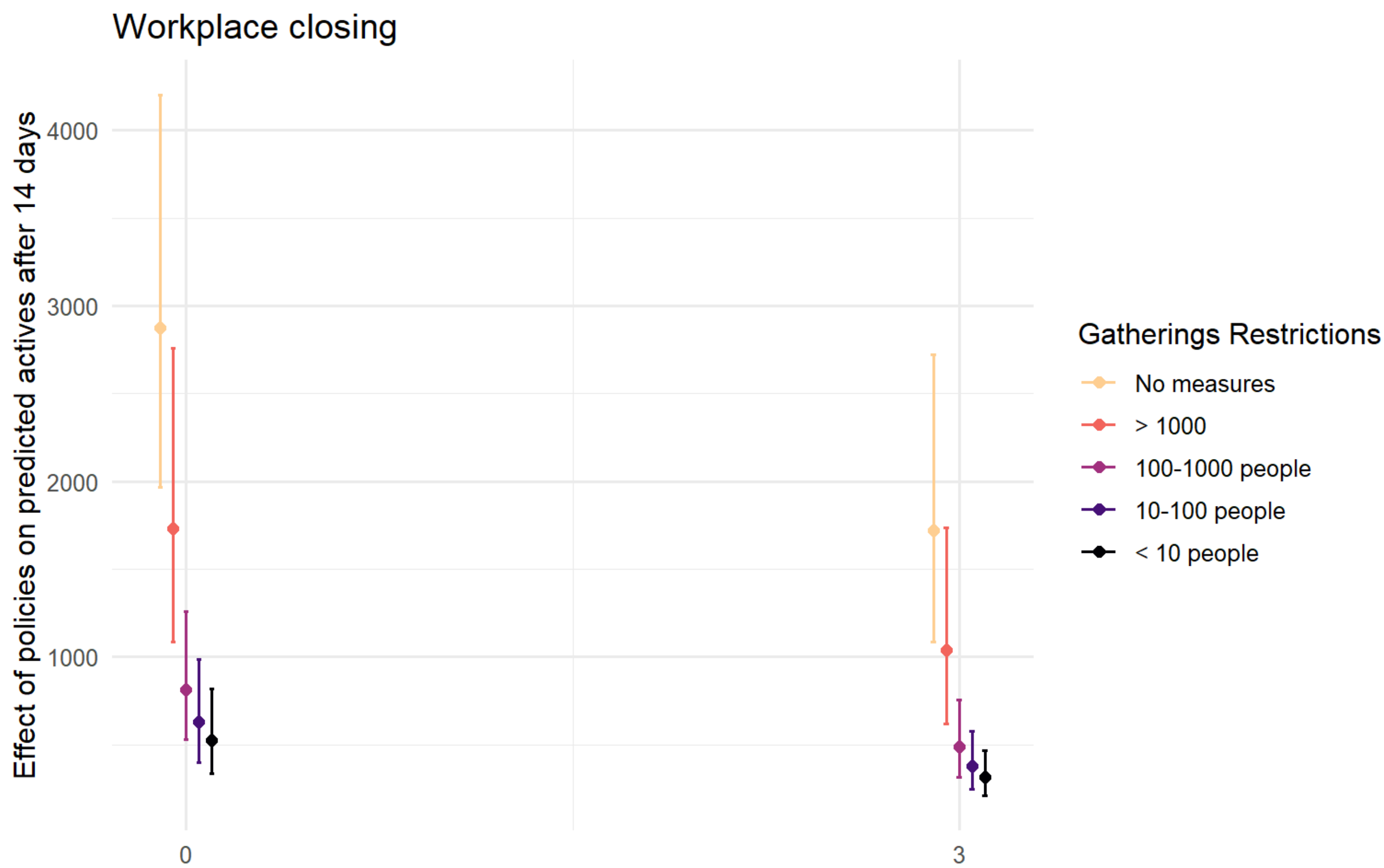
4.2.1 LOCKDOWN POLICIES | 4.2.2 CLUSTERS | 4.2.3 INTERACTION LOCKDOWN POLICIES AND CLUSTERS | 4.2.4 COUNTRIES

In the following plot, we can see the effect of lockdown policies on predicted actives after 14 days.



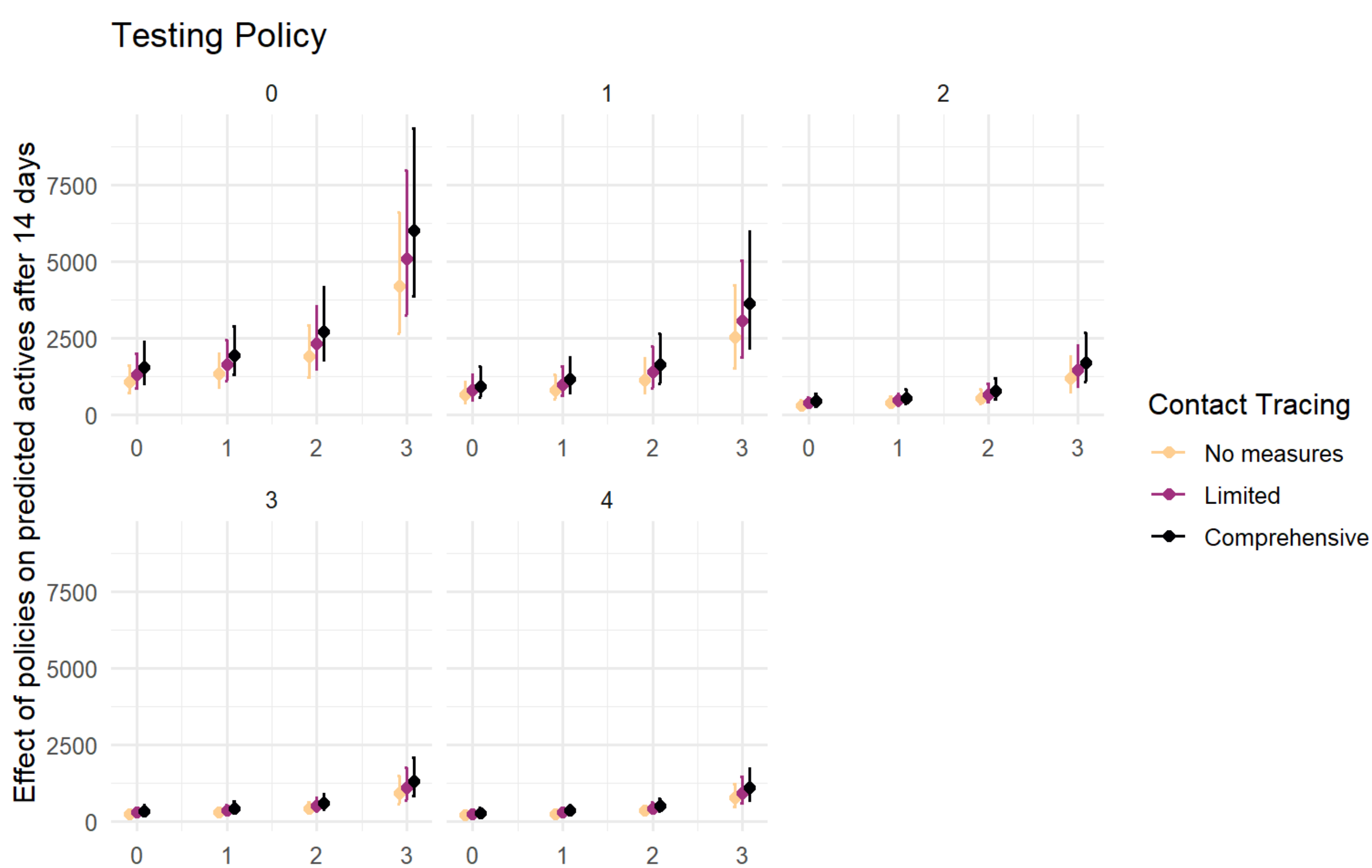
We can note that in general, the strong lockdown policies work respect to impose no measure. For example, if the government prohibits most citizens from using it, the number of active people diminishes around 39.4% respect to imposing no public transport measures. Also, we can note that weak gatherings restrictions still work concerning impose no action. For example, restrictions on gatherings between 100-1000 people diminish the number of active persons around 71.62%. However, we can see a reverse situation analyzing the effects regarding the variables describing the testing and tracing policies. Probably, strong testing and tracing policies lead to discovering more infected people.

The following plot represents the effects of two policies, i.e., workplace closing and gatherings restriction, on predicted active people 14 days after applying these policies.



The combination of gatherings restrictions and workplace closing works, the number of actives decreases, also if the weak limit on reunion is applied.

In the same way, the following plot represents the effects of the combination of tracing and testing policies.



These two policies lead to an increase in the number of active people recorded.

4.3 To sum up

1. Lockdown policies work! respect to impose no measure in general;
2. Weak gatherings restrictions still work, i.e., restrictions on gatherings between 100-1000 people;
3. Strong Testing and Tracing policies lead to discovering more infected people;
4. Korea and Singapore are the best countries that acted properly;
5. Sweden, Germany, Portugal, and Greece better than the other UE countries;
6. The USA, and Canada better than the other UE countries except for Sweden and Germany.

5 Italian lockdown and regional outcomes

6 Supplementary materials

All the codes used for this analysis is available on Github (https://github.com/angeella/Lockdown_policies_COVID19). The report was written by rmarkdown, fully reproducible. You can find the rmakrdown file in Github (https://github.com/angeella/Lockdown_policies_COVID19/Report).

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1. https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data (https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data)↩
2. https://github.com/OxCGRT/covid-policy-tracker (https://github.com/OxCGRT/covid-policy-tracker)↩